Investigation of the Link Between Macroscopic Traffic Flow Characteristics and Individual Vehicle Fuel Consumption

Final Report
October 2017

Center for Transportation Research and Education

Sponsored by
Midwest Transportation Center
U.S. Department of Transportation
Office of the Assistant Secretary for Research and Technology

MIDWEST TRANSPORTATION CENTER

IOWA STATE UNIVERSITY
Institute for Transportation

About MTC

The Midwest Transportation Center (MTC) is a regional University Transportation Center (UTC) sponsored by the U.S. Department of Transportation Office of the Assistant Secretary for Research and Technology (USDOT/OST-R). The mission of the UTC program is to advance U.S. technology and expertise in the many disciplines comprising transportation through the mechanisms of education, research, and technology transfer at university-based centers of excellence. Iowa State University, through its Institute for Transportation (InTrans), is the MTC lead institution.

About InTrans

The mission of the Institute for Transportation (InTrans) at Iowa State University is to develop and implement innovative methods, materials, and technologies for improving transportation efficiency, safety, reliability, and sustainability while improving the learning environment of students, faculty, and staff in transportation-related fields.

About CTRE

The mission of the Center for Transportation Research and Education (CTRE) at Iowa State University is to develop and implement innovative methods, materials, and technologies for improving transportation efficiency, safety, and reliability while improving the learning environment of students, faculty, and staff in transportation-related fields.

ISU Non-Discrimination Statement

Iowa State University does not discriminate on the basis of race, color, age, ethnicity, religion, national origin, pregnancy, sexual orientation, gender identity, genetic information, sex, marital status, disability, or status as a U.S. veteran. Inquiries regarding non-discrimination policies may be directed to Office of Equal Opportunity, Title IX/ADA Coordinator, and Affirmative Action Officer, 3350 Beardshear Hall, Ames, Iowa 50011, 515-294-7612, email eooffice@iastate.edu.

Notice

The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the information presented herein. The opinions, findings and conclusions expressed in this publication are those of the authors and not necessarily those of the sponsors.

This document is disseminated under the sponsorship of the U.S. DOT UTC program in the interest of information exchange. The U.S. Government assumes no liability for the use of the information contained in this document. This report does not constitute a standard, specification, or regulation.

The U.S. Government does not endorse products or manufacturers. If trademarks or manufacturers' names appear in this report, it is only because they are considered essential to the objective of the document.

Quality Assurance Statement

The Federal Highway Administration (FHWA) provides high-quality information to serve Government, industry, and the public in a manner that promotes public understanding. Standards and policies are used to ensure and maximize the quality, objectivity, utility, and integrity of its information. The FHWA periodically reviews quality issues and adjusts its programs and processes to ensure continuous quality improvement.

Technical Report Documentation Page

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
4. Title and Subtitle Investigation of the Link Between Macroscopic Traffic Flow Characteristics and Individual Vehicle Fuel Consumption		**5. Report Date** October 2017 **6. Performing Organization Code**
7. Author(s) Jing Dong and Liang Hu		**8. Performing Organization Report No.**
9. Performing Organization Name and Address Center for Transportation Research and Education Iowa State University 2711 South Loop Drive, Suite 4700 Ames, IA 50010-8664		**10. Work Unit No. (TRAIS)** **11. Contract or Grant No.** Part of DTRT13-G-UTC37
12. Sponsoring Organization Name and Address Midwest Transportation Center 2711 S. Loop Drive, Suite 4700 Ames, IA 50010-8664	U.S. Department of Transportation Office of the Assistant Secretary for Research and Technology 1200 New Jersey Avenue, SE Washington, DC 20590	**13. Type of Report and Period Covered** Final Report **14. Sponsoring Agency Code**
15. Supplementary Notes		

16. Abstract

This project investigated the factors impacting individual vehicle energy consumption, including vehicle characteristics, ambient temperature, season, speed, driving behavior, and traffic flow. A fleet of 18 vehicles with a variety of ownership, size, model, year, and powertrain characteristics was monitored using on-board diagnostics II (OBD-II) loggers to collect each vehicle's controller area network (CAN) bus data for a one-year period. Traffic data, including flow rate, space mean speed, and density, were also collected and linked with the vehicle data. Based on vehicle CAN bus data, fuel consumption models for gasoline vehicles were calibrated, and a new electricity consumption model for electric vehicles was proposed. Both models can reliably estimate individual vehicle energy consumption.

17. Key Words		**18. Distribution Statement**	
fuel consumption—macroscopic traffic characteristics—vehicle CAN bus data		No restrictions.	
19. Security Classification (of this report)	**20. Security Classification (of this page)**	**21. No. of Pages**	**22. Price**
Unclassified.	Unclassified.	42	NA

Form DOT F 1700.7 (8-72) **Reproduction of completed page authorized**

INVESTIGATION OF THE LINK BETWEEN MACROSCOPIC TRAFFIC FLOW CHARACTERISTICS AND INDIVIDUAL VEHICLE FUEL CONSUMPTION

Final Report
October 2017

Principal Investigator
Jing Dong, Transportation Engineer
Center for Transportation Research and Education, Iowa State University

Research Assistant(s)
Liang Hu

Authors
Jing Dong and Liang Hu

Sponsored by
Midwest Transportation Center and
U.S. Department of Transportation
Office of the Assistant Secretary for Research and Technology

A report from
Institute for Transportation
Iowa State University
2711 South Loop Drive, Suite 4700
Ames, IA 50010-8664
Phone: 515-294-8103 / Fax: 515-294-0467
www.intrans.iastate.edu

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACKNOWLEDGMENTS

The authors would like to thank the Midwest Transportation Center and the U.S. Department of Transportation Office of the Assistant Secretary for Research and Technology for sponsoring this research. The authors would also like to thank Kathy Wellik and Butch Hansen from Transportation Services at Iowa State University for their help with data collection.

EXECUTIVE SUMMARY

This project investigated the factors impacting individual vehicle energy consumption, including vehicle characteristics, ambient temperature, season, speed, driving behavior, and traffic flow. A fleet of 18 vehicles with a variety of ownership, size, model, year, and powertrain characteristics was monitored by on-board diagnostics II (OBD-II) loggers to collect each vehicle's controller area network (CAN) bus data for a one-year period. Traffic data were collected using side-fired radar sensors and linked with the vehicle data. Relationships between vehicles' miles per gallon (MPG) and various factors were established using statistical analyses. In addition, using data collected from each vehicle's CAN bus, Virginia Tech microscopic energy and emission (VT-Micro) fuel consumption models for gasoline vehicles were calibrated, and a new electricity consumption model was proposed for battery electric vehicles (BEVs) that considers vehicle specific power (VSP) and temperature .

The key findings of this project are as follows:

1. The MPG of gasoline vehicles varies greatly by model, year, and engine technology. As expected, compacts and sedans are more fuel efficient than SUVs and pickup trucks. Electric vehicles have a much higher MPG equivalent (MPGeq) than gasoline vehicles.

2. Ambient temperature has a significant impact on fuel economy. Vehicle MPG declines in cold temperatures and increases in warm temperatures. The optimal ambient temperature for vehicle energy efficiency is 60°F to 70°F. In hot weather (above 70°F), the use of air conditioning reduces vehicle energy efficiency.

3. Three different relationships between trip average speed and MPG were observed. In general, vehicles consume more fuel at low speeds. For each vehicle, there is an optimal speed range that achieves the best fuel economy.

4. For gasoline vehicles, quiet driving behaviors featuring less variation in speeds, less hard acceleration, and less hard braking consume less fuel than aggressive driving behaviors. However, the electricity consumption of electric vehicles is lowest when 30% to 40% of braking events in a trip involve hard braking, due to regenerative braking.

5. By matching vehicle MPG data with Wavetronix traffic data, it was observed that when traffic density is over 26 veh/h/ln, gasoline vehicles' MPG decreases by 8% to 27% and electric vehicles' MPGeq decreases by 10%.

6. The calibrated VT-Micro fuel consumption models for gasoline vehicles and the proposed power-based electricity consumption models for BEVs can reliably estimate vehicle energy consumption.

INTRODUCTION

Ambient temperature, congestion, traffic signal progression, and driving style affect vehicles' emissions and fuel economy. To investigate the effects of various factors on fuel consumption, 10 Iowa State University rental vehicles and 8 private vehicles, with a variety of sizes, models, years, and powertrain types, were monitored for one year using on-board diagnostics II (OBD-II) loggers. The OBD-II loggers, linked to GPS trackers, were plugged into each vehicle's controller area network (CAN) bus and recorded vehicle location, speed, ambient temperature, and energy consumption rate.

Vehicle CAN bus data collected by OBD-II loggers have been used in many fuel economy studies. Typical parameters that are read by OBD-II loggers from gasoline vehicles are instantaneous speed, engine revolutions, throttle position, mass air flow (MAF), manifold absolute pressure (MAP), intake air temperature (AIT), absolute load, corrected air to fuel ratio (AFR), etc. Using these parameters, the actual fuel consumption can be obtained. Lee et al. (2011) developed a regression model that reveals the impacts of engine revolutions per minute and throttle position on vehicle fuel consumption. Bifulco et al. (2015) estimated vehicle fuel consumption based on vehicle speed, acceleration, throttle position, and intake air. Ribeiro et al. (2013) developed polynomial models using instantaneous fuel consumption as the dependent variable and speed and acceleration as independent variables. Meseguer et al. (2015) classified drivers into three groups (quiet, normal, and aggressive) based on CAN bus data and studied the impact of driving behavior on fuel economy.

Furthermore, because vehicle speed and acceleration data can be collected by various devices, such as OBD-II loggers, on-board trackers, and smartphones, instantaneous speed and acceleration are widely used as predictors to estimate vehicle fuel consumption (Ahn et al. 2002, Kamal et al. 2011, Rakha et al. 2004). Road inclination, as an extra variable, was considered along with speed and acceleration in the fuel consumption models developed by Ribeiro et al. (2013). In addition, some power-based models (Park et al. 2013, Rakha et al. 2011) first calculate instantaneous engine power based on speed and acceleration and then estimate fuel consumption.

OBD-II loggers can also be used to collected data from the CAN bus of battery electric vehicles (BEV) and plug-in hybrid electric vehicles (PHEV) (Zhou et al. 2016) by reading the battery's state of charge (SOC), current, and voltage. Duarte et al. (2014) studied the impacts of battery SOC on the energy consumption and gaseous pollutant emissions of PHEVs and concluded that SOC levels significantly impact energy use and tailpipe emissions under low power requirements. Several electricity consumption models for BEVs considering various impacting factors have been proposed in the literature. Yao et al. (2014) developed a BEV energy consumption model similar to the Virginia Tech microscopic energy and emission (VT-Micro) model that takes speed and acceleration as input. In subsequent work, the authors further improved the model by taking SOC into account because electricity consumption rate was found to be negatively correlated with SOC based on the data they collected (Zhang and Yao 2015). Wang et al. (2017) found that ambient temperature significantly impacts the energy efficiency of electric vehicles (EVs) and fitted a third-order polynomial regression model in terms of temperature to estimate energy usage. Liu et al. (2017) used vehicle probe and road gradient data to show that the impact of road gradient on EV electricity consumption increases almost linearly with increasing absolute gradient. Another important factor impacting electricity consumption is vehicle specific power (VSP), which can be calculated using vehicle speed and acceleration. One of the advantages of the power-based models is the consideration of regenerative braking of electric motors. For example, Alves et al. (2016) established regression relationships between VSP and BEV energy consumption based on levels of VSP, and Fiori et al. (2016) estimated EV energy consumption by modeling the energy efficiency of instantaneous regenerative braking as a function of deceleration levels.

This project investigated the relationships between individual vehicle fuel consumption and vehicle characteristics, ambient temperature, season, trip average speed, driving styles, and other factors. Previous studies showed that vehicle energy consumption increases considerably under traffic congestion for both gasoline vehicles (Feng et al. 2014) and electric vehicles (Xiao et al. 2016). In order to study the impacts of macroscopic traffic measurements on vehicle fuel consumption, vehicle CAN bus data were combined with traffic data collected by Wavetronix detectors on highways and freeways. The traffic data include flow rate, space mean speed, and density. Fuel consumption under congested traffic conditions was compared with fuel consumption under free flow conditions. In addition, using the vehicle speed, acceleration, and fuel consumption data collected from CAN buses, existing gasoline vehicle fuel consumption models were calibrated for specific vehicles and a new electric vehicle fuel consumption model was developed.

This report is organized as follows. In Data Collection, the process of collecting vehicle CAN bus data and traffic data is described. The Data Analysis section explains how data from multiple sources were fused and examines different factors influencing the energy consumption of gasoline vehicles and electric vehicles, including vehicle type, model, engine displacement, ambient temperature, season, trip speed, driving behavior, and macroscopic traffic characteristics. In Vehicle Energy Consumption Models, the report describes the development and validation of energy consumption models for gasoline vehicles and BEVs. Finally, the conclusions are presented.

DATA COLLECTION

Vehicle CAN Bus Data

OBD-II Data Logger

The way that vehicle CAN bus data were collected is shown in Figure 1.

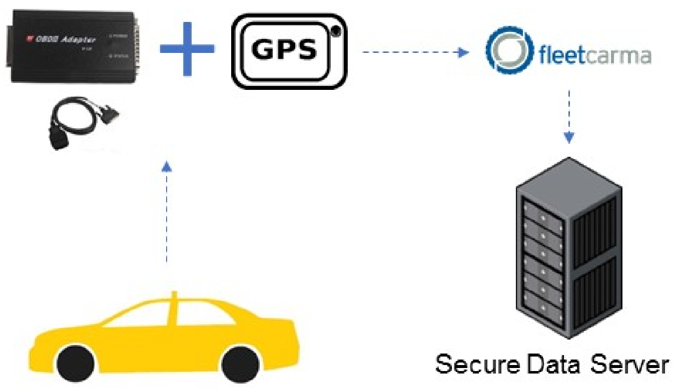


Figure 1. Collection of vehicle CAN bus data

The OBD-II loggers, with GPS tracking modules, were installed in a fleet of 18 passenger vehicles (16 gasoline vehicles and 2 electric vehicles) to read data from each vehicle's CAN bus. The data were temporarily stored in a memory card in the logger and then uploaded via cellular network to the data service provider, FleetCarma. The background system generated data and trip summary files that could be downloaded through a web data portal. The downloaded data were stored in a secure data server at Iowa State University.

Table 1 lists the data fields collected from the gasoline vehicles, including engine revolutions per minute, GPS location, vehicle speed, ambient temperature, and fuel consumption parameters. The actual fuel consumption rate was calculated using Equation 1.

Table 1. CAN bus data for gasoline vehicles

Data Field	Description	Frequency of Collection (sec)
Timestamp	Date and time when data are collected	-
Engine_RPM	Engine revolutions per minute (rpm)	5
GPS_Alt	Altitude of vehicle location (m)	15
GPS_Lat	Latitude of vehicle location (°)	15
GPS_Lon	Longitude of vehicle location (°)	15
GPS_Speed	Speed of GPS device (km/h)	15
GPS_Time	Time of GPS device	15
LTFT	Long-term fuel trim parameter (%)	5
STFT	Short-term fuel trim parameter (%)	5
MAF	Mass air flow (g/s)	5
Outside_Air_Temp	Ambient temperature (°C)	5
Veh_Speed	Vehicle speed (km/h)	1

$$FC=1000\times MAF\times(1+LTFT)\times\rho^{-1} \qquad (1)$$

where
FC is the instantaneous fuel consumption (mL/s)
MAF is the mass air flow (g/s)
$LTFT$ is the long-term fuel trim parameter (%)
ρ is gasoline density (719.7 g/L)

The data collected from electric vehicles were different than the data collected from internal combustion engine vehicles. For battery electric vehicles, the battery SOC, current, and voltage were recorded (see Table 2).

Table 2. CAN bus data for BEVs

Data Field	Description	Frequency of Collection (sec)
Timestamp	Date and time when data are collected	-
GPS_Alt	Altitude of vehicle location (m)	60
GPS_Lat	Latitude of vehicle location (°)	60
GPS_Lon	Longitude of vehicle location (°)	60
GPS_Speed	Speed of GPS device (km/h)	60
GPS_Time	Time of GPS device	60
HVBatt_Current	Current of batteries (A)	2
HVBatt_Voltage	Voltage of batteries (V)	2
HVBatt_SOC	State of charge (SOC) of batteries (%)	10
Outside_Air_Temp	Ambient temperature (°C)	5
Veh_Speed	Vehicle speed (km/h)	2

The actual electricity consumption rate is calculated using Equation 2.

$$EC = I \times U \tag{2}$$

where
EC is instantaneous electricity consumption (W)
U is battery voltage (V)
I is battery current (A)

The value of EC could be negative, indicating that electricity was generated and stored in the batteries due to the regenerative braking of electric motors.

Participant Recruiting

To ensure that the rights and safety of human participants in the study were protected, the researchers obtained approval from Institutional Review Board (IRB) at Iowa State University. Eighteen drivers of university rental or private vehicles participated in this study. All participants were informed of the study's objectives, collected data, risks, potential benefits, confidentiality, and rights. A consent form was signed prior to data collection. Participation in the study was voluntary. Participants had the right to leave the study at any time without any penalty or loss of benefits to which they were entitled. No driver left the study during the data collection period. Data were stored on an encrypted and password-protected data server located in a locked server room at the Institute for Transportation, Iowa State University. Only the principal investigator and authorized graduate research assistants had access to the data. The identifiable driver information was kept separate from the data.

The fleet from which data were collected consisted of 10 university rental vehicles and 8 private vehicles, with a variety of makes, models, years, engine displacements, and powertrain characteristics, as listed in Table 3.

Table 3. Characteristics of participating vehicles

No.	Make	Model	Year	Engine	Type	Ownership
2903	Mazda	CX-7	2009	2.3L I4 MFI	SUV	Private
3813	Chevrolet	Impala	2011	3.5L V6 SFI	Sedan	University
3950	Ford	Taurus	2015	3.5L V6 SMPI	Sedan	University
4347	Chevrolet	Silverado	2007	5.3L V8 SFI	Pickup truck	University
4358	Ford	Taurus	2014	3.5L V6 SMPI	Sedan	University
4359	Ford	Fusion	2010	3.0L V6 SMPI	Sedan	University
4380	Ford	Taurus	2014	3.5L V6 SMPI	Sedan	University
4385	Chevrolet	Impala	2011	3.5L V6 SFI	Sedan	University
5017	Chevrolet	Equinox	2016	2.4L I4 SIDI	SUV	University
5020	Chevrolet	Equinox	2016	2.4L I4 SIDI	SUV	University
5034	Chevrolet	Impala	2016	3.6L V6 SIDI	Sedan	University
5118	Honda	Civic	2008	1.8L I4 MPI	Compact	Private
5158	Honda	CR-V	2010	2.4L I4 MPI	SUV	Private
5828	Nissan	Leaf	2013	80kW electric motor	Compact	Private
5956	Pontiac	G6	2009	3.5L V6 SFI	Sedan	Private
6289	Honda	CR-V	2014	2.4L I4 MPI	SUV	Private
7306	Buick	Regal	2016	2.0L I4 SIDI	Sedan	Private
7507	BMW	i3	2015	125kW electric motor	Compact	Private

The university rental vehicles were long-term rentals to ISU employees. Thus, only one driver was associated with each vehicle. Among the participating vehicles, the 2013 Nissan Leaf is a BEV, and the 2015 BMW i3 is a PHEV. The other vehicles are gasoline powered. The fleet included diverse vehicle types: three compacts, nine sedans, five SUVs, and one pickup truck.

Seven of the private vehicles drove mainly in the Des Moines and Ames areas of Iowa. The other private vehicle, 2014 Honda CR-V, primarily drove in Beaumont, Texas. The university rental vehicles traveled mostly in the state of Iowa and sometimes traveled to the neighboring states, including Illinois, Kansas, Minnesota, Missouri, Nebraska, and Wisconsin. Data collection for most vehicles lasted for about one year with varied starting dates, as shown in Figure 2.

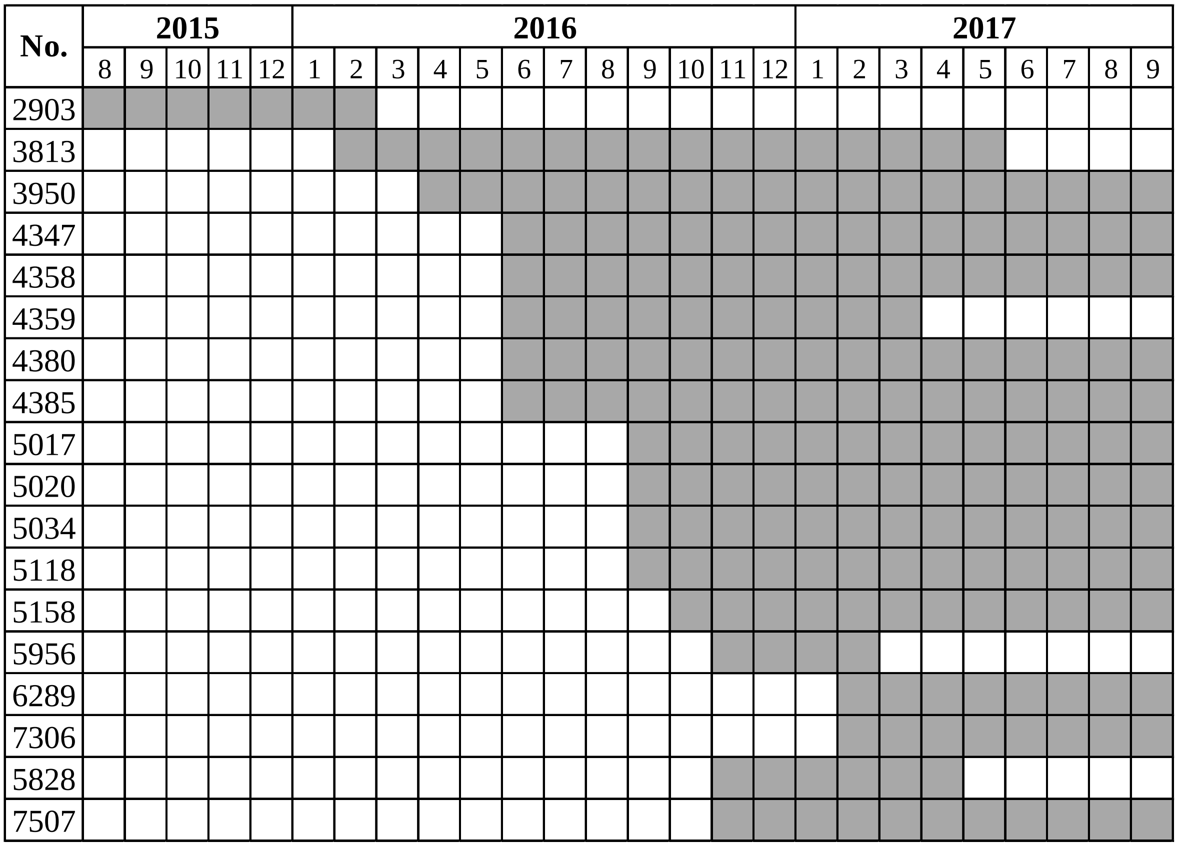


Figure 2. Period of data collection

The earliest data collection started in August 2015 for one of the researchers' personal vehicles using a trial data logger. The purpose of this was to try out the data logger and collect preliminary data to verify the proposed method. All of the other participants were recruited in February 2016 or later after IRB approval.

Wavetronix Traffic Data

Iowa DOT has been installing radar detectors manufactured by Wavetronix along Interstates and major highways in Iowa to monitor real-time traffic conditions. The detector inventory and GPS locations were provided by the Iowa DOT. The Wavetronix detectors count vehicles, detect traffic speeds, and calculate occupancy by direction and by lane every 20 seconds (see Figure 3).

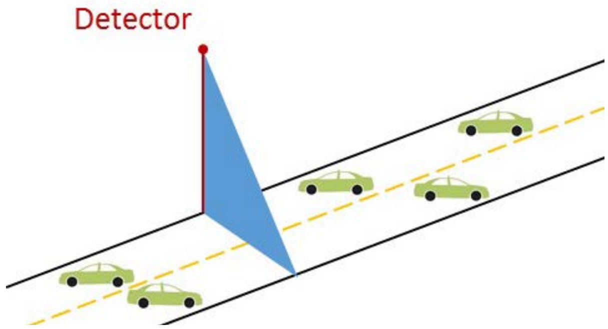


Figure 3. Wavetronix detectors collecting traffic data

The 20-second raw Wavetronix data can be aggregated at 5 min, 15 min, 30 min, 1 h, and 24 h intervals. This study used 5 min aggregated traffic data. Table 4 lists the data fields and the descriptions of the Wavetronix traffic data.

Table 4. Description of Wavetronix traffic data

Data Field	Description
Station	Name of Wavetronix detector
Timestamp	Date and time of traffic data
Interval	Time interval of traffic data (5 min in this study)
Dir	Direction of traffic
Lanes	Number of lanes in the direction of traffic
Cnt	Vehicle count during the time interval
Spd	Space mean speed of traffic during the time interval (mph)
Occ	Detector occupancy during the time interval (%)

DATA ANALYSIS

This section explains how the vehicle and traffic data were fused and describes the data analysis conducted to determine the factors that influence individual vehicle energy consumption.

Data Fusion

Vehicle CAN bus data were matched with Wavetronix traffic data spatially and temporally, as shown in Figure 4.

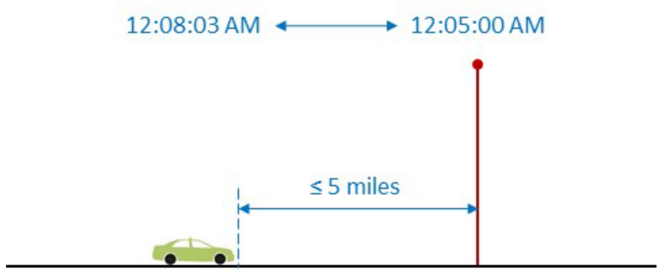


Figure 4. Matching vehicle location data and Wavetronix data spatially and temporally

First, a vehicle's GPS location was linked to the nearest Wavetronix detector. The distance between the vehicle and the detector needed to be within 5 miles. Second, the timestamp of the vehicle location was floor-rounded to nearest 5 min and linked to the Wavetronix traffic data with the same timestamp. For example, if a vehicle at 4/3/2017 12:08:30 AM was within 5 miles of a detector, the Wavetronix data timestamped at 4/3/2017 12:05:00 AM was matched.

Factors Influencing Vehicle Energy Consumption

Vehicle Characteristics

Based on the vehicle CAN bus data, FleetCarma provided a trip summary that included the travel distance and energy consumption of each trip. The vehicle MPG was calculated as the total travel distance divided by the total energy consumption during the data collection period. The electricity consumption was converted to gasoline gallon equivalent (GGE), where 1 GGE equals 33.4 kWh of electricity. Therefore, the fuel economy of electric vehicles was indicated by MPG equivalent (MPGeq).

The driver of the 2010 Honda CR-V manually recorded the odometer readings and gallons of gasoline filled, based on which the actual MPG was computed. The manually recorded MPG was 6% to 8% lower than the FleetCarma MPG. One of the reasons for the discrepancy is that the OBD-II logger usually starts collecting fuel consumption data 10 to 20 seconds after the engine starts. Therefore, the recorded fuel consumption tends to be lower than the actual value.

However, this measurement error affected all vehicles and thus did not impact the ranking of vehicles in terms of MPG below.

Figure 5 plots the MPG of all gasoline vehicles in the fleet in descending order.

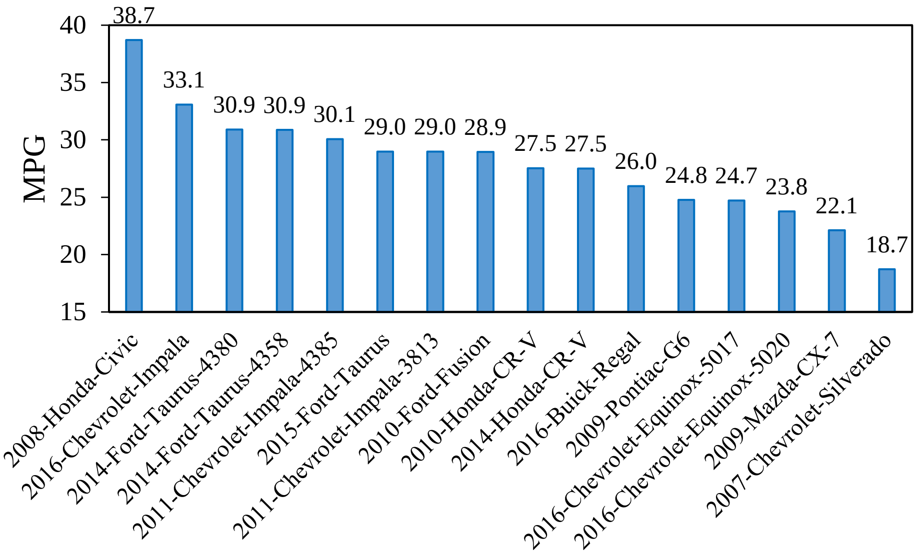


Figure 5. MPG of gasoline vehicles

The 2008 Honda Civic had the highest MPG of 38.7. The two Chevrolet Impalas and two Ford Tauruses also had efficient fuel consumption, with MPG values higher than 30. The two Honda CR-Vs shared the same MPG value, 27.5, and were the most fuel-efficient SUVs in the fleet. The 2009 Mazda CX-7 and 2007 Chevrolet Silverado had poor fuel economy, especially the Silverado pickup truck, which had a low MPG of 18.7.

As expected, the electric vehicles had much better fuel economy, 125.7 MPGeq for the 2013 Nissan Leaf BEV and 126.8 MPGeq for the 2015 BMW i3 PHEV, compared to the average MPG of the gasoline vehicles in the fleet (27.8), as shown in Figure 6.

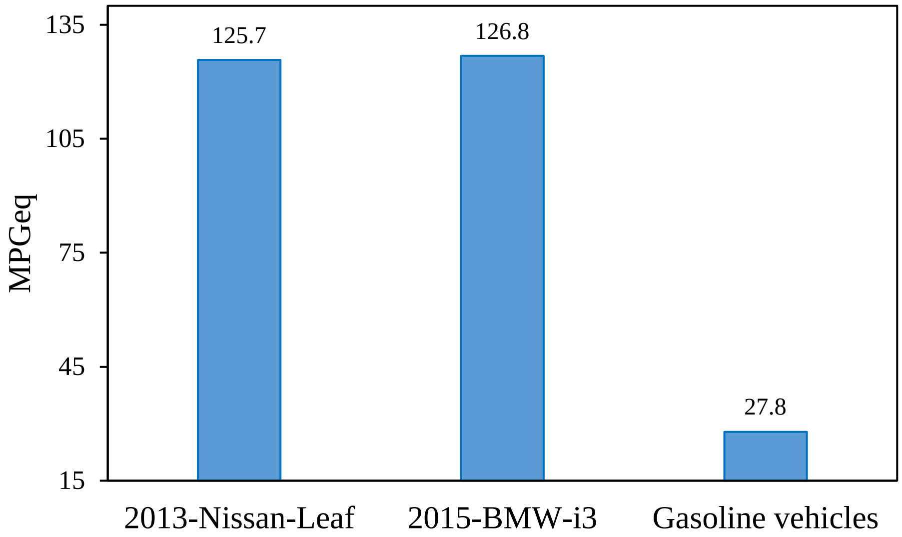


Figure 6. MPGeq of EVs and comparison with average for gasoline vehicles

The MPG values of the vehicles in the study were also compared by type (see Figure 7).

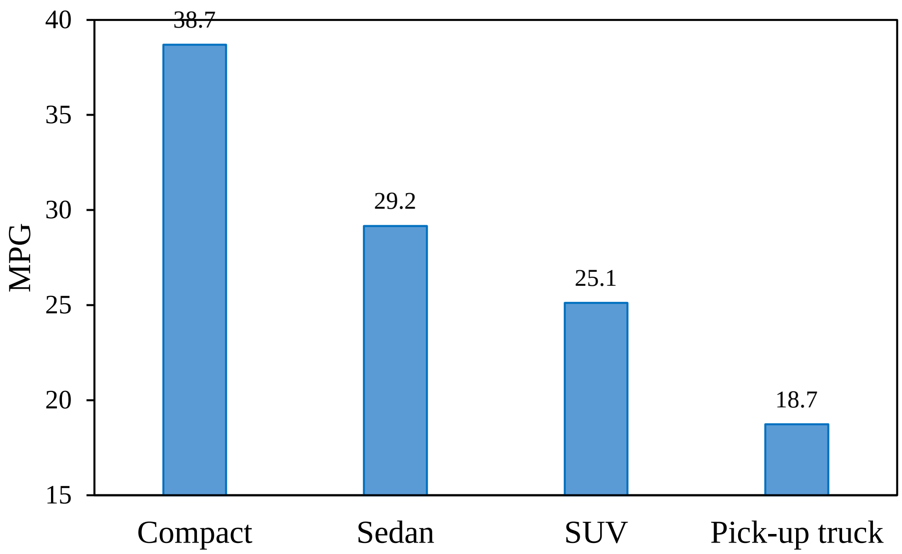


Figure 7. MPG by gasoline vehicle type

Larger vehicle size led to more fuel consumption and lower MPG. Compact vehicles were the most fuel efficient. The sedans in this study had an average MPG of 29.2. The fuel economy of the SUVs was lower than the average value of 27.8 MPG. The pickup trucks, with the largest sizes among the passenger vehicles, consumed the most fuel per mile.

Figure 8 compares MPG by vehicle model.

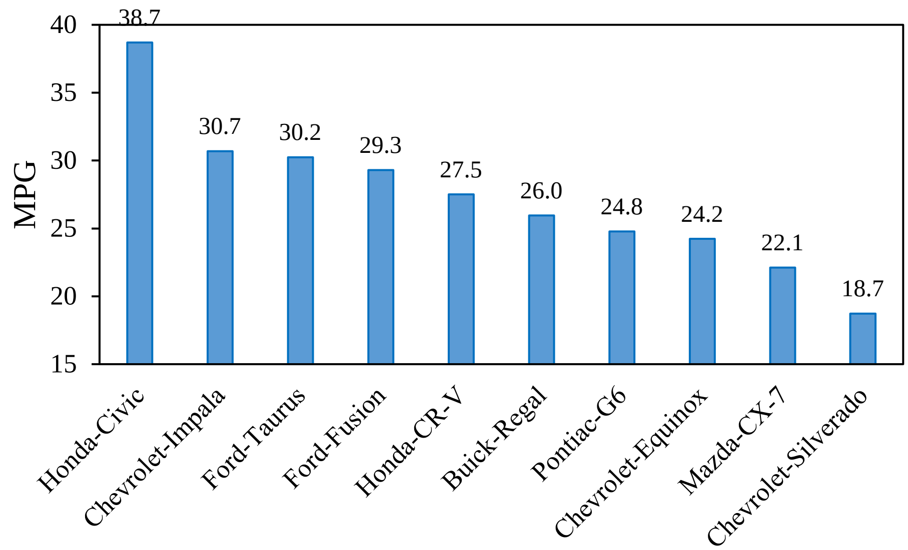


Figure 8. MPG by gasoline vehicle model

The MPG of the Honda Civic was almost 40. The Chevrolet Impala, Ford Taurus, and Ford Fusion had MPG values of around 30; these are considered fuel-efficient models. The Honda CR-V was the best fuel-efficient SUV, a class that includes the Chevrolet Equinox and Mazda CX-7. The MPG values of the Buick Regal and Pontiac G6 were close to those of the SUVs. The Chevrolet Silverado, not surprisingly, had the lowest MPG.

Engine displacement also has an impact on vehicle fuel consumption. In general, for the same engine technologies, engines with a larger displacement have a higher fuel consumption rate and a lower MPG (Essenhigh et al. 1979). However, due to the variety of vehicle years, types, models, and engine technologies in the fleet, the results in Figure 9 do not show MPG decreasing as engine displacement increases.

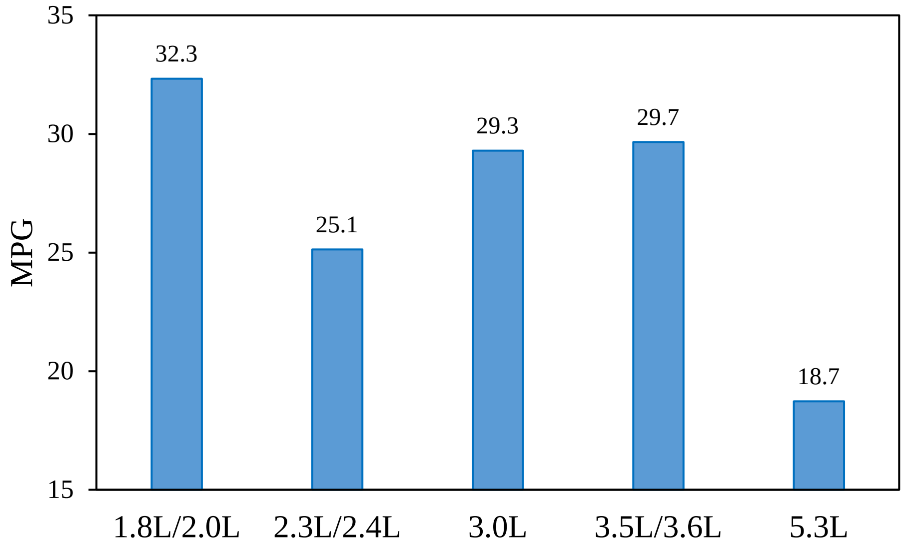


Figure 9. MPG by gasoline vehicle engine displacement

The vehicles using 2.3L/2.4L engines were generally older SUVs, while the vehicles using 3.5L/3.6L engines were sedans of more recent years.

Ambient Temperature

Vehicle energy consumption is affected by ambient temperature. Cold temperatures reduce the thermal efficiency of internal combustion engines and battery efficiency. The use of air conditioners in hot weather increases engine loads and thus reduces fuel economy. The optimal temperature range for fuel efficiency was found to be 60°F to 70°F in the US (Greene et al. 2017).

To examine the impacts of ambient temperature on the fuel consumption of the gasoline vehicles in the fleet, the temperature data collected by the OBD-II loggers were classified into groups at intervals of 10°F. The fleet average MPGs for the different temperature groups were calculated. The results are shown in Figure 10.

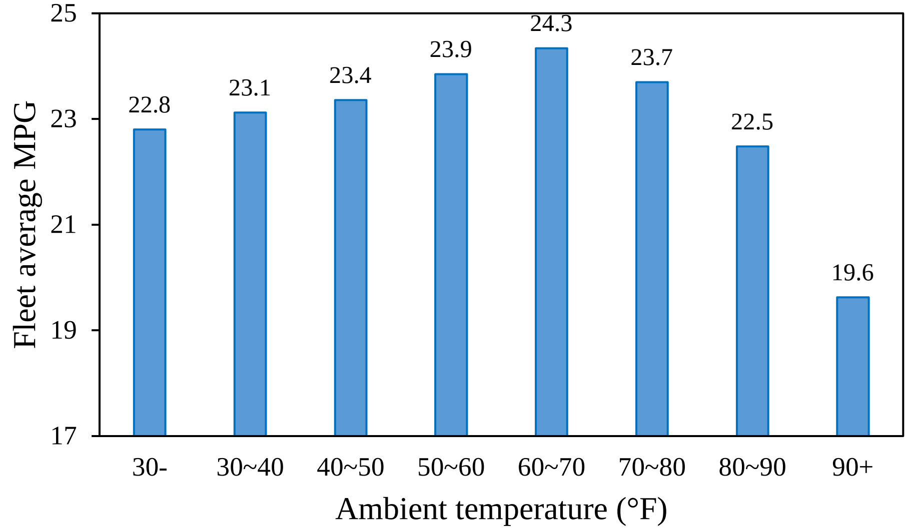


Figure 10. Variation in fleet average MPG by ambient temperature for gasoline vehicles

The average fleet MPG for gasoline vehicles was 22.8 when the ambient temperature dropped below 30°F. As the temperature increased, the fleet average MPG increased until it arrived at the peak (24.3) between 60°F and 70°F. This finding agrees with Greene et al. (2017). When the temperature is above 70°F, engines inject less fuel to warm up, but the use of air conditioners increases the engine load and thus leads to more fuel consumption. The fleet MPG dropped to only 19.6 when the ambient temperature was above 90°F.

Ambient temperature had similar impacts on the electricity consumption of electric vehicles, as shown in Figure 11.

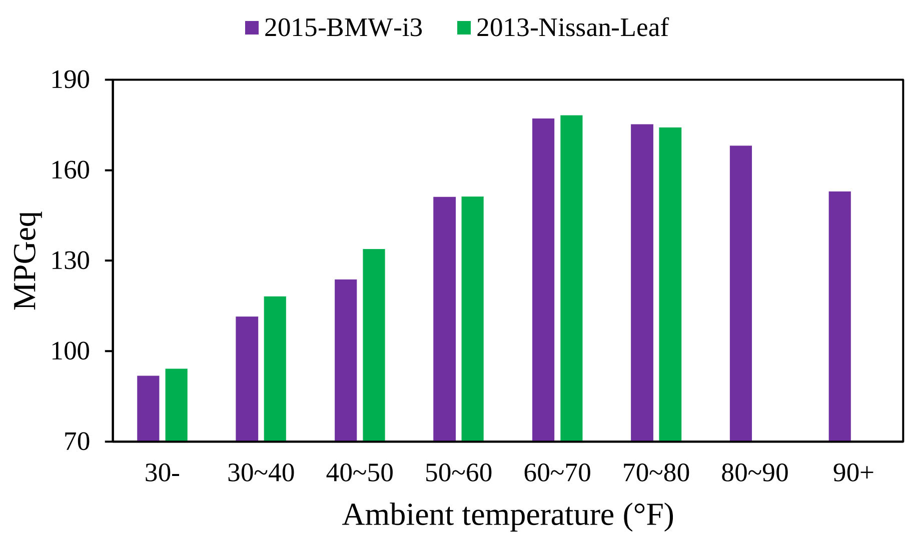


Figure 11. Variation in MPGeq by ambient temperature for EVs

Note that no MPGeq data were collected above 70°F for the Nissan Leaf. Additionally, 60°F to 70°F is also the optimal temperature range for EV energy efficiency. In cold temperatures, the two EVs' MPGeq values were much lower due to the decline of battery efficiency and the use of heaters. The rate at which MPGeq decreased at cold temperatures was larger than the rate at which MPG decreased for gasoline vehicles at cold temperatures, which indicates that EV energy efficiency is more sensitive to cold temperatures. When the ambient temperature rises above 70°F, the MPGeq decreases because using air conditioning increases the auxiliary load.

Season

Vehicle fuel economy also changes with the seasons. Figure 12 shows the average MPG of the gasoline vehicles in Iowa over a one-year period from August 2016 through July 2017.

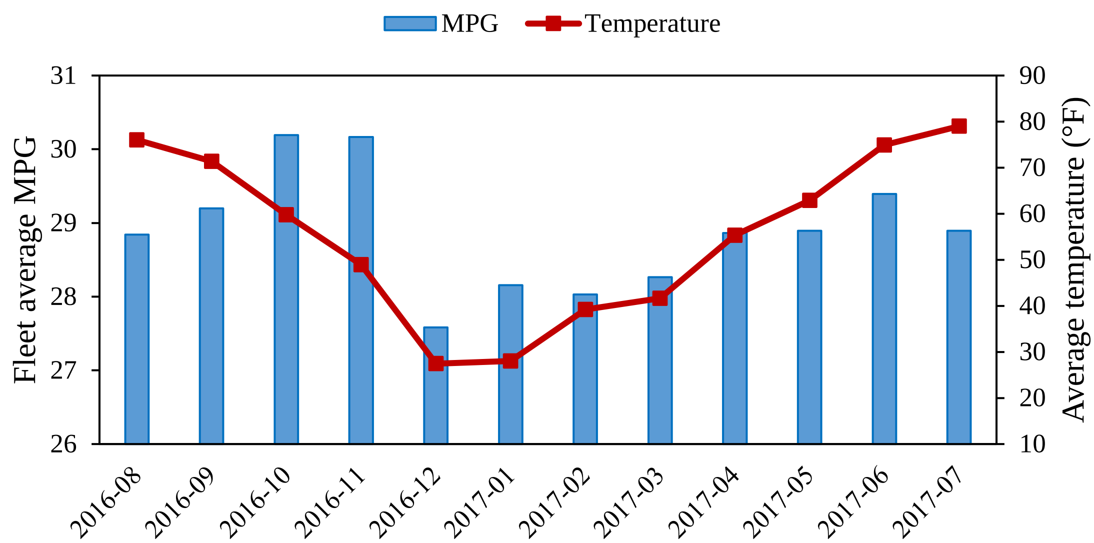


Figure 12. Fleet average MPG of gasoline vehicles and monthly average temperature over one year

The monthly average temperature of the Des Moines metropolitan area declined from August to December/January and then climbed again until July. It can be seen that during the winter months, especially in December and January when the average temperatures were the lowest of the year, the fleet average MPG was the lowest. The reason is that more gasoline is needed to warm up engines during cold weather. In the fall (September to November), when temperatures were cool, the fleet was the most fuel efficient, with an average MPG of over 30. The average temperature in the spring (March to May) was slightly lower than in the fall, resulting in a lower fleet average MPG in the spring than in the fall. Another possible reason for lower MPG in the spring is that drivers might have kept using the heaters right after the winter due to habit. The fleet average MPG in the summer between June and August was second to that in the fall because drivers use air conditioners more often in the summer.

The two Honda CR-Vs were driven in Iowa and Beaumont, Texas, respectively. Figure 13 shows a comparison of their monthly MPG from February 2017 to July 2017.

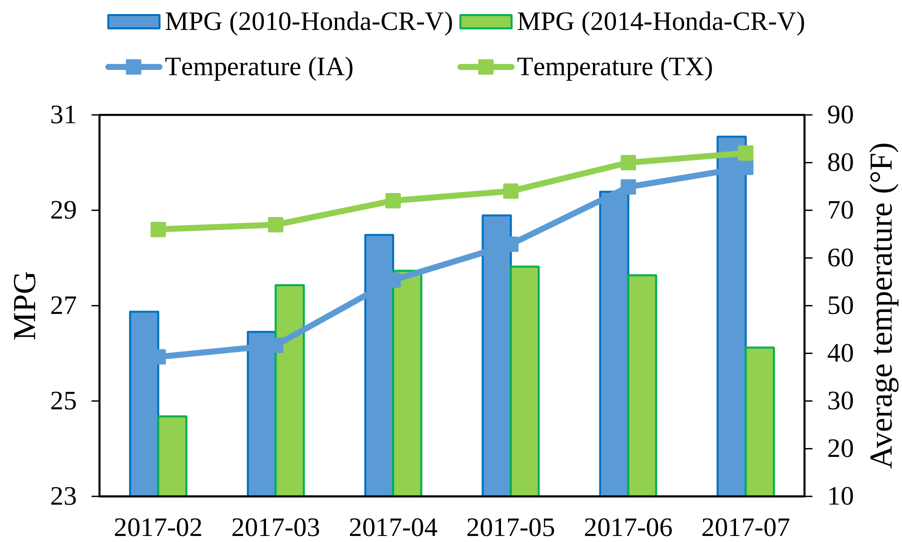


Figure 13. Comparison of MPG of two Honda CR-Vs, one in Iowa and one in Texas

The 2014 Honda CR-V in Texas had a lower MPG in general, which might be because the impacts of gasoline thermal efficiency were offset by the frequent use of air conditioning.

Because data were collected for the two EVs for less than one year, the monthly MPGeq and temperatures between November 2016 and July 2017 (with no data from the Nissan Leaf after April 2017) are plotted separately in Figure 14.

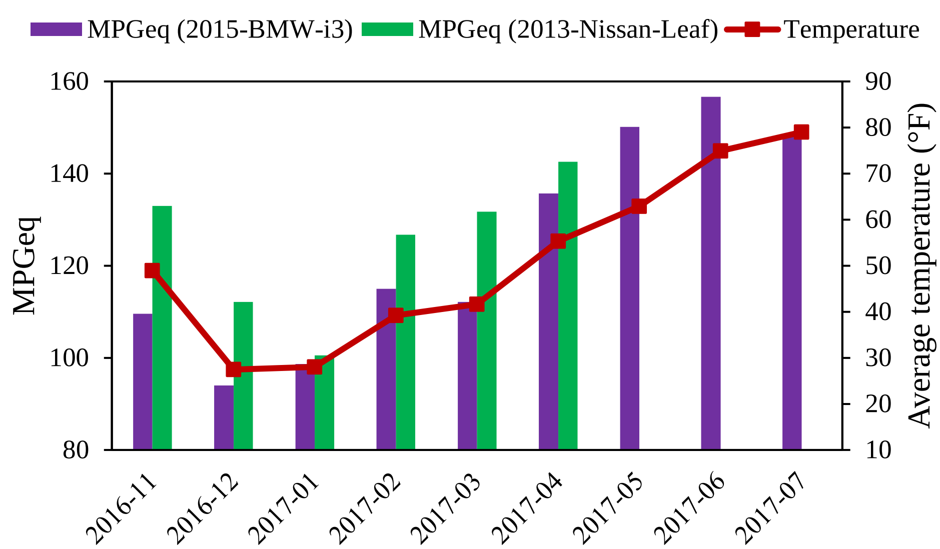
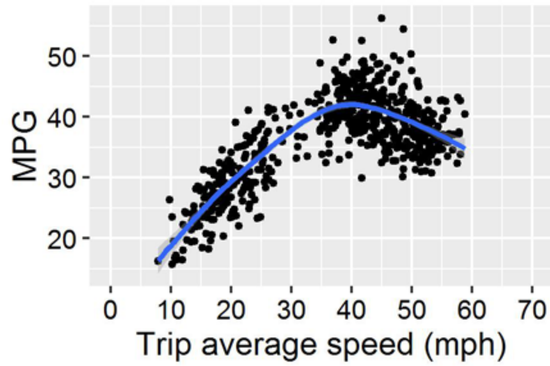


Figure 14. Comparison of MPGeq of two EVs

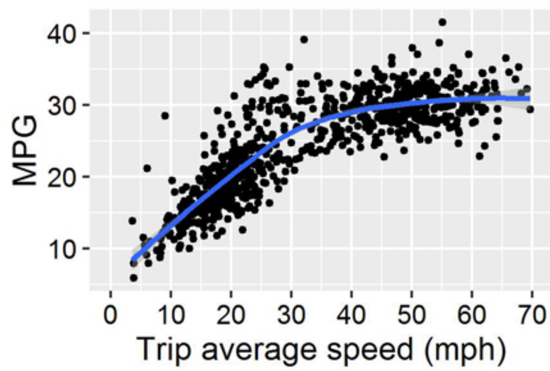
The energy consumption also changed significantly with the season. MPGeq was the lowest in the winter and rose during warmer months. The electricity consumed per mile by the BMW i3 was the lowest in June 2016 when the monthly average temperature was 75°F.

Trip Average Speed

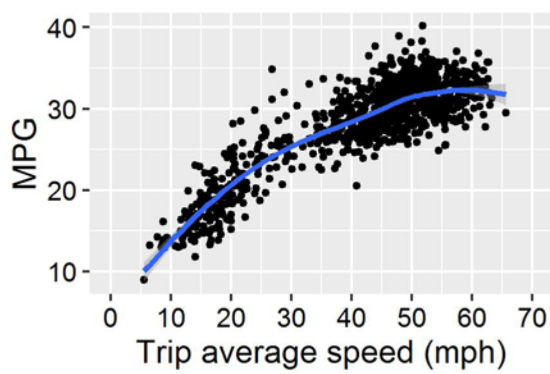
The influence of trip average speed on energy consumption varied by individual vehicle. Figure 15 presents three scatter plots of trip average speed versus trip MPG, representing three different relationships between trip speed and MPG. The blue lines are the LOESS curves fitted between the two variables.



(a) 2010 Honda CR-V, No, 5158



(b) 2011 Chevrolet Impala, No. 3813



(c) 2014 Ford Taurus, No. 4380

Figure 15. Relationships between trip average speed and MPG for gasoline vehicles

It can be seen from Figure 15(a) that vehicle MPG increased as the trip average speed increased until an optimum speed was reached. For the 2010 Honda CR-V (No. 5158), the most fuel-efficient speed was around 40 mph. After that, vehicle MPG decreased. The gasoline vehicles in the fleet that shared similar relationships included the 2010 Ford Fusion (No. 4359) and 2016 Chevrolet Impala (No. 5034).

In contrast, MPG did not decrease at high speeds for some vehicles. Figure 15(b) shows that for the 2011 Chevrolet Impala (No. 3813), the MPG increased in the speed range of 0 to 50 mph and remained almost constant if the trip average speed surpassed 50 mph. The high-speed trips did not consume more fuel than the medium-speed trips. These trends were also found in the 2009 Mazda CX-7 (No. 2903), 2014 Ford Taurus (No. 4358), 2016 Chevrolet Equinox (No. 5017 and No. 5020), and 2014 Honda CR-V (No. 6289).

Figure 15(c) shows the relationship between trip average speed and MPG for one of the 2014 Ford Tauruses (No. 4380). The relationship for this vehicle is different than that of the other 2014 Ford Taurus (No. 4358), which follows a pattern similar to that shown in Figure 15(b). In Figure 15(c), MPG continues to increase as trip speed increases. The high-speed trips used more fuel than the medium-speed and low-speed trips. Different driving styles and traffic environments might have played a role in the distinct speed versus MPG curve. Vehicles having similar speed-MPG curves include the 2015 Ford Taurus (No. 3950), 2007 Chevrolet Silverado (No. 4347), 2011 Chevrolet Impala (No. 4385), 2009 Pontiac G6 (No. 5956), and 2016 Buick Regal (No. 7306).

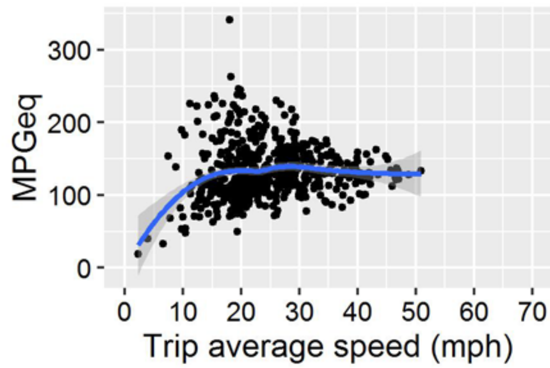
Based on the above analysis of the relationship between trip speed and MPG, an optimal speed or speed range that achieved the best fuel economy was found for each vehicle, as listed in Table 5.

Table 5. Optimal trip speed or speed range for fuel efficiency

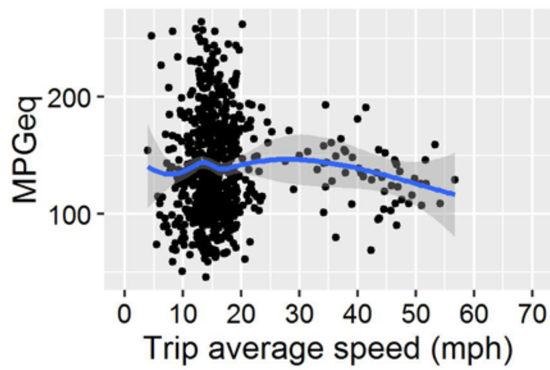
No.	Optimal Trip Speed or Speed Range for Fuel Efficiency (mph)
2903	50~70
3813	50~70
3950	65
4347	65
4358	50~70
4359	45
4380	60
4385	65
5017	50~70
5020	40~60
5034	50
5118	40
5158	40
5956	65
6289	50~70
7306	55

Previous studies have shown that drivers could increase fuel efficiency by 7% to 30% by driving at optimal speeds under free-flow traffic conditions (Hooker 1988).

For the two electric vehicles, Figure 16 shows that trip MPGeq did not change significantly when trip average speed was over 10 mph.



(a) 2013 Nissan Leaf



(b) 2015 BMW i3

Figure 16. Relationships between trip average speed and MPGeq for electric vehicles

High-speed trip data for the 2013 Nissan Leaf were not available (no trips were made at 50 to 70 mph on average), and the majority of trips were at low speeds for the 2015 BMW i3, which might result in bias in the conclusions. More vehicle data need to be collected on highways and freeways to support the analysis of the relationship between trip speed and MPGeq for electric vehicles.

Driving Behavior

For each trip, we calculated the ratio of cruising, acceleration, deceleration, and stopping, respectively, based on the tracked vehicle speed and acceleration data. Taking the 2010 Honda CR-V as an example, Figure 17 plots the trips of this vehicle, with the percentages of acceleration and deceleration on the x-axis and the percentages of cruising and stopping on the y-axis.

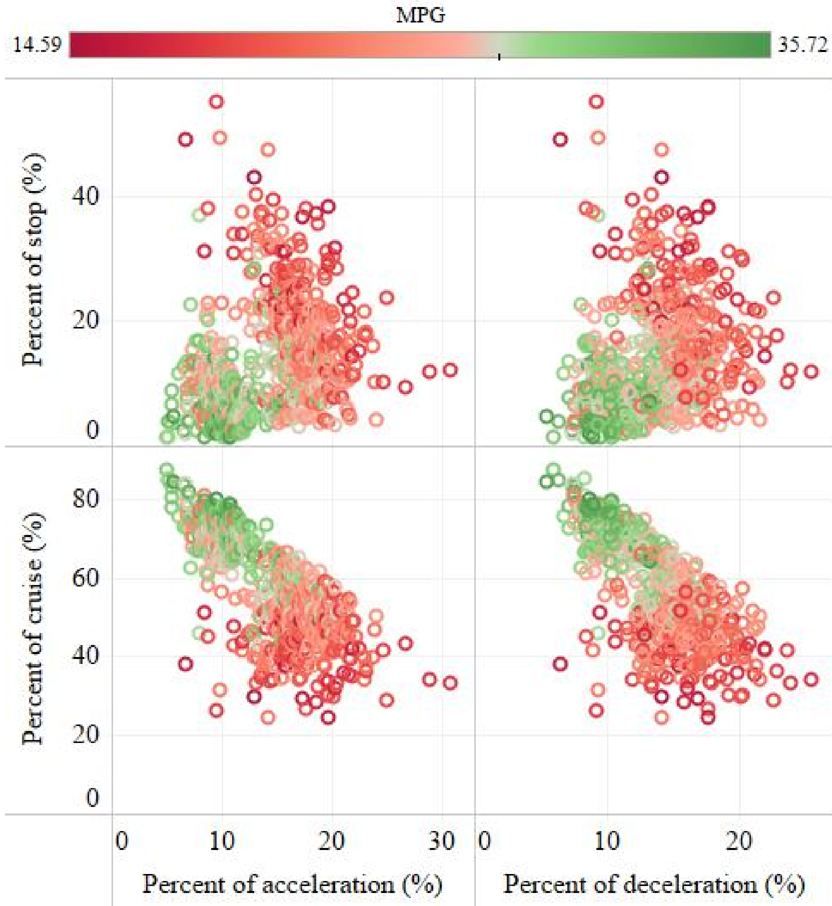


Figure 17. Impacts of acceleration, deceleration, cruising, and stopping on MPG (2010 Honda CR-V)

The trips are colored based on their MPG values. Green trips are fuel-efficient trips whose MPG values are above the average MPG of 27.5 for all vehicles, while the red trips' MPG values are below the average. This plot clearly shows the difference between trips with above average or below average fuel efficiency. The green, fuel-efficient trips are clustered at the lower-left or upper-left corner of each subplot, indicating that driving with less variation in speed (less acceleration, deceleration, and stopping and more cruising) can save fuel.

The percentages of hard acceleration and hard deceleration are used to describe driving behaviors, either quiet or aggressive. FleetCarma suggests that acceleration above the range of -1.7 to 1.7 m/s^2 can be considered hard. The percentage of hard acceleration/deceleration is the number of hard acceleration/deceleration events divided by all acceleration/deceleration events in a trip. The impacts of the percentages of hard acceleration and hard deceleration during the trips on the fleet average MPG are illustrated in Figure 18.

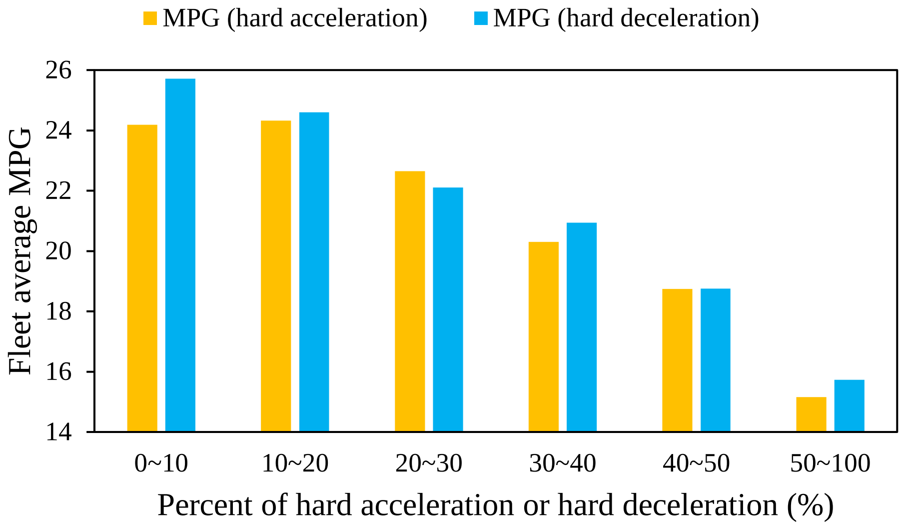


Figure 18. Impacts of hard acceleration and hard deceleration on fleet MPG

It can be seen that more aggressive driving behaviors (i.e., higher percentages of hard accelerations and hard decelerations) decrease the fleet MPG. When over half of acceleration/deceleration events are hard, the fleet average MPG drops below 16, which is almost 40% less than the MPG for quiet driving (i.e., when less than 10% of acceleration/deceleration events are hard). Drivers who want to improve MPG should avoid hard acceleration and deceleration as much as possible.

However, the electricity consumption of electric vehicles is not significantly influenced by the split of acceleration, deceleration, cruising, and stopping, as seen in the scatter plots in Figure 19.

Figure 19. Impacts of acceleration, deceleration, cruising, and stopping on MPGeq (2013 Nissan Leaf)

The green trips (above average electricity efficiency) and red trips (below average electricity efficiency) do not have an evident boundary of separation. This is likely due to the regenerative braking feature of electric vehicles. Figure 20 further demonstrates the impacts of braking on the EVs' MPGeq. In contrast to gasoline vehicles, the EVs' electricity consumption is the lowest when 30% to 40% of deceleration events during the trips are hard.

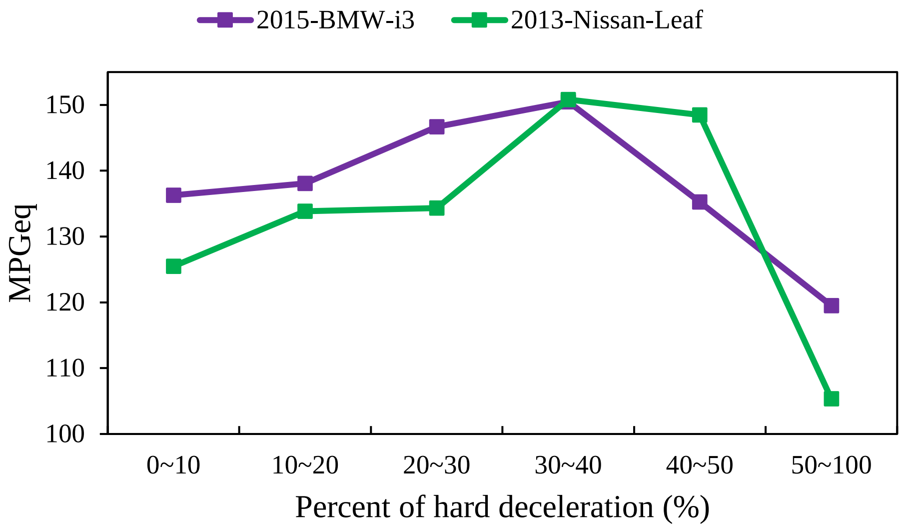


Figure 20. Impacts of hard deceleration on MPGeq of EVs

Macroscopic Traffic Characteristics

To analyze the impacts of macroscopic traffic characteristics on vehicle MPG, the vehicle energy consumption data were linked with Wavetronix traffic data. We calculated a vehicle's MPG in the minute after the vehicle's location matched a detector. The macroscopic traffic characteristics included flow rate, speed, and density. Note that this study used 5 min aggregated vehicle count data. Therefore, the corresponding hourly flow rate was calculated by multiplying the 5 min count by 12. Traffic density is not directly measured by the Wavetronix detectors but was computed using Equation 3.

$$Q=S\times D \tag{3}$$

where
Q is traffic flow rate (veh/h/ln)
S is space mean speed of traffic stream (mi/h)
D is density (veh/mi/ln)

Using the 2011 Chevrolet Impala (No. 4385) as an example, a speed-flow scatter plot is illustrated in Figure 21.

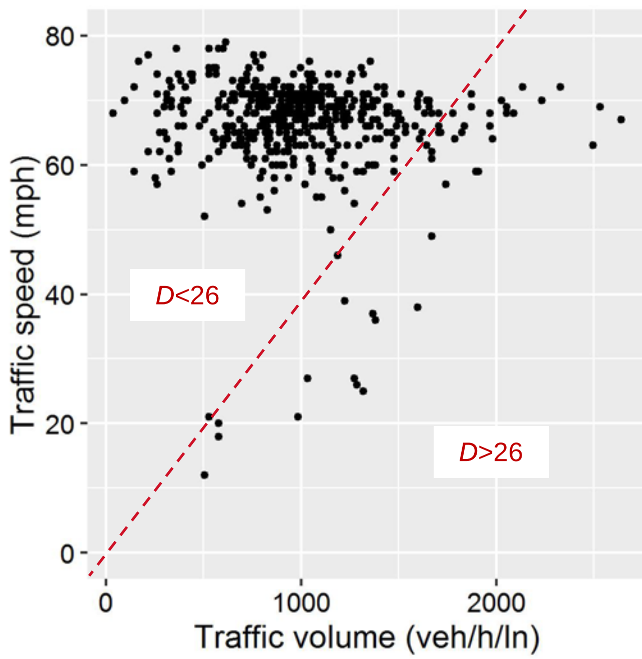


Figure 21. Speed-flow scatter plot for 2011 Chevrolet Impala (No. 4385) on freeways

In most cases, this vehicle was driven at high speeds and in low to moderate traffic on freeways. Freeway traffic starts to slow down with increasing flows when density exceeds 26 pc/mi/ln (TRB 2010). In this study, traffic with a density above 26 veh/mi/ln was considered congested.

Vehicle MPG decreased by different amounts for different vehicles under congestion. Figure 22 compares the MPG of nine gasoline vehicles in congested and non-congested traffic conditions and illustrates the extent to which MPG decreases under congestion for each vehicle.

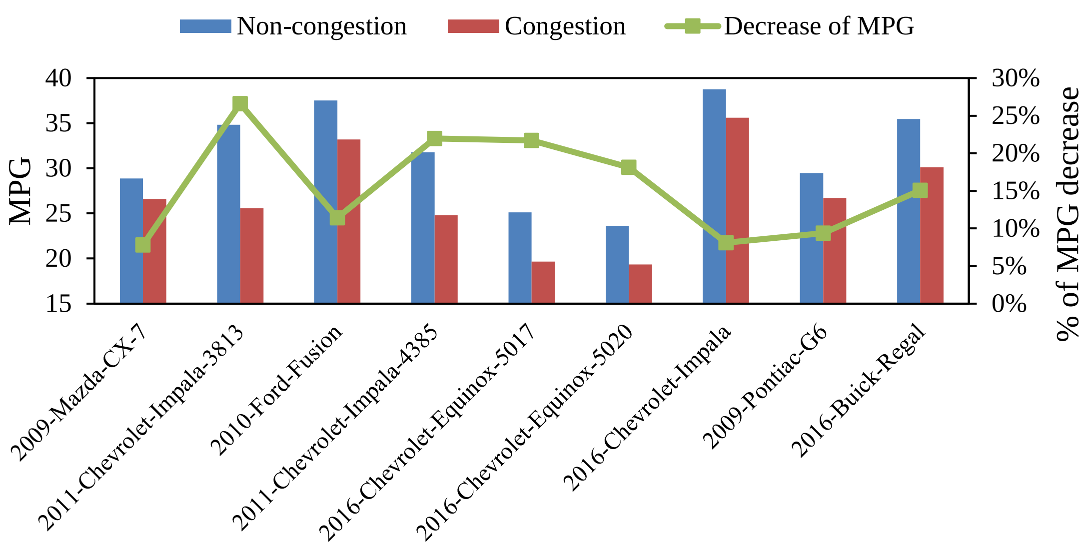


Figure 22. Decrease in vehicle MPG under congestion

The most significant decline in MPG was for the 2011 Chevrolet Impala (No. 3813), whose MPG decreased by 27%. The fuel consumption rates of the 2011 Chevrolet Impala (No. 4385), 2016 Chevrolet Equinox (No. 5017), and 2016 Chevrolet Equinox (No. 5020) were also sensitive to congestion, dropping by about 20% in high-density traffic. The 2016 Buick Regal’s MPG decreased moderately by 15%, while the decrease in MPG of the other vehicles was within 8% to 11%.

The electricity consumption rates of electric vehicles under congested and uncongested conditions were also studied. Figure 23 compares the MPGeq values of the 2013 Nissan Leaf under different traffic conditions. The average MPGeq was 116.5 in uncongested traffic but decreased by 10% when traffic density was above 26 veh/mi/ln.

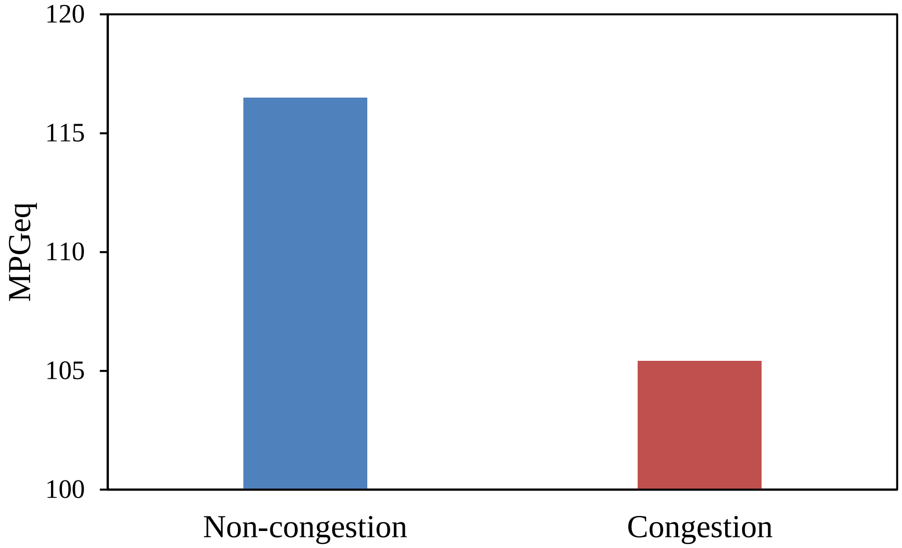


Figure 23. MPGeq of 2013 Nissan Leaf under non-congestion and congestion

VEHICLE ENERGY CONSUMPTION MODELS

Fuel Consumption Model for Gasoline Vehicles

This study adopted the VT-Micro model proposed by Ahn et al. (2002) to estimate the vehicle fuel consumption of gasoline vehicles. VT-Micro is a hybrid linear regression model that includes a combination of linear, quadratic, and cubic speed and acceleration terms, as shown in Equations 4 and 5.

$$\ln FC = \sum_{i=0}^{3}\sum_{j=0}^{3} L_{i,j} v^i a^j \quad (a \geq 0) \tag{4}$$

$$\ln FC = \sum_{i=0}^{3}\sum_{j=0}^{3} M_{i,j} v^i a^j \quad (a < 0) \tag{5}$$

where
v is vehicle speed (m/s)
a is vehicle acceleration (m/s^2)
$L_{i,j}$ are regression parameters for $a \geq 0$
$M_{i,j}$ are regression parameters for $a < 0$

For each gasoline vehicle in the fleet, we used the actual fuel consumption, vehicle speed, and acceleration data to calibrate the VT-Micro model with regression parameters specific to that vehicle. Taking the 2010 Honda CR-V as an example, the adjusted R^2 of the calibrated model was found to be 0.8245 if $a \geq 0$ and 0.6616 if $a < 0$. The regression parameters are listed in Tables 6 and 7.

Table 6. Parameters of the calibrated VT-Micro model for $a \geq 0$ (2010 Honda CR-V)

$a \geq 0$	Constant	v	v^2	v^3
Constant	-1.23E+00	6.05E-02	3.62E-04	-2.22E-06
a	4.69E-01	3.39E-01	-1.91E-02	2.56E-04
a^2	-4.54E-02	-1.33E-01	7.45E-03	-5.44E-05
a^3	1.34E-02	2.08E-02	-2.01E-03	3.19E-05

Table 7. Parameters of the calibrated VT-Micro model for $a < 0$ (2010 Honda CR-V)

a < 0	Constant	v	v^2	v^3
Constant	-7.89E-01	-2.14E-02	5.61E-03	-9.16E-05
a	2.83E-01	-1.02E-01	2.01E-02	-4.43E-04
a^2	1.39E-01	-7.45E-02	1.40E-02	-3.44E-04
a^3	9.13E-03	-9.58E-03	2.16E-03	-5.77E-05

To evaluate the accuracy of the calibrated VT-Micro model, we compared the actual trip-level fuel consumption with the estimates from the regression model for the same trip. As shown in Figure 24, the dots are mostly distributed along the diagonal line. Therefore, the calibrated VT-Micro model can reliably estimate trip-level vehicle fuel consumption.

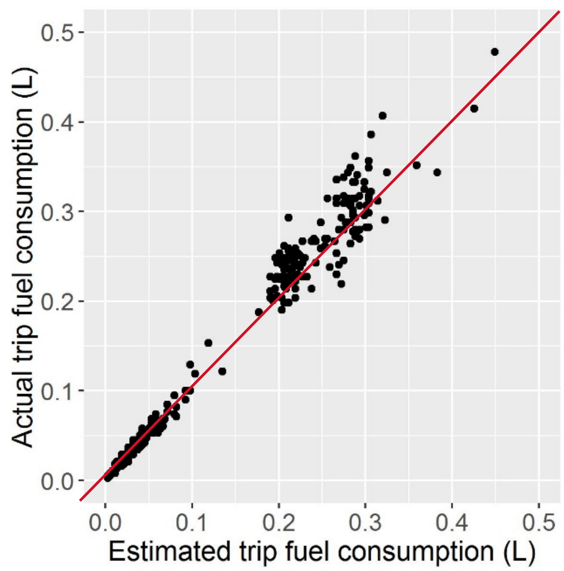


Figure 24. Validation of fuel consumption model for gasoline vehicles (2010 Honda CR-V)

Electricity Consumption Model for BEVs

This study proposes a power-based BEV electricity consumption model that considers VSP and ambient temperature. The data used to calibrate the model were collected from the 2013 Nissan Leaf. The model is a hybrid linear regression model, as follows.

$$EC=b_0+b_1VSP+b_2P_{aux} \tag{6}$$

$$VSP=v(1.1a+C_{rr})+C_{aero}v^3 \tag{7}$$

$$\ln P_{aux}=c_0+c_1T \tag{8}$$

where
VSP is vehicle specific power (W/kg)
P_{aux} is vehicle auxiliary load (W)
C_{rr} is rolling resistance coefficient (N/kg)
C_{aero} is aerodynamics drag coefficient (N s^2/m^2 kg)
T is ambient temperature (°C)
b_0, b_1, b_2, c_0, c_1 are model parameters

For the 2013 Nissan Leaf, C_{rr} equals 0.0981 N/kg and C_{aero} equals 0.0002 N s^2/m^2 kg. The model parameters were calibrated based on the VSP levels (>0, =0, or <0) and the instantaneous speed levels (≥12.5 m/s, or <12.5 m/s) because electricity consumption is heterogeneous under different VSP levels combined with speed levels. The regression parameters are listed in Table 8.

Table 8. Parameters of the electricity consumption model for the 2013 Nissan Leaf BEV

VSP	***v***	b_0	b_1	b_2	c_0	c_1
>0	<12.5	3.22E+03	1.16E+03	2.15E+00	-8.94E-02	6.71E+00
	≥12.5	8.43E+03	7.57E+02	2.60E+00		
=0	<12.5	6.10E+02	—	1.19E+00		
	≥12.5	—	—	—		
<0	<12.5	7.20E+02	5.58E+02	2.10E+00		
	≥12.5	8.12E+03	5.94E+02	2.57E+00		

To evaluate the accuracy of the electricity consumption model, we compared the actual trip-level electricity consumption of the 2013 Nissan Leaf BEV with the estimates from the model for the same trip. Figure 25 shows that the dots are mostly distributed along the diagonal line. Therefore, the proposed energy consumption model is appropriate for estimating the electricity consumption of BEVs.

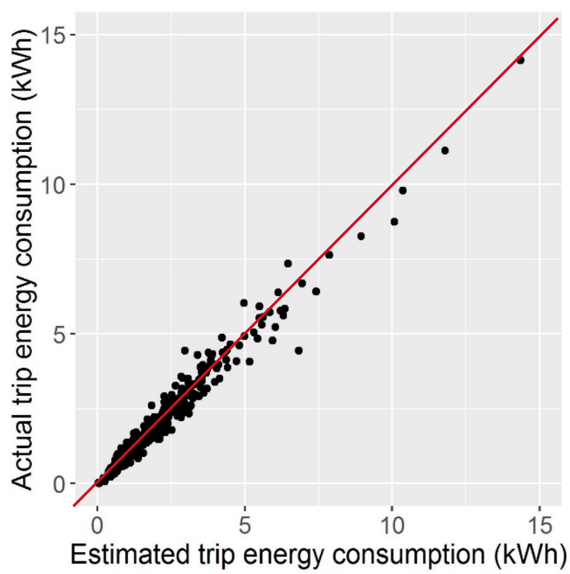


Figure 25. Validation of electricity consumption model for BEVs (2013 Nissan Leaf)

CONCLUSIONS

A fleet of 18 vehicles with a variety of ownership, size, model, year, and powertrain characteristics was monitored by OBD-II loggers for a one-year period. Wavetronix traffic data were also used and were linked with the vehicles' CAN bus data. By conducting statistical analyses, this project studied the factors impacting individual vehicle energy consumption, such as vehicle characteristics, ambient temperature, season, trip average speed, driving behavior, and macroscopic traffic characteristics. Based on vehicle CAN bus data, VT-Micro fuel consumption models for gasoline vehicles were calibrated, and a new electricity consumption model was proposed for BEVs that takes advantage of VSP and temperature.

The key findings of this project are as follows:

1. The MPG of gasoline vehicles varies greatly by model, year, and engine technology. As expected, compacts and sedans are more fuel efficient than SUVs and pickup trucks. Electric vehicles have a much higher MPG equivalent (MPGeq) than gasoline vehicles.

2. Ambient temperature has a significant impact on fuel economy. Vehicle MPG declines in cold temperatures and increases in warm temperatures. The optimal ambient temperature for vehicle energy efficiency is 60°F to 70°F. In hot weather (above 70°F), the use of air conditioning reduces vehicle energy efficiency.

3. Three different relationships between trip average speed and MPG were observed. In general, vehicles consume more fuel at low speeds. For each vehicle, there is an optimal speed range that achieves the best fuel economy.

4. For gasoline vehicles, quiet driving behaviors featuring less variation in speeds, less hard acceleration, and less hard braking consume less fuel than aggressive driving behaviors. However, the electricity consumption of electric vehicles is lowest when 30% to 40% of braking events in a trip involve hard braking, due to regenerative braking.

5. By matching vehicle MPG data with Wavetronix traffic data, it was observed that when traffic density is over 26 veh/h/ln, gasoline vehicles' MPG decreases by 8% to 27%, and electric vehicles' MPGeq decreases by 10%.

6. The calibrated VT-Micro fuel consumption models for gasoline vehicles and the proposed power-based electricity consumption models for BEVs can reliably estimate vehicle energy consumption.

REFERENCES

Ahn, K., H. Rakha, A. Trani, and M. Van Aerde. 2002. Estimating vehicle fuel consumption and emissions based on instantaneous speed and acceleration levels. *Journal of Transportation Engineering*, Vol. 128, No. 2, pp. 182–190.

Alves, J., P. C. Baptista, G. A. Gonçalves, and G. O. Duarte. 2016. Indirect methodologies to estimate energy use in vehicles: Application to battery electric vehicles. *Energy Conversion and Management*, Vol. 124, pp. 116–129.

Bifulco, G. N., F. Galante, L. Pariota, and M. R. Spena. 2015. A linear model for the estimation of fuel consumption and the impact evaluation of advanced driving assistance systems. *Sustainability*, Vol. 7, No. 10, pp. 14326–14343.

Duarte, G. O., R. A., Varella, G. A. Gonçalves, and T. L. Farias. 2014. Effect of battery state of charge on fuel use and pollutant emissions of a full hybrid electric light duty vehicle. *Journal of Power Sources*, Vol. 246, pp. 377–386.

Essenhigh, R. H., H. E. Shull, T. Blackadar, and H. McKinstry. 1979. Effect of vehicle size and engine displacement on automobile fuel consumption. *Transportation Research Part A: General*, Vol. 13, No. 3, pp. 175–177.

Feng, Y. Q., J. Q. Leng, Y. P. Zhang, and Y. He. 2014, April. Fuel economy of urban road networks based on traffic flow. *Proceedings of the Institution of Civil Engineers-Transport*, Vol. 167, No. 2, pp. 100–110.

Fiori, C., K. Ahn, and H. A. Rakha. 2016. Power-based electric vehicle energy consumption model: Model development and validation. *Applied Energy*, Vol. 168, pp. 257–268.

Greene, D. L., J. Liu, A. J. Khattak, B. Wali, J. L. Hopson, and R. Goeltz. 2017. How does on-road fuel economy vary with vehicle cumulative mileage and daily use? *Transportation Research Part D: Transport and Environment*, Vol. 55, pp. 142–161.

Hooker, J. N. 1988. Optimal driving for single-vehicle fuel economy. *Transportation Research Part A: General*, Vol. 22, No. 3, pp. 183–201.

Kamal, M. A. S., M. Mukai, J. Murata, and T. Kawabe. 2011. Ecological vehicle control on roads with up-down slopes. *IEEE Transactions on Intelligent Transportation Systems*, Vol. 12, No. 3, pp. 783–794.

Lee, M. G., K. K. Jung, Y. K. Park, and J. J. Yoo. 2011. Effect of in-vehicle parameters on the vehicle fuel economy. *Advanced Computer Science and Information Technology*, pp. 132–142.

Liu, K., T. Yamamoto, and T. Morikawa. 2017. Impact of road gradient on energy consumption of electric vehicles. *Transportation Research Part D: Transport and Environment*, Vol. 54, pp. 74–81.

Meseguer, J. E., C. T. Calafate, J. C. Cano, and P. Manzoni. 2015. Assessing the impact of driving behavior on instantaneous fuel consumption. *2015 12th Annual IEEE Consumer Communications and Networking Conference (CCNC)*, pp. 443–448.

Park, S., H. Rakha, K. Ahn, and K. Moran. 2013. Virginia Tech comprehensive power-based fuel consumption model (VT-CPFM): model validation and calibration considerations. *International Journal of Transportation Science and Technology*, Vol. 2, No. 4, pp. 317–336.

Rakha, H. A., K. Ahn, K. Moran, B. Saerens, and E. Van den Bulck. 2011. Virginia Tech comprehensive power-based fuel consumption model: Model development and testing. *Transportation Research Part D: Transport and Environment*, Vol. 16, No. 7, pp. 492–503.

Rakha, H., K. Ahn, and A. Trani. 2004. Development of VT-Micro model for estimating hot stabilized light duty vehicle and truck emissions. *Transportation Research Part D: Transport and Environment*, Vol. 9, No. 1, pp. 49–74.

Ribeiro, V., J. Rodrigues, and A. Aguiar. 2013. Mining geographic data for fuel consumption estimation. *2013 16th International IEEE Conference on Intelligent Transportation Systems-(ITSC)*, pp. 124–129).

TRB. 2010: *Highway Capacity Manual (HCM) 2010*. Transportation Research Board, Washington, DC.

Wang, J. B., K. Liu, T. Yamamoto, and T. Morikawa. 2017. Improving estimation accuracy for electric vehicle energy consumption considering the effects of ambient temperature. *Energy Procedia,* Vol. 105, pp. 2904–2909.

Xiao, H., H. J. Huang, and T. Q. Tang. 2016. An electricity consumption model for electric vehicular flow. *Modern Physics Letters B*, Vol. 30, No. 26, p. 1650325.

Yao, E., M. Wang, Y. Song, and Y. Zhang. 2014. Estimating energy consumption on the basis of microscopic driving parameters for electric vehicles. *Transportation Research Record: Journal of the Transportation Research Board*, No. 2454, pp. 84–91.

Zhang, R. and E. Yao. 2015. Electric vehicles' energy consumption estimation with real driving condition data. *Transportation Research Part D: Transport and Environment,* Vol. 41, pp. 177–187.

Zhou, B., F. Yao, T. Littler, and H. Zhang. 2016. An electric vehicle dispatch module for demand-side energy participation. *Applied Energy,* Vol. 177, pp. 464–474.

THE INSTITUTE FOR TRANSPORTATION IS THE FOCAL POINT FOR TRANSPORTATION AT IOWA STATE UNIVERSITY.

InTrans performs transportation research for public and private agencies and companies,

InTrans manages its own education program for transportation students and provides K-12 resources, and

InTrans conducts local, regional, and national transportation services and continuing education programs.