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Accounting for Electric Vehicles in Air Quality Conformity–Final Report

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16. Abstract

Electric vehicles (EVs) obtain at least a part of the energy required for their propulsion from electricity. The market for EVs, including hybrid, plug-in hybrid, and battery electric vehicles continues to grow, as many new and affordable models have become available in recent years. The proliferation of EVs in the vehicle fleet has implications for energy use and emissions. The mobile source (vehicle exhaust) emissions component is of particular relevance to transportation agencies, especially those in nonattainment and attainment maintenance areas that need to meet transportation conformity requirements. This report presents a framework to incorporate EVs into mobile source emissions estimations. The framework uses the United States Environmental Protection Agency's Motor Vehicle Emissions Simulator (MOVES) model. It integrates EV driving characteristics, emissions rates, and market penetration information into a MOVES-based emissions inventory analysis. Vehicle activity data collection and drive schedule development, along with in-use emissions measurements, were conducted for a sample of EVs in Texas. Additionally, market penetration scenarios were developed using a consumer choice model. The collected data and market penetration scenarios were then used in the framework to conduct a pilot application for a large county in Texas. The pilot application demonstrated successful use of the framework and showed that including EVs in emissions analyses can potentially have an impact on the overall analysis results specifically for future years.

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LIST OF ABBREVIATIONS

ABM	Agent-Based Method
AEO	Annual Energy Outlook
ANL	Argonne National Laboratory
AVID	Advanced Vehicle Introduction Decision
BEV	Battery Electric Vehicle
CAA	Clean Air Act
CARB	California Air Resources Board
CD	Charge Depletion
CO_2	Carbon Dioxide
CO	Carbon Monoxide
CS	Charge Sustaining
CV	Conventional Vehicle
DMV	Department of Motor Vehicles
DOE	Department of Energy
EERF	Environmental and Emissions Research Facility
EPA	Environmental Protection Agency
EPRI	Electric Power Research Institute
EV	Electric Vehicle
FHWA	Federal Highway Administration
GCV	Gasoline Conventional Vehicle
GHG	Greenhouse Gas
GIS	Geographic Information System
GPS	Global Positioning System
GREET	Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation
HC	Hydrocarbon
HEV	Hybrid Electric Vehicle
HGB	Houston-Galveston-Brazoria
ICE	Internal Combustion Engine
I/M	Inspection and Maintenance
IRB	Institutional Review Board
LA	Los Angeles
LDV	Light-Duty Vehicle

MA^3T	Market Acceptance of Advanced Automotive Technologies
MOVES	Motor Vehicle Emission Simulator
NA	Nonattainment
NEDC	New European Driving Cycle
NO_x	Nitrogen Oxide
NRDC	National Resources Defense Council
OBDII	On-board Diagnostics
OpMode	Operating Mode
ORNL	Oak Ridge National Laboratory
PEMS	Portable Emissions Measurement System
PEV	Plug-in Electric Vehicle
PHEV	Plug-in Hybrid Electric Vehicle
PM	Particulate Matter
R&D	Research and Development
SIP	State Implementation Plan
SO_2	Sulfur Dioxide
SUT	Source Use Type
SUV	Sport Utility Vehicle
TAMUS	Texas A&M University System
TDM	Travel Demand Model
THC	Total Hydrocarbons
TTI	Texas A&M Transportation Institute
TxDOT	Texas Department of Transportation
TxLED	Texas Low Emission Diesel
UDDS	Urban Dynamometer Driving Schedule
US	United States
USEPA	United States Environmental Protection Agency
VMT	Vehicle Miles Traveled
VSP	Vehicle-Specific Power

EXECUTIVE SUMMARY

Electric vehicles (EVs), including hybrid, plug-in hybrid, and battery electric vehicles, differ from conventional gasoline vehicles in that they obtain at least a part of the energy required for their propulsion from electricity. These vehicles have become more accessible to the public in recent years, as many new and affordable models have entered the market. Additionally, infrastructure to support the use of electric vehicles continues to grow, further increasing their popularity.

The increase in EVs in the vehicle fleet has an impact on energy consumption and emissions. EVs have the potential for higher energy efficiencies and lower tailpipe emissions when compared with conventional internal combustion engine vehicles. However, there is limited research on the emissions implications of increased EVs in the vehicle fleet. In the case of plug-in electric vehicles (plug-in hybrids and battery electric vehicles), the energy and emissions associated with the electricity needed to charge the vehicle batteries also need to be considered.

The main goals of this research were to study the implications of EVs in terms of mobile source emissions and to develop an approach for incorporating EVs into emissions estimation procedures. This is a topic of significance to transportation planning agencies, especially those in nonattainment and attainment maintenance areas needing to meet transportation conformity requirements. The research team focused on the Texas context, keeping in mind the current practices of conducting regional emissions analyses using the United States Environmental Protection Agency's (USEPA) Motor Vehicle Emission Simulator (MOVES) mobile source emissions model.

As a first step, the research team conducted a literature review covering key topics related to the EV market, future market penetration scenarios, and EV impacts on air quality and emissions. The research team then conducted an extensive vehicle activity data collection exercise from a sample of EVs in major Texas metropolitan areas. Researchers used these data to develop representative Texas-specific electric vehicles drive schedules. In-use emissions testing of EVs was conducted using portable emissions measurements systems to obtain operating-mode-based emissions rates, which were combined with the drive schedules to obtain distance-based emissions rates for each type of EV by speed bin and road class. Additionally, a set of Texas-specific market penetration scenarios were developed through the application of a consumer choice model.

A framework was then developed to incorporate the EV parameters (region-specific EV driving characteristics, emissions rates, and market penetrations) into a MOVES-based emissions inventory analysis. The Texas-specific data and market penetration scenarios were then used to conduct a pilot application for Harris County, Texas. The pilot application demonstrated successful use of the framework and investigated the impact of incorporating EVs on the modeled on-road exhaust emissions of criteria pollutants or their precursors as well as greenhouse gases.

In conclusion, this research provided an overview of electric vehicles, the factors affecting the market penetration of EVs, and the implications for air quality, specifically mobile source emissions. Texas-specific data on EV activities and emissions were also collected, and a framework was developed to allow transportation agencies to estimate EVs' impacts on mobile source emissions. The intent of the framework is to be flexible and practical, and it uses a MOVES-based emissions inventory process that is familiar to transportation agencies involved with air quality and mobile source emissions issues.

CHAPTER 1: INTRODUCTION

BACKGROUND

Electric vehicles (EVs), also sometimes termed *electrified vehicles*, refer broadly to vehicles that obtain at least a part of the energy required for their operation from electricity. In this research, EVs were defined as including hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), and battery electric vehicles (BEVs). According to the Bureau of Transportation Statistics and the Alternative Fuel Data Center, EVs accounted for 7.5 percent of annual new passenger car sales and 0.3 percent of annual new passenger truck sales in 2013 (*1*,*2*). With many new and affordable models coming into the market and an increasing availability of supporting infrastructure, it is expected that the number of EVs in the vehicle fleet will continue to grow in the future.

By obtaining part or all of the energy needed for propulsion from electricity, EVs can potentially achieve higher energy efficiencies and result in less exhaust emissions when compared with conventional vehicles (CVs) powered solely by internal combustion engines. However, there is limited research on the emissions implications of increased EVs in the vehicle fleet. Depending on the type of vehicle, the emissions that need to be considered include vehicle exhaust (tailpipe) emissions as well as the emissions associated with the electricity generation used for the charging of vehicle batteries in the case of plug-in hybrid and battery electric vehicles.

From the perspective of transportation agencies, the mobile source emissions component of (vehicle) exhaust emissions is particularly relevant, especially in nonattainment and attainment maintenance areas that need to meet transportation conformity requirements. These agencies have an interest in better understanding and quantifying the emissions and air quality implications of increasing EVs in the vehicle fleet, and understanding what it means for transportation and air quality conformity.

The United States (US) Environmental Protection Agency's (EPA's) mobile source emissions estimation model—Motor Vehicle Emission Simulator (MOVES)—forms the basis for conformity analyses, state implementation plan (SIP) development, and other mobile source emissions estimations conducted in Texas and much of the United States. The current state of the practice in the use of MOVES does not account for electric vehicles with regard to location-specific driving characteristics, emissions rates, and market penetration. However, MOVES provides a platform and has the flexibility to accurately incorporate these aspects into emissions estimations. Therefore, there is an opportunity to develop methods and approaches by which EVs can be accurately incorporated into mobile source emissions estimations, including the transportation conformity analysis framework.

RESEARCH GOALS AND APPROACH

The main goals of this research were to study the implications of EVs in terms of mobile source emissions, and to develop an approach for incorporating EVs into emissions estimation procedures, including regional emission inventories. The focus was on the Texas context, and the research addressed emissions of criteria pollutants and their precursors, including nitrogen oxide (NO_x), hydrocarbons (HCs), and carbon monoxide (CO), as well as greenhouse gases, i.e., carbon dioxide (CO_2).

This research covered three types of EVs: hybrid electric vehicles, plug-in hybrid electric vehicles, and battery electric vehicles. HEVs, such as the Toyota Prius, are vehicles that employ both an internal combustion engine and an electric motor to provide propulsion. The electricity source for HEVs is from regenerative braking, which is used to recharge the vehicle batteries. PHEVs, such as the Chevrolet Volt, are powered partly by batteries that are recharged by plugging into the electric grid and partly by an alternative energy source such as an internal combustion engine. BEVs, such as the Nissan Leaf, rely solely on electricity from the power grid (stored in batteries) to provide propulsion. PHEVs and BEVs are also often collectively termed plug-in electric vehicles (PEVs), as both types of vehicles can be charged by plugging into a power outlet.

Therefore, while PHEVs and BEVs operating on battery power alone do not contribute to mobile source emissions, these vehicles indirectly generate emissions through the electricity generation needed to power PEVs. While the electricity generation component and associated emissions were not a focus of this project, the broader policy questions arising due to this issue are briefly covered in this report.

This project was conducted through several distinct activities, as shown in Figure 1. The initial stages of the project included two parallel tracks. The first focused on gathering background information and conducting a literature review on key topics, followed by developing Texas-specific EV market penetration scenarios. The second track focused on data collection for EVs in Texas. This included the collection of real-world activity data to establish driving characteristics, through development of drive schedules, as well as measurement of EV exhaust emissions rates using a portable emissions measurement system (PEMS). The research team then established an analytical framework to incorporate EV market penetration information along with EV driving characteristics and emissions rates into a MOVES-based analysis framework. A pilot application was then conducted to demonstrate the use of the framework and to establish the project's findings and conclusions.

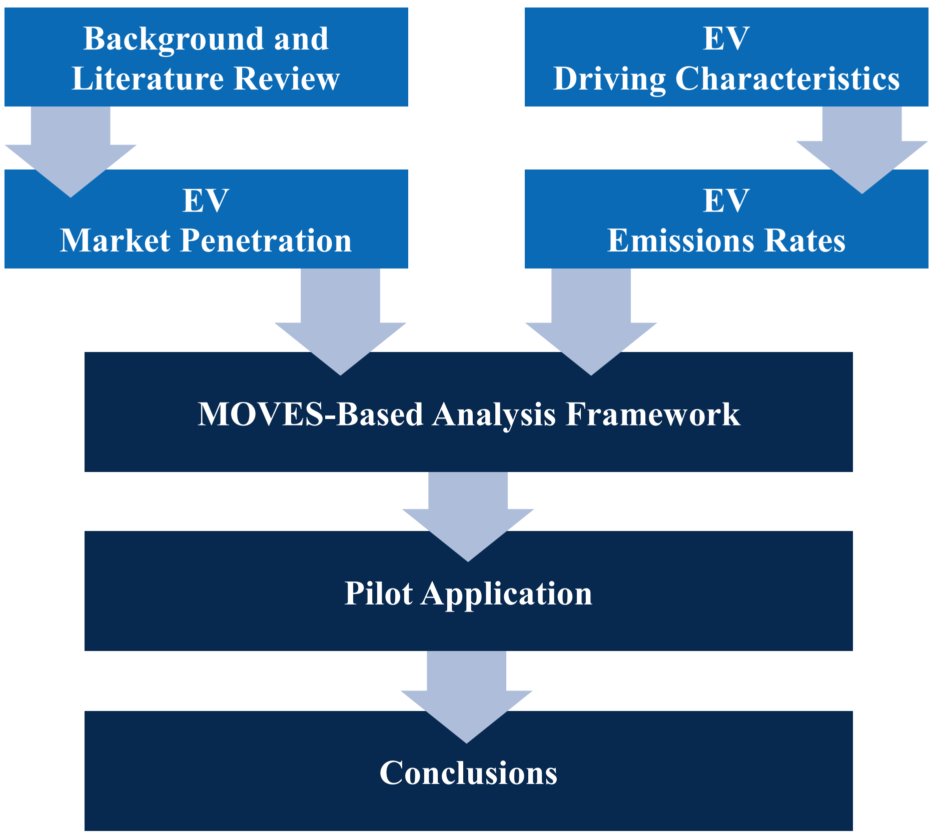


Figure 1. Work Plan Flow Diagram.

REPORT OUTLINE

Following this introductory chapter, Chapter 2 provides a review of current literature and the state of the practice with regard to the market for EVs, their emissions impacts, and other related studies. In addition, different methods for predicting EV market penetration are presented, including a vehicle consumer choice model used for the pilot application described in

Chapter 4. Chapter 3 then discusses the development of distance-based EV emissions rates using Texas-specific EV drive schedules (obtained through collection of vehicle activity data) and in-use measurements of EVs' emissions rates under real-world driving conditions. Chapter 4 describes the framework developed to incorporate EVs into a MOVES-based analysis and presents the results for the pilot application conducted for Harris County, Texas. Chapter 5 offers concluding remarks and identifies possible directions for future research.

CHAPTER 2:
BACKGROUND AND STATE OF THE PRACTICE

The research team reviewed available literature and conducted a state-of-the-practice assessment on several topics related to electric vehicles. Specifically, the literature review presented in this chapter focuses on the background of electric vehicles in the US market, the factors that influence market penetration, and those studies related to the emissions impacts of electric vehicles, including HEVs, PHEVs, and BEVs.

ELECTRIC VEHICLES IN THE UNITED STATES

The history of electric vehicles in the US goes back over a hundred years; EVs outsold all other types of cars between 1899 and 1900 (*3*). Electric vehicles had many advantages over their competitors in the early years, as they did not have the vibration, smell, and noise associated with gasoline cars. Electric vehicles enjoyed success into the 1920s with production peaking in 1912. However, after the 1920s, the proliferation of internal combustion engine (ICE) vehicles led to the decline of electric vehicles. ICE vehicles allowed for longer ranges of travel, and the affordable price of gasoline further helped increase their popularity. Electric vehicles almost disappeared from the market by 1935 but were brought back into market in the 1960s and 1970s due to concerns regarding conventional vehicles' tailpipe emissions, as well as concerns regarding US dependence on imported oil.

Several legislative and regulatory actions have renewed electric vehicle development efforts in recent years. These include national-level legislation such as the 1990 Clean Air Act Amendments and the 1992 Energy Policy Act, as well as state-level actions such as the regulations issued by the California Air Resources Board (CARB) on greenhouse gas emissions and several states' zero-emission vehicle requirements (*4*). The Big Three automobile manufacturers (General Motors [GM], Ford, and Chrysler) and the Department of Energy (DOE), as well as a number of vehicle conversion companies, are actively involved in electric vehicle development through the Partnership for a New Generation of Vehicles (*5*). Tesla Motors Inc. is a well-known electric vehicle company in the US, and their Tesla Roadster was introduced in 2008. According to USEPA, the Roadster can travel 244 mi (393 km) on a single charge (*6*). Starting in 2000, car manufacturers began to develop and offer hybrid and electric vehicles to individual consumers. The most popular among these is the Toyota Prius (an HEV), which had sold more than 3 million vehicles around the world by July 2013 (*7*).

As mentioned previously, the focus of this project was on three categories of EVs currently available in the market—HEVs, BEVs, and PHEVs. The project focused on light-duty vehicles (LDVs) because it is expected that for the short and medium term, the EV market will be almost exclusively light-duty vehicles. This is consistent with the Energy Information Administration's Annual Energy Outlook (AEO) forecasts, which focus exclusively on light-duty EVs, noting that they have the most significant impact on future fleets (*8*). Table 1 outlines the characteristics of the different types of EVs based on various literature sources (*5,6,8,9,10*). Table 2 shows a list of the currently available and future/upcoming models as of August 2014.

Table 1. Electric Vehicle Characteristics.

Type	HEVs	PHEVs	BEVs
Propulsion	• Electric motor drives • ICE	• Electric motor drives • ICE	• Electric motor drives
Energy system	• Battery • Ultracapacitor • ICE generating unit	• Battery • Ultracapacitor • ICE generating unit	• Battery • Ultracapacitor
Energy source & Infrastructure	• Gasoline stations	• Electric grid charging facilities • Gasoline stations	• Electric grid charging facilities
Characteristics	• Low emissions at tailpipe and higher fuel economy compared with ICE vehicles • Dependence on crude oil • Higher cost compared with ICE vehicles • Increase in fuel economy and decrease in emissions depending on the power level of motor and battery as well as driving cycle • Commercially available	• Very low emissions at tailpipe • Higher fuel economy compared with ICE vehicles • Higher cost compared with ICE vehicles • Increase in fuel economy and decrease in emissions depending on the power level of motor and battery as well as driving cycle • Commercially available	• Zero emissions at tailpipe • High energy efficiency • No dependence on crude oils • Limited driving range • High initial cost • Commercially available
Major issues	• Multiple energy sources' control, optimization, and management	• Multiple energy sources' control, optimization, and management • Battery sizing and management	• Battery and battery maintenance • Charging facilities

Table 2. Electric Vehicle Models on the Market.

	HEVs	PHEVs	BEVs
Currently Available	Honda Insight, Civic Hybrid, Toyota Prius, Camry Hybrid, Ford Fusion Hybrid, Mercedes-Benz ML450 Hybrid	BMW i8, Cadillac ELR, Chevy Volt, Fisker Karma, Toyota Plug-In Prius, Ford C-Max Energi, Ford Fusion Energi, Honda Plug-in Accord	BMW-i3, Chevrolet Spark, Coda Automotive, Fiat 500e, Ford Focus, Ford Azure Transit Connection, Honda Fit, Kia Soul, Mercedes-Benz B-Class, Mitsubishi i-MiEV, Nissan Leaf, Scion iQ EV, Smart ForTwo, Tesla Model S, Tesla Roadster, Toyota RAV 4 EV, Wheego LiFe
Future/Upcoming	Infiniti Etherea, Subaru Tourer, Fisker Nina, Lexus LC 600h	Fisker Surf, Volvo V60.2, VIA Motors VTrux, Porsche Panamera S E-Hybrid	BYD Auto e6 and VIA Electric Truck, Smart ED, BMW ActiveE

FACTORS INFLUENCING EV ADOPTION

Since electric vehicle models have been increasingly introduced into the market, the sales of electric vehicles have increased significantly in recent years. Hybrid vehicles are the fastest-growing segment of the light-duty vehicle market. The number of registered HEVs in the US grew to nearly 2 million in 2012, and nine of the 10 most fuel-efficient vehicles in the market today are EVs. Virtually all major vehicle manufacturers and several start-up companies are offering or are planning to offer plug-in electric vehicles or battery electric vehicles for sale in the US market. The major factors influencing EV market penetration could be categorized as energy cost, battery cost and capacity, charging infrastructure, and government policies.

The unpredictability of gasoline prices and energy costs can impact the EV market penetration. As gasoline prices rise, EVs can be considered an economical option for consumers. HEVs and PHEVs offer significant reductions in fuel usage, which cuts consumers' fuel cost, and BEVs eliminate fuel usage at the pump entirely because they rely solely on a battery for propulsion. Therefore, the cost of fuel can directly impact the future market of plug-in electric vehicles.

The future market penetration of plug-in electric vehicles also depends on the advancement of technology and improvements in plug-in electric vehicle battery technology. The majority of electric vehicles use lithium-ion batteries because of their high power and energy density characteristics. However, lithium batteries have limited life cycles that can increase the costs of vehicle ownership over time. Most automotive manufacturers are planning for a 10-year battery life span, including expected degradation. Therefore, consumers expect to face replacement costs for batteries after 10 years of driving. Another limitation related to PHEVs and

BEVs is the driving range, particularly for BEVs. Currently, BEVs have shorter ranges per charge than most conventional vehicles have per tank of gasoline. BEV batteries usually have a target range of 100 mi, which according to the Federal Highway Administration (FHWA) accounts for 90 percent of all household vehicle trips in the United States (*11*). Assuming that the battery weighs around 250 kg—about 20 to 25 percent of the total weight of typical small cars—then the battery would give a range of 190 mi in the next 10 years, which is still less than conventional vehicles' average travel range of 312 mi.

The development of a charging infrastructure can greatly influence consumers' decisions on PHEV/BEV investments and, hence, heavily impact the market penetration of PHEVs and BEVs. Major recharging options include recharging at home, recharging at commercial properties (such as shopping centers, schools, etc.), and exchanging depleted batteries with fully charged ones (*12*). Government and private sectors have been developing charging stations to satisfy demand from electric vehicle users. Pike Research estimated that 1.5 million charging stations will be available in the US by 2017 (*13*). Many studies have shown that the number of charging stations per vehicle and the cost of building each station are key determinants of the adoption rates of EVs (*4,5,10,12,13*).

Government policies are another important factor that influence EV adoption. Examples of government policies promoting EV adoption include providing financial incentives to new EV purchasers, funding research aimed at reducing battery production costs, enforcing more stringent emissions standards on vehicles, and giving EVs access to high occupancy vehicle lanes. In the US, the federal government currently is providing tax credits up to $7500 to PHEV and BEV owners (*14*). CARB has also established the Clean Vehicle Rebate Project to promote zero-emission vehicles, which include neighborhood electric, battery electric, plug-in hybrid electric, and fuel cell vehicles and trucks (*15*). The US Department of Energy allocated funds from the American Recovery and Reinvestment Act of 2009 to support and develop more efficient and cheaper batteries (*16*). Furthermore, EPA has increased its regulation of the use of carbon-intensive fuels in transportation and intends to increase regulation of fossil fuels in the electricity generation mix (*9*).

Given the above-discussed factors that influence EV adoption, predicting future EV market penetration is a task involving complex processes and uncertainties. The following section summarizes the most common methods of predicting EV market penetration based on the literature review.

ELECTRIC VEHICLES' MARKET PENETRATION

Many research institutes, government agencies, and non-governmental organizations have studied electric vehicles' market penetration and developed scenarios and prediction models based on the factors discussed in the previous section. Among those studies, the electric vehicle market penetration scenario set developed in the US Department of Energy's Annual Energy Outlook is one of the most cited references. In the AEO 2012 report, a projection of EVs' annual sales was provided for the years 2011 to 2035 (*8*). As Figure 2 shows, it is predicted that by 2035, annual sales of HEVs, PHEVs, and BEVs in the US will increase to about 720,000, 190,000, and 90,000, respectively.

In a summary report prepared by Indiana University, the researchers summarized various projections based on six major global consulting groups' reports (*17*). The projections from the consulting groups suggested that PHEVs' new vehicle sales would account for 2 percent to 5 percent of all new vehicles by 2020, and 5 percent to 9 percent by 2030. The BEVs' share of new vehicle sales is also expected to increase, from 1 percent to 3 percent by 2020 to 8 percent to 10 percent by 2030 (*17*).

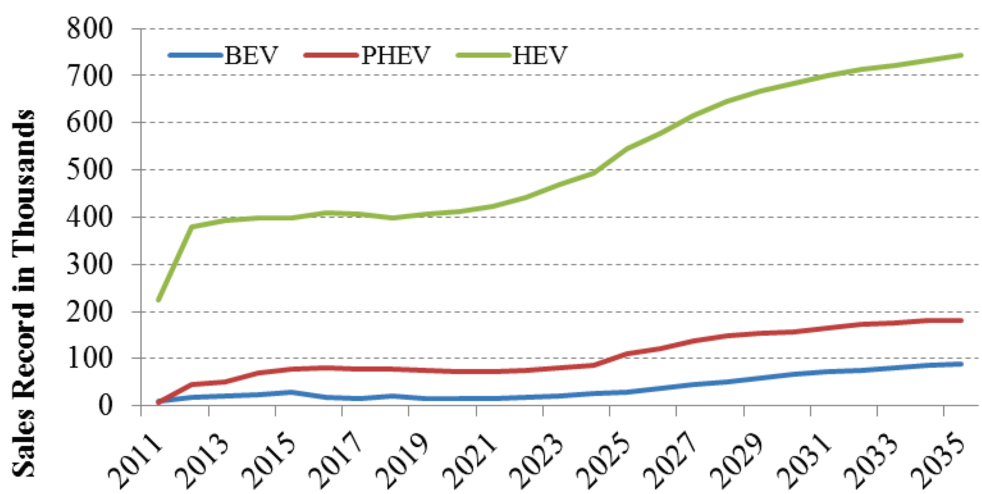


Figure 2. Prediction of HEV, PHEV, and BEV Sales for 2011–2035 (*17*).

Market Penetration Forecasting Methods

This section will describe the various models commonly used by national labs, universities, and industry to forecast market penetration scenarios for PHEVs, HEVs, and BEVs. These methodologies include the agent-based method, consumer choice method, diffusion rate/time series method, and other methods.

Agent-Based Method

The agent-based method (ABM) is a computer-based approach that simulates the actions and interactions of defined agents to assess their impact on a marketplace. ABM is widely used to anticipate shifts and evolving trends in the automotive sector, including the introduction of more sustainable automotive products into the marketplace (*18*). The agents can be defined as individuals or organizations. Hence, the method is aptly suited to represent the interactions of a diverse and varied population of consumers, manufacturers, regulators, and fuel producers and to understand their impact on an evolving marketplace. ABM vehicle technology market forecasting studies have defined different agents that operate in the modeling environment, such as consumers, automakers, policymakers, and fuel suppliers (*19*).

Sullivan et al. used ABM and found that under a scenario with no federal subsidies, the PHEV fleet penetration rate would be insignificant, with PHEVs having less than 1 percent of the market over 10 years. A scenario with an active federal policy including a combination of tax rebates, PHEV subsidies, and sales tax exemptions could enable a significant increase in the penetration rate of the PHEV technology. Under more active policy scenarios, PHEVs are estimated to reach 4 to 5 percent of sales by 2020 (*20*). The authors noted that the results from the study depend on many parameters, such as consumer behavior and the turnover rate at which consumers replace their cars. The results also showed that a PHEV fleet penetration rate of 18 percent would reduce gasoline consumption by 20 percent and decrease fossil carbon emissions by the same approximate amount.

Sikes et al. used the same method in their study and found the projected PHEV fleet penetration would range from 2.5 percent to 4 percent for the period from 2015 to 2020 (*21*). Sikes et al. assumed that the new technology penetrations and policy conditions would largely influence the PHEV market penetration. The study also showed that lower vehicle sticker price would allow PHEVs to be more cost competitive with HEVs and that the HEV market penetration increases under assumptions of lower incremental costs or higher conventional vehicle operation costs. The study did not provide HEV sales projections for future market penetration.

Eppstein et al. developed an ABM-based model to estimate the adoption rate of PHEVs and HEVs using one individual consumer agent and not a household. This model incorporates a variety of spatial, social, and media effects (*22*). The study showed that after 10 years, the penetration rate of HEVs would increase by 25 to 38 percent. Eppstein et al. assumed that each agent's age and social network were static, there were uniform daily driving patterns, and there was availability of daily recharging methods, and they modeled a small subset of vehicle options. In the study, consumers' unfamiliarity with PHEV technology, PHEV battery life, battery replacement cost, long recharging time, future fuel price uncertainty, and short driving range were assumed to negatively influence the PHEV market penetration. Furthermore, the study noted that incentive programs such as government tax credits would not have long-term effects on the fuel efficiency of the fleet.

Consumer Choice Method

The consumer choice method uses a combination of discrete choice models and logit models to describe individual and collective decision-making. This method is widely used to model vehicle purchase and holding decisions. The sensitivities of the purchasing decision to the attributes of the vehicle are obtained through surveys. The attributes estimated in consumer preference modeling of new vehicle technologies include sensitivity to technology incremental costs, battery replacement, refueling/charging infrastructure availability, refueling/recharging time, maintenance costs, and driving range.

The Advanced Vehicle Introduction Decision (AVID) Model was developed by Argonne National Laboratory (ANL) to predict consumers' vehicle purchase decisions (*23*). AVID was developed using multinomial logit models to predict consumers' preferences using weighted scores for individual vehicle technologies and vehicle shares. The researchers of ANL, Santini and Vyas, used this model to estimate that the HEV adoption rate would increase by 41 percent with an increase in fuel price of $1.5 per gallon (*23*). Their study showed that the HEV share under the unconstrained vehicle production decision was estimated to be 17 percent in 2020 and 23 percent in 2035 to 2050. Vehicle adoption rates were found to be sensitive to gasoline price and HEV technology incremental costs. In the case of a gasoline price increase from $1.50 per gallon to $3.00 per gallon, HEV sales share increased to 56 percent in 2020 and 64 percent from 2030 to 2050. In the case of an 18 percent increase in HEV incremental costs and gasoline prices at $3.00 per gallon, HEV sales share was estimated to be between 5 percent and 8 percent from 2020 to 2050. The study considered scenarios including changes in consumer market preference, vehicle attributes, fuel prices, and technology production decisions. There were 13 vehicle attributes in their model, including vehicle price, fuel cost, range, battery replacement cost, acceleration, home refueling, maintenance cost, luggage space, fuel availability, and top speed. The base case assumption used a gasoline price of $1.50 per gallon and a 7 percent HEV incremental price increase relative to the CV.

In a Harvard University study, Bandivadekar used discrete choice modeling to estimate the market penetration rates of EVs (*24*). Four different scenarios were considered, and the author estimated that in 2035, the HEV sales would range from 15 percent to 40 percent, and PHEV sales would range from 0 percent to 15 percent. Bandivadekar noted the initial purchase price of the vehicle is assumed to be significant in consumers' choice when selecting electric vehicles. Charging infrastructure availability is also believed to predict the adoption rate of the vehicles.

Greene et al. used a nested multinomial logit consumer choice method to examine numerous scenarios associated with hybrid purchases (*25*). The scenarios covered multiple time periods and assumptions regarding competing technologies. The study considered future market penetration for light-duty diesel vehicles and hybrids, but for this project, only the hybrid market penetration results were reviewed. The results showed that hybrid vehicles' purchase rate would be 4 to 7 percent by 2008 and 15 to 20 percent by 2012 (*25*).

Sikes et al. also developed a model of consumer choice and estimated that HEV sales would range from 13 to 17 million in 2020 and PHEV sales would range from 332,975 current policy cases to 3,569,400 in 2020 (*21*).

The research team determined that a consumer choice modeling approach would best fit the requirements and data availability for this study. The team selected the Market Acceptance of Advanced Automotive Technologies (MA^3T) model for this purpose (*26*).

Diffusion Rate and Time Series Method

Time series models examine the process of acceptance of a new invention or product on the market. The diffusion rate is the speed a product or innovation spreads through the market. Diffusion rate and time series models seek to capture the life cycle of new products over time. They have been applied to the prediction of diffusion in a variety of different markets. The most widely used models are the Bass, Gompertz, and Logistic models. These models have been used extensively to model innovation diffusion in automotive markets.

Lamberson examined the adoption rate of HEVs using the Bass and Gompertz models. The study compared diffusion of HEV technologies to that of other automotive innovations and extrapolated results to the US fleet. Each model provided different results, though the Gompertz model was found to perform more favorably than the Bass model. Lamberson used a nonlinear least squares method to estimate the parameters of the Bass and Gompertz models based on historical monthly US HEV sales (*27*). In Lamberson's study, the total market penetration was estimated to be 1.6 million for the Bass model and 25.7 million for the Gompertz model. The Bass model estimated that HEV sales would peak in the summer of 2008 and then decline, whereas the Gompertz model estimated that HEV sales would increase until 2015 and then decline. Lamberson estimated that in 2015, the annual HEV sales would be 2636 and 1,296,310 based on the Bass and Gompertz models, respectively. Lamberson assumed that government incentives and regulation would play a major role in HEV adoption.

Cao and Mokhtarian used an extended Bass model with variable market potential to model HEV market diffusion (*28*). They included forecasted gasoline prices for the period from 2003 to 2025 and a prediction of consumers' evolving awareness of HEV technology. The results showed two peaks in diffusion rate due to first-time HEV purchases and replacement purchases in year 2023. HEV sales were estimated to reach 510,000 in 2008 and 2 million in 2013. The average annual HEV sales were estimated to be 2.2 million and 2.8 million from 2011 to 2025. In Cao's study, some of the assumptions considered were that the coefficients of the Bass model do not change over time, no interaction among vehicle technologies exists, vehicle technology supply always equals or exceeds demand, and diffusion rate is not affected by government policies or marketing strategies. The model was tested under different scenarios such as HEV awareness influence, gasoline price change, and market potential scenarios. In the scenarios analysis, the market potential was assumed to be around 10 percent of the total US registered vehicles in 2000, and consumer awareness was assumed to increase by 2 percent per year. Gasoline price was assumed to increase by 25 cents and 50 cents per gallon per year from 2007 onward.

Jeon examined the penetration rate of HEVs, PHEVs, and BEVs until 2030 based on the Bass diffusion model (*29*). His model used the concept of successive generations to overcome the limitations and market saturation problems of the Bass model. The generations were defined by either a start of new technology carline or a new generation of current carline technology. The market potential was estimated for each generation as the approximate average sales of the US vehicle fleet or class in which the technology existed multiplied by the generation period. His model estimated the annual US sales of HEVs, PHEVs, and BEVs would reach 5 million, 1 million, and 2.1 million, respectively.

Becker reported the rate of electric vehicle adoption using the Bass model under two gasoline price scenarios accounting for vehicle purchase price and operating costs. In the baseline scenario, BEVs would have a penetration rate of 3 percent in 2015, 18 percent in 2020, 45 percent in 2025, and 64 percent in 2030 of the total US light vehicle sales (*30*).

Researchers at the University of California Los Angeles (UCLA) conducted a study on the market penetration scenarios for electric vehicles for the city of Los Angeles (LA) (*31*). The study used standard marketing analysis techniques to forecast the market penetration including a conjoint survey and Bass diffusion model. The study also looked at cities with comparable demographics, climate initiatives, and commuting profiles as LA, which included two Texas cities: Austin and Houston. In the study, researchers interviewed city officials and stakeholders to understand the local incentives and policies for EV adoption. Researchers forecasted HEVs, PHEVs, and BEVs as a whole to have a market share of 11.7 percent of the LA fleet by 2020.

Other Methods

Other studies developed market penetration scenarios using various forecast models. A study by Balducci at the Pacific Northwest National Laboratory examined the market potential for PHEVs in the US (*32*). Balducci conducted a literature review and contacted technical experts and industry leaders to present three market penetration rates for PHEVs for the time period of 2013 to 2045, as summarized below. Table 3 summarizes the findings of that study.

- Hybrid Technology Assessment: In this scenario, PHEV technology adoption was accelerated as a result of lessons learned through development of hybrid technology, and the ultimate PHEV share of the hybrid market was based on the penetration definition by the Electric Power Research Institute (EPRI) and Natural Resources Defense Council (NRDC). EPRI and NRDC forecasts of hybrid and PHEV market penetration were based on the choice-based market modeling of customer preference between PHEVs, HEVs, and conventional vehicle options. The market penetration forecast for this scenario for PHEV was 9.7 percent by 2023 and 11.9 percent by 2035.
- Research and Development (R&D) Goals Achieved: The second scenario was based on asking domain experts for the best judgment under a given set of PHEV conditions that ranged from marginal cost to tax incentives. The second scenario assumed that the major goals specified in the US DOE's Plug-In Hybrid Electric Vehicle R&D Plan were achieved and the tax incentives and positive regulatory environment governing current hybrid technologies were extended to PHEVs. The DOE goals range from many factors involved in the development of PHEVs including energy storage, vehicle efficiency technologies, deployment, engines and fuels, and power electronics. The market penetration forecast for PHEVs for this scenario was 9.9 percent by 2023 and 27.8 percent by 2035.
- Supply Constrained: The last scenario was based on estimates of the supply capabilities of automakers and battery manufacturers and assumed that with sufficiently high consumer demand for EVs generated through various financial incentives and national energy security priorities and mandates, ultimate market penetration would be limited only by the idle off-peak capacity of electric infrastructure to meet the demand placed on it by light-duty vehicles, and near-term penetration would be limited only by the battery and automotive industries' ability to meet the surging demand. The scenario forecasted that PHEVs would reach 26.9 percent by 2023 and 68.4 percent by 2035.

Table 3. PHEV Market Penetration Forecasting (*32*).

	Market Penetration Rates for Each Scenario		
Period Ending	**Hybrid Technology-Based Assessment**	**R&D Goals Achieved**	**Supply Constrained**
2013	--	--	--
2023	9.7%	9.9%	26.9%
2035	11.9%	27.8%	68.4%
2045	11.9%	29.8%	72.7%
Total Market Penetration	11.9%	30.0%	73.0%

A study by Eggers and Eggers developed a choice-based conjoint adoption model to predict HEV, PHEV, and BEV penetration rates using a consumer preference modeling approach (*33*). The results predicted that new vehicle sales would increase to 56.5 percent by 2018 for hybrid vehicles and 8.4 percent by 2018 for PHEVs. This estimation was based on assumptions that gas prices would continue to increase, meaning operating costs for ICE cars would rise.

Curtin et al. at the University of Michigan examined the purchasing probability of HEVs and PHEVs (*34*). The analysis was based on the results of interviewing a nationally representative sample of 2513 adults in the US from July to November 2008. The data showed that while social factors can change consumers' purchasing decisions, economic incentives dominate automobile purchasing decisions. The study did not provide market penetration forecasts but assessed the current state of knowledge of PHEVs among US consumers. Table 5 provides a summary of the market projection forecasts discussed in this document and notes the stakeholders that cite the forecasts and scope of the projection as part of their studies/literature.

Table 4. US Electric Vehicles Forecasts from Various Models.

Estimation Model/Developed By	Cited By	Market Penetration	Assumptions/Model Considerations
Agent-based models			
Sullivan et al. (2009)	– University of Michigan – Ford Motor Company	PHEV: 4–5% by 2020	– Fixed population – Constant wages – All prices in real dollars
Sikes et al. (2004)	Oak Ridge National Laboratory (ORNL)	PHEV: 2.5–4% for 2015–2020	– Gasoline tax increase of 1.5 cents per gallon between 2010 and 2020 – Positive policy conditions: sales tax exemptions around 2% & PHEV tax credit extended from 2015 to 2020
Eppstein et al. (2010)	Colorado State University	HEV: 25–38% for 2010–2020, 30–60% for 2010–2030	– Consumers' age and social network static – Uniform daily driving patterns and availability of daily recharging – People with higher vehicle miles traveled tend to buy cars more often
Consumer choice models			
Santini & Vyas (2005)	Argonne National Laboratory	HEV: 5–8% for 2020–2050	– 18% increase in HEV incremental cost – Gasoline price at $3.00 per gallon
Bandivadekar (2008)	Massachusetts Institute of Technology	HEV: 15–40% in 2035 PHEV: 0–15% in 2035	– Average annual growth rate of new vehicle sales of 0.8% per year – Average per-vehicle kilometers traveled decrease from 0.5% between 2005 and 2020 – Constant fuel consumption
Greene et al. (2004)	– ORNL – J.D. Power and Associates	HEV: 15–20% in 2012	– Fuel economy increase to 38 mpg, at a cost increase of 7–9% – Same HEV technology performance – Total market volume of approximately 17.5 million units – 33% baseline fuel availability in 2008

Table 4. US Electric Vehicles Forecasts from Various Models (Continued).

Estimation Model/Developed By	Cited By	Market Penetration	Assumptions/Model Considerations
Cao and Mokhtarian (2004)	– University of California – California Department of Transportation	HEV: increase by 2% per year	Gasoline price increase by 25–50 cents per gallon per year
Becker, Sidhu, and Tenderich (2009)	University of California, Berkeley	EV: 3% in 2015, 18% in 2020, 45% in 2025, and 64% in 2030	– Conservative estimate for battery life: a 10-year life before batteries hold an 80% charge and are no longer useful – Per-mile cost is 10 cents in 2012 – Percentage of light vehicles produced in US remains constant through 2030
University of California at Los Angeles Luskin Center for Innovation (2011)*	University of California at Los Angeles	EV: 11.7% by 2020	– Oil price stays below $100 per barrel – No con considerate subsidies provided to EV sector – 5% of multi-unit residents and renters will have access to charging facility – Consumer attitudes, preferences, and behavior remain consistent – HEV and BEV leave circulation after 8 years
Other models			
Balducci (2008)	Pacific Northwest National Laboratory	PHEV: 9.7% by 2023 and 11.9% by 2035	– PHEV technology development accelerated as a result of advancements in hybrid technology – $4000 marginal cost of PHEV technology – 40-mi battery range

Market Acceptance of Advanced Automotive Technologies Model

Based on the review of the existing methodologies, the research team selected the MA^{3}T model for the pilot application of this study, which is described in Chapter 4. The MA^{3}T model is a consumer choice model developed by Oak Ridge National Laboratory as a tool for analyzing scenarios of demand for various automotive powertrain technologies in response to changes in technologies, infrastructure, energy prices, consumer preferences, and policies (*26*). Implemented using Microsoft® Excel for Windows, MA^{3}T simulates market demand by representing relevant attributes of technologies and consumer behavior, such as technological learning by doing, range anxiety, access to recharging points, daily driving patterns, and willingness to accept technological innovation.

Currently, MA^{3}T includes 40 choices, consisting of 20 powertrain technologies for each of the two vehicle size classes—passenger cars and light-duty trucks. MA^{3}T considers the US household users of LDVs as the consumer market, which is disaggregated into 1458 segments by six dimensions: nine census divisions, three residential areas, three attitudes toward novel technology, three driving patterns, three home recharging situations, and two work recharging situations. MA^{3}T currently has a study period from 2005 to 2050, which includes a calibration period of 2005 to 2013, a validation year of 2014, and the projection period of 2015 to 2050. All prices are expressed in 2012 US dollars.

In its core, MA^{3}T uses the nested multinomial logit method to predict purchase probabilities among 40 choices by each of the 1458 consumer segments, based on value components associated with vehicle attributes, driver behavior, infrastructure, energy prices, and policies (Figure 3). The segment purchase probabilities are translated into market share, sales, vehicle populations, petroleum use, and greenhouse gas (GHG) emissions. Some of the outputs serve as feedback signals and, together with other exogenous inputs from various sources, affect the purchase probabilities. ORNL continuously updates and improves the model (*26*).

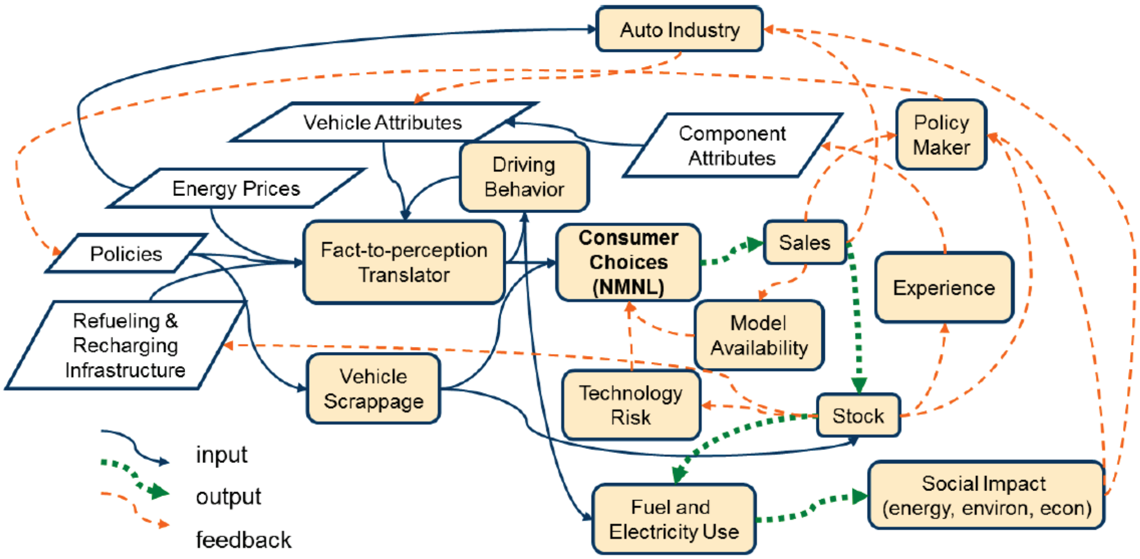


Figure 3. MA[3]T Model Framework from (*26*).

EMISSIONS IMPACTS OF ELECTRIC VEHICLES

The transportation sector is a major contributor to criteria pollutant and greenhouse gas emissions in the US, accounting for 28 percent of energy use, 28.1 percent of GHG emissions, 54 percent of CO, 61 percent of NO_x, and 24 percent of volatile organic compound (VOC) emissions in 2012 (*35,36,37*). Governments around the world are taking steps to address the energy and air pollution problems caused by transportation activities. One of the strategies being used for this purpose is to expand penetration of electric vehicles in private and public transportation sectors (*38,39*). Because part of their power source is from electricity, electric vehicles have the potential to achieve higher energy efficiency, reduce fuel consumption, and mitigate pollutant emissions.

Among the three common types of EVs (HEVs, PHEVs, and BEVs), HEVs are the closest EV type to conventional vehicles because they still mainly rely on an internal combustion engine for propulsion, and the electric battery assists the engine and is recharged through regenerative braking and the internal combustion engine (*39*). HEVs do not use electricity from a power grid, i.e., their batteries cannot be charged by plugging into a power outlet. Therefore, HEVs only produce tailpipe emissions and are similar to conventional vehicles in evaluation of emissions impacts.

The literature identifies two electric vehicle operating modes to describe the electric portion of PHEV and BEV operations. Charge depletion (CD) mode is when the battery is charged above a threshold and the vehicle is powered solely by the battery. Charge sustaining (CS) mode is when the battery is discharged below a threshold and the vehicle is powered intermittently by a gasoline-powered engine and the battery (*39*). In the CS mode, tailpipe emissions will be produced because the internal combustion engine is operating during that mode. In the CD mode, only grid emissions in generating electricity will be produced. A BEV is operated solely in the CD mode. A PHEV is operated in the CD mode when the battery is charged above a threshold, and after that, it is operated in CS mode. Therefore, if only mobile source emissions are considered—which is the system boundary of transportation air quality conformity analysis and the objective of this study—EVs could potentially provide benefits in reducing emissions. If emissions from power grids are included, it is still unclear whether EVs can produce fewer emissions. Many studies have investigated EV emission impacts at both the disaggregated level (i.e., individual vehicle) and aggregated level (i.e., regional or national vehicle fleet).

In a disaggregated-level analysis, EVs' distance-based emissions rates are calculated and compared with conventional internal combustion engine vehicles. The emissions evaluated include both criteria pollutants and GHG emissions. The methods used in obtaining EVs' distance-based emissions rates are mainly in-use testing using PEMS and automobile operation simulation models. In studies using PEMS testing methods, distance-based emissions rates are calculated for vehicles driving on predetermined driving routes. However, the vehicles' driving characteristics on the selected routes might not be representative of vehicles driving in that region. In studies using automobile simulation models, vehicles' emissions rates have usually been assessed based on national average drive schedules, such as Federal Test Procedure US06, which are not representative of region-specific driving characteristics. In addition, emissions generated in simulation models might deviate from the emissions under real-world driving situations. Some of the disaggregated-level literature is summarized below.

Graver et al. developed a framework to estimate real-world emissions of a plug-in hybrid electric vehicle (*40*). PHEV running exhaust emissions were measured by PEMS, and grid emissions were based on the electricity consumption data and regional power grid resource mix. The study reported distance-based emissions rates of CO_2, NO_x, sulfur dioxide (SO_2), and particulate matter (PM) for running exhaust emissions only and running exhaust plus grid emissions. The results showed the tested PHEV's running exhaust emissions rates were 3 percent to 140 percent lower than the corresponding legislation limits. However, when grid emissions were included, the distance-based emissions rates were similar or higher than the legislation limits.

Sonntag et al. estimated the relationship between particle number concentrations and operating characteristics through in-use testing of a diesel-electric bus (*41*). The operating characteristics considered were fuel rate, engine speed, bus velocity, and acceleration. The results indicated that velocity and acceleration were good supplemental prediction variables to engine characteristic variables. In addition, variables such as driving route, after-treatment technology, and atmospheric conditions had important impacts on particle numbers.

Robinson and Holmen compared second-by-second particle numbers from a 2010 hybrid electric vehicle and a comparable conventional vehicle under the same real-world driving conditions (*42*). The particle number concentrations were recorded using PEMS. The researchers found that the average particle number per trip for the HEV was two times higher than the conventional vehicle. The high particle number emissions from the HEV were mainly due to the restart behavior at low or stop-and-go driving conditions, which resulted in air quality concerns in areas such as intersections.

Karabasoglu and Michalek investigated the potential of HEVs, PHEVs, and BEVs to reduce lifetime GHG emissions under various driving cycles and charging scenarios (*43*). The driving cycles considered were the Urban Dynamometer Driving Schedule (UDDS), Highway Fuel Economy Test, US06, and LA92. The results showed that EVs could achieve most CO_2 emissions reductions under urban driving conditions (such as UDDS). At aggressive driving conditions, such as US06, the benefits of EVs in reducing CO_2 emissions diminished significantly.

Millo et al. analyzed the CO_2 emissions benefits and operating cost reduction of a PHEV and a comparable conventional vehicle under real-world driving conditions (*44*). They developed an optimal control model that optimized the PHEV's driving and charging activities. The running exhaust emissions and electricity consumptions of the PHEV under the New European Driving Cycle (NEDC) were simulated using the MATLAB program, and grid emissions were later calculated based on electricity consumptions. The results indicated the PHEV could reduce 10 to 30 percent of CO_2 emissions depending on the electricity generation resource mix.

Strecker et al. investigated the well to wheels GHG emissions impacts of converting a 1974 Volkswagen Super Beetle into a plug-in hybrid electric vehicle (*45*). On-road testing of emissions was conducted using PEMS. In addition, the Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation (GREET) model was used to analyze the emissions impacts based on a lifecycle assessment framework. The results showed significant GHG emissions reduction could be achieved by converting the conventional vehicle into a PHEV, and additional GHG emissions reduction could be achieved if the electricity was generated from solar energy.

In a study by EPRI and NRDC, the authors concluded that a PHEV could reduce 40 to 65 percent or more GHG emissions than a conventional vehicle and 7 to 46 percent or more than an HEV in 2050 if a large number of PHEVs enter the vehicle fleet from 2010 to 2050 (*46*). Findings of a study by Thomas suggest that BEVs with a 300-mi range will have higher GHG emissions compared with conventional vehicles if electricity generation is based on the current coal technology (*47*).

Other studies assessed EVs' emissions impacts at the aggregated level and evaluated the percentage of emissions reductions due to various EV penetration scenarios at regional or national levels. The majority of the studies focused on PHEVs and BEVs and evaluated their emissions impacts due to such things as different market penetrations, power generation resource mixes, and EV charging scenarios. GHG emissions were the major emission type analyzed in the current literature, but increasingly studies are looking at EV criteria pollutants' emissions impacts. Those studies are summarized below.

Doucette and McCulloch conducted a study that simulated BEVs' CO_2 emissions due to electricity consumptions in four countries (US, France, China, and India) and compared those CO_2 emissions with similarly configured conventional ICE vehicles (*48*). They found that in countries that have high CO_2 emissions per unit of electricity (such as China and India), driving a BEV could potentially lead to higher CO_2 emissions compared with a conventional ICE vehicle. Depending on factors such as BEV battery range and charging infrastructure locations, the differences in CO_2 emissions in driving a BEV could range from −2 percent to 30 percent compared with a conventional ICE vehicle.

In another study conducted by Doucette and McCulloch, the authors developed a model that evaluated the prospects of plug-in hybrid electric vehicles in reducing CO_2 emissions. Compared with a conventional ICE vehicle, a plug-in hybrid electric vehicle uses both an ICE and electric motor as power sources (*49*). Hence, driving a plug-in hybrid electric vehicle could reduce fuel demand and achieve higher energy efficiency. However, if the CO_2 intensity in electricity is higher than the transportation fuel, driving a plug-in electric vehicle could actually result in higher CO_2 emissions compared with driving a conventional ICE vehicle.

Jansen et al. developed a resource dispatch and emissions model to evaluate plug-in electric vehicle emission impacts on the western power grid system (*50*). The study used a modeled dispatch approach based on a correlation between actual historical dispatch and system load data to show the emissions impacts associated with various plug-in electric vehicles' penetration on the western grid. The authors found that PHEV fleet charging behaviors could determine the electricity demand and power generation source mix for every hour of a day. Furthermore, hourly power grid emissions were determined by the hourly electricity demand and power generation source mix. Reduction in grid emissions could be achieved by optimizing PHEV fleet-wide charging profiles. For example, a 3.5 percent reduction in daily grid CO_2 emissions could be achieved by shifting PHEV fleet charging from hours 17–21 to hours 9–17.

Kim and Rahimi studied the future energy loads for a large-scale adoption of plug-in electric vehicles in the city of Los Angeles and the associated impacts on greenhouse gas emissions (*51*). They developed a demand-supply equilibrium model to estimate hourly greenhouse gas emissions under various electric vehicle adoption scenarios. The results indicate peak hour charging of plug-in electric vehicles is preferable to off-peak hour charging in the Los Angeles area due to its unique power generation resource mix in the short run. However, in the long run, as Los Angeles is shifting the power generation resource mix into more renewable energy resources, off-peak hour charging of plug-in electric vehicles would provide greater benefits in reducing greenhouse gas emissions than peak hour charging scenarios.

Ma et al. investigated the true ability of BEVs to reduce GHG emissions through a life cycle assessment based on various BEV driving patterns in the United Kingdom and California (*52*). The driving patterns included different profiles in speed, loading, accessory usage, and more. The results showed that BEVs can deliver significant driving GHG emissions savings compared with conventional vehicles under conditions in which the grid GHG intensity used to charge the batteries is sufficiently low. The study also showed that BEVs perform best relative to ICE vehicles in terms of driving GHG emissions at low speeds and lightly loaded driving.

However, the overall vehicle life cycle emissions are higher for BEVs than ICE vehicles due to the GHG emissions associated with battery manufacturing.

Sharma et al. quantified the economic and greenhouse gas emission performance of conventional, hybrid, and battery electric vehicles in Australia (*53*). The evaluations were based on Australian-specific driving conditions. They used the Powertrain System Analysis Toolkit simulation package to simulate economic and greenhouse gas emission performance of various types of vehicles. The results showed that for large vehicles such as light commercial vehicles, the BEV had higher life cycle GHG emissions than an equivalent conventional vehicle. For passenger cars, hybrid electric vehicles were the most effective in terms of cost and GHG emissions under life cycle assessment.

Silva studied the impacts of introducing HEVs, PHEVs, and BEVs in terms of criteria pollutants, such as CO, THC, NO_x, PM, and CO_2 in Portugal (*54*). The study assumed that the emissions from each vehicle followed a probability distribution and executed a Monte Carlo simulation to estimate emissions as a result of various increasing patterns of the EVs' market shares. The results indicated that 10 percent to 53 percent reductions in various criteria pollutants could be achieved with a scenario of 50 percent fleet replaced with EVs. In addition, a 23 percent reduction in CO_2 could be achieved.

Smith conducted research to examine EVs' impacts on GHG emissions in Ireland considering factors such as electricity generation and distribution systems and proportion of vehicle kilometers completed by electric motors (*55*). The study revealed substantial and immediate reductions in GHG emissions for urban-type driving cycles with electrified vehicles. If all urban-mode vehicle kilometers were executed by electric vehicles instead of conventional ICE vehicles, 25 to 40 percent of GHG emissions from passenger cars could be reduced. However, electric vehicles were not found to have much potential in reducing GHG emissions from inter-city travel.

Varga analyzed the CO_2 emissions impacts from introducing electric vehicles in the Romanian market (*56*). The CO_2 emissions were calculated by combining energy consumptions based on NEDC and power grid generation emissions. A vehicle and power train system-level simulation tool, AVL CRUISE, was used to estimate energy consumptions. Varga reported that the average CO_2 emissions rate ranged from 90 g/km to 220 g/km depending on the current power generation resource mix in Romania from 2004 to 2008. The CO_2 emissions per km could potentially be reduced by 50 percent to 70 percent if the power were all generated by nuclear power plants and windmills.

Zhou et al. studied electric vehicles in China from the perspectives of energy consumptions and GHG emissions (*57*). A life cycle analysis module, Tsinghua-LCAM, was used to estimate transportation GHG emissions under the Chinese government's electric vehicle development route map plan for 2015 and 2020. The authors showed that the projected EVs in the fleet could achieve various GHG emissions reductions in different regions given the power generation resource mix. In general, electric vehicles are expected to reduce 25 percent of the GHG emissions from the transportation sector by the year 2020.

Finally, the state of Texas leads the United States in electricity generation and consumption. The electric grid is an integrated system of transmission and distribution lines for which electricity flows. The US has three electric grids that power the country, and each of them support a portion of Texas. Electricity demands fluctuate over the course of a day, week, and season, and the demand is also impacted by location, population, and climate (*58*,*59*). Studies have shown that when PHEVs' and BEVs' market penetration rates increase significantly, consequent recharging activities are expected to significantly change the power demand pattern (*60*).

Electricity used to recharge PHEVs and BEVs through electrical grids is generated from different fuel sources such as coal, natural gas, petroleum, and renewable sources including solar and wind. The electricity generation mix for recharging impacts the PHEVs' and BEVs' overall emission estimations because each source produces different amounts of emissions. The electricity generation mix varies by region and time. Table 5 shows examples of the breakdown of sources for electricity generation in Texas from 2008 to 2010 (*61*). As shown in Table 5, natural gas was the second highest source for electricity generation in Texas at 38 percent, which was very close to the largest source, coal, at 40 percent. Therefore, while PHEVs and BEVs can potentially reduce overall pollutant emissions compared to conventional vehicles, the emission reductions greatly depend on the generation mix and charging patterns (*60*,*61*,*62*).

Table 5. Fuel Sources for Electric Power Generation in Texas from (*61*).

Fuel Type	2010	2009	2008
Coal	39.5 %	37.1%	37.4%
Natural Gas	38.2%	42.1%	43%
Nuclear	13.1%	13.6%	13.2%
Wind	7.8%	6.2%	4.9%

EVS' IMPLICATION FOR AIR QUALITY AND CONFORMITY

The increase in EVs in the vehicle fleet has an impact on tailpipe emissions but also has broader impacts and implications on local and regional air quality. It is particularly important for nonattainment and attainment areas to understand the overall impact of EVs on regional emissions. While EVs in general have lower emissions than conventional internal combustion vehicles, a portion of emissions associated with PHEV and BEV battery charging are generated by power plants. These plants are considered point sources, along with other sources such as chemical plants, refineries, electric utility plants, and other industrial sites.

This study was undertaken in the context of transportation conformity and air quality issues traditionally dealt with by the transportation sector. Only mobile source emissions were considered in the transportation conformity context. Because PEVs do not produce tailpipe emissions when they are in electric mode, the expected increase in the number of these vehicles in the future means that there will potentially be a notable reduction of mobile source emissions captured in a conformity determination emissions inventory. However, this reduction may not necessarily lead to better regional air quality because emissions generated for charging EVs are not accounted for in transportation air quality conformity determinations. Though beyond the scope of this study, it is important to note that in a broader air quality perspective, it is essential to take into consideration the emissions from electricity generation when accounting for EVs' impacts on air quality, and doing so may have broader future policy implications.

EVs in Nonattainment Areas

Accurately projecting EVs within future fleet mixes is important for metropolitan planning organizations and districts within nonattainment and attainment maintenance areas to account for their impact in the air quality planning. Market penetration scenarios can help local and state transportation and air quality agencies plan for future fleet changes and the potential impact on nonattainment and maintenance areas.

The Clean Air Act (CAA) defines EPA's responsibilities for protecting public health and improving the nation's air quality (*63*). The CAA requires EPA to set limits on the amount of certain pollutants, called criteria pollutants, allowed in the air. When the level of any of these pollutants exceeds the standard in an area, EPA designates that area as being in nonattainment (NA) for that particular pollutant.

After an area is designated as an NA area by EPA, the state is required to develop a SIP for the area to implement, maintain, and enforce to reduce the pollutant level in the NA area down to equal or lower than the standard(s) (*64*). To accomplish this, for each NA area, the SIP must:

- Estimate emissions from all sources (mobile, point, and area).
- Establish goals for emissions from each of these sources.
- Develop strategies to attain (or maintain) those goals.

In transportation planning, the primary concern is with on-road mobile source emissions. The on-road mobile source emissions goal for the SIP is known as the motor vehicle emissions budget. The total emissions from on-road mobile sources cannot exceed this budget. After the standard is re-attained by a previously designated NA area, EPA re-designates the area as being back in attainment, but the area is required to demonstrate how it will maintain this level of air quality. These previously nonattainment areas are called attainment maintenance areas.

NA and attainment maintenance areas must demonstrate that emissions resulting from future actions, as identified by the transportation planning and programming process and documented in the metropolitan transportation plans and transportation improvement programs, will not exceed the area's emissions budget. This task is achieved through a process known as demonstrating transportation conformity, which must be conducted periodically, i.e., within two years of the initial budget and every four years thereafter, if the plan is updated, or if the SIP changes. If conformity cannot be demonstrated by a specified deadline, or if the plan expires before a new one is adopted, the area enters into a conformity lapse. For areas in a conformity lapse, federal transportation funds cannot be spent on capacity-enhancing projects, though certain safety, transit, and air quality projects may go forward.

EV Activity Data for Emissions Modeling

EPA's current emissions model, MOVES (in this case, version MOVES2010b), utilizes a database-centered software framework and a disaggregate emissions estimation algorithm that includes many new features and provides much more flexibility for input and output options than the previous-generation emissions model (*64*). This approach enables MOVES to perform estimations at different analysis levels such as at the national, state, and local levels. Users of the model specify vehicle types, time periods, geographical areas, pollutants, vehicle operating characteristics, and road types being modeled. MOVES also incorporates estimates of energy consumption along with several coefficients, including heating value, oxidization fraction, and carbon content. The model was designed to work with databases, allowing for new and updated data to be more easily incorporated into the model. The default database summarizes emissions information for the entire US and is drawn from EPA research studies, Census Bureau vehicle surveys, FHWA travel data, and other federal, state, local, industry, and academic sources.

The MOVES model is equipped with default drive cycles that are based on national-level data and are thus less reliable in accurately estimating emissions at the local level. The accuracy of local emission estimates can thus be increased if this information is developed and made available.

MOVES currently does not adequately account for electric-powered vehicles with regard to location-specific market penetration, driving characteristics, and emissions rates. The underlying structure of MOVES is adaptable for new vehicle technologies and has the ability to include new vehicle types into future vehicle fleets. However, EPA at this point has not established default emission estimates for EVs. Furthermore, EPA has not defined what constitutes a hybrid vehicle (*65*).

The total amount of driving by each vehicle type (i.e., source type vehicle miles traveled [VMT]) and the vehicles' driving and emissions characteristics (i.e., drive schedules and emissions rates) are the key parameters for accurately estimating on-road emissions impacts of EVs in a MOVES-based framework. In Chapter 3, the two major aspects of quantifying EV emissions impacts—drive schedules and emissions rates—will be established, and the methodologies and approaches for each of these will be discussed in detail.

CONCLUDING REMARKS

This chapter provided a review of the literature on topics related to electric vehicles and their impacts on emissions. The research team reviewed characteristics of the major makes and models of EVs in the US market. They discussed major factors influencing electric vehicles' adoption rates. The researchers also reviewed major methods of predicting the future market for electric vehicles used by academic institutes, government agencies, and private companies. Finally, emissions impacts of EVs and their implications for air quality conformity were discussed. The research team used this information to develop a framework to incorporate EVs into a travel-demand-based emissions analysis.

CHAPTER 3:
DATA COLLECTION AND ESTABLISHMENT OF EV EMISSIONS RATES

This chapter summarizes the collection of vehicle activity and emissions data from EVs, and the process of establishing distance-based EVs' exhaust emissions rates using the collected data. In MOVES and other mobile source emissions inventory models, emissions are estimated based on mobile source activity profiles and emissions characteristics (generally in the form of distance-based emissions rates for on-road activities). While mobile source activity characteristics are usually obtained through region-specific travel demand models, emissions characteristics are often developed based on national average driving patterns and emissions rates contained in the models. In this project, the research team established a set of distance-based emissions rates for EVs in Texas, based on two sets of collected data: global positioning system (GPS) data from a sample of EVs in major Texas metropolitan areas, and tailpipe emissions collected through in-use emissions testing on a sample of EVs using PEMS equipment.

The distance-based tailpipe emissions were developed for average speed bins on different road types for HEVs and PHEVs, for CO, NO_x, and total hydrocarbons (THCs; criteria pollutants and precursors), as well as CO_2. Data regarding the energy consumption associated with BEVs' and PHEVs' battery operations were also collected as part of this research. However, these results are not presented in detail in this report, which focuses on the mobile source emissions associated with EVs. The detailed procedures in establishing EV emissions rates are discussed in the remaining sections of this chapter.

OVERVIEW OF APPROACH

Figure 4 shows an overview of the approach used to establish the MOVES-compatible Texas-specific emissions rates for EVs. The local distance-based EV emissions rates were required at each average speed bin and each road type. The process started with obtaining drive schedules under each average speed bin and road type based on a large-scale activity data collection exercise for EVs operating in Texas' major metropolitan areas.

The drive schedules were essentially a series of data points depicting speed over time. The drive schedules could provide time distribution of operating modes under each average speed bin and road type. In addition, operating-mode-based emissions rates for each individual EV were measured through in-use testing of a sample of EVs that covered the major models of EVs in the on-road fleet. The operating mode distributions from the drive schedules were combined with operating-mode-based emissions rates to generate distance-based emissions rates (g/mi) for individual vehicles by average speed and road type. Market shares (within each category, i.e., HEVs/PHEVs) were estimated from historical vehicle sales data and used to calculate the market-share weighted average emissions rates (g/mi) for each vehicle type category by average speed and road type. These emissions rates were then converted to a MOVES-compatible emissions rate table by vehicle type to be used as an input to a previously developed script, called MOVESemscalc, to estimate regional mobile source emissions using MOVES. This process is discussed further in Chapter 4.

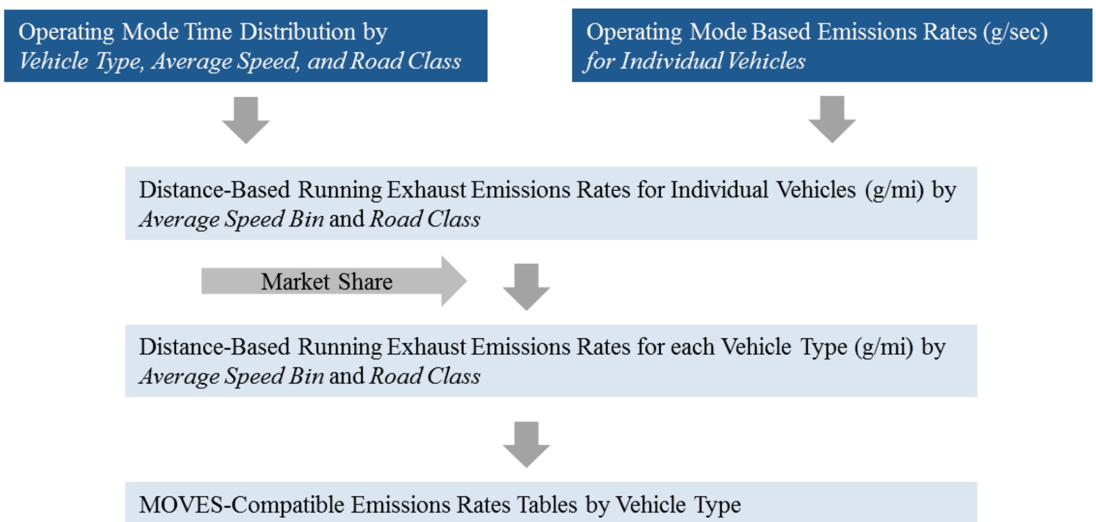


Figure 4. Approach for Developing Distance-Based Exhaust Emissions Rates.

DEVELOPMENT OF EV DRIVE SCHEDULES

This section describes the approach of developing Texas-specific driving schedules based on GPS data from a sample of EVs in major Texas metropolitan areas. Drive schedules are important in quantifying vehicle emissions by providing vehicle speeds over time. Many mobile source emissions inventory models, such as MOVES, use default drive schedules that are based on national-level data to generate emissions rates.

There is strong agreement in the scientific community that the driving characteristics of each area are unique due to different vehicle fleet compositions, driving behaviors, and road network topographies. Therefore, national emissions rates are less reliable in accurately estimating emissions at the regional level. In the case of EVs, the development of drive schedules using local vehicle activity data is especially important in order to accurately characterize and reflect EV operations, which are likely to differ from default drive schedules contained in MOVES.

Data Collection Protocol

Researchers developed and executed a data collection protocol based on related literature and the research team's previous experiences, specifically Texas Department of Transportation (TxDOT) Report 0-6629-1, *Texas-Specific Drive Cycles and Idle Emissions Rates for Using with EPA's MOVES Model* (*66*). The test protocol included an unsupervised GPS data collection for developing the representative drive cycles and a supervised on-road emissions testing to develop basic emissions rates for EVs.

Data were collected from the following three categories of EVs: HEVs, PHEVs, and BEVs. Vehicles from these categories were identified, recruited separately for each data collection effort (drive cycles and emissions), and equipped with data loggers. Researchers processed and analyzed the data following the MOVES model format for vehicle activity characterization.

The data collection plan consisted of the following major items:

- Vehicle sample sizes for each vehicle category.
- Technology, methodology, and installation procedures for data collection.
- Required duration of the data collection.
- Procedures for protecting participants' privacy.

The focus of the data collection effort was on the nonattainment and near-nonattainment urban areas of Texas: Houston, Dallas–Fort Worth, Austin, and San Antonio. The research team also recruited a few vehicles from an area in attainment: Bryan–College Station.

Protecting Participants' Privacy

Because the collected data can potentially reveal an individual's residence or work place, the data collection process required procedures to ensure that participants' identity and location information were properly protected per instructions of the Title 45 Code of Federal Regulations Part 46. The research team followed the procedures that were developed under TxDOT Research

Project 0-6629 to ensure the privacy of the participants was protected. The team obtained the necessary approvals from The Texas A&M University System (TAMUS) Institutional Review Board (IRB) to conduct this project.

Following are the main items in the IRB-approved procedures. The details for each item have been documented in the report for TxDOT Research Project 0-6629 (*66*).

- Participant consent.
- Data labeling and storage procedures.

Data Collection Technologies

The research team previously determined that GPS technology would be the best candidate for collecting speed and location data required for the types of applications being reviewed. In this project, the research team used the GPS units that were identified and obtained in TxDOT Project 0-6629, the QStarz BT-Q1000eX Xtreme Recorder (*67*). Figure 5 shows the QStarz BT-Q1000eX unit. The details on the characteristics of the Xtreme Recorder are documented in the TxDOT Project 0-6629 final report (*66*).

Figure 5. QStarz BT-Q1000eX Unit and Its Extended Battery Pack.

Duration of Data Collection

Based on the findings of TxDOT Project 0-6629, researchers determined that a two-week period would provide the necessary amount of data (*66*).

Data Collection Methodology

The data collection process consisted of requiring individual vehicles to record their normal activity during an extended period of time. The research followed the standardized methodology that was previously developed (*66*). Figure 6 shows an overall outline of the data collection methodology.

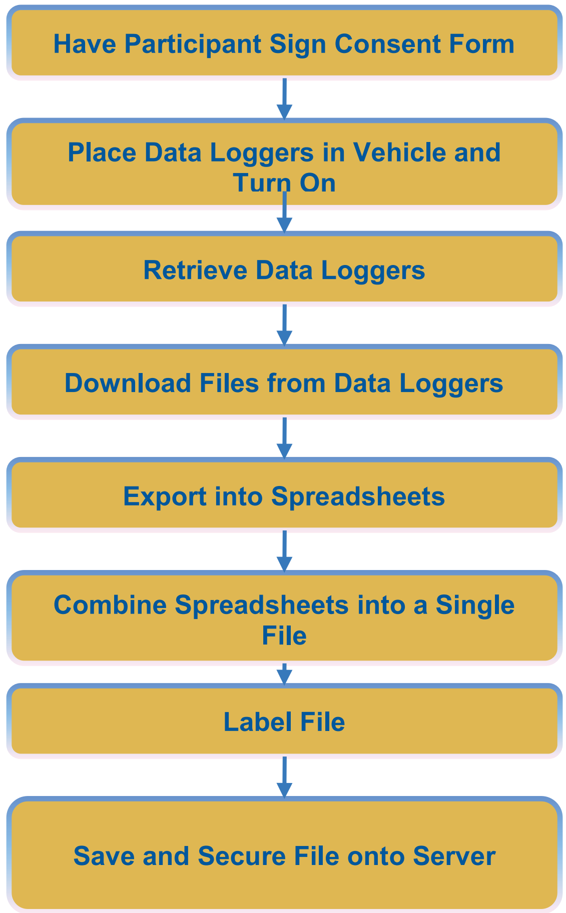


Figure 6. Data Collection Process Flowchart.

Each vehicle was equipped with three GPS data loggers to ensure accuracy in case one unit malfunctioned or provided erroneous data. Information from each of the three data loggers was downloaded onto a central server and was merged into one document that was labeled with variables describing unit number, date of initial activation, and type of vehicle observed.

Vehicle Recruiting for Drive Schedules

Thirty-three vehicles were recruited for GPS data collection. Per the TAMUS Institutional Review Board requirement, a signed consent form was obtained from each individual participant as part of the recruiting effort. Participants were compensated $75 for their participation.

Vehicle Sample Sizes

A goal of seven to 10 vehicles per vehicle category—HEV, BEV, and PHEV—was set. Each vehicle was observed for a period of one to two weeks, depending on the level of driving activity. Table 6 shows the distribution of vehicles observed by vehicle type and area. The research team recruited 33 individual vehicles for drive cycle data collection. Table 7 shows the distribution of vehicles recruited by make and model.

Table 6. Recruited Vehicles by Vehicle Type and Region.

Vehicle Type	Austin	Dallas–Fort Worth	Bryan–College Station	Houston	San Antonio	Total
HEV	2	6	–	–	2	10
BEV	8	1	2	1	–	12
PHEV	4	–	–	7	–	11
Total	14	7	2	8	2	33

Table 7. Recruited Vehicles by Brand.

Vehicle Type	Nissan Leaf	Ford Focus	Ford Escape	Toyota Prius	Chevy Volt	Total
HEV	–	–	6	4	–	10
BEV	11	1	–	–	–	12
PHEV	–	–	–	7	4	11
Total	11	1	6	11	4	33

Potential participants for the research project were recruited through a variety of methods. Advertisements were made through the web-based classified listing Craigslist, as well as the Facebook social media account maintained by the Texas A&M Transportation Institute (TTI). Direct e-mail messages were distributed to electric vehicle enthusiast groups such as the North Texas Electric Auto Association from the Dallas–Fort Worth region and the Houston Electric Auto Association. E-mail messages were also sent directly to the managers of Nissan and Chevrolet dealerships in the Houston and Dallas–Fort Worth regions in an attempt to reach owners of Nissan Leaf and Chevy Volt vehicles.

Drive Schedule Data Collection

As mentioned in the previous section, the research team recruited 33 individual vehicles for drive schedule data collection per previously established procedures. Data collection followed an unsupervised procedure in which drivers were instructed to follow their normal driving activities for a period of two weeks. The result of this effort was a database of second-by-second speed for all participating vehicles.

GPS Assembly Vehicle Installation

As Figure 5 shows, each GPS assembly consisted of three high accuracy GPS logger units. The installation of the units followed the procedures established in TxDOT Project 0-6629.

The assemblies were placed near the driver seat as a way to maximize the chance for each GPS unit to self-actuate after detecting vibrations from the physical movement of entering and leaving the vehicle. The GPS units were equipped with an actuation sensor in order to save power when the vehicle was not moving.

Data Transferring and Labeling

Data were transferred from each individual GPS unit to a secured central server using the QSport® software, a proprietary software that came with the GPS unit. The data transfer and file labeling followed the procedures established in TxDOT Project 0-6629 because the data contained location information. Only authorized researchers who had valid training through the Collaborative Institutional Training Initiative had access to the data files.

Development of Drive Schedules

Three GPS units were used on each vehicle to increase the precision and fidelity of the data, per project director approval. The data processing and analysis were conducted according to the methodology developed in TxDOT Project 0-6629 consisting of the following general steps. Details of these steps are documented in the final research report for that project (*66*).

1. Raw data quality control and validation.
2. Data processing.
3. Data analysis and drive schedule development.
4. MOVES default drive schedule comparison.

The goal of this study was to develop local drive schedules for each of the EV types according to MOVES road types (rural and urban arterials and freeways/highways). Therefore, the location information of each second of the data needed to have study area and road type information assigned. The research team processed the data in a geographic information system

(GIS) environment for this purpose. Figure 7 shows an example of the polygons used to determine location and area type in the GIS.

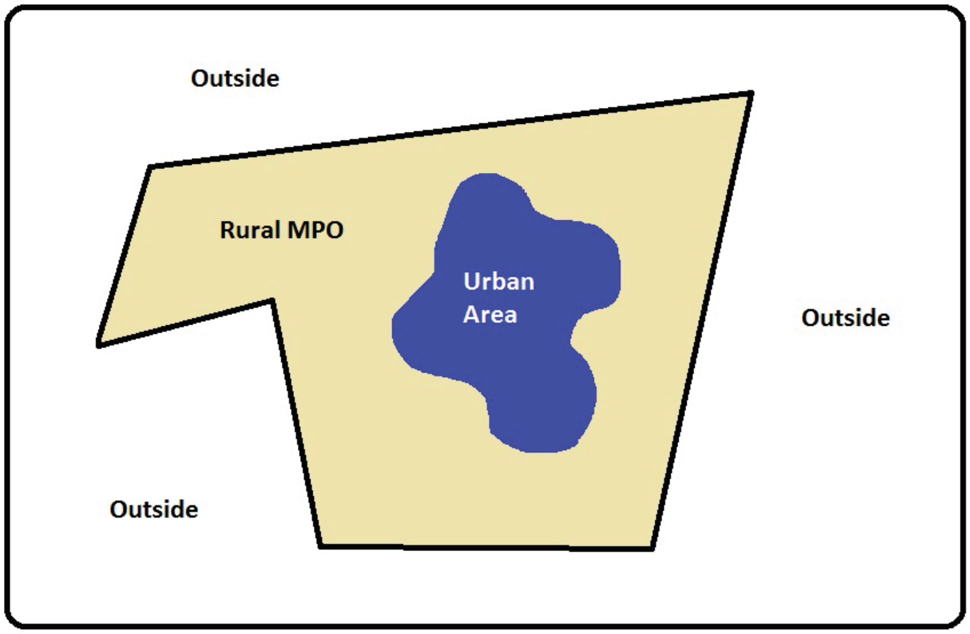


Figure 7. Basic Diagram of the Shapes to Determine Location and Area Type.

The approach used for development of the drive schedules is documented in detail in the final report for TxDOT Research Project 0-6629 (*66*). It is based on the methodology that was used by Eastern Research Group (ERG) to develop MOVES' default drive cycles for heavy-duty vehicles (*68*). The research team made necessary modifications to ERG's methodology based on the characteristics of the data from EVs. The approach is based on a process of building up cycles from individual micro-trips extracted from the GPS data (i.e., the GPS data for all vehicles were broken down into micro-trips).

All micro-trips were assigned a unique micro-trip identification number, and their time index for the starting point was set to zero; thus, all micro-trips started at zero seconds. The micro-trip identification number indicated the type of vehicle and a number showing the order they were extracted, regardless of their location. The following list shows the format for micro-trip ID numbers:

- Battery electric vehicle: E + micro-trip order number − E00256.
- Hybrid electric vehicle: H + micro-trip order number − H04257.
- Plug-in hybrid electric vehicle: P + micro-trip order number − P03652.

A summary table was created containing the following information for all valid micro-trips:

- Micro-trip ID.
- Average speed (mph) and duration (seconds).
- Distance traveled (miles).
- Location.
- Road classification (freeway [FWY] or arterial [ART]).
- Area type (rural or urban).

The extracted micro-trips were grouped together in separate data files based on the following parameters:

- Area and area type − the statewide urban + the statewide rural.
- Average speed bin as shown in Table 8.

Table 8. Speed Bin Definitions for Grouping Micro-Trips.

	Cases	Average Speed Bin (mph)	Speed Bin Definition (mph)
Non-Freeway	A_0	<2.5	<2.5
	A_5*	5	2.5≤ & <7.5
	A_10	10	7.5≤ & <12.5
	A_15	15	12.5≤ & <17.5
	A_20	20	17.5≤ & <22.5
	A_25	25	22.5≤ & <27.5
	A_30	30	27.5≤ & <35
	A_40	40	35≤ & <45
	A_50	50	45≤ & <55
	A_60	60	>55
Freeway	F_0**	2.5	0≤ & <5
	F_10	10	5≤ & <15
	F_20	20	15≤ & <25
	F_30	30	25≤ & <35
	F_40	40	35≤ & <45
	F_50	50	45≤ & <55
	F_60	60	55≤ & <65
	F_70	70	>65
	F_HS	>75	>75

* "A_x" refers to arterial/non-highway roadways at an average speed of x mph.
** "F_x" refers to freeway/highway roadways at an average speed of x mph.

Data Analysis and Drive Schedule Development

The MOVES model converts the speed profile information into a time distribution of activity unit bins called operating modes (opModes) and then applies appropriate emissions rates to this distribution.

An ideal drive schedule for a given driving condition is the one that has the maximum amount of information regarding that condition (i.e., in the context of this study, the one that has all the observations corresponding to that driving condition). However, using an entire database of second-by-second speed data is impractical. Therefore, a sub-ideal solution is a continuous short drive schedule constructed from a limited number of micro-trips, which will closely represent the ideal solution. This suboptimal solution is easy to implement and is currently used in MOVES in the form of default drive schedules.

In addition to second-by-second speed data, MOVES lets the user input vehicle activity information in terms of the equivalent operating mode distribution. This method provides an opportunity to implement the ideal solution (i.e., all observations) in a practical way. The research team analyzed the data and developed both ideal and sub-ideal solutions. For a specific speed bin, the ideal solution is the opMode distribution of the entire database for that bin, while the sub-ideal solution is a relatively short continuous speed profile representing that average speed bin.

Constructing a sub-ideal solution from a micro-trip database requires a methodology to examine the representativeness of each micro-trip. The research team decided to use a modified version of ERG's approach based on opMode distribution as MOVES' basic unit of activity. This approach is documented in detail in the TxDOT Project 0-6629 final report (*66*).

The final drive schedules and target opMode distributions are submitted to TxDOT in a database format. By providing this information, the users can pick the solution that fits their specific applications best. While the target opMode distribution is considered the ideal solution, it may not be easy to implement for simple analyses. On the other hand, the developed drive schedules (i.e., cycle) are sub-ideal but easy to implement in most cases.

Comparison to MOVES Default Drive Schedules

The resulting target opMode distributions (i.e., target) and drive schedules (i.e., cycles) were compared to the default drive schedules of MOVES in terms of their corresponding distribution of modal operating bins. A single analysis year of 2012 was used for this purpose. The comparison process consisted of the following steps:

- Establish opMode distribution (target, cycle, and MOVES default):
- Calculate opMode distribution for the target (for opMode comparison purpose only).
- Calculate opMode distribution for the cycle (for opMode comparison purpose only).
- Extract the MOVES default drive schedule that is closest to the target and cycle and calculate its opMode distribution (for opMode comparison purpose only).
- For all other parameters, use the default values for the target area and vehicle type.

Figure 8 and Figure 9 show an example of the results of this comparison effort. Figure 8 and Figure 9 show opMode distributions for the 50 mph speed bin on arterial/local and freeway/highway of the same scenario from plug-in hybrid vehicles in the statewide urban area.

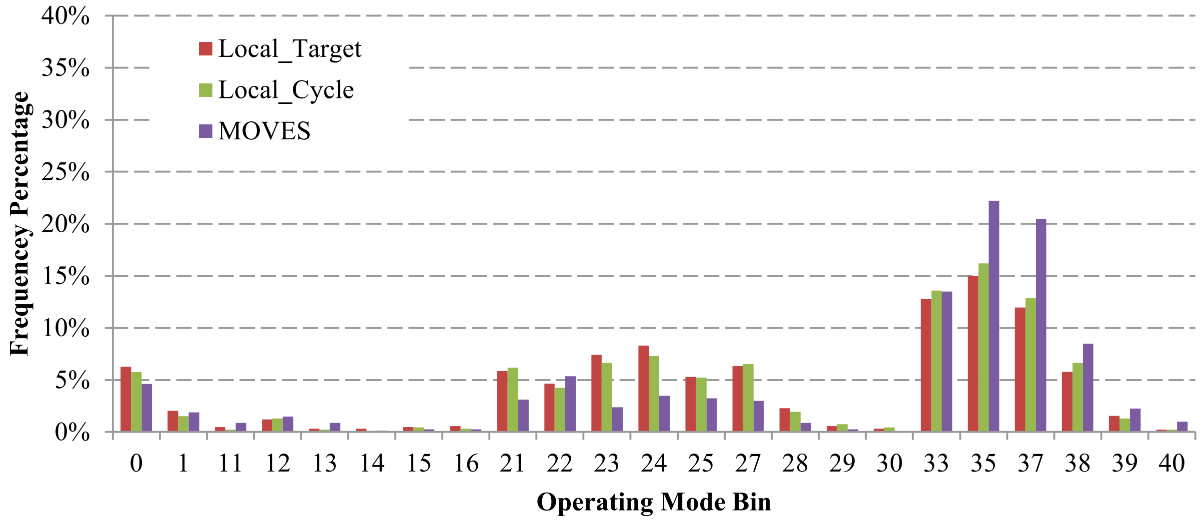


Figure 8. OpMode Distribution Comparisons for Plug-in Hybrid Vehicles—Arterial, Statewide Urban, Speed Bin 50 mph.

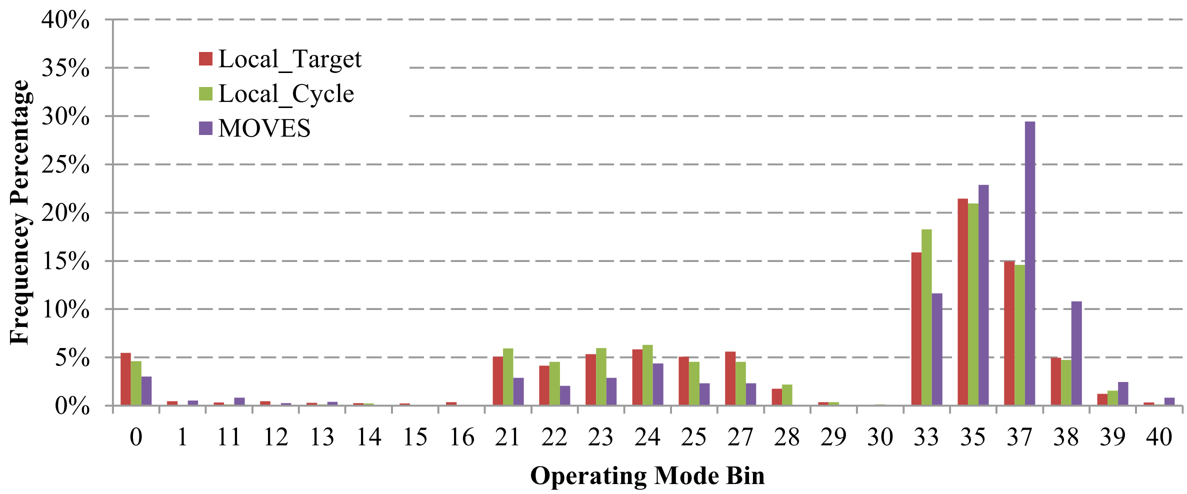


Figure 9. OpMode Distribution Comparisons for Plug-in Hybrid Vehicles—Freeway/Highway, Statewide Urban, Speed Bin 50 mph.

Average Drive Schedules

The research team also created the average drive schedules for each vehicle type (i.e., combined all the valid observations into a single drive schedule). The purpose of generating the average drive schedule was to provide information to review the driving behavior at a macroscopic level. Table 9 and Figure 10 show an example of the results of this effort. Table 9 lists the basic data statistics of plug-in hybrid vehicles on freeways in statewide urban areas. Figure 10 shows the opMode distributions of both targets and the cycle.

Table 9. Basic Statistics of FWY of PHEVs in Urban Areas.

	Local Target	Local Cycle
Avg. speed (mph)	46.183	47.422
Std. dev. speed (mph)	18.819	18.640
Max. speed (mph)	88.700	81.700
Avg. acceleration ($mph\ s^{-1}$)	0.696	0.716
Std. dev. acceleration ($mph\ s^{-1}$)	1.078	1.047
Max. deceleration ($mph\ s^{-1}$)	10.300	5.000
Max. acceleration ($mph\ s^{-1}$)	7.200	5.100
Idle (in % of time)	2.800	3.200
Duration (seconds)	122,848	1696
Number of trip segments		17

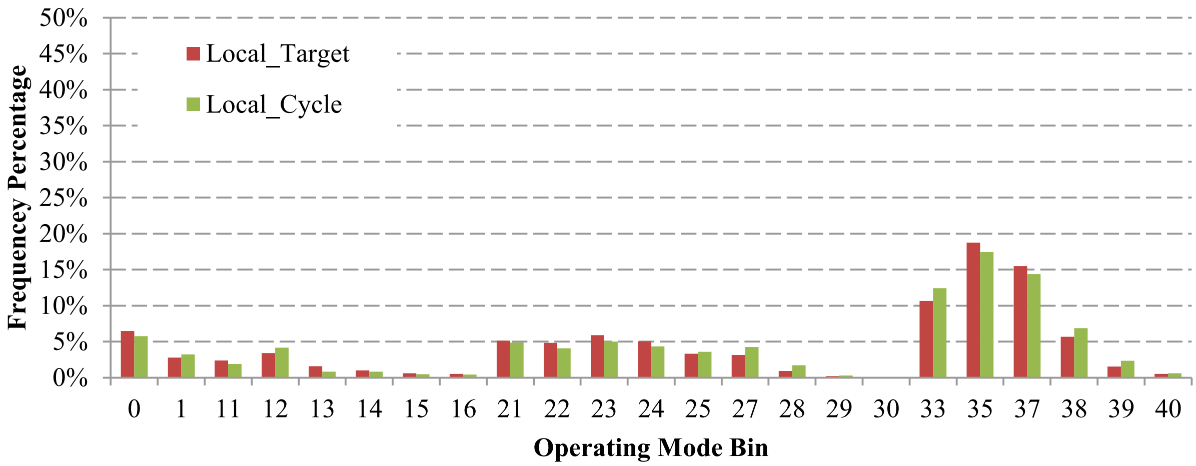


Figure 10. Average Activity OpMode Distribution for Plug-in Hybrid Vehicles—Freeway/Highway, Statewide Urban.

The research team also found that there were differences among the average opMode distributions of the three vehicle types investigated in this study. Most significantly, BEVs had a lower percentage of high-power bins for each average speed group. Instead, they had a higher percentage of low-power opMode bins, e.g., bins 21 and 30. This effect is potentially a result of drivers avoiding high-power driving events such as excessive acceleration and higher speeds to conserve battery charge and extend the driving range. Figure 11 shows an example of the results of this effort in statewide urban areas for arterial roads.

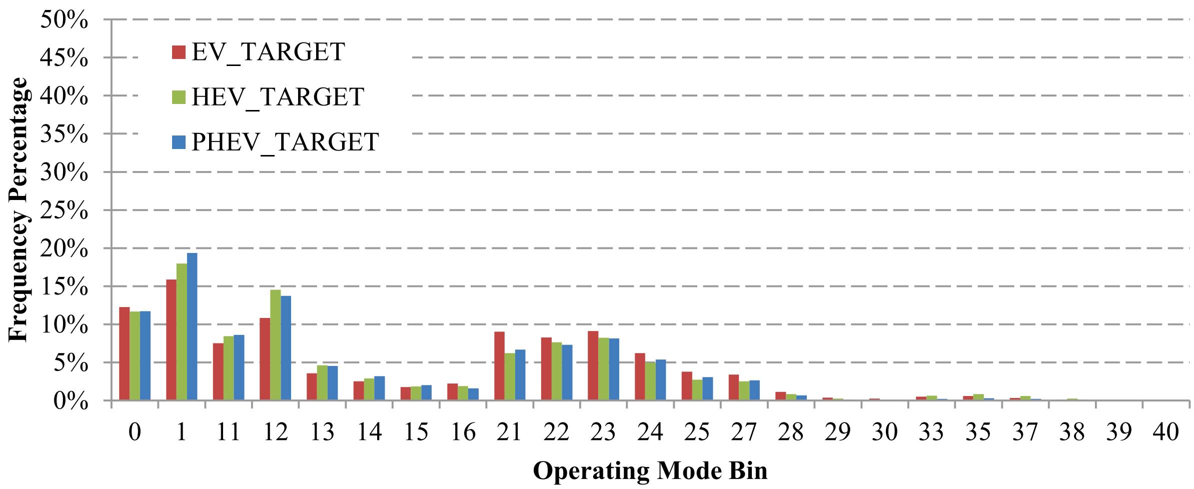


Figure 11. OpMode Distribution Comparisons for Plug-in Hybrid Vehicles, Hybrid Vehicles, and Pure Electric Vehicles on Arterial, Statewide Urban Areas.

IN-USE TESTING OF ELECTRIC VEHICLES

EVs' driving schedules provide an operating mode distribution for each road type and average speed bin. Additionally, operating-mode-based emissions rates are required in order to estimate distance-based emissions rates for EVs. In this project, these operating-mode-based emissions rates were estimated based on in-use testing of EVs, using PEMS equipment. It is important to note that the drive schedules developed for EVs were not used for the emissions testing. The in-use testing of EVs was used to obtain emissions rates for each operating mode bin (in units of g/s of emissions). These rates were then combined with operating mode distributions obtained from the drive schedules to calculate distance-based emissions rates (in units of g/mi) at each speed bin for each road type. The detailed process is discussed in the following sections.

Data Collection Protocol

The data collection protocol for developing emissions rates for electric vehicles consisted of the following major components:

- Test procedures for driving activities.
- Test procedures for idling.
- Data collection equipment and installation procedures.
- Vehicle samples from each vehicle category.

Test Procedures for Driving Activities

The research team investigated the possibility of testing each vehicle during normal daily operation, i.e., real-world testing. Researchers found that this approach was not feasible due to the operational characteristics of the vehicles. These vehicles were operated for only a few hours or less each day during normal operation, which would not provide enough data to cover all the desired operating conditions. To ensure that sufficient data were collected for each vehicle, the driving tests were conducted as a supervised data collection effort at TTI and surrounding areas in Bryan–College Station. This allowed the team to collect data from each vehicle under real-world driving conditions while giving the flexibility to collect more data in a more efficient time frame. Each vehicle was transported to TTI's Environmental and Emissions Research Facility (EERF) at the Texas A&M Riverside Campus in Bryan, Texas, for approximately one week of testing. Both the idling and driving tests were conducted that week.

The procedures for driving activities were developed to ensure that the test vehicles were put through a test route that would replicate different types of driving conditions, including both city and highway modes at different speeds. By combining both city and highway driving, the test route ensured that the vehicle was operated in each MOVES opMode bin in order to establish the emissions rates. Figure 12 outlines the test route that was followed for the driving test. The total distance for each test was approximately 31 mi. Each vehicle was driven on the test route for a minimum of three runs in order to collect sufficient data for establishing the rates.

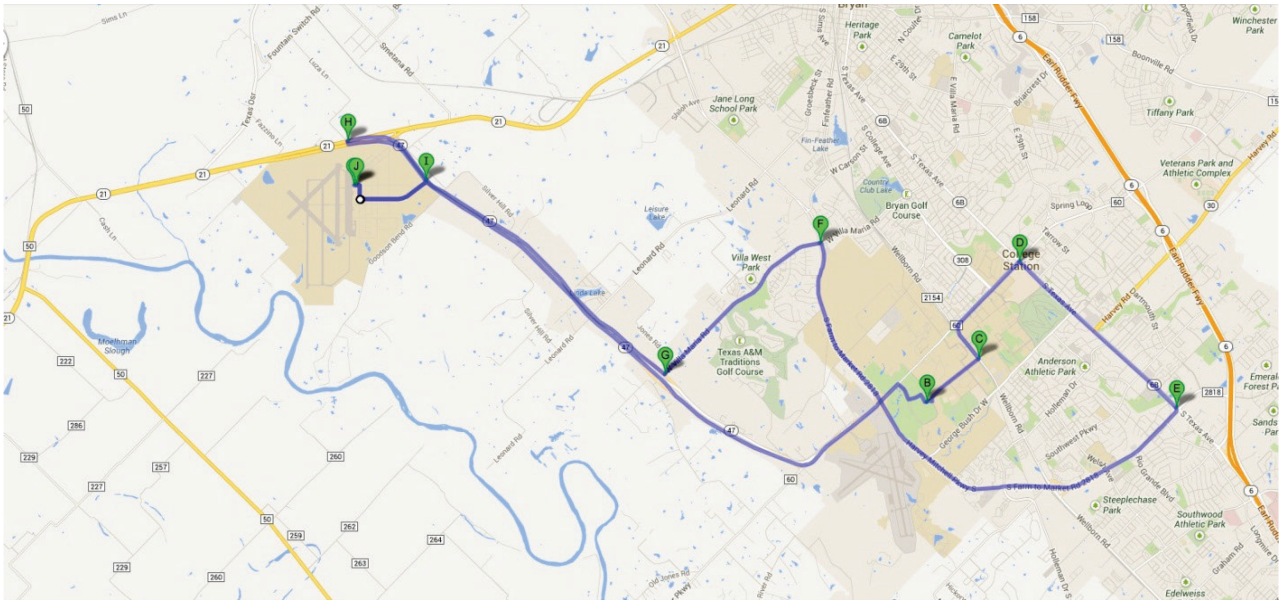


Figure 12. Test Route for Driving Tests. (Source: Google Maps)

Test Procedures for Idling

In addition to the driving test, data were collected while each vehicle was idling under controlled conditions. The idle testing was conducted inside the environmental chamber at TTI's EERF facility under the conditions shown in Table 10. The EERF facility includes an environmentally controlled test chamber that allows for testing at various conditions.

Researchers selected the test conditions in order to replicate both summer and winter conditions that an EV might be subjected to in Texas. Each vehicle was placed in the chamber and allowed to soak in the target temperature for two to three hours prior to the start of the test. The test began as a cold start test, which was done with the air conditioner (AC) or heater on, depending on the test condition. When available, the cabin temperature was set to be maintained automatically at 72 °F. The cold start idling test lasted for 30 minutes, after which time the test was considered a non-cold-start idling test. The total time for the test was approximately three hours per condition. During the testing, emissions and battery performance data were collected to create the emissions rates of each vehicle.

Table 10. Idle and Battery Depletion Testing Conditions.

Condition	Temperature	Relative Humidity	Load
Hot Test	95 °F (35 °C)	70%	AC
Cold Test	23 °F (−5 °C)	N/A	Heat

Data Collection Equipment

During both driving and idling testing, each vehicle was equipped with instruments to collect data needed to establish the emissions rates. Two types of data were collected during testing: emissions and battery/electricity consumption data. TTI's PEMS was used to collect emissions data. The PEMS used is an ECOSTAR® system from Sensors Inc. The system, shown in Figure 13, measures CO, CO_2, NO_x, and THC, and also includes a flow meter that measures the volumetric flow of the exhaust. Figure 14 shows the PEMS installed in a test vehicle. The PEMS was used on each of the PHEVs and HEVs. Because BEVs have no tailpipe emissions, they were not included in the PEMS data collection.

Figure 13. ECOSTAR Gaseous PEMS.

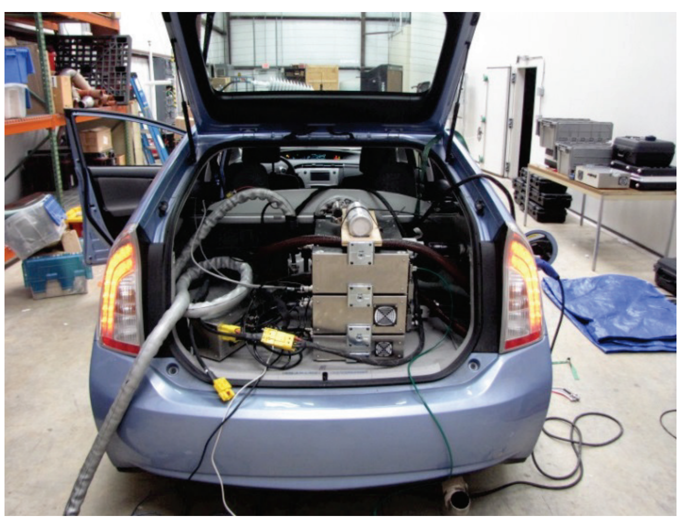


Figure 14. PEMS Equipment in Test Vehicle.

The research team used an on-board diagnostics (OBDII) data logger from AutoEnginuity® to collect the battery and electricity consumption information from the PHEVs and BEVs. Figure 15 shows the OBDII data logger used for OBDII data collection. The device reads and records battery information, such as state of charge and remaining battery power. The researchers calculated the power consumption of the vehicles for each opMode bin based on the collected data.

Figure 15. AutoEnginuity OBDII Data Logger.

Test Vehicles

Twelve vehicles were recruited for data collection of in-use testing, including four vehicles from each target vehicle category. The test vehicles were selected based on availability and because they were considered to be as representative as possible of the existing overall fleet. In some vehicle categories, such as the BEVs, where one make of vehicle is more prevalent than others, multiple vehicles of the same make were recruited for testing. Participants were compensated $200 for their effort. The following sections describe the details of the recruited vehicles.

Battery Electric Vehicles

Between 2011 and 2013, approximately 22 different BEV models were produced and sold in the United States, with 13 additional models available for 2014 (*69*). Of these models, the most popular are the Nissan Leaf, Tesla Model S, and Ford Focus Electric (*70*). These three vehicles made up almost 92 percent of all BEV sales in 2013, according to available sales data. Based on these numbers, the research team located three units of the Nissan Leaf and one unit of the Ford Focus Electric for testing. A Tesla was also considered for testing, but the available data loggers needed to collect the information on the battery performance did not support Tesla vehicles. Table 11 shows the vehicle specifications of the BEV units that were tested, and Figure 16 includes pictures of a Leaf and the Focus that researchers used in the data collection (*71*,*72*).

Table 11. BEV Tested Vehicle Specifications.

Vehicle Parameter	2011 Nissan Leaf	2013 Ford Focus Electric
Electric Motor	80 kW, 107 HP	107 kW, 143 HP
Battery	24 kWh	23 kWh
Battery Charger	3.3 kW (pre-2013 models) 6.6 kW (2013 model)	6.6 kW
Approximate Range	75 mi	76 mi
2013 Units Sold	22,610	1738

Note: Both Photos Were Taken at the EERF.

Figure 16. Nissan Leaf Vehicle (Left); Ford Focus Electric Vehicle (Right).

Plug-In Hybrid Electric Vehicles

From 2011 to 2013, only eight different PHEV models were available for sale in the United States, while 10 models were available beginning with model year 2014. PHEVs differ from BEVs in that they can operate in two different modes:

- Charge depletion mode when the hybrid battery is charged above a threshold and the vehicle is powered solely by the battery.
- Charge sustaining mode when the battery is discharged below a threshold where the vehicle cannot be powered solely by the battery. In this mode, the vehicle is powered intermittently by a gasoline-powered engine and the battery.

The gasoline-powered engine gives PHEVs a much longer range than BEVs, but the range of their CD mode is shorter than the range of BEVs.

The Chevy Volt is the most popular PHEV on the market, having sold over 23,000 units in 2013, making it 135th in the overall sales numbers of vehicles in the United States, just ahead of the Nissan Leaf BEV (*73*). The next most popular PHEVs on the market in 2013 were the Toyota Prius plug-in and the Ford C-Max. For this project, three Chevy Volts and one Toyota Prius plug-in were selected to be tested. Table 12 includes the details of the PHEVs tested, and Figure 17 shows one of the Volts and the Prius that were tested (*74*,*75*).

Table 12. PHEV Tested Vehicle Specifications.

Vehicle Parameter	2012 Chevy Volt	2011 Chevy Volt	2012 Prius Plug-in
Electric Motor	111 kW, 149 HP	111 kW, 149 HP	60 kW, 80 HP
Battery	16 kWh	16 kWh	4.4 kWh
All Electric Range	35 mi	35 mi	15 mi
Internal Combustion Engine	1.4 L, 84 HP	1.4 L, 84 HP	1.8 L, 98 HP
2013 Units Sold	23,094		12,088

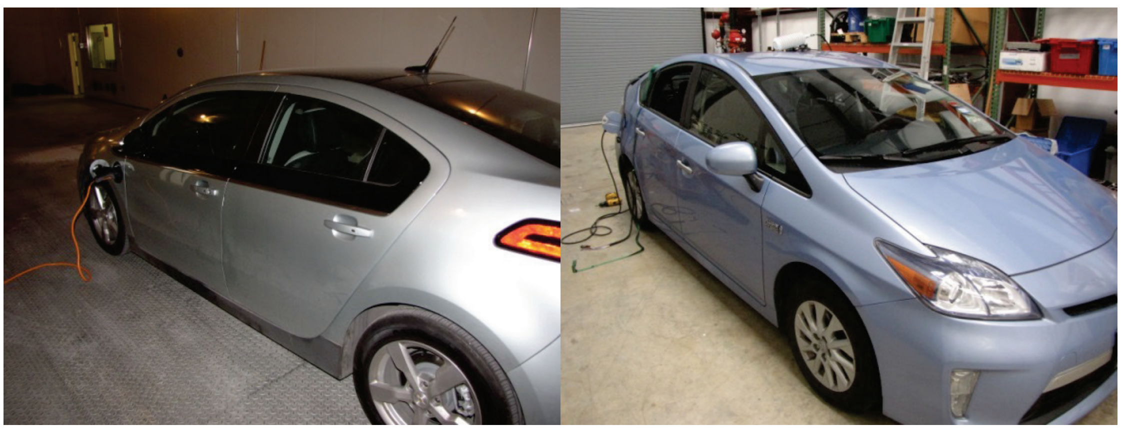


Figure 17. Chevy Volt (Left); Toyota Prius Plug-In (Right).

Hybrid Electric Vehicles

HEVs are the most common type among the target vehicle types for this project. Between 2011 and 2014, 134 different HEVs have been available in the United States. The HEV, like the PHEV, combines an internal combustion engine and a battery-powered electric motor. Unlike the PHEV models, HEV batteries cannot be charged by an external power source; instead, HEVs switch between the ICE and the electric motor.

For this project, the research team selected test vehicles to cover different classes of available hybrid vehicles. Unlike the PHEV and BEV models, where options are limited to smaller passenger car models, there are different classes of HEVs on the market, including passenger cars, trucks, and sport utility vehicles (SUVs). The vehicles selected for testing were the Ford Fusion, Toyota Camry, Ford Escape SUV, and Toyota Prius. Table 13 details the specifications of the hybrid vehicles recruited for testing (*76,77,78,79,80*). Figure 18 includes pictures of these vehicles.

Table 13. Tested HEV Vehicle Specifications.

Vehicle Parameter	2012 Ford Fusion Hybrid	2012 Toyota Camry Hybrid	2012 Ford Escape Hybrid	2011 Toyota Prius
Engine	2.5 L, 156 HP	2.5 L, 156 HP	2.5 L, 155 HP	1.8 L, 98 HP
Electric Motor	106 HP	141 HP	94 HP	80 HP
Combined HP (electric motor and ICE engine)	188 HP	200 HP	177 HP	134 HP

Figure 18. Ford Escape Hybrid (Top Left); Ford Fusion (Top Right); Toyota Camry (Bottom Left); Toyota Prius (Bottom Right).

EMISSIONS DATA ANALYSIS

In this section, operating-mode-based emissions rates from in-use testing of EVs are reported. Furthermore, distance-based EV emissions rates are calculated based on the operating-mode-based emissions rates and localized drive schedules developed from GPS data.

Operating-Mode-Based Emissions Rates

In-use testing of EVs provided second-by-second emissions of tested vehicles under real-world driving conditions. In addition, driving characteristics of each second (i.e., instantaneous speed and acceleration) were recorded. Therefore, each second of driving condition was categorized into one MOVES-based operating mode bin. By averaging emissions under each operating mode, time-based EV emissions rates per operating mode bin were prepared and later used to establish distance-based EV emissions rates.

The PEMS units used in testing included a vehicle interface connection and GPS unit that allowed for the collection of second-by-second speed data during all testing. These second-by-second speed profiles were then used to calculate a second-by-second vehicle-specific power (VSP), which was then used to determine the opMode that the vehicle was in during a given second of operation. The emissions data from each second were then averaged for each opMode bin.

The calculation used to determine the opMode bin was based on the MOVES model. The equation for VSP is as follows:

$$VSP = \left[S * \frac{rollingTermA + S * (rotatingTermB + dragTermC * S)}{sourceMass}\right] + S * Acc. + (9.81 * \sin(\text{atan}(G)) * S$$

Where:

- S: Speed (m/s).
- Acc.: Acceleration (m/s).
- rollingTermA, rotatingTermB, dragTermC: variables defined in MOVES based on vehicle type.
- sourceMass: mass of vehicle (metric ton).

The MOVES variables (rollingTermA, rotatingTermB, dragTermC) are all defined in MOVES based on the vehicle type. All the vehicles in this test, except for the Ford Escape, were classified as passenger cars (MOVES source type 21) and therefore had the same MOVES variable values for these parameters. The Ford Escape was considered a passenger truck (MOVES source type 31) and, therefore, had slightly different values. The sourceMass of each vehicle was calculated by taking the vehicle's curb weight and adding the weight of the PEMS unit and the driver of the vehicle to give a total sourceMass. The values used in the calculations for each vehicle are shown in Table 14.

Appendix A presents the emissions rates per operating mode bin for EVs. Although the focus of this study was on running exhaust emissions, idling emissions rates were also collected and reported and could be used in future analysis. In addition, the electricity consumptions of

BEVs and PHEVs in CD mode were recorded and then used to calculate associated power grid emissions.

Table 14. MOVES Variables for VSP Calculation.

Test Vehicle	MOVES Variables			
	rollingTermA	rotatingTermB	dragTermC	sourceMass
2011 Nissan Leaf	0.156461	0.00200193	0.0049265	1.61206728
2013 Ford Focus Electric	0.156461	0.00200193	0.0049265	1.85564639
2011 and 2012 Chevy Volt	0.156461	0.00200193	0.0049265	1.71503275
2012 Toyota Prius Plug-In	0.156461	0.00200193	0.0049265	1.63250049
2012 Ford Escape Hybrid	0.221120	0.00283757	0.00698282	1.8134623
2012 Ford Fusion Hybrid	0.156461	0.00200193	0.0049265	1.86880056
2012 Toyota Camry Hybrid	0.156461	0.00200193	0.0049265	1.77309257
2011 Toyota Prius Hybrid	0.156461	0.00200193	0.0049265	1.56126494

Distance-Based Emissions Rates

Researchers combined the time distribution of operating mode at each road type and average speed bin and time-based EV emissions rates at each operating mode bin. The outputs were distance-based emissions rates (g/mi) at each average speed bin and road type for all pollutants and vehicle types. Three of the four tested HEVs were passenger cars, which represented the majority of available hybrid models on the market. The research team applied a market-share weighted average method to obtain a set of representative emissions rates for HEV passenger cars. The same procedure was applied to PHEV and BEV passenger cars. HEV passenger truck emissions rates were from the Ford Escape HEV, which was the only passenger truck tested. In order to obtain running exhaust emissions rates for PHEV passenger trucks, the same set of ratios between HEV and PHEV passenger cars were applied to HEV and PHEV passenger trucks. A limitation of the study is the lack of data for PHEV passenger trucks despite the research team's best efforts to find and recruit at least one vehicle from each category. The main reason for this issue was that PHEV passenger trucks constitute less than 0.01 percent of the passenger truck fleet in the US.

These emissions rates were then converted to a MOVES-compatible emissions rate table by vehicle type to be used as an input to the MOVESemscalc script. Figure 19 visually shows the process.

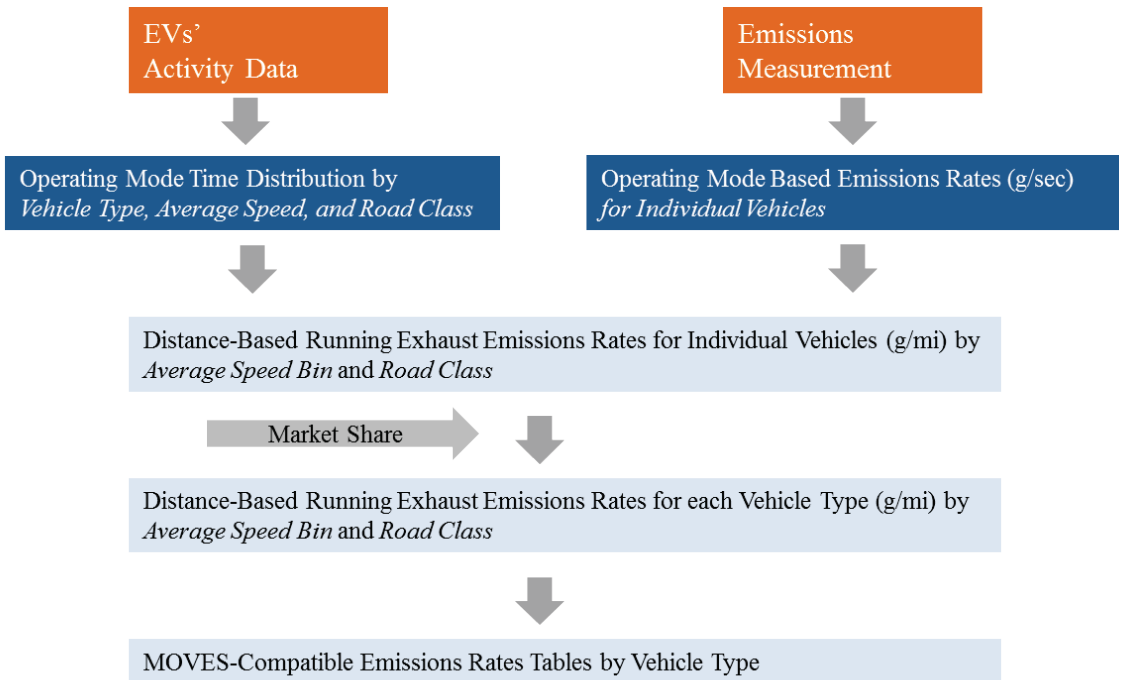


Figure 19. Methodology for Developing Distance-Based Emissions Rates.

Calculating Distance-Based Emissions Rates for Individual Vehicles

Researchers observed that there were not many observations for certain combinations of average speeds and road types. Enough observations were needed to be able to represent average vehicle operation conditions for an average drive speed. The research team decided to discard the observations when there were fewer than 500 seconds of observations for a speed bin. In such instances, a substitute opMode distribution from other road types was then used to calculate the emissions rates for that speed bin. The team developed the following criteria to assign a substitute for such cases:

- Step 1. Use opMode distribution for the same speed bin and road class from the alternative area type (e.g., if it is *rural restricted*, then use *urban restricted*).

- Step 2. If Step 1 did not yield a valid opMode distribution, use opMode distribution for the same speed bin and area type from the alternative road class (e.g., if it is *rural restricted*, then use *rural unrestricted*).
- Step 3. If Steps 1 and 2 did not yield a valid opMode distribution, use opMode distribution for the same speed bin from the alternative road class and area type (e.g., if it is *rural restricted*, then use *urban unrestricted*).
- Step 4. If none of the above steps work, use the opMode distribution from the MOVES database for the corresponding speed and road type.

First, the opMode emissions rates for each individual vehicle were combined with the operating mode distributions developed earlier to generate distance-based emissions rates (g/mi) for each average speed. Because the actual average speeds of the opMode distributions were slightly different from the assigned speed of MOVES speed bins, and because not all bins had a local opMode distribution, the team used a linear interpolation to calculate emissions rates at the exact assigned speeds of MOVES speed bins. Figure 20 shows a sample of the resulting distance-based emissions rates for individual vehicles.

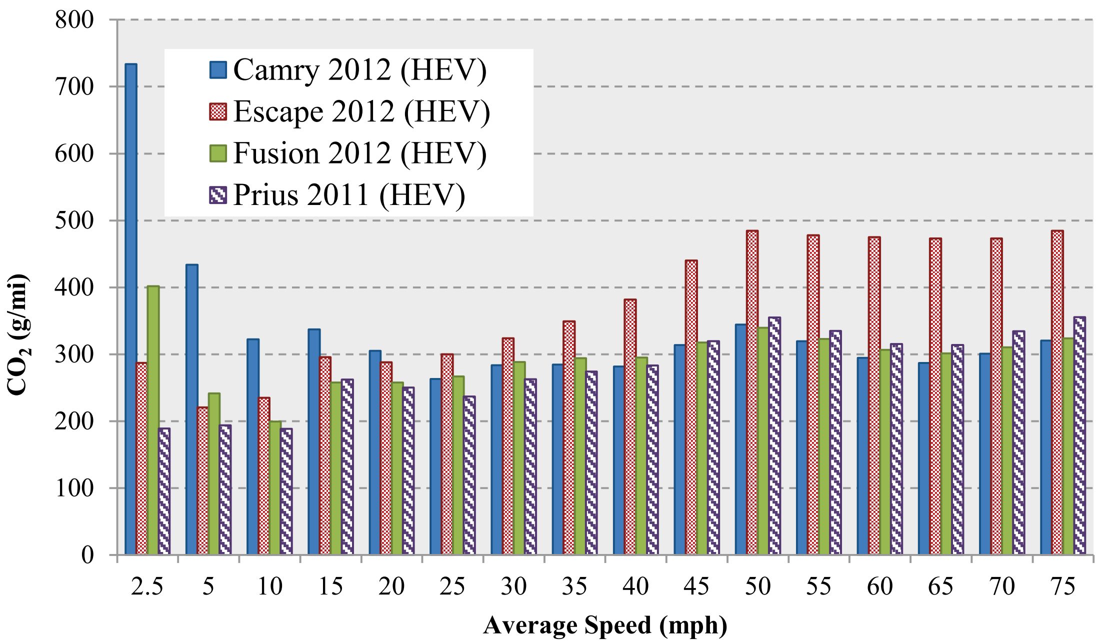


Figure 20. CO_2 Emission Rates for HEVs on Rural, Arterial Road.

Calculating Market-Share Weighted Average Emissions Rates for Vehicle Type

MOVES-based emissions estimations require average emissions rates for each vehicle type. Three vehicle types were included in this study: hybrid electric passenger cars, hybrid electric passenger trucks, and plug-in hybrid passenger cars.

Researchers assumed that the difference in the age of the vehicles would have only a minimal impact on their tailpipe emissions. This assumption is consistent with the MOVES age grouping assumption that vehicles of age 0 to 3 years are in the same age group. To develop emissions rates that are representative of the average HEV and PHEV in the US market, the team aggregated the individual vehicles' emissions rates (g/mi) based on their current market share (i.e., market-share weighted averages of emissions rates were calculated). This aggregation was performed on each speed bin.

In the current electric vehicle market, HEVs are the most common electric vehicle type. However, PHEV and BEV sales are also increasing rapidly. Table 15 provides a summary of current electric vehicle market shares. The data indicate that the tested vehicles are good representatives of the current electric vehicles in the US market. As shown in Table 15, the tested vehicles account for approximately 70 percent and 60 percent of passenger car HEVs and PHEVs in the US market, respectively (*70*).

Table 15. Electric Vehicle Market Status.

Vehicle Type	Market Models	Tested Vehicle Share
HEV	134 models until 2014	Prius (58%) Camry (11%) Fusion (3%)
PHEV	8 models from 2011–2013 10 models in 2014	Volt (46.6%) Prius (24.4%)
BEV	22 models from 2011–2014	Leaf (60%) Focus (3.4%)

The market-share-averaged emissions rates were generated for HEV passenger cars, PHEV passenger cars, and HEV passenger trucks. The rates for the HEV passenger truck were based on a single HEV Ford Escape tested by the TTI team. The HEV passenger car emissions factors were based on three HEV passenger cars, and PHEV passenger car values were based on four PHEV passenger cars.

Figure 21 through Figure 24 show the final distance-based emissions rates for all three vehicle types on rural unrestricted roads. The results for all road types are included in the appendices. The data indicate that the CO_2 and NO_x emissions rates for HEV and PHEV passenger cars are comparable under the rural arterial road type. HEV passenger truck emissions rates at high speeds (over 40 mph) are significantly higher than those of HEV and PHEV passenger cars, except for THC. The PHEV passenger car THC emissions at speeds lower than 40 mph are much higher than those of the other vehicles.

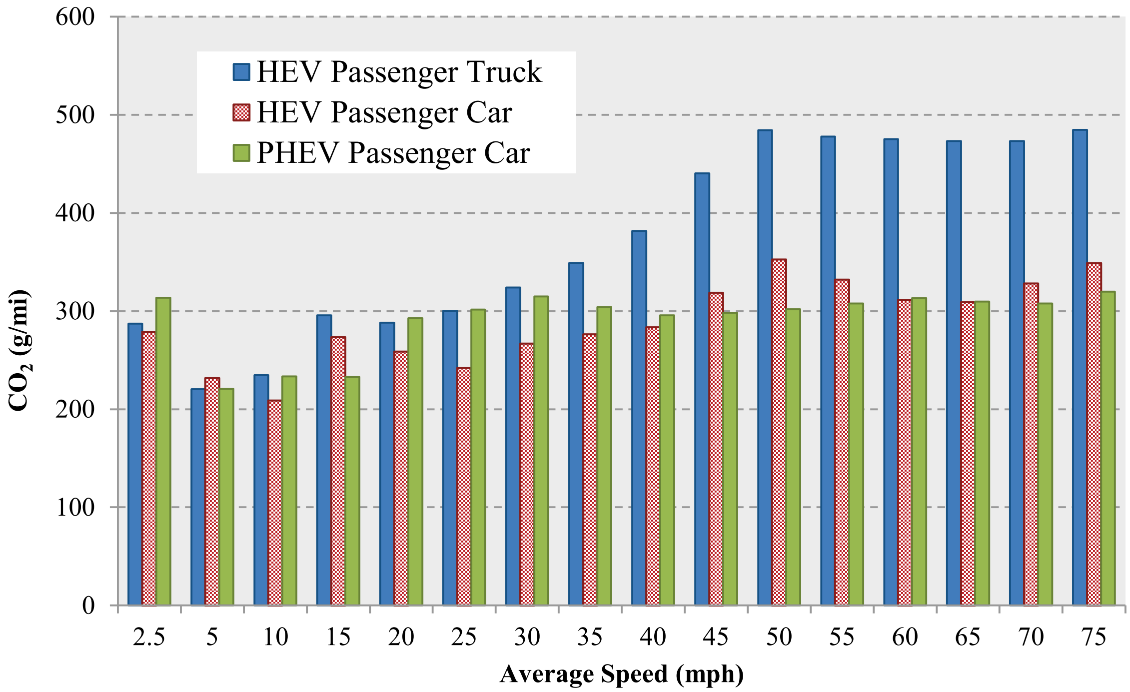


Figure 21. Aggregated CO_2 Emission Rates for the Rural Unrestricted Road Type.

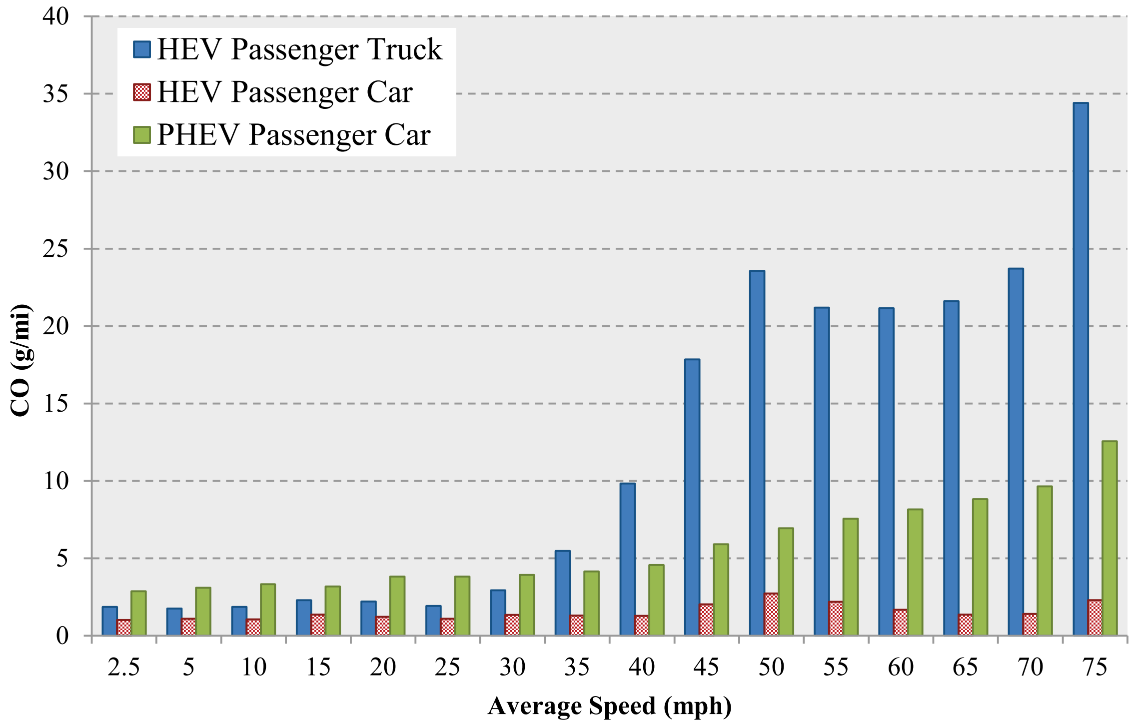


Figure 22. Aggregated CO Emission Rates for the Rural Unrestricted Road Type.

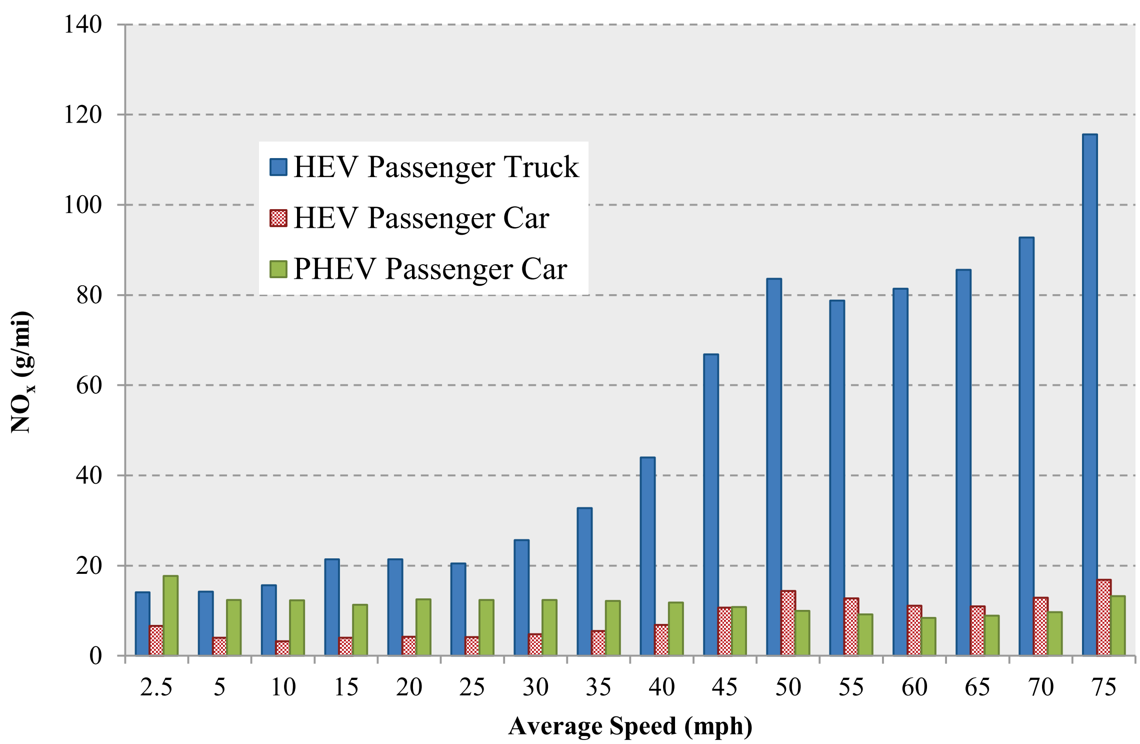


Figure 23. Aggregated NO_x Emission Rates for the Rural Unrestricted Road Type.

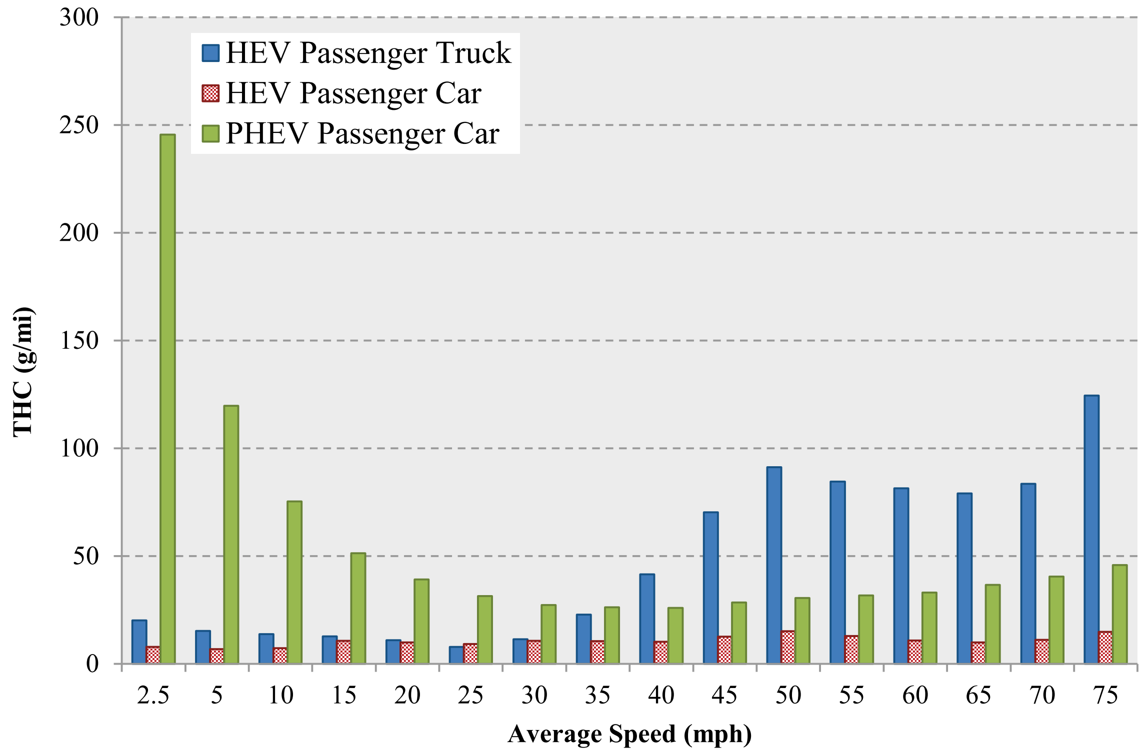


Figure 24. Aggregated THC Emission Rates for the Rural Unrestricted Road Type.

Characterizing PHEVs' Electric Mode Operation

The distance-based emissions rates calculated for PHEVs in the previous section were done only for the charge sustaining mode where the vehicle switched between its internal combustion engine and electric motor. PHEVs produce no tailpipe emissions when driving in CD mode. A transportation conformity analysis includes only mobile source emissions (i.e., emissions associated with electricity production are not included). Therefore, understanding percentages of PHEV miles driven on electricity is important for estimating PHEVs' average distance-based tailpipe emissions rates in CD and CS modes.

A study conducted by the US Department of Energy's Clean Cities Program estimated that 70 percent of PHEV miles are driven on electricity. This study was based on travel behavior data from a 2001 National Household Travel Survey (*69*). Several online electric vehicle consumer forums let electric vehicle users report their EV mile reading from the odometer of their vehicles. These data can be used to develop a relatively accurate estimate of the overall electric mode percentage for PHEVs in the US market. *VoltStats.net* collects data from electric vehicle users and reports the total miles driven, electricity miles driven, and overall fuel economy (*81*). Researchers obtained volt usage data for the entire US and three states (Texas, California, and New York) and analyzed them to estimate the percentage of PHEVs' electric mode operation. Table 16 and Table 17 show summary statistics in 2013 of PHEV mileage and percentage of miles driven on electricity, respectively.

Table 16. Total Miles Driven by Electric Cars.

	US	TX	CA	NY
Min	7	626	193	88
Max	149,090	69,271	78,399	57,500
Mean	16,670	16,467	15,270	16,985
Standard Deviation	12,322	12,707	13,245	12,770

Table 17. Percentage of Electric Miles Driven.

	US	TX	CA	NY
Min	1.4	31.2	20.9	40.4
Max	100	99.8	99.0	97.4
Mean	76.0	74.2	79.8	75.7
Standard Deviation	14.8	18	14.2	16.7

The data indicate that the percentages of miles driven on electricity ranged between 74 percent and 80 percent in the three states, and the national average was at 76.0 percent. Those real-world observations are consistent with the 70 percent electric miles driven estimated by the National Renewable Energy Laboratory, whose study was based on nationwide transportation survey data and considered both electric vehicle battery technology evolvement and users' driving behaviors (*69*).

Based on literature and analysis of PHEV user reported data, 76 percent (value of national average) was selected as the share of PHEVs' VMT on electricity. This means that 24 percent of PHEVs' VMT are driven using the ICE, thus producing running exhaust emissions, while the other 76 percent of PHEVs' VMT do not produce exhaust emissions. Therefore, after obtaining the distance-based running exhaust emissions rates for PHEVs, a reduction factor equaling the share of total PHEV miles driven using the ICE was applied. This factor allowed equivalent distance-based emissions rates for PHEVs to be established per VMT as a whole, instead of only for ICE engine operation.

Battery technology is the main factor determining the extent of the full electric/zero-emission miles of PHEVs. Thus, more miles driven on electricity are expected if higher-capacity batteries at a reasonable price become available. To determine the future share of the ICE miles required for an emissions analysis, one needs to make appropriate assumptions regarding the improvements in the capacity of the batteries used in PHEVs.

MOVES-Compatible Emission Table

The calculated market-share averaged emissions rates were converted into MOVES-compatible emission tables to be input into the MOVESemscalc script. Table 18 shows a sample of content in the emission table for the MOVESemscalc script.

Table 18. Sample MOVES-Compatible CO_2 Emission Table.

pollutantID	avgSpeedBinID	processID	hourID	roadTypeID	sourceTypeID	fuelTypeID	ratePerDistance
90	1	1	1	3	21	1	279.132
90	2	1	1	3	21	1	231.845
90	3	1	1	3	21	1	208.993
90	4	1	1	3	21	1	273.344
90	5	1	1	3	21	1	258.783
90	6	1	1	3	21	1	242.117
90	7	1	1	3	21	1	266.986
90	8	1	1	3	21	1	276.536
90	9	1	1	3	21	1	283.677
90	10	1	1	3	21	1	318.736
90	11	1	1	3	21	1	352.683
90	12	1	1	3	21	1	332.169
90	13	1	1	3	21	1	311.656
90	14	1	1	3	21	1	309.198
90	15	1	1	3	21	1	328.257
90	16	1	1	3	21	1	349.012

CONCLUDING REMARKS

This chapter summarizes the collection of electric vehicle activity and emissions data from EVs, as well as the process of establishing distance-based EV exhaust emissions rates using the collected data. The electric vehicle activity data were collected based on GPS data from a sample of EVs in major Texas metropolitan areas. The electric vehicle activity data were then used to develop Texas-specific driving schedules. The research team conducted electric vehicle in-use emissions testing using PEMS equipment. Finally, the testing results were processed with

Texas-specific driving schedules to generate distance-based emissions rates for HEVs, PHEVs, and BEVs, respectively.

CHAPTER 4: INCORPORATING EVS INTO MOVES-BASED EMISSIONS ANALYSIS

This chapter discusses the framework developed to incorporate EVs into a conformity-type analysis. This involved the integration of EV-specific parameters into a travel-demand-model-based emission inventory. EPA's MOVES model has been used widely as a mobile source emission inventory model in national-, state-, and regional-level air quality analyses and formed the basis for the framework described in this chapter. Chapter 3 described how a set of distance-based running exhaust emissions rates were established for HEVs and PHEVs at each average speed bin and road type based on Texas-specific driving schedules and in-use emissions testing. Currently, the MOVES model does not have EV emissions rates; however, the MOVES model has the flexibility to accept user-prepared inputs for more representative results based on local data. This chapter describes how the EV emissions rates and activity input were integrated with previously developed MOVES-based emissions estimation processes. The remainder of this chapter presents the framework for integrating EVs into a MOVES-based emissions analysis.

FRAMEWORK TO INCORPORATE ELECTRIC VEHICLES INTO MOVES-BASED EMISSIONS ANALYSIS

An overview of the analytical framework is shown in Figure 25. This framework integrates a vehicle consumer choice model and a MOVES-based emission inventory script to incorporate EVs into a regional emissions inventory.

EVs' market penetration (i.e., the number of vehicles or the share of overall fleet) is a key piece of information required for this process. While historical sales data/trends can be used for base year analyses, predicting future market penetration is more complex, as described in detail in Chapter 2. Two of the major factors influencing EVs' market penetrations are the future energy price (i.e., cost of fuel) and the presence of any government policies and/or incentives promoting EVs. In this research, the research team used the MA^{3}T model to project future EVs' market penetration for a set of future energy prices and government policy scenarios. MA^{3}T is a well-established automobile market simulation model developed by researchers at the US Department of Energy's Oak Ridge National Laboratory (*26*).

Using the EV market shares predicted by the MA^{3}T model, the TTI research team developed VMT assignments for EVs, which can be used to adjust VMT shares for gasoline passenger cars and passenger trucks to account for EVs. Similarly, modified EV exhaust emissions rates were developed (based on the rates generated from in-use testing of EVs) to include the impact of EVs in the vehicle fleet (Figure 25). The results from the previous step were combined with other parameters previously prepared by TTI to serve as input data to run a MOVES-based emission calculation script (MOVESemscalc), also previously developed by TTI (*82*).

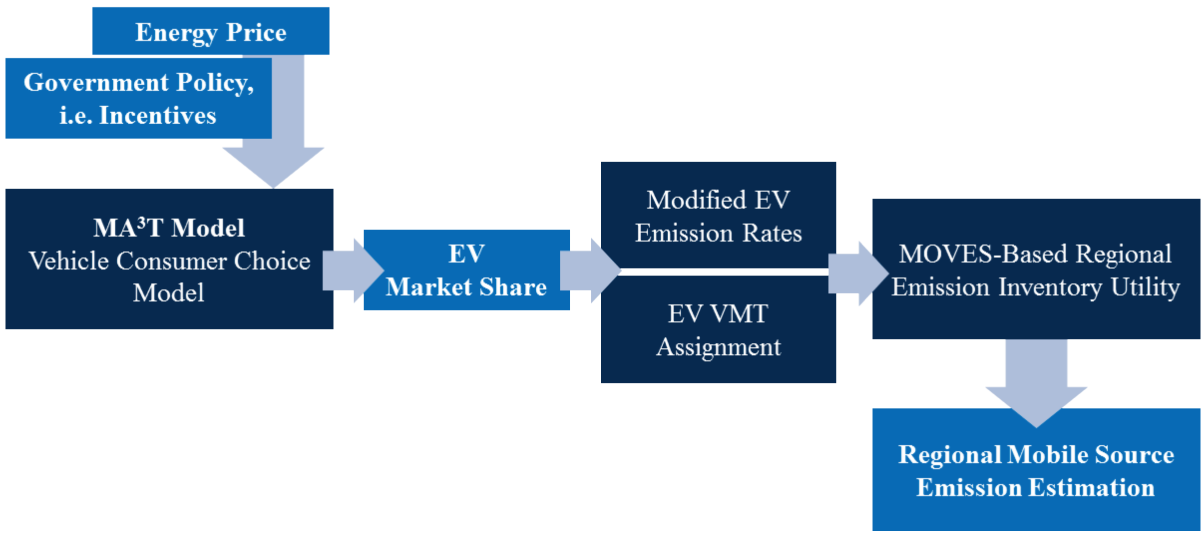


Figure 25. Analysis Framework for Incorporating EVs into Regional Emissions Estimations.

PILOT APPLICATION OF FRAMEWORK

The above framework was applied in order to demonstrate its use and to investigate the impacts of including EVs in the modeled on-road exhaust emissions of greenhouse gases (i.e., CO_2) and criteria pollutants or their precursors (CO, NO_x, and THC) in Harris County, Texas. Analyses were conducted for the years 2014 and 2026. Harris County is the most populous county in Texas and encompasses a large part of the Houston metropolitan area. The TTI research team had access to local data and previous emissions inventories conducted for Harris County, which were used for the pilot application. The analysis years were selected based on data availability and to provide a realistic platform to assess the implications of including EVs in the context of transportation conformity under current and future conditions.

Methodology

This section describes the analysis methodology in further detail, including:

- Use of the consumer choice model to predict EV market penetration.
- Adjustments for VMT assignments and EV emissions factors.
- Incorporation into a conformity-type analysis (i.e., integration into emissions inventory).

EV Market Penetration Prediction Using Consumer Choice Model

The research team developed four scenarios to demonstrate how the analytical framework developed in this study could be used to account for the impact of EVs in regional emission inventories. Table 19 shows the descriptions of these scenarios. As seen in the table, the scenarios varied by analysis year, incorporation of EVs, and assumptions used for the MA^3T model where future EV market penetration was projected. The government policy in the model assumption refers to the $2,500~7,500 tax credit (depending on battery capacity) that the US government currently offers to the owners of the first 200,000 plug-in electric vehicles (i.e., PHEVs and BEVs) from each vehicle manufacturer. It is likely that this tax credit will be discontinued around the year 2020, and this was the assumption employed for most 2026 scenarios. However, an Extended Incentives 2026 scenario was also included to study the impact of extending the government tax credit until the end of 2026.

Table 19. Scenario Developed for Pilot Application.

Scenario	Analysis Year	EVs in Fleet	EV Market-Share Source	Assumptions in MA^3T Model	
				Energy Price Source	Government Policy on PEVs
Base Case 2014	2014	No	N/A	–	–
EV 2014	2014	Yes	Pre-2014: Historical Sales Data	–	–
Base Case 2026	2026	No	N/A	–	–
High Oil Price 2026	2026	Yes	Pre-2014: Historical Sales Data 2014–2026: Projections from MA^3T Model	AEO 2014 High Oil Price	Tax Credits until 2020
Medium Oil Price 2026	2026	Yes	Pre-2014: Historical Sales Data 2014–2026: Projections from MA^3T Model	AEO 2014 Reference Oil Price	Tax Credits until 2020
Low Oil Price 2026	2026	Yes	Pre-2014: Historical Sales Data 2014–2026: Projections from MA^3T Model	AEO 2014 Low Oil Price	Tax Credits until 2020
Extended Incentives 2026	2026	Yes	Pre-2014: Historical Sales Data 2014–2026: Projections from MA^3T Model	AEO 2014 Reference Oil Price	Tax Credits until 2026

The research team ran the MA^3T model using inputs and assumptions described in Table 19. The energy prices were based on various price scenarios of the AEO 2014 report. AEO's reference oil price case assumes trends that are consistent with historical and current market behavior, technological and demographic changes, and current laws and regulations. The AEO's high and low oil price cases are predicted based on trends that would lead to high and low future oil prices. Figure 26 shows the expected market share of EVs as the MA^3T model predicted. The results indicate that passenger car HEVs' market shares will peak in the year 2020 and then start declining for all scenarios. In addition, the projected passenger truck HEV market shares will increase from 2014 to 2026; however, after 2020, the projected market share will remain flat. On the other hand, the results show that the market shares of plug-in electric vehicles, including PHEVs and BEVs, will experience a sharp decrease around 2020, which is the year that tax credits are planned to be discontinued. The only exception is under the extended incentive scenario, where the projected market shares for BEVs and PHEVs continue to increase.

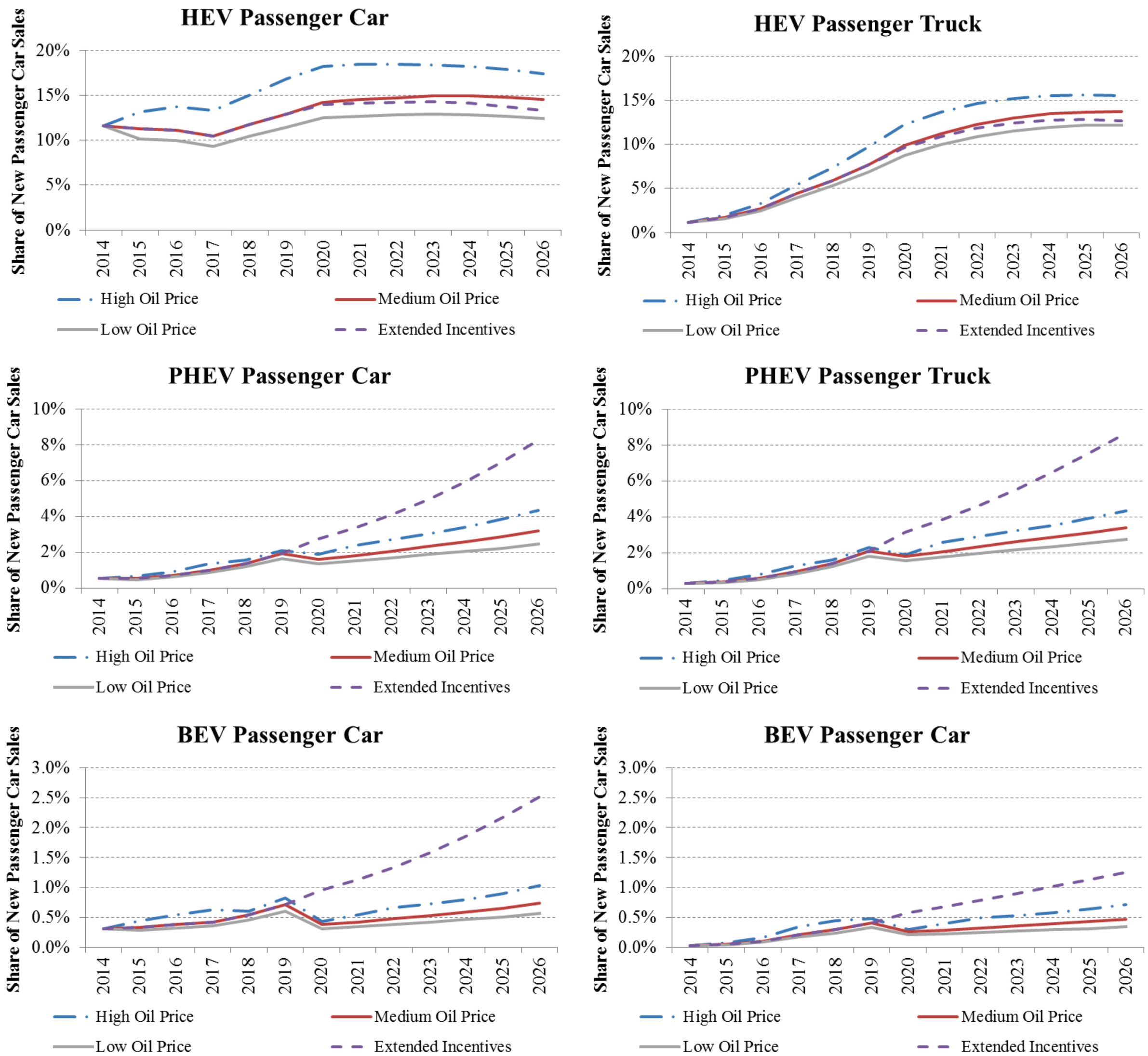


Figure 26. Electric Vehicles' Market Penetration Share for Different Scenarios.

Adjustment for EV VMT Shares and EV Emissions Factors

Understanding electric vehicles' market penetration was only the first step in evaluating their emissions impact. In order to use the MOVESemscalc script, additional steps required included creating modified emission factors representing a combination of conventional vehicle and EV rates as well as apportioning the VMT between the vehicle types. Therefore, two additional processes were required: EV VMT assignment and EV emissions rates adjustments. These are described in further detail below.

- **EV VMT Shares.** The MOVESemscalc script calculated link-level emissions estimates by multiplying hourly link-level VMT with emissions rates for each vehicle type and then aggregating them for 24 hours of a day and over all links. The link-level VMTs were designated for each MOVES source use type (SUT). In the EV VMT share development process, link-level VMTs for all SUTs remained unchanged, except for the gasoline passenger car and gasoline passenger truck categories. For these two SUTs, link-level VMT from a travel demand model was redistributed from gasoline conventional vehicle (GCV) only to GCV, HEV, PHEV, and BEV categories. The assumption in this process was that consumers purchase an electric car/truck as a substitute to a gasoline passenger car/passenger truck. The calculation steps as applied to gasoline passenger cars and gasoline passenger trucks were as follows:
    - **Step 1:** Obtain EV market-share data (historical sales until 2014 and sales projections based on the MA^{3}T model for 2014–2026), and GCV population/age distribution in years 2014 and 2026 (see Table 20 for assumptions).
    - **Step 2:** Calculate vehicle type and age distribution in years 2014 and 2026 (i.e., percent of GCV, HEV, PHEV, and BEV in passenger car and passenger truck SUTs).
    - **Step 3:** Calculate number of vehicles by type and age in years 2014 and 2026.
    - **Step 4:** Obtain vehicle annual VMT by type and age (see assumptions in Table 20).
    - **Step 5:** Calculate subtotal VMT by vehicle type/age.
    - **Step 6:** Calculate VMT share by vehicle type.
- **EV Emissions Rate Adjustments.** After the EV VMT assignment was completed, EV emissions rates in the years 2014 and 2026 were needed to calculate EV emissions. Because this study specifically dealt with exhaust emissions in the context of MOVES-based conformity-type analysis, BEVs were not considered (i.e., assigned emission rates = 0) since they do not produce exhaust emissions. As described in Chapter 3, researchers used PEMS equipment to measure the running exhaust emission rates for a sample of HEVs and PHEVs in charge sustaining mode (i.e., with the engine in operation). The tested HEVs and PHEVs covered the major make and models in the Texas market, and the TTI research team used market-share weighted average emissions

rates to represent emissions rates for HEV and PHEV categories. However, due to sampling constraints, the representative emissions rates for HEVs and PHEVs were from model year 2012 EVs in the year 2014 (i.e., a two-year-old vehicle in the year 2014). In MOVESemscalc, the emissions rates needed to calculate hourly link-level emissions estimates were a set of hourly VMT share weighted average emission rates for HEVs and PHEVs based on vehicle age 0 to 30 in the years 2014 and 2026. The detailed steps are shown below:

- **Step 1:** Obtain emissions rate deterioration trends for HEVs and PHEVs by model year (assumptions are listed in Table 20).
- **Step 2:** Obtain zero-mile emissions rate (emissions rates at brand new condition) trends for model year 2014–2026 for HEVs and PHEVs (assumptions are listed in Table 20).
- **Step 3:** Calculate emissions rates for HEVs (model year 2000–2014) and PHEVs (model year 2010–2014) in year 2014; calculate emissions rates for HEVs (model year 2000–2026) and PHEVs (model year 2010–2026) in year 2026.
- **Step 4:** Obtain VMT share by age for HEVs and PHEVs in the years 2014 and 2026 (from EV VMT assignment).
- **Step 5:** Calculate weighted average emissions rates for HEV and PHEV fleets in the years 2014 and 2026 by multiplying corresponding VMT share by age and emissions rates by age.
- **Step 6:** Apply the weighted average emissions rates for HEV and PHEV fleets to each hour or period in a day.
- **Step 7:** Apply a reduction factor to PHEV emissions rates to account for PHEV miles driven on electricity (which also result in zero emissions, similar to the BEV category).

Table 20. Assumptions and Data Sources Used for Pilot Application.

Attributes	Data Source
Fuel Attributes	The Environmental Protection Agency's latest available (2013) summer season Houston retail outlet reformulated gas survey data used in 2014 and 2026, except sulfur content in 2026 set to 10 ppm (Tier 3 rule annual average standard).*
Inspection and Maintenance (I/M) Program	Locality-specific set-ups based on current I/M rules, prior modeling set-ups, and available MOVES I/M parameters.*
Conventional Vehicle Fleet Attributes	Age distribution in 2014 and 2026: Harris County mid-year (2013) Texas Department of Transportation/Department of Motor Vehicles (DMV) vehicle registration.* Annual mileage by age: MOVES2010b default. Population: Harris County mid-year (2013) TxDOT/DMV vehicle registration.*
Electric Vehicle Fleet Attributes	*Annual mileage by age*: same as conventional vehicle for HEVs and PHEVs, half of conventional vehicle for BEV (*83*,*84*,*85*). PHEV battery capacity: 25% increase in capacity for model year 2020 and after. This will lead to decrease in percentage of miles with engine on for PHEVs. BEV battery capacity: 25% increase in capacity for model year 2020 and after. This will lead to increase of BEV VMT shares in passenger cars and trucks. *Percentage of miles with engine on for PHEV*: 24% for 2014 and 14% for 2026 based on PHEV battery capacity assumptions (*83,85*).**
Meteorology Attributes	Local, hourly temperature and relative humidity for Harris County based on Texas Commission on Environmental Quality data.*
Link Attributes/VMT and Speeds	Harris–Galveston Area Council Travel Demand Model processed to reflect summer weekday travel.*
Emission Factor (EF) Attributes	*Conventional vehicle EFs*: MOVES-based EFs based on Harris County attributes for all model year vehicles.* *Electric vehicle EFs*: Established in Chapter 3. (Deterioration trends follow MOVES2010b default for conventional vehicles. Zero-mile emissions rates for new model year follow MOVES2010b trends.)

* Previously prepared by TTI.
** Assuming the battery capacity could cover 76% of VMT for PHEV model years between 2014 and 2020, and the battery capacity would increase 25% (i.e., higher VMT share on electricity) for model year 2020 and after.

MOVES-Based Emission Inventory Utility

TTI's MOVES-based regional mobile source emissions estimation script, MOVESemscalc (*82*), calculates emissions estimates for a region using link-level emissions from MOVES emissions rates based on:

- Local attributes.
- Travel demand model (TDM) link-based hourly VMT and speeds.
- VMT mix, which is used to disaggregate the link-level VMT to each of the MOVES source use type/fuel types.

Consistent with TTI's link-based emissions inventory development process shown in Figure 27, two base case emissions estimates were established for Harris County with no electric vehicles included in the fleet. The base case emissions estimates for 2014 and 2026 were calculated by applying the analysis year base case VMT mix to the analysis year link-based VMT and speeds to allocate the link-level VMT to each of the MOVES source use type/gasoline and diesel fuel type categories (i.e., vehicle type). This VMT was then applied to the base case emissions rates to calculate the emissions estimates.

Each EV scenario consisted of a VMT share and emissions rates (by pollutant, MOVES roadway type, and MOVES average speed bin) for each of the three electric vehicle categories (HEV, PHEV, and BEV) for both passenger car and passenger truck vehicle types. The emissions estimates for each of the EV scenarios were calculated using a process similar to the base case emissions, with the only difference being that the process utilized sets of emissions rates and VMT mix that took into account electric vehicles, as explained in the previous section.

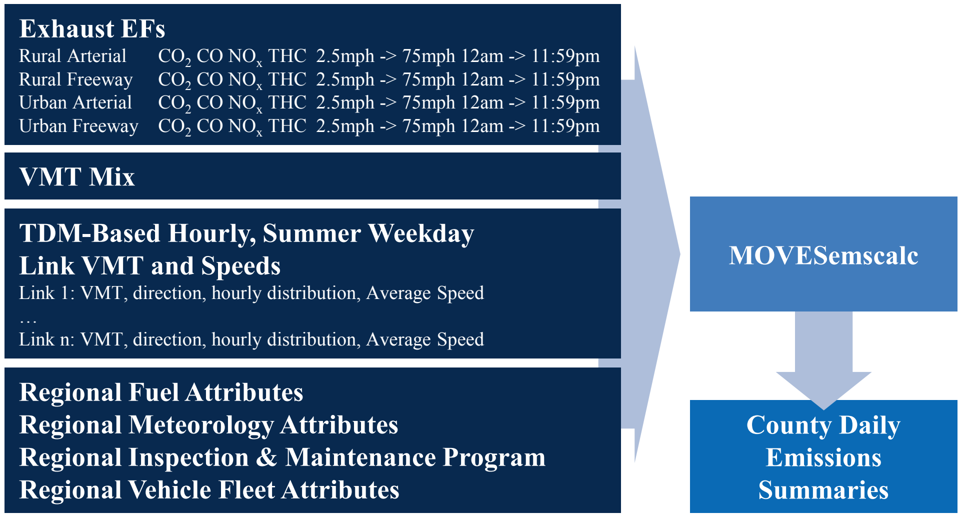


Figure 27. Link-Based Hourly Emissions Estimation by MOVESemscalc.

Base Case TDM-Based Hourly, Summer Weekday Link VMT and Speeds

In MOVESemscalc, total emissions estimations are the sum of emissions estimations of each individual link in the regional road network for a specified county. To obtain emissions estimations for each link, link VMT and average speed are needed. In MOVESemscalc, TTI researchers used data sets extracted from the latest four-period, time-of-day, directional, regional Houston-Galveston-Brazoria (HGB) travel demand models, provided by the Houston–Galveston Area Council. The research team also developed growth rates (for inventories between TDM years), seasonal adjustment, and hourly allocation factors to estimate the summer weekday hourly directional, link VMT, and associated average fleet speed inputs to the emissions calculations. The link VMT was developed in order to be consistent with the Highway Performance Monitoring System (HPMS) VMT.

The seasonal period, day type, and hourly distributions used were based on factors developed with TxDOT Automatic Traffic Recorder data from the Houston area. The hourly average operational fleet speeds were estimated corresponding to the link VMT estimates using the Houston speed model, which estimates operational speeds based on a link's estimated free-flow speed and congestion-related speed reduction. The link VMT and speeds were developed for each analysis year.

Base Case VMT Mix

The VMT mix designates the vehicle types included in the analysis and specifies the fraction of on-road fleet VMT attributable to each vehicle type by MOVES road type. In MOVESemscalc, TTI researchers developed a 24-hour average VMT mix method and expanded the method to produce the four-period, time-of-day estimates. The VMT mix method sets Texas vehicle registration category aggregations for MOVES SUT categories to be used in the VMT mix estimates. The current VMT mix method produced a set of four time-of-day period average vehicle type VMT allocations by MOVES road type, estimated for each TxDOT district associated with the eight-county HGB area (i.e., Houston and Beaumont Districts). The data sources used were recent, multi-year TxDOT vehicle classification counts; year-end TxDOT/DMV registration data; and MOVES default data, where needed. A separate base case VMT mix was used for each analysis year (i.e., 2014 and 2026).

Base Case MOVES-Based Emissions Rates

Emissions rates were multiplied by link VMT to produce emissions estimations at the link level. The county-level emissions rates from all SUTs, which did not include EVs, were developed using MOVES2010b for the MOVES weekday day type. Local emissions rates modeling input parameters were developed and used to produce emissions rates reflective of the local conditions (e.g., weather and fleet characteristics, fuel properties, and inspection and maintenance program). To reflect the Texas Low Emission Diesel (TxLED) program, TxLED adjustments were applied to the county-level diesel vehicle NO_x emission rates. These emissions rates (by hour, pollutant, process, SUT, fuel type, road type, and average speed bin) were developed for each analysis year.

Emissions Calculations

Based on the above information, the base case emissions were calculated for each analysis year using:

- The base case VMT mix.
- The TDM-based hourly, summer weekday link VMT and speeds.
- The base case emissions rates.

TDM network road type/area type to VMT mix road type and hour-of-day to time-of-day period designations were used to match the appropriate VMT mixes with the link VMT. The VMT mixes were multiplied by the link fleet VMT to distribute each link's VMT to the 23 different vehicle type categories. Using the base case emissions rates, the vehicle-type-specific emissions rates for each link's average speed were interpolated using the emissions factors and corresponding index speeds (i.e., the average bin speeds of 2.5, 5.0, 10.0, 15.0,… 75.0 mph), bounding the link's average speed. For link speeds below or above the minimum and maximum average bin speeds of 2.5 and 75 mph, the rates for those bounding speeds were used. The estimated vehicle type and link speed-specific emissions factors for each pollutant were multiplied by the associated VMT to produce the link-based emissions estimates, which were aggregated by TDM road type (including totals) to produce the hourly, link-based emissions. Researchers performed this process for each hour, thus producing hourly (including 24-hour) CO, CO_2, NO_x, and THC emissions for each analysis year base case. Emissions were also calculated for each analysis year and scenario using the base case VMT mix; the base case TDM-based hourly, summer weekday link VMT and speeds; and the analysis year/scenario-specific modified emissions rates.

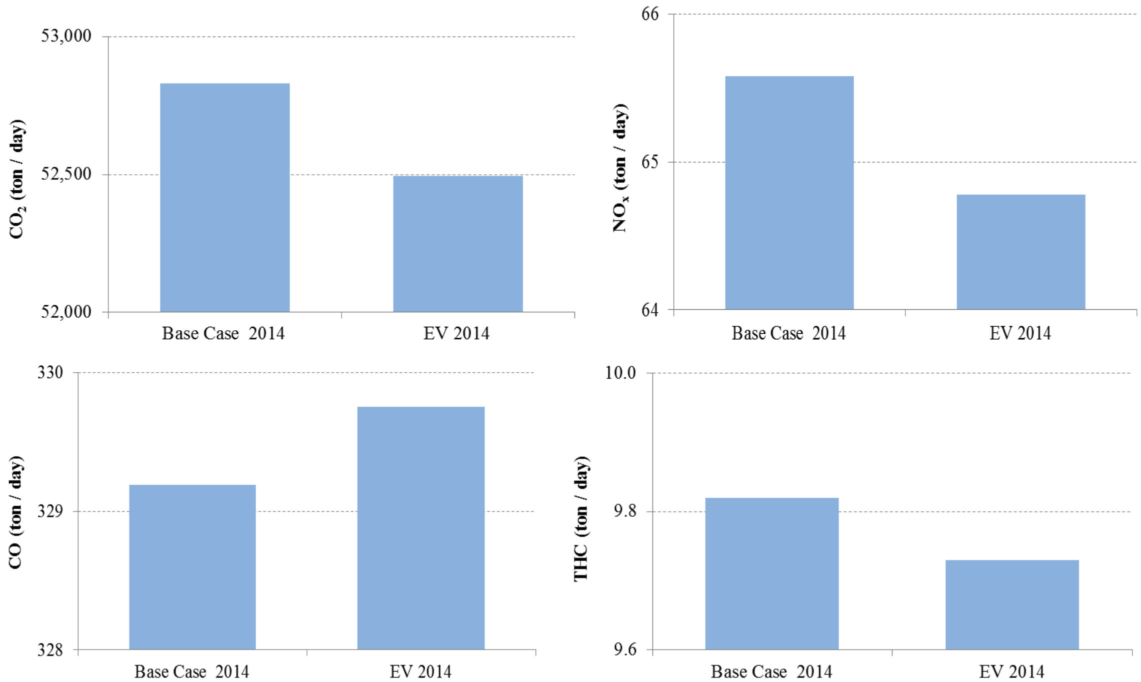
The processes for emissions calculations of other scenarios were similar to base cases. The only difference was that for each scenario with consideration of EVs, a set of VMT mixes that included EVs and a set of hourly emissions rates for EVs were established, as discussed in the previous section. The VMT mix was applied to the TDM-based hourly, summer weekday link VMT to designate VMT into different vehicle types (including EVs). The vehicle type and link speed-specific emissions factors were multiplied with associated VMT to produce link-level emissions estimations.

Results

This section discusses the results of the pilot application in two parts: the total regional mobile source emissions estimates for various EV market penetration scenarios, and the cost effectiveness of government EV tax credits in reducing mobile source emissions.

Emissions Impacts

Figure 28 shows the estimated on-road exhaust emissions (in tons/day) of four pollutants for the two 2014 scenarios. The tables in Appendix C provide further tabulations and comparisons of these results.



Note: The higher CO emissions observed for the EV 2014 case are explained by the higher CO emissions for the test HEVs (mainly the test Camry) when compared to the MOVES rates for conventional vehicles. Please see Figure 29 and explanatory text for further details.

Figure 28. On-Road Exhaust Emissions Estimations for 2014 Scenarios.

Comparing the Base Case 2014 case with the EV 2014 case for 2014, researchers found that on-road CO_2 and NO_x exhaust emissions were slightly lower when EVs were incorporated into the analysis than when no EVs were considered in the vehicle fleet. For the 2014 analysis year, the CO_2 emissions were reduced by 0.6 percent, the NO_x emissions were reduced by 1.2 percent, and THC emissions were reduced by 0.9 percent when EVs were included. These results were expected since a portion of the original gasoline passenger car and passenger trucks' VMT in the 2014 base case were redistributed among the HEV, PHEV, and BEV categories based on historical EV sales up to 2014. The HEV and PHEVs' CO_2, NO_x, and THC exhaust emissions (established through in-use testing) were lower than corresponding conventional vehicles at the majority of speed bins on each road type. Conventional vehicles' average emissions rates were calculated using MOVES2010b based on Harris County local attributes.

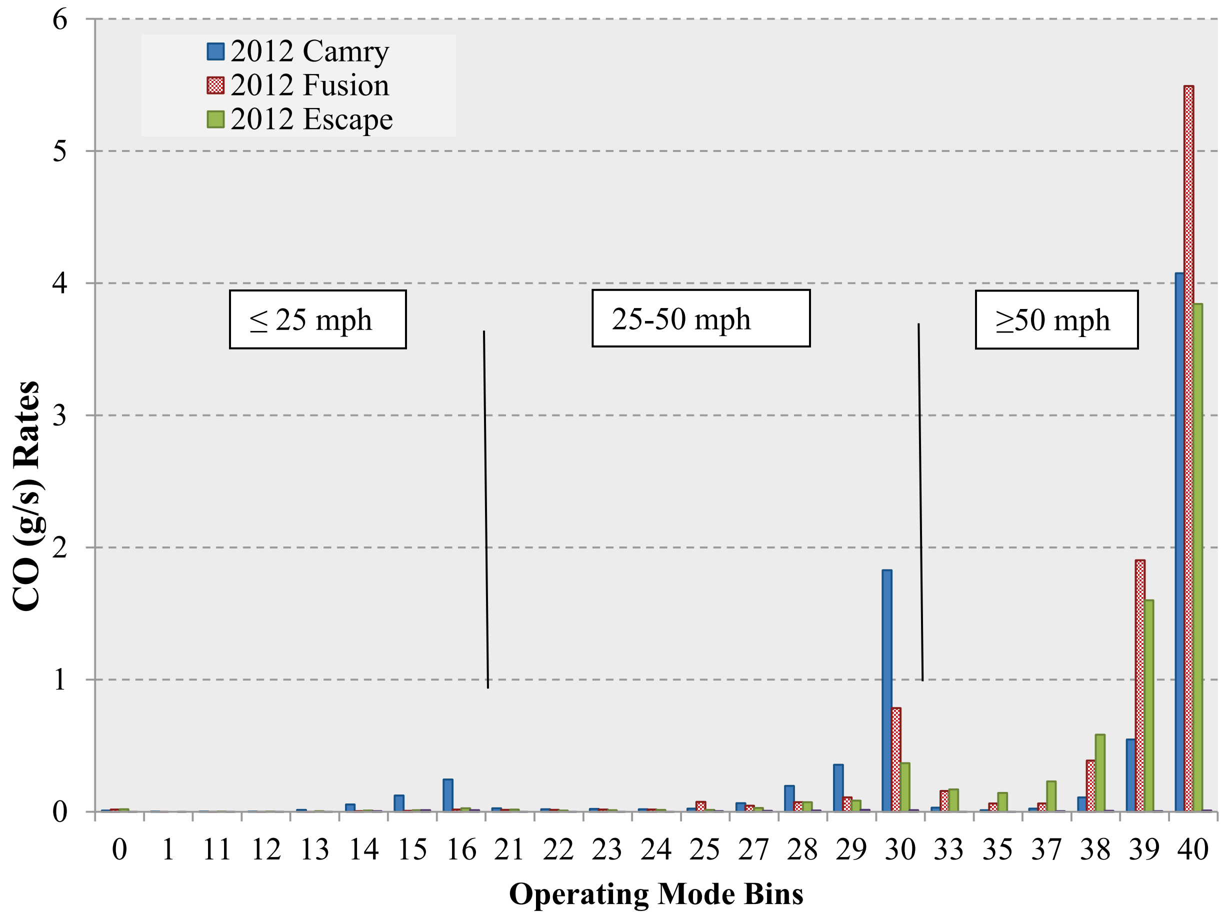
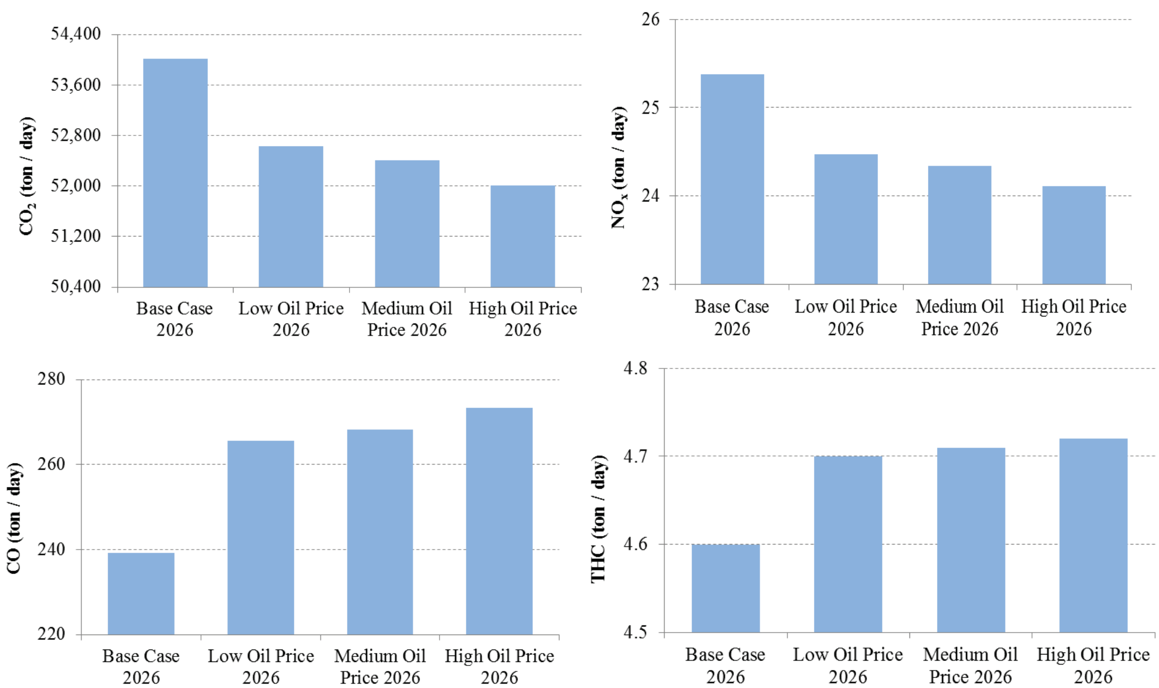


Figure 29. CO Emission Rates for HEVs.

The results, however, also showed that on-road CO exhaust emissions were higher for the scenario with EVs than the ones without EVs in the vehicle fleet. The CO emissions increased by 0.2 percent in 2014. While seemingly counterintuitive, this observation is explained by the fact that the average measured CO exhaust emission rates for HEVs are higher than MOVES conventional vehicles' emissions rates. More specifically, the reason for the high average CO exhaust emissions rates for HEVs is due to the observations from a hybrid Camry tested in this study. As shown in Figure 29, the tested hybrid Camry's emissions rates were significantly higher than the other three HEVs, particularly at operating mode bin 14 to 16 and 28 to 30 for speeds up to 50 mph. These operating mode bins represented high engine load bins, which corresponded to higher acceleration rates observed in medium- to low-speed driving conditions in urban areas. Additionally, HEVs, being the most popular type of electric vehicle, accounted for more than 90 percent of all EVs in the analysis. Therefore, the effective CO emission rates were higher than those of conventional vehicles in the analysis, resulting in an increase in the estimated CO emissions.

Figure 30 shows the results for the 2026 scenarios. When comparing results for Base Case 2026 with the Medium Oil Price 2026 case, researchers found that on-road CO_2 and NO_x emissions were lower for the case with EVs than the one without EVs in the vehicle fleet. When EVs were included, the CO_2 emissions were reduced by 3.0 percent and the NO_x emissions were reduced by 4.1 percent in 2026. These differences are greater in magnitude compared with the 2014 analysis year results, which can be explained by the higher EV market shares according to MA^3T model predictions.



Note: The higher CO emissions for scenarios with higher EV market penetration are again explained by the higher CO emissions for the test HEVs when compared to the MOVES rates for conventional vehicles. Please see Figure 29 and explanatory text for further details. Unlike the 2014 analysis year, for 2026, the THC emission rates are also higher when EVs are taken into consideration compared to the base case, due to the emission rate deterioration effects and zero-mile emissions trends observed for THCs. See Figure 31 and the explanatory text for further details.

Figure 30. On-Road Exhaust Emissions Estimations for 2026 Scenarios.

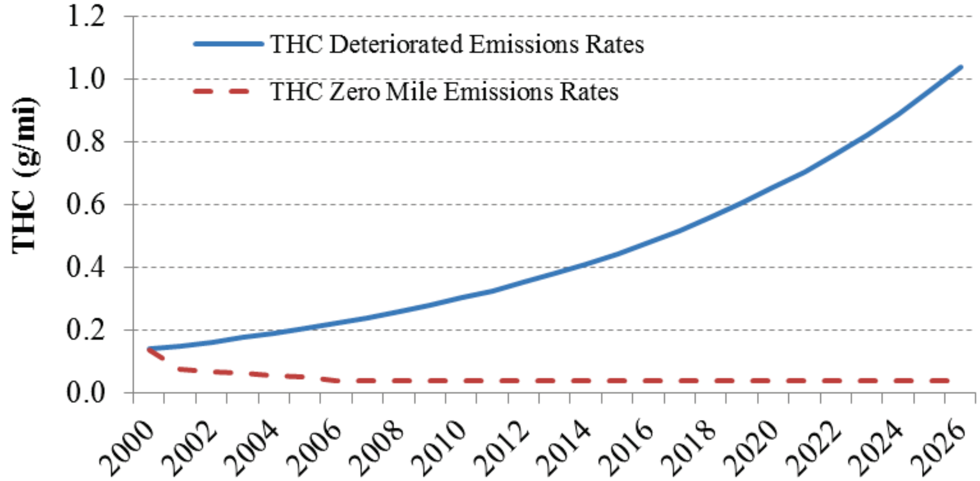


Figure 31. THC Emission Rate Deterioration Effects and Zero-Mile Emission Effects.

The on-road CO and THC exhaust emissions estimated for the 2026 scenarios were higher for the cases with EVs included than the case without EVs. For the Medium Oil Price scenario, CO emissions increased by 12.1 percent and THC emissions increased by 2.4 percent in 2026 compared to the base case (with no EVs). The explanation for the CO emissions is similar to that of the 2014 analysis year results—findings are attributable to the comparatively high measured emissions for HEVs. In the case of THC emissions, considering EVs in the analysis resulted in reductions in emissions over the base case for the 2014 analysis year. However, in analysis year 2026, all cases considering EVs resulted in higher THC emissions estimates compared to the base case. This result is explained by a combined effect of fewer older age (>15 years) HEVs in 2014 compared with 2026, new vehicles' zero-mile emissions rate reductions, and aging vehicles' emissions deterioration. As emissions regulation is becoming stricter, newer model year vehicles' zero-emissions rates are decreasing. The solid line in Figure 31 represents MOVES national default zero-mile THC emissions rates for model year 2000 to 2026 passenger cars. The dashed line in Figure 31 represents a 2000 model year vehicle's emissions rates in each analysis year from 2000 to 2026. Over the 26-year timeframe, the new vehicle's zero-mile THC emission rate is only reduced by 70 percent; however, for a year 2000 passenger car, the THC emission rate increases about 500 percent by 2026.

In this study, HEVs' THC emission rate deterioration and zero-mile emissions rates were assumed to follow MOVES national default trends. In the year 2014, the oldest HEVs and PHEVs in the vehicle fleet were 14 and 5 years old, respectively. Therefore, the total THC emissions from EVs were lower than corresponding conventional vehicles due to a lack of old electric vehicles (aged between 15 to 30 years) in the fleet. However, in the 2026 scenarios, conventional and electric vehicle fleets had similar numbers of older vehicles (>15 years), which led to higher THC emissions for cases with EVs in the fleet.

As shown in Figure 30, for scenarios with different oil price projections, generally higher future oil prices were shown to produce lower CO_2 and NO_x emissions in the year 2026 from passenger cars and passenger trucks, and vice versa. Compared with Base Case 2026 (no EVs in 2026), high, medium, and low oil price scenarios resulted in −3.71 percent, −2.98 percent, and −2.57 percent changes in CO_2 exhaust emissions and −5 percent, −4.1 percent, and −3.6 percent changes in NO_x exhaust emissions in 2026, respectively.

On the other hand, higher oil price scenarios resulted in higher estimates of CO and THC emissions. As explained previously, these findings can be explained by the HEV behavior of CO and THC emissions rates, as discussed earlier in this section. Compared with Base Case 2026, high, medium, and low oil price scenarios resulted in 14.28 percent, 12.11 percent, and 11 percent increases in CO exhaust emissions and 2.8 percent, 2.4 percent, and 2.3 percent increases in THC exhaust emissions in 2026, respectively.

The pilot application's intention was to demonstrate the application of the framework, and thus the results should not be taken as definitive indications of the impacts of EVs on mobile source emissions. The context and limitations of the collected data and actual analysis results need to be considered, especially the fact that the EV emissions rates were established using emissions data from a limited number of vehicles (four HEVs, four PHEVs, and four BEVs). Although the tested vehicles covered the major models available in the US market, the limited sample size does not allow the variability of vehicle emissions, even for the same make and model, to be accounted for. For example, the results from the Camry HEV, which exhibited high CO and THC emissions when compared with conventional gasoline vehicles, may not be representative of all Camry HEVs. Secondly, the emissions rates were only measured for the current year and for available EV models; thus, the aging effects and trends in zero-mile emissions of new vehicles in future years could not be independently assessed for EVs. The emissions deterioration trends and new vehicle emissions reduction trends of gasoline vehicles based on the MOVES national default were used for HEVs and PHEVs under the assumption that HEV and PHEV gasoline engines will exhibit similar trends to those of a conventional gasoline vehicle.

Cost Effectiveness of Extended Government Tax Credit on PHEVs and BEVs

The pilot application also provided the platform to evaluate the cost effectiveness of the government incentive policy on electric vehicles by extending the PEV tax credit until the end of 2026. An Extended Incentives 2026 scenario was developed and assumed that the current \$2500~7500 tax credits for plug-in electric vehicles would continue until the end of 2026, instead of 2020 as assumed in the other scenarios described in the previous section. The extended tax credit policy resulted in an incremental purchase of 34,881 plug-in electric passenger cars (25,084 PHEVs and 9797 BEVs) and 6997 plug-in electric passenger trucks (5923 PHEVs and 1075 BEVs) in the total fleet, made between 2020 and 2026. Plug-in electric vehicles were estimated to account for 1.7 percent of new passenger cars and 1.1 percent of new passenger trucks in 2026. The assumption was that new plug-in electric vehicles substitute for consumers' choices of other types of vehicles. Therefore, the total estimated vehicle population in Harris County in 2026 was not changed. In this extended incentive scenario, the government would spend a total of \$73 million (2012 US dollars) to subsidize consumers who purchased PEVs between 2020 and 2026.

Compared to Base Case 2026 (all other parameters held except the extension on PEV tax credits), the extended incentive policy led to reductions of 641 tons per day (1.2 percent) of CO_2, 3.9 tons per day (1.5 percent) of CO, 0.15 tons per day (0.05 percent) of NO_x, and 0.05 tons per day (1.0 percent) of THC. Based on the estimated additional government expenditure, the cost effectiveness of emissions reductions due to the extension of the incentive was \$1.4, \$233, \$5830, and \$17,500 (in 2012 US dollars) for reducing a ton of CO_2, CO, NO_x, and THC per day, respectively, in 2026.

CONCLUDING REMARKS

This chapter covered the development of an analytical framework to incorporate EVs into a conformity-type analysis. First, the research team prepared a MOVES-based emissions inventory model with network information based on a regional travel demand model. Then, a set of EV-specific parameters were input into a MOVES-based emissions inventory script to estimate regional emissions estimations. The framework was developed and successfully applied through a pilot application for Harris County.

CHAPTER 5: CONCLUSIONS

As electric vehicles continue to grow in popularity and form a larger part of the existing vehicle fleet, the transportation sector is looking to address the proliferation of EVs and their impacts on a range of issues. This research project focused on the issue of mobile source emissions, specifically for agencies operating in the context of transportation conformity. The main goals of this research were to study the implications of EVs in terms of mobile source emissions and to develop an approach for incorporating EVs into emissions estimation procedures, including regional emissions inventories.

This project developed a framework to incorporate EVs into mobile source emissions estimations, specifically for transportation conformity-type analyses. The framework integrates region-specific EV driving characteristics, emissions rates, and market penetrations into a MOVES-based emissions inventory analysis.

An extensive literature review was conducted, covering the state of the EV market in the US and Texas, factors influencing EV market penetration, and studies related to the emissions impacts of EVs. The future market penetration of EVs is influenced by a range of factors, including future energy and oil prices, the evolution of battery and other EV technology, the existence of government policies and incentives, and the presence of supporting infrastructure. There are existing studies that have investigated the emissions impacts of EVs at a disaggregated level (i.e., individual vehicle-specific emissions) and aggregated level (i.e., regional/national-level emissions). These studies show that driving characteristics of EVs, including drive schedules and overall market penetration levels, are the key factors in determining EVs' impacts on mobile source emissions. When expanding the picture to examine emission impacts of EVs as a whole, the emissions associated with electricity needed to charge plug-in electric vehicles also need to be considered. In these cases, EV charging patterns and the mix of sources used for power generation resources also affect the overall impact of EVs.

In this project, the research team collected a wealth of Texas-specific EV activity and emissions data that were used to establish a set of distance-based emissions rates for EVs. The emissions rates were established at each average speed bin and road type and were based on Texas-specific drive schedules and in-use testing of EV emissions. The Texas-specific drive schedules were developed based on a sample of EV GPS activity data in major Texas metropolitan areas. The main GPS data collection effort consisted of recruiting individual and fleet vehicles to record their normal activities during an extended period. The data obtained from the GPS units were processed and analyzed following a four-step process to develop Texas-specific drive schedules. In-use emissions testing of EVs were conducted using PEMS equipment to prepare operating-mode-based emissions rates. Finally, distance-based EV emissions rates for each individual vehicle were calculated by combining Texas-specific drive schedules and operating-mode-based emissions rates. A set of market-share weighted average emissions rates were calculated for each vehicle type.

The framework developed was used to conduct a pilot application for Harris County, Texas, to investigate EVs' impacts based on modeled on-road exhaust emissions of greenhouse gases (i.e., CO_2) and criteria pollutants or their precursors (CO, NO_x, and THC). Analyses were conducted for the years 2014 and 2026 under various energy price scenarios. The pilot application demonstrated successful implementation of the framework and found that including EV parameters into regional emissions analyses can have an effect on the analysis results when compared to baseline estimates that do not take EVs into consideration.

In conclusion, this research provided an overview of electric vehicles, the factors affecting the market penetration of EVs, and the implications for air quality, specifically mobile source emissions. Texas-specific data on EV activities and emissions were also collected, and a framework was developed to allow transportation agencies to estimate EVs' impacts on mobile source emissions. The intent of the framework was to be flexible and practical, and it uses a MOVES-based emissions inventory process that is familiar to TxDOT, metropolitan planning organizations, and other transportation agencies involved in the air quality arena.

Some of the limitations of this work, as well as areas for future study, are discussed below:

- Given the focus on mobile source emissions and transportation conformity, the emissions associated with electricity generation (for charging of PEVs) were not given detailed consideration in this work. However, electricity generation emissions (which depend in large part on the source of electricity) are an important factor to consider when discussing emissions and air quality impacts of EVs. The "tailpipe to smokestack" shift of emissions and the broader policy issues in terms of what it means for transportation conformity and air quality are topics that deserve further study but were beyond the scope of this project.

This issue is particularly relevant to BEVs, which are essentially treated as zero-emission vehicles from a mobile source emissions perspective.

- The emissions rates established for EVs as part of this project were based on a limited sample of vehicles currently operating in Texas. The recruitment of a larger sample of EVs in activity data collection and in-use emissions rates testing could further improve the representativeness of the results. Additional in-use emissions testing for other pollutants such as PM could also expand the application of the developed framework.
- Given that EVs have not been in the market for very long, longer-term studies are also required to better understand the deterioration effects and impacts on emissions for older-model EVs. In this research, emissions rate deterioration trends of HEVs and PHEVs were assumed to be the same as those of conventional vehicles in the absence of other data.
- The pilot application of the framework showed that in addition to EV emissions rates, the market penetration levels and other activity assumptions also influence the emissions impacts of EVs. Consideration of different market penetration scenarios or the use of other market penetration models, along with further sensitivity analyses, could provide a better understanding of the most important factors affecting EV emissions at the transportation system level.

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APPENDIX A: OPERATING-MODE-BASED EV ENERGY CONSUMPTION AND EMISSIONS RATES

Table A.1. BEV Electricity Consumption Rates.

Electricity (kWh/s)				
opMode Bin	**2011 Leaf 1**	**2011 Leaf 2**	**2011 Leaf 3**	**2013 Focus**
0	0.001136	0.001504	0.000851	−0.004366
1	0.000392	0.000000	0.000074	0.000231
11	0.001183	0.002000	0.001604	0.000018
12	0.000472	0.001880	0.001531	0.000897
13	0.001852	0.002778	0.001892	0.001568
14	0.001027	0.005319	0.004878	0.003066
15	0.002151	0.003425	0.000568	0.003540
16	0.006596	0.008438	0.008730	0.005224
21	0.001172	0.000545	0.001343	0.001104
22	0.002370	0.001431	0.000965	0.001661
23	0.003284	0.003033	0.003270	0.002596
24	0.004246	0.004108	0.003492	0.004036
25	0.007270	0.006923	0.005734	0.005798
27	0.009808	0.008146	0.007339	0.008126
28	0.008571	0.023780	0.013918	0.012792
29	0.018519	0.018966	0.026316	0.013575
30	0.020062	0.023723	0.019048	0.019480
33	0.004678	0.003302	0.004362	0.003909
35	0.007584	0.006774	0.006031	0.005914
37	0.009208	0.010904	0.009487	0.008162
38	0.012255	0.014898	0.012216	0.010389
39	0.017969	0.013736	0.013415	0.013539
40	0.019444	0.028516	0.025000	0.023547

Table A.2. BEV CO_2 Emission Rates.

	CO_2 g/s			
opMode Bin	**2011 Leaf 1**	**2011 Leaf 2**	**2011 Leaf 3**	**2013 Focus**
0	0.609257	0.806359	0.456228	0.000000
1	0.210391	0.000000	0.039773	0.123820
11	0.634493	1.072292	0.860128	0.009689
12	0.252899	1.007794	0.820632	0.480770
13	0.992863	1.489295	1.014331	0.840539
14	0.550835	2.851841	2.615347	1.643596
15	1.153003	1.836117	0.304629	1.897957
16	3.536283	4.523733	4.680641	2.801037
21	0.628296	0.292443	0.720196	0.592057
22	1.270489	0.767489	0.517516	0.890757
23	1.760650	1.625949	1.753318	1.391989
24	2.276531	2.202300	1.872019	2.163668
25	3.897799	3.711781	3.074233	3.108371
27	5.258357	4.367483	3.935018	4.356539
28	4.595539	12.749818	7.461828	6.858625
29	9.928633	10.168290	14.109110	7.278368
30	10.756019	12.718796	10.212308	10.444234
33	2.508046	1.770294	2.338893	2.095949
35	4.065890	3.631759	3.233663	3.170840
37	4.936737	5.845931	5.086515	4.376223
38	6.570419	7.987484	6.549513	5.570041
39	9.633877	7.364645	7.192205	7.259058
40	10.425065	15.288543	13.403655	12.624725

Table A.3. BEV NO_x Emission Rates.

NO_x g/s				
opMode Bins	**2011 Leaf 1**	**2011 Leaf 2**	**2011 Leaf 3**	**2013 Focus**
0	0.0003711	0.0004912	0.0002779	−0.0014258
1	0.0001282	0.0000000	0.0000242	0.0000754
11	0.0003865	0.0006532	0.0005239	0.0000059
12	0.0001541	0.0006139	0.0004999	0.0002929
13	0.0006048	0.0009072	0.0006179	0.0005120
14	0.0003355	0.0017372	0.0015931	0.0010012
15	0.0007023	0.0011184	0.0001856	0.0011561
16	0.0021541	0.0027556	0.0028512	0.0017062
21	0.0003827	0.0001781	0.0004387	0.0003606
22	0.0007739	0.0004675	0.0003152	0.0005426
23	0.0010725	0.0009904	0.0010680	0.0008479
24	0.0013867	0.0013415	0.0011403	0.0013180
25	0.0023743	0.0022610	0.0018726	0.0018934
27	0.0032031	0.0026604	0.0023970	0.0026537
28	0.0027993	0.0077664	0.0045453	0.0041778
29	0.0060479	0.0061939	0.0085944	0.0044335
30	0.0065519	0.0077475	0.0062207	0.0063620
33	0.0015277	0.0010784	0.0014247	0.0012767
35	0.0024767	0.0022122	0.0019697	0.0019315
37	0.0030071	0.0035610	0.0030984	0.0026657
38	0.0040023	0.0048655	0.0039896	0.0033929
39	0.0058684	0.0044861	0.0043810	0.0044218
40	0.0063503	0.0093128	0.0081647	0.0076902

Table A.4. BEV Idling Electricity Consumption Rates.

Electricity (kWh/hr)				
Idle Condition	**2011 Leaf 1**	**2011 Leaf 2**	**2011 Leaf 3**	**2013 Focus**
Hot Test (Cold Start)	1.1	2.8	2.3	1.07
Hot Test	1.3	1.3	1.9	1.06
Cold Test (Cold Start)	5.9	6	5.4	0.99
Cold Test	2.66	2.2	1.86	0.53

Table A.5. BEV Idling CO_2 Emission Rates.

CO_2 (kg/hr)				
Idle Condition	**2011 Leaf 1**	**2011 Leaf 2**	**2011 Leaf 3**	**2013 Focus**
Hot Test (Cold Start)	0.589760	1.501209	1.233136	0.573676
Hot Test	0.696990	0.696990	1.018677	0.568314
Cold Test (Cold Start)	3.163262	3.216877	2.895189	0.530784
Cold Test	1.426148	1.179521	0.997231	0.284157

Table A.6. BEV NO_x Emission Rates.

NO_x (g/s)				
Idle Condition	**2011 Leaf 1**	**2011 Leaf 2**	**2011 Leaf 3**	**2013 Focus**
Hot Test (Cold Start)	0.359245	0.914442	0.751149	0.349448
Hot Test	0.424562	0.424562	0.620514	0.346182
Cold Test (Cold Start)	1.926860	1.959519	1.763567	0.323321
Cold Test	0.868720	0.718490	0.607451	0.173091

Table A.1. HEV CO_2 Emission Rates.

CO_2 g/s				
opMode Bins	**2012 Camry**	**2012 Fusion**	**2012 Escape**	**2011 Prius**
0	0.365073	0.287213	0.386488	0.122702
1	0.080126	0.015570	0.004818	0.001792
11	0.417030	0.314915	0.245168	0.035260
12	0.753863	0.453852	0.260933	0.147989
13	1.759853	0.904752	1.319938	1.113666
14	2.859207	1.600896	2.529170	2.468767
15	4.168468	1.897867	3.876917	4.062188
16	7.999704	3.213770	5.895249	7.045531
21	0.705555	1.199351	1.013722	0.481253
22	1.119949	1.595872	1.752760	0.919888
23	1.777407	2.303797	2.566005	1.825046
24	2.739932	3.261941	3.614464	2.886988
25	3.750586	4.866190	4.585699	3.690668
27	5.624362	5.989404	6.120155	5.819124
28	8.422664	7.515248	8.227269	8.398206
29	12.198247	8.584713	9.982388	10.750631
30	15.873501	11.612053	12.306090	12.065563
33	2.077309	3.172939	4.617433	2.311581
35	4.055320	4.441802	6.633997	4.158741
37	5.742125	5.956587	8.722042	6.525088
38	7.528892	7.364041	10.388982	8.516787
39	10.670617	10.014668	12.665871	11.493461
40	16.481212	17.730033	16.617982	15.348814

Table A.2. HEV CO Emission Rates.

CO g/s				
opMode Bins	**2012 Camry**	**2012 Fusion**	**2012 Escape**	**2011 Prius**
0	0.009156	0.017772	0.019121	0.000307
1	0.000375	0.000120	0.000001	0.000006
11	0.000340	0.002486	0.001058	0.000026
12	0.001641	0.001041	0.001254	0.000302
13	0.016132	0.002827	0.004162	0.001906
14	0.055057	0.005663	0.010740	0.005492
15	0.123927	0.006987	0.012363	0.012777
16	0.245433	0.016518	0.027682	0.013199
21	0.026296	0.015934	0.017722	0.000407
22	0.018921	0.014573	0.009000	0.000889
23	0.023031	0.017184	0.013188	0.001954
24	0.020597	0.016504	0.014170	0.003427
25	0.025806	0.075010	0.014434	0.005883
27	0.066277	0.046277	0.028757	0.008090
28	0.195703	0.072169	0.072353	0.008967
29	0.355439	0.110018	0.084791	0.016084
30	1.827817	0.786168	0.369574	0.013556
33	0.031614	0.158044	0.170829	0.001403
35	0.011642	0.062639	0.142243	0.002966
37	0.024431	0.063174	0.230425	0.004905
38	0.108399	0.388163	0.583551	0.006565
39	0.547740	1.904010	1.602040	0.004892
40	4.076912	5.492487	3.844132	0.010200

Table A.3. HEV NO_x Emission Rates.

	NO_x g/s			
opMode Bins	**2012 Camry**	**2012 Fusion**	**2012 Escape**	**2011 Prius**
0	0.000008	0.000015	0.000030	0.000003
1	0.000001	0.000000	0.000000	0.000000
11	0.000016	0.000013	0.000010	0.000001
12	0.000010	0.000009	0.000010	0.000008
13	0.000016	0.000025	0.000114	0.000018
14	0.000038	0.000028	0.000100	0.000017
15	0.000063	0.000109	0.000191	0.000020
16	0.000162	0.000190	0.000562	0.000036
21	0.000001	0.000047	0.000115	0.000009
22	0.000054	0.000028	0.000120	0.000020
23	0.000090	0.000043	0.000142	0.000016
24	0.000141	0.000045	0.000164	0.000029
25	0.000076	0.000142	0.000260	0.000154
27	0.000011	0.000073	0.000455	0.000069
28	0.000030	0.000144	0.000810	0.000108
29	0.000054	0.000251	0.001190	0.000268
30	0.000151	0.000211	0.002901	0.000195
33	0.000016	0.000031	0.000395	0.000028
35	0.000050	0.000027	0.000596	0.000037
37	0.000051	0.000035	0.001153	0.000259
38	0.000069	0.000058	0.002919	0.000416
39	0.000277	0.000086	0.003153	0.000297
40	0.000315	0.000262	0.006755	0.006432

Table A.4. HEV THC Emission Rates.

THC g/s				
opMode Bins	**2012 Camry**	**2012 Fusion**	**2012 Escape**	**2011 Prius**
0	0.000024	0.000034	0.000160	0.000006
1	0.000002	0.000000	0.000000	0.000000
11	0.000015	0.000003	0.000013	0.000000
12	0.000029	0.000002	0.000018	0.000002
13	0.000043	0.000006	0.000022	0.000017
14	0.000080	0.000020	0.000033	0.000063
15	0.000128	0.000036	0.000051	0.000323
16	0.000278	0.000098	0.000148	0.000226
21	0.000094	0.000025	0.000044	0.000015
22	0.000087	0.000011	0.000027	0.000026
23	0.000065	0.000020	0.000035	0.000046
24	0.000066	0.000014	0.000036	0.000103
25	0.000145	0.000126	0.000063	0.000170
27	0.000276	0.000056	0.000100	0.000281
28	0.000926	0.000286	0.000227	0.000172
29	0.000641	0.000373	0.000346	0.000407
30	0.004704	0.001118	0.000612	0.000481
33	0.000108	0.000368	0.001532	0.000022
35	0.000107	0.000164	0.000755	0.000051
37	0.000163	0.000156	0.000601	0.000162
38	0.000311	0.000780	0.002158	0.000348
39	0.000934	0.003963	0.005783	0.000253
40	0.012448	0.012022	0.013972	0.001012

Table A.5. HEV Idling CO_2 Emission Rates.

CO_2 (kg/hr)				
Idle Condition	**2012 Camry**	**2012 Fusion**	**2012 Escape**	**2011 Prius**
Hot Test (Cold Start)	2.750307	0.841169	1.713542	1.157686
Hot Test	2.341956	1.383516	2.231909	0.579873
Cold Test (Cold Start)	3.698844	3.024137	5.038863	2.029318
Cold Test	1.327737	1.063962	2.175022	0.707301

Table A.6. HEV Idling CO Emission Rates.

CO (g/hr)				
Idle Condition	**2012 Camry**	**2012 Fusion**	**2012 Escape**	**2011 Prius**
Hot Test (Cold Start)	0.519471	0.728559	3.202272	0.626233
Hot Test	0.279013	1.177158	3.229870	0.207660
Cold Test (Cold Start)	0.882350	1.14521	2.919946	3.029951
Cold Test	0.193622	0.163502	0.463530	0.673760

Table A.7. HEV Idling NO_x Emission Rates.

NO_x (g/hr)				
Idle Condition	**2012 Camry**	**2012 Fusion**	**2012 Escape**	**2011 Prius**
Hot Test (Cold Start)	0.041496	0.190988	0.223930	0.092818
Hot Test	0.194314	0.017790	0.011310	0.000390
Cold Test (Cold Start)	0.018611	0.025663	0.128594	0.034007
Cold Test	0.002241	0.005709	0.007770	0.026380

Table A.8. HEV Idling THC Emission Rates.

THC (g/hr)				
Idle Condition	**2012 Camry**	**2012 Fusion**	**2012 Escape**	**2011 Prius**
Hot Test (Cold Start)	0.266032	0.348020	0.253001	0.225929
Hot Test	0.038370	0.033650	0.130612	0.103350
Cold Test (Cold Start)	0.359479	0.132604	0.365208	0.345565
Cold Test	0.023889	0.020936	0.036670	0.272640

Table A.9. PHEV CS Mode CO_2 Emission Rates.

	CO_2 (g/s)			
opMode Bins	**2012 Prius Plug-In**	**2012 Volt #1**	**2012 Volt #2**	**2011 Volt**
0	0.206783	1.333387	1.272569	1.482505
1	0.000463	0.000000	0.002604	0.005736
11	0.051390	0.563226	0.798368	0.649222
12	0.128727	0.399483	0.263888	0.281637
13	0.532042	0.363181	0.246944	0.784084
14	1.315419	0.213024	0.137802	0.943388
15	1.647568	0.009778	0.339438	0.870624
16	4.579736	0.410949	0.487599	2.095498
21	0.584957	3.702920	3.954628	3.732634
22	0.701817	3.681557	4.252467	4.077050
23	1.209607	3.603238	4.325095	4.462875
24	1.993175	3.663943	4.203815	4.761698
25	3.350772	2.862536	3.542550	4.609354
27	5.157832	3.068476	3.015615	4.237427
28	7.482269	3.381069	4.272620	5.753311
29	8.905616	2.371842	2.600308	6.249510
30	10.499794	3.516168	3.629108	8.309426
33	2.020278	5.121783	4.995272	4.835124
35	3.197797	5.676577	6.033376	6.279651
37	4.727359	5.799194	6.923858	7.471811
38	5.739957	6.307525	7.887537	7.954388
39	7.407253	7.004445	8.026057	8.518603
40	13.255866	8.865968	8.580918	8.988292

Table A.10. PHEV CS Mode CO Emission Rates.

CO (g/s)				
opMode Bins	**2012 Prius Plug-In**	**2012 Volt #1**	**2012 Volt #2**	**2011 Volt**
0	0.000317	0.063584	0.046440	0.070734
1	0.000003	0.000000	0.000008	0.000083
11	0.000131	0.001452	0.001608	0.002472
12	0.000275	0.002750	0.000501	0.001566
13	0.000513	0.004303	0.000429	0.002904
14	0.000880	0.001293	0.000186	0.003119
15	0.001156	0.003585	0.000496	0.004918
16	0.006190	0.012915	0.001557	0.006303
21	0.000366	0.123586	0.025677	0.062198
22	0.000307	0.091880	0.013095	0.065597
23	0.000661	0.116399	0.015739	0.062491
24	0.001131	0.075597	0.011150	0.074826
25	0.001101	0.024308	0.012157	0.034323
27	0.003562	0.021143	0.015407	0.028796
28	0.006373	0.103817	0.035974	0.032176
29	0.008567	0.042188	0.018251	0.129693
30	0.006362	0.189774	0.039630	0.113369
33	0.000816	0.280725	0.124609	0.154771
35	0.001334	0.287252	0.106790	0.135706
37	0.002700	0.308050	0.214637	0.259250
38	0.004173	0.473494	0.348864	0.338701
39	0.003116	0.747390	0.763204	0.485535
40	0.004793	1.036054	0.980230	0.839810

Table A.11. PHEV CS Mode NO_x Emission Rates.

	NO_x (g/s)			
opMode Bins	**2012 Prius Plug-In**	**2012 Volt #1**	**2012 Volt #2**	**2011 Volt**
0	0.000011	0.000011	0.000151	0.000099
1	0.000000	0.000000	0.000000	0.000000
11	0.000000	0.000003	0.000026	0.000038
12	0.000006	0.000002	0.000027	0.000046
13	0.000019	0.000002	0.000020	0.000038
14	0.000034	0.000001	0.000007	0.000169
15	0.000074	0.000000	0.000011	0.000095
16	0.000693	0.000006	0.000035	0.000293
21	0.000013	0.000051	0.000269	0.000190
22	0.000032	0.000027	0.000130	0.000209
23	0.000018	0.000027	0.000200	0.000208
24	0.000017	0.000026	0.000145	0.000237
25	0.000093	0.000029	0.000126	0.000216
27	0.000222	0.000044	0.000365	0.000207
28	0.000208	0.000035	0.000421	0.000607
29	0.000504	0.000040	0.000515	0.000981
30	0.001831	0.000387	0.000655	0.001054
33	0.000075	0.000024	0.000220	0.000230
35	0.000030	0.000015	0.000202	0.000281
37	0.000076	0.000016	0.000280	0.000374
38	0.000119	0.000011	0.000410	0.000424
39	0.000068	0.000010	0.000314	0.000431
40	0.002975	0.000087	0.000519	0.000451

Table A.12. PHEV CS Mode THC Emission Rates.

	THC (g/s)			
opMode Bins	**2012 Prius Plug-In**	**2012 Volt #1**	**2012 Volt #2**	**2011 Volt**
0	0.000008	0.000656	0.000553	0.000251
1	0.000000	0.000000	0.000005	0.000004
11	0.000000	0.000918	0.000074	0.000142
12	0.000002	0.001030	0.000187	0.000169
13	0.000006	0.001296	0.000381	0.000156
14	0.000009	0.000613	0.000066	0.000166
15	0.000004	0.000001	0.000002	0.000098
16	0.000067	0.000416	0.000004	0.000199
21	0.000003	0.000343	0.000727	0.000079
22	0.000007	0.000962	0.000089	0.000070
23	0.000006	0.000570	0.000207	0.000078
24	0.000006	0.000373	0.000254	0.000097
25	0.000034	0.000179	0.000860	0.000110
27	0.000029	0.000269	0.001104	0.000099
28	0.000052	0.000689	0.000024	0.000118
29	0.000121	0.000158	0.000116	0.000158
30	0.000274	0.002693	0.000714	0.000175
33	0.000049	0.000861	0.000170	0.000228
35	0.000041	0.001153	0.000273	0.000318
37	0.000058	0.001524	0.001544	0.000800
38	0.000067	0.002033	0.002205	0.001031
39	0.000099	0.003586	0.000988	0.000680
40	0.000468	0.004461	0.001716	0.000684

Table A.13. PHEV CS Mode Idling CO_2 Emission Rates.

CO_2 (g/hr)				
Idle Condition	**2012 Prius Plug-In**	**2012 Volt #1**	**2012 Volt #2**	**2011 Volt**
Hot Test (Cold Start)	0.304364	1.304041	2.581410	2.408431
Hot Test (Auto)	0.650506	1.755424	2.320106	3.077833
Cold Test (Cold Start)	1.662147	2.164913	2.363869	1.786422
Cold Test (Auto)	0.679624	1.420467	1.423375	1.741813

Table A.14. PHEV CS Mode Idling CO Emission Rates.

CO (g/hr)				
Idle Condition	**2012 Prius Plug-In**	**2012 Volt #1**	**2012 Volt #2**	**2011 Volt**
Hot Test (Cold Start)	0.132666	5.104767	4.387454	5.836191
Hot Test	0.122120	0.661294	1.324737	1.801881
Cold Test (Cold Start)	7.955499	6.151218	1.881553	1.688279
Cold Test	0.167451	0.690750	1.180267	2.403380

Table A.15. PHEV CS Mode Idling NO_x Emission Rates.

NO_x (g/hr)				
Idle Condition	**2012 Prius Plug-In**	**2012 Volt #1**	**2012 Volt #2**	**2011 Volt**
Hot Test (Cold Start)	0.001866	0.004526	0.128984	0.127490
Hot Test	0.004040	0.001549	0.098122	0.023907
Cold Test (Cold Start)	0.000000	0.060000	0.009477	0.126928
Cold Test	0.000000	0.000000	0.000000	0.015211

Table A.16. PHEV CS Mode Idling THC Emission Rates.

THC (g/hr)				
Idle Condition	**2012 Prius Plug-In**	**2012 Volt #1**	**2012 Volt #2**	**2011 Volt**
Hot Test (Cold Start)	0.087288	0.176099	0.471595	0.629596
Hot Test	0.082800	0.058742	0.006052	0.004781
Cold Test (Cold Start)	0.198780	0.386509	0.246265	0.372259
Cold Test	0.027565	0.022363	0.016300	0.059179

Table A.17. PHEV CD Mode Electricity Consumption Rates.

	Electricity (kWh/s)			
opMode Bins	**2012 Prius Plug-In**	**2012 Volt #1**	**2012 Volt #2**	**2011 Volt**
0	0.000000	0.000000	0.000000	0.000000
1	0.000000	0.000387	0.000291	0.000404
11	0.000000	0.000000	0.000000	0.000000
12	0.005893	0.000768	0.001434	0.002006
13	0.002506	0.002916	0.003986	0.005413
14	0.006171	0.004216	0.006050	0.007157
15	0.008125	0.004399	0.007689	0.009175
16	0.014848	0.010441	0.014138	0.015584
21	0.000000	0.000000	0.000000	0.000000
22	0.001192	0.001411	0.001422	0.001276
23	0.003003	0.002633	0.002892	0.003032
24	0.006415	0.003760	0.004727	0.004420
25	0.009397	0.005407	0.007426	0.007315
27	0.015131	0.008010	0.009565	0.010164
28	0.018300	0.012266	0.016542	0.014094
29	N/A	0.016352	0.021783	0.020891
30	N/A	0.026611	0.029266	0.028739
33	0.004135	0.002436	0.001029	0.001286
35	0.007575	0.005580	0.006016	0.006123
37	0.011144	0.008210	0.008437	0.009401
38	N/A	0.011279	0.012260	0.012794
39	N/A	0.013207	0.018364	0.021680
40	N/A	0.027728	0.029557	0.031663

Note: N/A means the vehicle was never operated in CD mode in that operating mode bin. The various “0” values mean during those operating mode bins, the vehicle used regenerative braking to generate electricity and therefore did not consume electricity.

Table A.18. PHEV CD Mode CO_2 Emission Rates.

	CO_2 (g/s)			
opMode Bins	**2012 Prius Plug-In**	**2012 Volt #1**	**2012 Volt #2**	**2011 Volt**
0	0.000000	0.000000	0.000000	0.000000
1	0.000000	0.207754	0.156194	0.216679
11	0.000000	0.000000	0.000000	0.000000
12	3.159255	0.411675	0.769092	1.075517
13	1.343845	1.563611	2.136822	2.902338
14	3.308439	2.260376	3.243816	3.837275
15	4.355952	2.358362	4.122465	4.919020
16	7.960964	5.597711	7.579839	8.355127
21	0.000000	0.000000	0.000000	0.000000
22	0.639236	0.756325	0.762330	0.684259
23	1.610197	1.411562	1.550368	1.625619
24	3.439250	2.016105	2.534290	2.370010
25	5.038141	2.898726	3.981328	3.921879
27	8.112662	4.294286	5.128038	5.449595
28	9.811344	6.576528	8.868896	7.556239
29	N/A	8.767152	11.678796	11.200860
30	N/A	14.267322	15.690865	15.408516
33	2.217163	1.305857	0.551919	0.689385
35	4.061447	2.991931	3.225542	3.282891
37	5.974637	4.401708	4.523632	5.040133
38	N/A	6.047415	6.572914	6.859494
39	N/A	7.080964	9.845594	11.623649
40	N/A	14.866478	15.846867	16.976081

Note: N/A means the vehicle was never operated in CD mode in that operating mode bin. The various “0” values mean during those operating mode bins, the vehicle used regenerative braking to generate electricity and therefore did not consume electricity.

Table A.19. PHEV CD Mode NO_x Emission Rates.

	NO_x (g/s)			
opMode Bins	**2012 Prius Plug-In**	**2012 Volt #1**	**2012 Volt #2**	**2011 Volt**
0	0.000000	0.000000	0.000000	0.000000
1	0.000000	0.126551	0.095144	0.131987
11	0.000000	0.000000	0.000000	0.000000
12	1.924419	0.250767	0.468483	0.655137
13	0.818586	0.952454	1.301617	1.767922
14	2.015293	1.376879	1.975929	2.337426
15	2.653372	1.436566	2.511146	2.996358
16	4.849318	3.409773	4.617161	5.089417
21	0.000000	0.000000	0.000000	0.000000
22	0.389383	0.460706	0.464363	0.416807
23	0.980831	0.859835	0.944387	0.990225
24	2.094975	1.228084	1.543730	1.443661
25	3.068918	1.765721	2.425175	2.388962
27	4.941723	2.615809	3.123678	3.319551
28	5.976453	4.006007	5.402373	4.602785
29	N/A	5.340397	7.113987	6.822859
30	N/A	8.690754	9.557887	9.385898
33	1.350556	0.795446	0.336194	0.419930
35	2.473978	1.822496	1.964797	1.999731
37	3.639373	2.681244	2.755512	3.070132
38	N/A	3.683705	4.003805	4.178372
39	N/A	4.313278	5.997316	7.080395
40	N/A	9.055722	9.652914	10.340760

Note: N/A means the vehicle was never operated in CD mode in that operating mode bin. The various “0” values mean during those operating mode bins, the vehicle used regenerative braking to generate electricity and therefore did not consume electricity.

Table A.20. PHEV CD Mode Electricity Consumption Rates.

Electricity (kWh)				
Idle Condition	**2012 Prius Plug-In**	**2012 Volt #1**	**2012 Volt #2**	**2011 Volt**
Hot Test (Cold Start)	1.84	0.69	1.46	1.86
Hot Test	0.76	0.77	0.99	1.35
Cold Test (Cold Start)	N/A	1.98	4.73	4.66
Cold Test	N/A	2.03	1.84	2.89

Table A.21. PHEV CD Mode Idling CO_2 Emission Rates.

CO_2 (kg/hr)				
Idle Condition	**2012 Prius Plug-In**	**2012 Volt #1**	**2012 Volt #2**	**2011 Volt**
Hot Test (Cold Start)	0.990855	0.370369	0.782773	0.997231
Hot Test (Min)	0.409016	0.416371	0.530784	0.723797
Cold Test (Cold Start)	N/A	1.063177	2.535971	2.498441
Cold Test	N/A	1.092487	0.986508	1.549462

Table A.22. PHEV CD Mode Idling NO_x Emission Rates.

NO_x (g/hr)				
Idle Condition	**2012 Prius Plug-In**	**2012 Volt #1**	**2012 Volt #2**	**2011 Volt**
Hot Test (Cold Start)	0.603567	0.225605	0.476816	0.607451
Hot Test	0.249147	0.253627	0.323321	0.440892
Cold Test (Cold Start)	N/A	0.647621	1.544754	1.521893
Cold Test	N/A	0.665474	0.600919	0.943835

APPENDIX B: AGGREGATED DISTANCE-BASED EV EMISSIONS RATES

Table B.1. HEV Passenger Car Emissions Rates on Restricted Access Road.

Road Type	Area Type	Average Speed (mph)	CO_2 (g/mi)	CO (g/mi)	NO_x (g/mi)	THC (g/mi)
Restricted Access	Urban	**2.5**	204.442	0.711	0.005	0.005
		5	204.559	0.785	0.005	0.006
		10	204.794	0.932	0.004	0.007
		15	206.569	0.994	0.004	0.007
		20	208.730	1.036	0.004	0.008
		25	217.483	1.061	0.004	0.008
		30	229.062	1.079	0.005	0.009
		35	244.261	1.173	0.006	0.009
		40	259.953	1.278	0.007	0.010
		45	281.301	1.518	0.008	0.010
		50	302.515	1.757	0.010	0.011
		55	305.656	1.723	0.011	0.011
		60	308.798	1.688	0.012	0.011
		65	317.489	1.589	0.012	0.011
		70	328.383	1.684	0.014	0.012
		75	343.586	2.240	0.016	0.014
	Rural	**2.5**	326.590	1.164	0.008	0.009
		5	291.222	1.110	0.007	0.008
		10	220.487	1.003	0.004	0.007
		15	243.691	1.148	0.004	0.009
		20	282.186	1.334	0.005	0.011
		25	262.874	1.175	0.005	0.010
		30	239.872	0.994	0.004	0.009
		35	237.237	0.973	0.005	0.009
		40	250.797	1.081	0.005	0.009
		45	273.768	1.235	0.007	0.009
		50	296.740	1.389	0.008	0.010
		55	302.292	1.414	0.009	0.010
		60	307.845	1.439	0.010	0.010
		65	316.751	1.364	0.011	0.010
		70	328.257	1.418	0.013	0.011
		75	349.012	2.288	0.017	0.015

Table B.2. HEV Passenger Car Emissions Rates on Unrestricted Access Road.

Road Type	Area Type	Average Speed (mph)	CO_2 (g/mi)	CO (g/mi)	NO_x (g/mi)	THC (g/mi)
Unrestricted Access	Urban	2.5	242.011	0.850	0.006	0.007
		5	202.269	0.960	0.004	0.006
		10	216.320	1.108	0.003	0.008
		15	231.785	1.205	0.003	0.009
		20	239.726	1.184	0.004	0.009
		25	233.257	1.053	0.004	0.009
		30	242.303	1.077	0.005	0.009
		35	259.819	1.220	0.005	0.010
		40	279.300	1.428	0.007	0.011
		45	300.963	1.829	0.009	0.012
		50	317.857	2.134	0.012	0.013
		55	309.708	1.932	0.011	0.012
		60	301.560	1.730	0.011	0.011
		65	307.732	1.580	0.012	0.011
		70	328.383	1.684	0.014	0.012
		75	343.586	2.240	0.016	0.014
	Rural	2.5	279.132	1.019	0.007	0.008
		5	231.845	1.108	0.004	0.007
		10	208.993	1.066	0.003	0.007
		15	273.344	1.368	0.004	0.011
		20	258.783	1.226	0.004	0.010
		25	242.117	1.102	0.004	0.009
		30	266.986	1.342	0.005	0.011
		35	276.536	1.309	0.005	0.011
		40	283.677	1.295	0.007	0.010
		45	318.736	2.020	0.011	0.013
		50	352.683	2.721	0.014	0.015
		55	332.169	2.203	0.013	0.013
		60	311.656	1.685	0.011	0.011
		65	309.198	1.360	0.011	0.010
		70	328.257	1.418	0.013	0.011
		75	349.012	2.288	0.017	0.015

Table B.3. HEV Passenger Truck Emissions Rates on Restricted Access Road.

Road Type	Area Type	Average Speed (mph)	CO_2 (g/mi)	CO (g/mi)	NO_x (g/mi)	THC (g/mi)
Restricted Access	Urban	2.5	238.395	1.780	0.012	0.019
		5	234.545	2.113	0.014	0.018
		10	226.847	2.779	0.017	0.017
		15	233.426	2.774	0.018	0.015
		20	245.022	2.532	0.018	0.013
		25	267.122	2.861	0.021	0.013
		30	293.724	3.434	0.023	0.014
		35	323.103	5.784	0.031	0.025
		40	352.861	8.376	0.038	0.036
		45	392.117	12.549	0.050	0.053
		50	431.244	16.741	0.062	0.070
		55	444.714	18.668	0.068	0.076
		60	458.183	20.595	0.074	0.081
		65	465.653	22.254	0.083	0.083
		70	476.444	26.850	0.096	0.096
		75	495.876	38.343	0.119	0.138
	Rural	2.5	308.428	2.923	0.014	0.031
		5	293.682	2.803	0.016	0.026
		10	264.189	2.562	0.018	0.017
		15	291.755	3.441	0.024	0.019
		20	328.610	4.503	0.029	0.022
		25	319.036	3.777	0.027	0.017
		30	306.499	2.936	0.023	0.013
		35	316.159	4.144	0.027	0.018
		40	343.570	6.979	0.035	0.031
		45	386.123	10.718	0.046	0.046
		50	428.677	14.458	0.057	0.062
		55	443.042	16.839	0.065	0.069
		60	457.406	19.219	0.073	0.075
		65	465.674	20.815	0.082	0.077
		70	473.176	23.703	0.093	0.084
		75	484.660	34.410	0.116	0.125

Table B.4. HEV Passenger Truck Emissions Rates on Unrestricted Access Road.

Road Type	Area Type	Average Speed (mph)	CO_2 (g/mi)	CO (g/mi)	NO_x (g/mi)	THC (g/mi)
Unrestricted Access	Urban	**2.5**	267.718	2.146	0.013	0.022
		5	208.911	1.954	0.013	0.017
		10	212.770	1.734	0.015	0.013
		15	238.806	1.828	0.017	0.011
		20	273.931	2.037	0.020	0.010
		25	290.710	2.031	0.020	0.009
		30	309.366	2.995	0.024	0.012
		35	338.317	5.455	0.031	0.023
		40	370.536	8.637	0.041	0.036
		45	408.802	13.848	0.055	0.057
		50	445.218	18.527	0.067	0.075
		55	471.917	20.421	0.076	0.082
		60	474.735	21.621	0.082	0.084
		65	472.311	22.669	0.086	0.084
		70	476.444	26.850	0.096	0.096
		75	495.876	38.343	0.119	0.138
	Rural	**2.5**	287.244	1.867	0.014	0.020
		5	220.472	1.753	0.014	0.015
		10	234.830	1.859	0.016	0.014
		15	295.614	2.294	0.021	0.013
		20	288.048	2.209	0.021	0.011
		25	300.195	1.932	0.020	0.008
		30	324.042	2.942	0.026	0.011
		35	349.151	5.472	0.033	0.023
		40	381.567	9.841	0.044	0.042
		45	440.128	17.841	0.067	0.070
		50	484.378	23.560	0.084	0.091
		55	477.890	21.188	0.079	0.085
		60	475.063	21.140	0.081	0.081
		65	473.039	21.602	0.086	0.079
		70	473.176	23.703	0.093	0.084
		75	484.660	34.410	0.116	0.125

Table B.5. PHEV Passenger Car Emissions Rates on Restricted Road.

Road Type	Area Type	Average Speed (mph)	CO_2 (g/mi)	CO (g/mi)	NO_x (g/mi)	THC (g/mi)
Restricted	Urban	2.5	240.275	4.675	0.013	0.140
		5	228.370	4.145	0.013	0.121
		10	204.560	3.086	0.011	0.081
		15	221.644	3.128	0.011	0.060
		20	250.263	3.480	0.011	0.044
		25	270.091	3.727	0.011	0.036
		30	288.245	3.954	0.011	0.029
		35	290.224	4.550	0.011	0.028
		40	290.798	5.178	0.011	0.027
		45	297.794	6.137	0.010	0.029
		50	304.790	7.096	0.010	0.030
		55	308.107	7.911	0.010	0.032
		60	311.271	8.720	0.009	0.035
		65	309.671	9.537	0.010	0.038
		70	309.342	10.546	0.011	0.041
		75	312.906	12.103	0.013	0.044
	Rural	2.5	238.371	4.590	0.013	0.137
		5	228.370	4.145	0.013	0.121
		10	204.560	3.086	0.011	0.081
		15	281.560	3.934	0.013	0.058
		20	309.250	4.481	0.013	0.046
		25	296.889	4.595	0.012	0.039
		30	284.529	4.709	0.010	0.031
		35	279.737	4.170	0.010	0.026
		40	276.242	3.673	0.010	0.022
		45	292.272	5.210	0.010	0.026
		50	308.302	6.746	0.009	0.029
		55	311.954	7.528	0.009	0.031
		60	313.154	8.167	0.008	0.033
		65	309.753	8.814	0.009	0.037
		70	307.605	9.644	0.010	0.040
		75	319.877	12.564	0.013	0.046

Table B.6. PHEV Passenger Car Emissions Rates on Unrestricted Access Road.

Road Type	Area Type	Average Speed (mph)	CO_2 (g/mi)	CO (g/mi)	NO_x (g/mi)	THC (g/mi)
Unrestricted Access	Urban	**2.5**	301.066	2.735	0.017	0.237
		5	220.084	3.099	0.012	0.120
		10	210.319	3.013	0.011	0.072
		15	232.009	3.176	0.011	0.051
		20	270.601	3.562	0.012	0.039
		25	301.287	3.819	0.012	0.031
		30	301.849	3.727	0.012	0.027
		35	298.481	4.029	0.012	0.026
		40	295.644	4.569	0.012	0.026
		45	298.134	5.907	0.011	0.028
		50	301.563	7.044	0.010	0.031
		55	306.400	7.882	0.010	0.033
		60	311.238	8.719	0.009	0.035
		65	309.671	9.537	0.010	0.038
		70	309.342	10.546	0.011	0.041
		75	312.906	12.103	0.013	0.044
	Rural	**2.5**	313.526	2.865	0.018	0.246
		5	220.606	3.107	0.012	0.120
		10	233.557	3.321	0.012	0.075
		15	232.903	3.188	0.011	0.051
		20	292.797	3.823	0.012	0.039
		25	301.619	3.822	0.012	0.031
		30	314.842	3.923	0.012	0.027
		35	304.047	4.146	0.012	0.026
		40	295.644	4.569	0.012	0.026
		45	298.134	5.907	0.011	0.028
		50	301.913	6.952	0.010	0.030
		55	307.625	7.559	0.009	0.032
		60	313.154	8.167	0.008	0.033
		65	309.753	8.814	0.009	0.037
		70	307.605	9.644	0.010	0.040
		75	319.877	12.564	0.013	0.046

APPENDIX C: PILOT APPLICATION RESULTS

Table C.1. Harris County Emissions Summary for 2014 Scenarios.

Pollutant	Vehicle Type	Base Case 2014 (ton/day)	EV 2014 (ton/day)
CO_2	Passenger Car	30,213.78	29,890.54
	Passenger Truck	8048.70	8037.40
	Fleet Total	52,829.76	52,495.23
CO	Passenger Car	191.76	191.58
	Passenger Truck	80.22	80.96
	Fleet Total	329.19	329.75
NO_x	Passenger Car	19.02	18.27
	Passenger Truck	10.48	10.43
	Fleet Total	65.58	64.78
THC	Passenger Car	3.63	3.55
	Passenger Truck	2.30	2.29
	Fleet Total	9.82	9.73

Table C.2. Harris County Emissions Summary for 2026 Scenarios.

Pollutant	Vehicle Type	Base Case 2026 (ton/day)	Low Oil Price 2026 (ton/day)	Medium Oil Price 2026 (ton/day)	High Oil Price 2026 (ton/day)	Extended Incentive 2026 (ton/day)
CO_2	**Passenger Car**	29,859.74	28,674.57	28,484.21	28,136.42	27,959.78
	Passenger Truck	7477.30	7276.51	7244.85	7194.90	7127.88
	Fleet Total	54,019.82	52,633.87	52,411.85	52,014.11	51,770.45
CO	**Passenger Car**	147.26	159.92	161.11	163.61	158.67
	Passenger Truck	50.63	64.27	65.75	68.45	64.26
	Fleet Total	239.22	265.53	268.19	273.39	264.26
NO_x	**Passenger Car**	6.13	5.51	5.42	5.25	5.33
	Passenger Truck	4.41	4.12	4.08	4.02	4.02
	Fleet Total	25.38	24.47	24.34	24.11	24.19
THC	**Passenger Car**	1.59	1.69	1.70	1.71	1.67
	Passenger Truck	0.94	0.94	0.94	0.94	0.93
	Fleet Total	4.60	4.70	4.71	4.72	4.66