

Electric vehicles' energy consumption measurement and estimation



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ABSTRACT

Use of electric vehicles (EVs) has been viewed by many as a way to significantly reduce oil dependence, operate vehicles more efficiently, and reduce carbon emissions. Due to the potential benefits of EVs, the federal and local governments have allocated considerable funding and taken a number of legislative and regulatory steps to promote EV deployment and adoption. With this momentum, it is not difficult to see that in the near future EVs could gain a significant market penetration, particularly in densely populated urban areas with systemic air quality problems. We will soon face one of the biggest challenges: how to improve efficiency for EV transportation system? This research takes the first step in tackling this challenge by addressing a fundamental issue, i.e. how to measure and estimate EVs' energy consumption. In detail, this paper first presents a system which can collect in-use EV data and vehicle driving data. This system then has been installed in an EV conversion vehicle built in this research as a test vehicle. Approximately 5 months of EV data have been collected and these data have been used to analyze both EV performance and driver behaviors. The analysis shows that the EV is more efficient when driving on in-city routes than driving on freeway routes. Further investigation of this particular EV driver's route choice behavior indicates that the EV user tries to balance the trade-off between travel time and energy consumption. Although more data are needed in order to generalize this finding, this observation could be important and might bring changes to the traffic assignment for future transportation system with a significant share of EVs. Additionally, this research analyzes the relationships among the EV's power, the vehicle's velocity, acceleration, and the roadway grade. Based on the analysis results, this paper further proposes an analytical EV power estimation model. The evaluation results using the test vehicle show that the proposed model can successfully estimate EV's instantaneous power and trip energy consumption. Future research will focus on applying the proposed EV power estimation model to improve EVs' energy efficiency.

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Introduction

The transportation system is fundamental to the health of the economic growth. However, the current transportation system is overwhelmingly powered by internal combustion engines (ICE) fueled by petroleum. This not only causes the world

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be dependent on the whims of the global oil market (Pound, 2012); but more importantly, has made the transportation sector the economy's largest source of greenhouse gas (GHG) emissions (Greene and Schafer, 2003). Because of projected shortage of crude oil and the urgent need of reducing GHG emissions, more and more talents and resources are now focusing on shaping a sustainable transportation system that can address the climate change challenge as well as reduce oil dependence (US DOT, 2010). Among many innovative technologies, electrification of passenger vehicles is viewed by many as one that could significantly reduce oil dependence, operate vehicles more efficiently, and reduce carbon emissions.

Electric vehicles (EVs) include both plug-in hybrid (PHEVs) and battery-powered electric vehicles (BEVs). PHEVs usually have a moderately sized energy storage system and an internal combustion engine to ensure most miles are electrified while retaining the range capability of today's ICE vehicles. BEVs are entirely battery dependent and provide complete petroleum displacement for certain vehicle sectors. This research mainly focuses on BEV (simplified as EV for the rest of the paper). EV adoption has a great potential to play a significant role in addressing both energy and environmental crises brought by the current transportation system. First, electricity can help meet future transportation needs. Take U.S. as an example, since the vast majority of electric generation resources are domestic, electric vehicles are viewed as an excellent way to diversify transportation fuels. Although some challenges remain in regard to cost and battery technology, the availability of domestic electricity is not an issue so long as vehicles are charged at night, when excess electric generating capacity is available (Pound, 2012). In addition, fueling EVs is far less expensive than fueling ICE vehicles. With the average price of residential electricity at approximately 11.5 cents per kilowatt hour, a vehicle that runs only on electricity can travel approximately 30 miles on about 80 cents of electricity – almost one fourth of the cost of driving a similarly equipped ICE vehicle at \$3 a gallon for gasoline (Andersen, 2012). Second, electricity has a strong potential for GHG reduction. Electric vehicles themselves have zero emissions, although generating the electricity to power the vehicle is likely to create air pollution. If electricity is generated from the current U.S. average generation mix, EVs can reduce GHG emissions by about 33%, compared to today's ICE powered vehicles (US DOT, 2010). If we assume 56% light duty vehicle (LDV) penetration by 2050, this could provide a total reduction in transportation emissions of 26–30% (US DOT, 2010).

The huge potential benefits of EVs have already attracted significant interest and investment in EV technology. Since late 2010, more than 20 automakers have introduced BEVs or PHEVs. Within the United States, the government has allocated considerable stimulus funding to promote the use of alternative fuels (Skerlos and Winebrake, 2010). The American Recovery and Reinvestment Act (ARRA) of 2009 provided over \$2 billion for electric vehicle and battery technologies, geared toward achieving a goal of one million electric vehicles on U.S. roads by 2015 (Canis et al., 2011). (A recent post suggests that this goal will not be reached until 2018 (Car Congress, 2012)) Many states also have committed themselves to promoting EVs. For example, California has taken a number of legislative and regulatory steps to promote electric vehicle deployment and adoption, such as the Zero Emission Vehicle and Low Carbon Fuel Standard regulatory programs and rebates for purchasing electric vehicles (Elkind, 2012). These actions demonstrate the state's commitment to promote electric vehicles. With this momentum, it is not difficult to see that in the near future EVs may gain significant market penetration, particularly in densely populated urban areas with systemic air quality problems. We will soon face one of the biggest challenges: How to improve efficiency for the whole EV transportation system? (Here the EV transportation system includes any EV related applications of technologies and policies to the planning, functional design, operation and management of facilities and infrastructure in order to provide for the safe, efficient, economical, and environmentally compatible movement of people and goods.)

The majority of current EV research is focused on how to overcome technical barriers such as battery technology limitations (Axsen et al., 2010) and charging infrastructure problems (Morrowa et al., 2008). Extensive research efforts and investments have been given to address these barriers (Deutsche Bank, 2009; Frade et al., 2010; He et al., 2013; Ip et al., 2010; Pan et al., 2010; Sioshansi, 2012; Sovacool and Hirsh, 2009; Sweda and klabjan, 2011). For example, according to a research conducted by Deutsche Bank (2009), over \$7 billion was being invested in lithium-ion battery manufacturing to construct over 36 million kilowatt hour of battery production capacity which will be enough to power 15.0 million HEVs or 1.5 million EV. Many studies have also investigated the location problem of public charging stations. For example, Frade et al. (2010) formulated a maximum covering model to deploy a certain number of charging stations; Ip et al. (2010) applied a hierarchical clustering model to locate charging stations; Pan et al. (2010) developed a two-stage stochastic program to optimally set up PHEV battery swapping stations; Sweda and klabjan (2011) developed an agent-based decision support system for electric vehicle charging infrastructure deployment; and He et al. (2013) adopted a game theoretical approach to investigate the optimal deployment of public charging stations for PHEV.

However, very little research has been focused on how to improve the efficiency of the EV transportation system. People have yet to realize the importance of this question, partly because they have not foreseen the oncoming growth worldwide for EVs; but more importantly, due to lack of knowledge of electric vehicle performance and drivers' behaviors. We have yet to identify the unique features of both EVs and EV drivers that control energy consumption and efficiency. These unique features could fundamentally change our understanding of people's travel and driving behaviors and further impact the transportation system, our environment, and our society. This research begins to explore these features starting by investigating EVs' energy usage measurement and estimation.

Measuring and estimating EVs' electricity usage is an important requirement for the future improvement of energy efficiency of the EV transportation system. One of the most advanced features of an EV, compared to conventional ICE vehicles, is its ability to capture and store energy through the regenerative braking system (RBS) (Clegg, 1996; Xu et al., 2011; Zhang et al., 2008). RBS uses the electric motor to recharge the battery by applying negative torque to the drive wheels and

converting kinetic energy to electrical energy. Note many hybrid EVs (HEVs) have been installed RBS too. Because of RBS, EVs are much more efficient when driving on “interrupted” urban routes than uninterrupted freeway (Knowles et al., 2012). This is in contrast to ICE vehicles, which require much more energy in urban driving because of braking and thermal losses (Gao et al., 1999; Rajashekara, 2004).

The EV energy advantage in in-city driving could significantly impact people’s route choices and further shake the foundation of conventional theories of traffic assignment. Over the decades, following the seminal work done by Wardrop in 1952 (Wardrop, 1952), we always believe that people will follow Wardrop’s first principle, i.e. user equilibrium, to choose a path with shortest travel time when they make a trip (Sheffi, 1984), simply because saving time has been assumed to be the most important objective for travelers. While reducing fuel consumption has been an important, but secondary objective, searching for a path with less fuel consumption, in most situations, is consistent with minimizing travel time for ICE vehicle users (Ericsson et al., 2006). This alignment of time and fuel optimization has generally favored selection of routes along freeways. However, for EV drivers, choosing a route which requires less energy consumption can be totally different from selecting the shortest path, because power-saving favors low velocity routes (such as city roads) while time-saving generally favors high velocity routes (i.e. freeways). Therefore, when the number of EV users is large, EV drivers’ choices to either save energy or save travel time could significantly impact traffic assignment in transportation networks. This would lead to significant changes to the traffic flow on freeway and arterial systems. The potential for EV users to switch from the shortest path to energy-saving path is very plausible due, in part, to the visibility of energy use to EV drivers. EV drivers are keenly aware of real-time energy use and the advantages of regenerative braking. Therefore, when travel time gain is not significant, as typically occurs during peak traffic hours, EV users may often choose local city roads, instead of freeways, to save energy.

As EVs become a significant transportation mode, a challenge for transportation engineering will be to understand how we can take advantages of these unique features of EVs and EV drivers to improve the energy efficiency of the EV transportation system. The first step will be to carefully investigate the unique characteristics of EVs and EV drivers. This research fills this gap by first developing an EV data collection system which can collect both in-use EV data from both the battery system including battery state of charge, pack current, pack voltage, pack power and vehicle driving data including velocity, acceleration, and vehicle position (latitude, longitude, and elevation). This system has been installed in an EV conversion vehicle built in this research as a test vehicle, and approximately 5 months of EV data have been collected. Based on these data, this research then conducted a comprehensive analysis of the EV performance and driver behaviors. In particular, the analysis compared the efficiency between in-city driving and freeway driving. Furthermore, this analysis explored the relationships among EVs energy consumption, vehicle velocity, acceleration, and roadway grade. The derived relationships provide us an empirical foundation to create the EV energy consumption and estimation model proposed in this paper.

The paper is organized as follows. After introduction, an EV data collection system is introduced in section “An EV data collection system”. This system is able to collect both in-use EV data and driving information. Section “Data analysis” presents a comprehensive data analysis, followed by an EV energy consumption estimation model in Section “An energy consumption estimation model for electric vehicles”. Finally, we conclude this paper with a number of perspectives for future research.

An EV data collection system

An EV data collection system is developed in this research and this system can collect both in-use EV data and driving information. The data collection system has been installed in an EV conversion vehicle built in this research as a test vehicle. The data collection system has been collecting data from the test vehicle for approximately 5 months. This section explains the details of the EV conversion vehicle and the data collection system.

EV conversion vehicle

To support this research, an EV conversion vehicle was built by the research team. This EV is converted from a 1987 Nissan D21 pickup (see Fig. 1). The system currently consists of a 50 HP, 120v AC motor, with a Curtis controller. The battery pack consists of 36, 3.2v, 180aH LiPo batteries connected in series to form a single 115v, 180 aH battery. An Elithion® battery management system (BMS) is used to monitor the voltage and temperature of each cell and to control charging of the



Fig. 1. EV conversion vehicle and batteries.

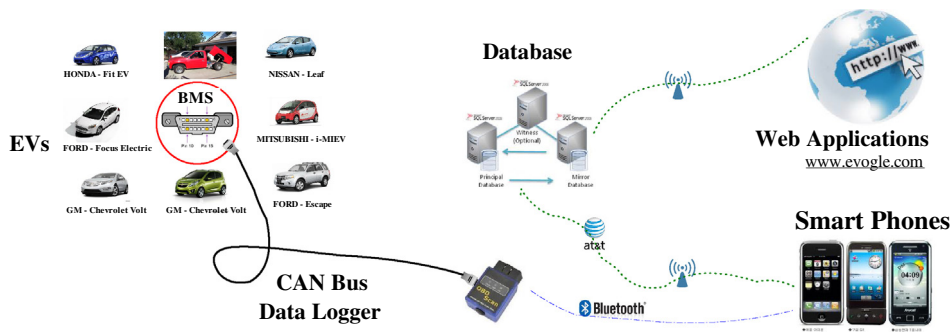


Fig. 2. Data collection system architecture.

system. A 2000w Elcon charger is installed onboard the EV. There are two data busses on board, one for the battery management system (BMS) and one for the motor controller. The BMS bus operates as a controller area network (CAN) bus and uses an on-board diagnostic (OBD-II) system data standard. The OBD-II provides information such as individual cell voltage, temperature and resistance; pack voltage, current, and power; and numerous diagnostic and control parameters. This vehicle serves as a test bed for this research. Note we did not use a current commercially produced EV in this research simply because this conversion EV provides us more opportunities to explore the characteristics of EV's energy consumption. But most of technologies used in this EV are up to date. First, the lithium-ion batteries used in this conversion vehicle have been used by most of today's PHEVs and BEVs including Nissan Leaf, Ford Focus Electric, Tesla Model S, and Smart ED (Elithion, 2014). Second, the conversion vehicle installs an AC motor which allows regenerative braking which is one of most important features for a commercially produced EV. Last but not least, the Elithion[®] BMS used in this vehicle is well suited for production EVs and has helped various EV production companies including Russian automaker AvtoVaz and Swedish production EV to leapfrog their competition (Elithion, 2014). Also, since the size of a D21 pickup is similar to a typical light-duty passenger car running on the road, the energy consumption behaviors from this test vehicle should be similar to a typical EV on the road. But the fact that this test vehicle is not one of the commercially produced vehicles might bring bias to our observations and conclusions which certainly need to be verified using current commercially produced EVs in future research.

Data collection system

A data collection system has been developed to collect in-use EV data and vehicles' driving information. In-use EV data includes battery usage, battery state of charge, current, pack voltage, off-vehicle charging event time, duration, location, power level and charger type, etc. Vehicles' driving information includes velocity, acceleration/deceleration, and vehicle position (latitude, longitude, and elevation). Data collection serves as the foundation for this research. The architecture of the data collection system is presented in Fig. 2. It consists of four parts. First, a CAN bus data logger (through BMS) is used to collect in-use vehicle data; the data then are sent to a Smartphone (or tablet) through Bluetooth. At the same time, the global positioning system (GPS) in a Smartphone collects vehicle location data and generates trip trajectories. The trajectory data is then synchronized with vehicle in-use data using an App application installed in the Smartphone. The synchronized data then are transmitted to a database through WiFi or cellular networks with a sampling frequency of 1 Hz. A web application has been further developed to publish some useful information derived from raw data to EV users.

The data collection system has been successfully tested using the EV conversion vehicle. A data sample is presented in Fig. 3. As shown in the figure, Column A records GPS time; Columns B and C record longitude and latitude; Column D is the vehicle speed measured by GPS (in m/s); Column E is the altitude measured by GPS; Column F is the acceleration information recorded by the accelerometer in the tablet; and Columns G–J are the energy usage related information including pack current (in ampere), pack total voltage (in voltage), pack power (in kilowatt), and state of charge (SOC, in%). Although this data collection system has been tested in only our test car, the concept of this system is general and should be able to apply to any other EVs.

Data analysis

The test vehicle has been used by a faculty member at Cal Poly Pomona for his daily commute since Nov. 2012. About 5 months of data (November 2012, December 2012, January 2013, April 2013, and May 2013) have been collected. As shown in Fig. 4, these data include 169 trips. For each trip, the in-use EV data and driving information have been collected. A comprehensive data analysis and some observations/conclusions are presented in this section. Note these conclusions are derived based on the data collected by a single EV. We do not intend to generalize these conclusions. But these observations/conclusions indicate some interesting behaviors of both electric vehicles and EV drivers, which could serve as a useful

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1	GPS Time	Longitude	Latitude	GPS Speed (M/sec)	Altitude	Acceleration (g)	Pack Current(A)	Pack Total Voltage(V)	Pack Power(kW)	State of Charge(%)	
14	Mon Dec 03 08:42:29 PST 2012	-117.72477	34.12169	11.471457	392.1571	0.01566211	214.3000031	109.0999985	23.3999962	76	
15	Mon Dec 03 08:42:30 PST 2012	-117.72492	34.12169	12.108709	392.4927	0.0045982	231.8999939	109.5	23.3999962	75	
16	Mon Dec 03 08:42:31 PST 2012	-117.72506	34.12169	12.7350855	393.1273	-0.0242881	194.199997	110.199997	25.2999924	75	
17	Mon Dec 03 08:42:32 PST 2012	-117.72521	34.1217	12.897027	393.9691	-0.05181026	173.8999939	111	19.2999924	75	
18	Mon Dec 03 08:42:33 PST 2012	-117.72537	34.12171	13.385689	395.0216	-0.01456756	149.1000061	111.9000015	19.2999924	75	
19	Mon Dec 03 08:42:34 PST 2012	-117.72553	34.12171	14.347867	395.0588	0.03336321	91.69999695	116.5999985	10.6999981	75	
20	Mon Dec 03 08:42:35 PST 2012	-117.72571	34.12172	14.9783945	394.5511	0.02614931	-17.20000076	119.5	10.6999981	75	
21	Mon Dec 03 08:42:36 PST 2012	-117.72588	34.12171	14.313869	394.1217	-0.07667585	-62	119.699997	-7.4000001	75	
22	Mon Dec 03 08:42:37 PST 2012	-117.72604	34.12171	14.117733	393.5269	-0.05349614	-62	119.9000015	-7.4000001	75	
23	Mon Dec 03 08:42:38 PST 2012	-117.7262	34.12171	13.395488	392.9295	-0.01359403	-59.70000076	119.9000015	-7.0999999	75	
24	Mon Dec 03 08:42:39 PST 2012	-117.72635	34.12171	12.9544735	392.4275	0.02876573	-57.20000076	119.9000015	-7.0999999	75	

Fig. 3. Data sample.

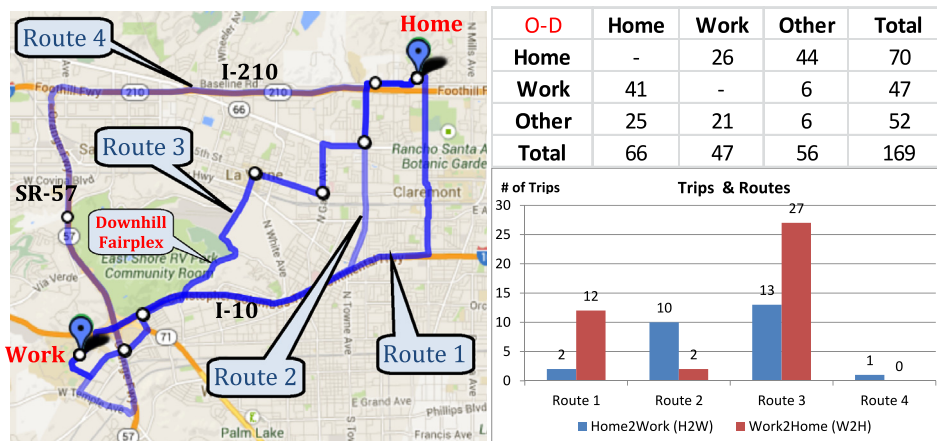


Fig. 4. Trips and routes.

reference for future research. In addition, the data analysis method and procedure presented here are general and can be applied by other research.

Driver's behaviors

To study EV driver's behaviors, we first categorize all 169 trips into the categories of Home-to-Work (H2W) trips, Home-to-Other (H2O) trips, Work-to-Home (W2H) trips, Work-to-Other (W2O) trips, Other-to-Home (O2H) trips, Other-to-Work (O2W) trips, and Other-to-Other (O2O) trips. The table in Fig. 4 shows the details about these types of trips. We are most interested in daily commute trips, i.e. H2W and W2H, because these trips are important for studying drivers' travel behaviors. Among the 169 recorded trips, 67 are completed commute trips (26 of H2W and 41 of W2H). Many other commute trips have been split into 2 trips because the driver stopped by some places. For example, a H2W trip becomes a H2O trip and an O2W trip because the driver stopped by a store. Through the examination of the data, we found some interesting phenomena which could be helpful for understanding EV drivers' behaviors.

EV driver's route choice

The first observation is about this particular EV user's route choice. From this participant's home to his work place, the Google map suggests three possible routes: Route 1, Route 2, and Route 4 (see Fig. 4). But from the data we collected, we found out the participant also often uses Route 3 (see Fig. 4). Four similar routes have been identified for the trips from work to home. Note although this EV user has been informed about our data collection, he makes his own route choice decisions. Among all these 4 routes, Route 4 mostly is on freeway, so it is a freeway-driving route; Route 3 is on urban arterials, so we call it an in-city driving route, and Routes 1 and 2 are half freeway driving and half in-city driving. Interestingly, among total 67 commute trips, the participant chose Route 3, the in-city driving route, for 40 times (13 of H2W trips and 27 of W2H trips); but only selected Route 4, the freeway driving route, for one time. So it is clear that this participant is in favor of in-city driving.

To better understand why this driver favored in-city routes over freeway routes, we summarize some important factors which we think could impact a driver's route choice. These factors include the total travel time (in min), total travel distance

(in miles), average travel speed (in mph), total energy usage (in kWh), and average energy efficiency (in kWh/100 miles). Two figures in Fig. 5 present the mean values of these measurements for all four routes shown in Fig. 4 for H2W and W2H trips respectively. From Fig. 5a, we can see that the possible reason why the driver chose Route 3, the in-city driving route, instead of Route 4, the freeway driving route is that Route 4 provides a very small travel time saving (1.3 min) at the cost of significantly higher energy consumption (3.0 kWh) compared to Route 3. Also, since Routes 2 and 3 for H2W trips have no significant difference in either travel time or energy consumption, the data shows that the driver does not have the preference between choosing these two routes indicating by the similar numbers of times of choosing these two routes (10 times for Route 2 and 13 times for Route 3, see the chart in Fig. 4). But overall the driver chose Routes 2 and 3 much more often than using Routes 1 and 4 because Route 1 has overlong travel time (27 min vs. 23 min on average) and Route 4 requires significantly higher energy consumption (4.7 kWh vs. 1.8 kWh on average) as shown in Fig. 5.

Similarly, when traveling from work to home, the participant chose Route 3, the in-city driving route, for most of the time (27 times over total 41 trips, see the table in Fig. 4). However, Route 3 is not the best choice based our data analysis. As shown in Fig. 5b, Route 1 requires less travel time (23.6 min vs. 24.9 min) and slightly less energy consumption (3.4 kWh vs. 3.5 kWh) comparing to Route 3. Route 2 actually has the highest energy efficiency (31.1 kWh/100-mile), but this conclusion is arguable since the sample size for Route 2 is only two. So overall this driver indeed made a good route choice decision in terms of energy and travel time saving.

The driver's in favor of in-city routes is interesting. But it is highly likely that the driver's choice of "in-city routes" might be caused by some specific reasons, such as congestion on surrounding freeway, or some specific weather conditions. Therefore, it would be interesting to use data to explore if there are causal relationships between driver's route choice and traffic conditions on surrounding freeways or local weather conditions. From Fig. 4, we can see the surrounding freeways include Interstate 10 (I-10), Interstate 210 (I-210), and State Route 57 (SR-57). I-10 is the freeway portion for Routes 1 and 2; and I-210 and SR-57 together cover almost the whole route of Route 4. Traffic congestion could be represented by the level of service (LOS). As suggested by the 2010 Highway Capacity Manual (HCM, 2010), LOS is determined based on traffic density, which can be estimated using the loop detector data collected by the California Department of Transportation's (Caltrans) Performance Measurement System (PeMs, 2014). For each H2W or W2H trip, based on the trip time, we first estimate the average density values for three freeway segments (I-10, I-210, and SR-57) as shown in Fig. 4 and then derive the LOS values.

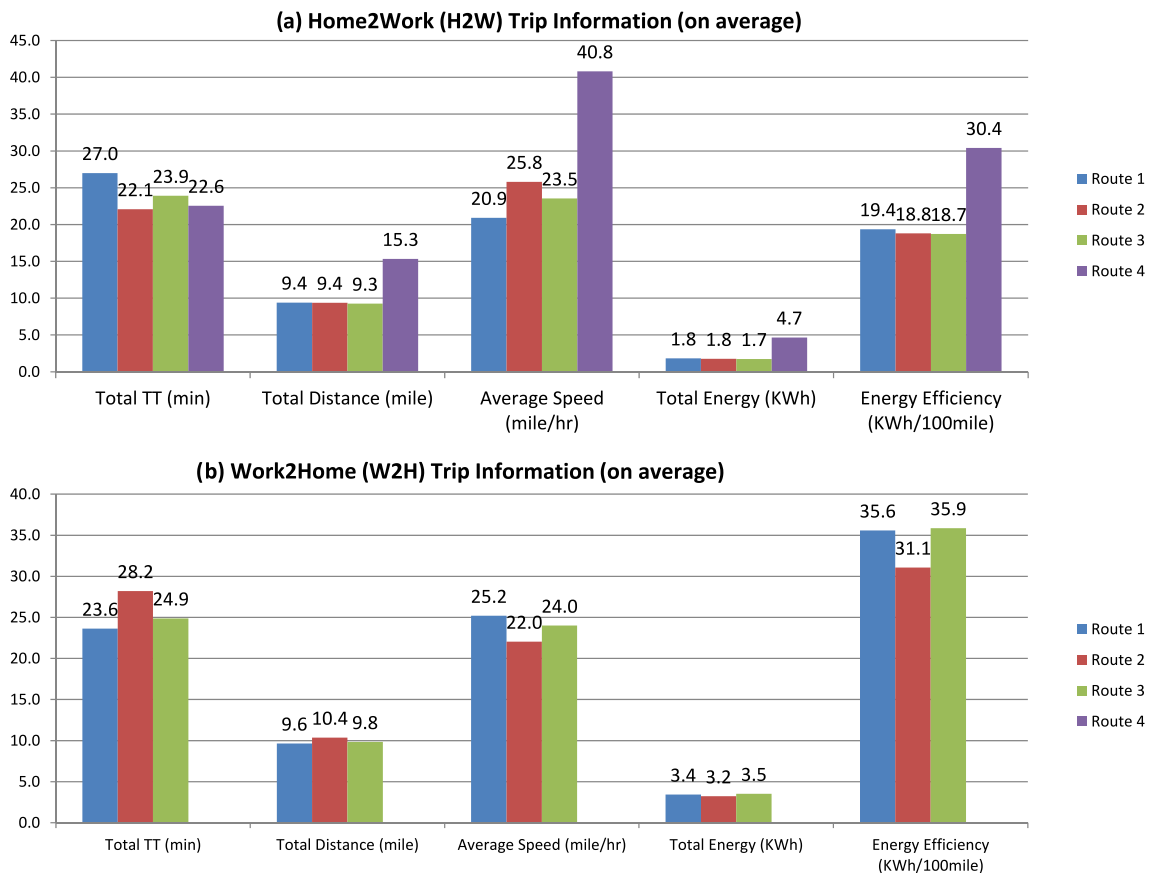


Fig. 5. Work2Home (W2H) and Home2Work (H2W) trip information.

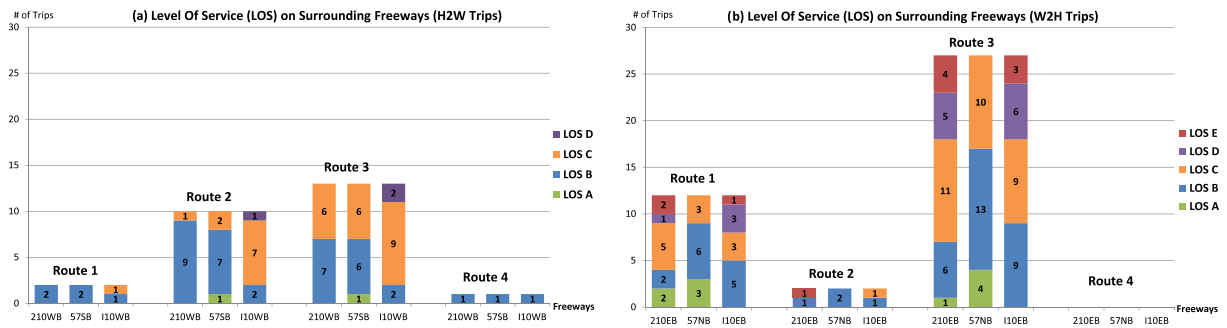


Fig. 6. Level of Service (LOS) of surrounding highways.

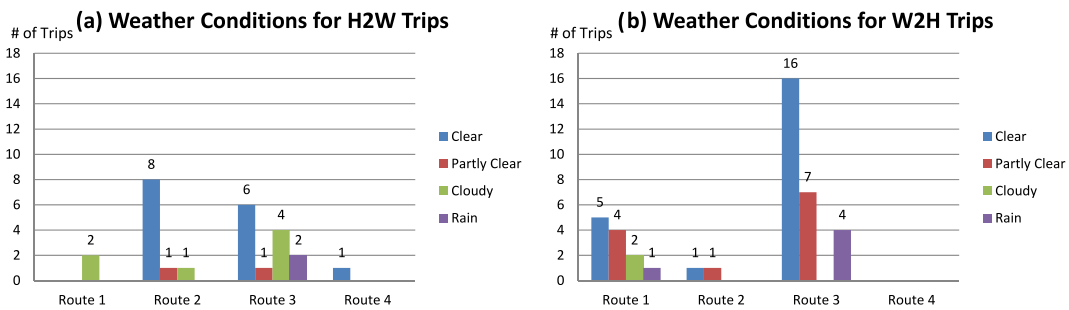


Fig. 7. Local weather conditions.

The data is presented in Fig. 6. As shown in the figure, for each route, we present the traffic congestion level indicated by LOS for three surrounding freeway segments including I-210, SR-57, and I-10. Different colors of bars indicate different LOS, and the number on each bar means the number of trips which were made on the same route and the congestion levels on the surrounding freeways were the same. For example, the first number of “6” on the yellow bar under “Route 3” in Fig. 6a means that there are 6 H2W trips which were on Route 3 and the traffic congestion level (i.e. LOS) on one of the surrounding freeways, I-210WB, was LOS C. From the figure we can see that when the driver chose Route 3, an in-city driving route, the traffic congestion on surrounding freeways was not necessary congested. It could be any LOS level from A to E as indicated by the bars with all different colors under “Route 3”. Also, when the driver chose Routes 1 or 2, the traffic condition on I-10 could be congested (i.e. LOS D or E) as shown by the purple and red bars under “Route 1” and “Route 2” in Fig. 6b. Therefore, from the data analysis, it is difficult to see any causal relationship between this particular driver’s choice of “in-city” route and traffic congestion levels on surrounding freeways.

A similar data analysis has been conducted to explore if there is a causal relationship between the driver’s choice of “in-city routes” and local weather conditions. It is very possible that a driver may choose to drive on local streets to avoid the impact of severe weather conditions on high-speed freeway driving since severe weather could significantly increases traffic incidents on freeway. To explore this possibility, we collect the weather data during each trip time from [The National Climate Data Center \(2014\)](#) and [AccuWeather \(2014\)](#). The weather conditions are classified as clear, partly cloudy, cloudy, and rain. Fig. 7 presents the analysis results. As shown in the figure, it is difficult to find any causal relationship between this particular driver’s route choice and weather condition. It looks like that the weather for most of days when the driver chose Route 3 was clear (55.0%), but this is simply because the weather for most of days in Southern California is clear (54.5%). Also, from the data we cannot see any significant influence of raining weather on this particular driver’s route choice.

More interesting findings have been discovered through an interview with the EV driver. The interview showed that for this particular EV user, travel time is not the only factor he considers when he makes a route choice decision; EV’s energy consumption has played a significant role which impacted this driver’s route choice. Particularly, the EV user tried to balance the trade-off between travel time and energy consumption. The interview with the driver further shows that the driver selected significantly different routes when driving an ICE vehicle rather than the EV. When driving an ICE vehicle, the driver consistently selected Routes 1, 2, and 4 which often included a significant leg of high speed travel on the freeway since the driver believed that these routes had least travel time. The driver barely selected the local street route, i.e. Route 3, except the driver had been informed of any major congestion on freeway. By contrast, when driving the EV, the driver seldom selected the pure freeway route, i.e. Route 4, because of its high energy cost. Additionally, the driver reported altering his EV route selection once data on energy expenditure by route was made available. Initially the driver had avoided Routes 1 and 2 for H2W trips because he perceived these routes would be much higher in energy consumption due to amount of freeway driving. However, after learning that the energy consumption for the H2W was essentially the same for Routes 1, 2 and 3, the driver started using Route 2 more often. Route 1 was still avoided because of the significantly longer trip time compared to Route 2.

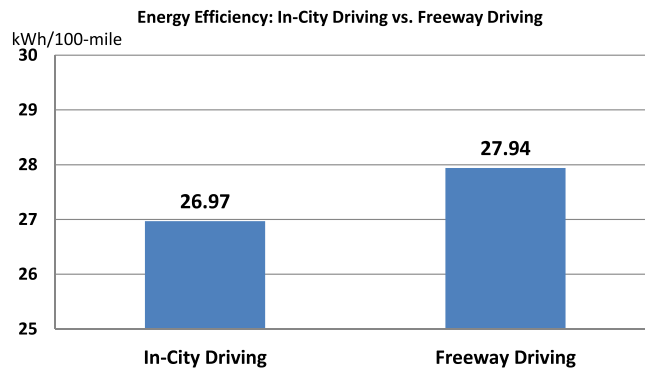


Fig. 8. Energy efficiency for in-city driving vs. freeway driving.

All above findings could be very important, although more data are needed to generalize them. As we know, for most of traditional ICE vehicle drivers, travel time is the only dominant factor when they make route choice decisions. But for EV users, their route choice decisions are not only determined by travel time, but also related to electricity consumption. This could impact the predication of drivers' route choices therefore bring changes to the overall traffic assignment for transportation system when EVs gain a significant share in the near future.

Energy efficiency on in-city driving vs. freeway driving

The data shows that this particular EV driver is in favor of in-city driving. The possible reason could be that EVs are much more energy efficient when driving on interrupted urban routes than on uninterrupted freeway routes. Similar EV behavior has been mentioned by Zahabi et al. (2013) and Chaudhry (2010), and recently observed by Knowles et al. (2012). To further verify this point of view, we separated all of the data from 167 trips into two categories: in-city driving and freeway driving; then for each category of data, we calculated the energy efficiency using the total consumed energy divided by the total travel distance. The results show that driving on urban city streets is indeed more efficient than driving on freeways (26.97 kWh/100-mile for in-city driving vs. 27.94 kWh/100-mile for freeway driving; see Fig. 8). The difference between these two numbers is relatively small. One of the main reasons is that most of trips made by this EV driver are in-city driving. The total travel distance for in-city driving is 529 miles, while for freeway driving the total travel distance is only 110 miles. In addition, many of these in-city trips are on uphill routes. This also downgrades the energy efficiency for in-city driving. With more freeway-driving data, the difference between the energy efficiency of in-city driving and freeway-driving might be enlarged.

Day-to-day energy efficiency

Another interesting observation from our data analysis is related to the improvement of the energy efficiency for this particular EV driver through 5 months' driving. Here we define EV's energy efficiency as the required kilowatt-hours for traveling 100 miles, i.e. kWh/100-mile (note a higher number indicates worse efficiency). We calculated the energy efficiency for each trip made by the participant during the 5-month data collection period. Since most of the travel for this driver is his daily commute, many of the trips have identical routes. Specifically, from the data, we identified three routes, on which the EV user has traveled for over 10 times: one H2O route (18 times), one O2H route (10 times), and one W2H route (27 times). Fig. 9 presents the energy efficiency for all the trips using these three routes. Note due to some technical issues, the data in February 2013 and March 2013 have not been collected. From Fig. 9, we can clearly see that the energy efficiency is gradually improving over time. This is a very interesting phenomenon. Through our interview with this participant we noticed that the driver adjusted his driving behaviors in order to save electricity usage during our data collection period after we provided him the energy efficiency for his daily trips. In particular, he identified some routes and segments which required high energy consumption and then adjusted his driving behaviors in order to drive more efficiently. He also tried to avoid some routes and segments with exceptionally high energy consumption. Note the research team did not provide any guidance or direction of energy saving for this driver. This driver made all the adjustments by himself. But we did provide him the information of energy consumption and efficiency for his daily travel; and the participant admitted (through the interview) that this kind of information helped him adjust his driving and travel behaviors in order to save electricity usage. Although it is based on the behaviors from one EV driver, this finding is encouraging since it indicates that by providing information or feedback on EVs' energy consumption, EV users may consciously adjust their driving behaviors in order to improve energy efficiency. No doubt, if it is a common behavior for most of EV drivers, it would be very important for the development of an EV performance system which can provide feedback to EV users. Further investigation of this topic is certainly desired.

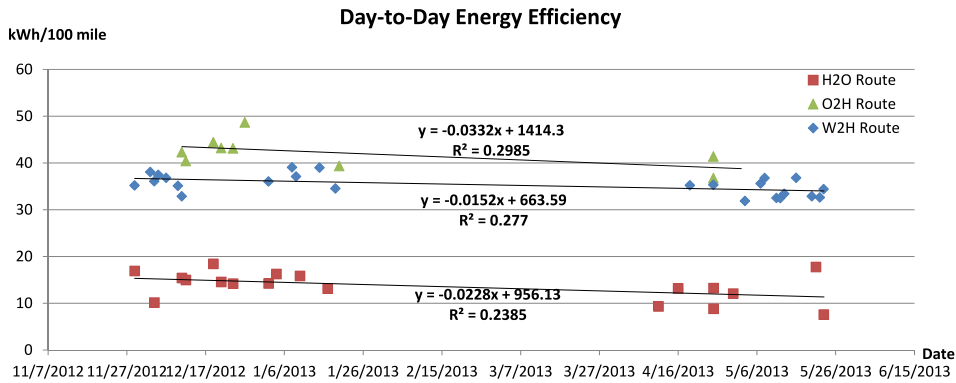


Fig. 9. Day-to-day energy efficiency for three routes.

EV performance

To understand the characteristics of an EV's energy consumption, one valuable research perspective is to investigate the relationships among power, velocity, acceleration, and roadway grade. Realizing that EVs' energy consumption characteristics could be different when driving on urban streets and freeways, we first categorized data into in-city driving and freeway driving according to whether the EV is on an in-city or freeway segment, and then analyzed the data of each category respectively. The results are presented in this section.

Power vs. velocity

The relationships between EV's energy usage (in kW) and velocity (in mph) are presented in Fig. 10a (for in-city driving) and Fig. 10b (for freeway driving). Consistently for both in-city and freeway driving, driving at higher speed required more

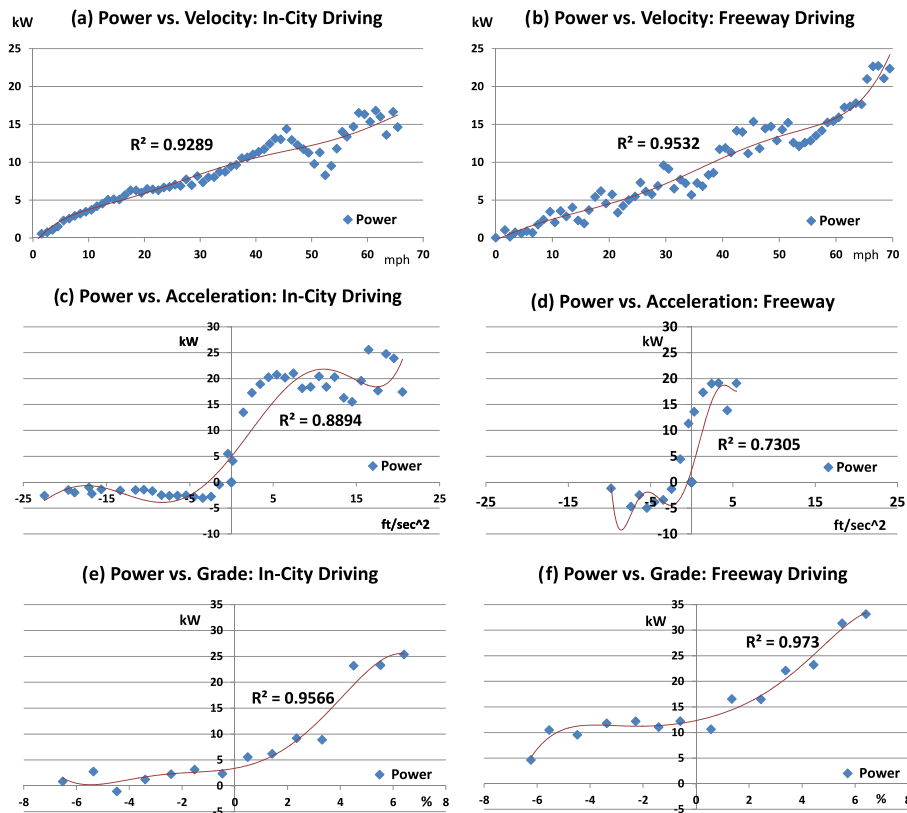


Fig. 10. Power vs. Velocity/Acceleration/Grade for In-City and Freeway driving.

power. But interestingly, the instantaneous power drops noticeably to a local minimum when the EV drives at a speed around 55 mph for both in-city and highway driving. A possible reason could be that the vehicle was traveling along a negative gradient (for example, the downhill on Fairplex Drive; see Fig. 4). When the vehicle speed reaches around 55 mph, the driver let go of the throttle thus requiring less energy. In addition, the figure shows that to maintain a similar speed, driving on freeway requires slightly higher power compared to driving on urban streets, although the difference is not significant.

Power vs. acceleration

One of the most advanced features of an EV, compared to conventional ICE vehicles, is its ability to generate electricity when decelerating through the regenerative braking system. Data in Fig. 10c and d confirms this conclusion. When acceleration is negative (i.e. decelerating), the power is negative indicating that the EV is re-generating energy; and when acceleration is positive, the power is positive indicating that the EV is consuming energy. More interestingly, from the figure, we can see that when the acceleration is between -5 and 5 ft/s^2 , the power proportionally increases with the increase of the acceleration. However, when the acceleration is lower than -5 ft/s^2 or higher than 5 ft/s^2 , the power keeps almost the same and does not change with the acceleration. This is especially clear from the power vs. acceleration plot derived from the in-city driving data (Fig. 10c). The upper bound of the power is about 20 kW and the lower bound is about -5 kW. A similar trend can be seen in Fig. 10d which is plotted based on the freeway driving data. It is not difficult to explain that the reason for the lower bound is because EVs' regeneration is limited by the battery pack's ability to accept a charge which is controlled by the battery management system. But the upper bound (20 kW) is significantly less than the maximum power the vehicle can deliver. This could be due to this driver's behavior. More investigation is needed to confirm our explanation.

Power vs. grade

Roadway grade also has significant impact on EVs' energy consumption. As shown in Fig. 10e and f, with the increase of roadway grade, the required instantaneous power is increasing too. Note we manually collected the elevation and grade information from Google Earth because GPS system used in our data collection has difficulties to provide accurate altitude. From the data, we also found out that the change of power is significantly larger when grade is positive (i.e. uphill) than when grade is negative (i.e. downhill). As shown in Fig. 10e, for the relationship of power vs. grade derived based on in-city driving data, the power increases from 5 kW to 25 kW (20 kW difference) when the grade changes from 0% to 6%; but when the grade changes from -6% to 0%; the power only increases from 0 kW to 5 kW (5 kW difference). Similarly, for power vs. grade relationship derived based on freeway driving data, the increase of power is about 20 kW (from 12 kW to 32 kW) when the grade changes from 0% to 6%; but the increase of power is only 7 kW (from 5 kW to 12 kW) when the grade changes from -6% to 0%. This could be because that the driver just let go of the throttle on downhill no matter what percentage the grade is thus requiring similar energy, while on uphill the required power is sensitive to the grade in order to maintain a certain speed. In addition, from Fig. 10e and f, we can see that freeway driving requires higher power than in-city driving even when the grades are the same. This could simply because that the driving speed on freeway is usually higher than the speed on city streets.

Distribution of EV's power usage

Fig. 10 only describes the general relationships between EV's instantaneous power and velocity, acceleration, and roadway grade since each point in the figure only represents an average value of the instantaneous power under many different situations. For example, the point in Fig. 10a indicates an average value of power required for the EV driving at a specific speed but for all kinds of situations with different accelerations and roadway grades. In order to gain a better understanding of the relationships among power, velocity, acceleration, and roadway grade, we need a deeper investigation of the data. Therefore, we further subdivided the data into specific ranges of velocity, acceleration, and roadway grade. Then based on the subdivided data, we derived more precise relationships of power vs. velocity, power vs. acceleration, and power vs. grade. Most importantly, by statistically analyzing the subdivided data, we can quantify the variation range of the required power (using a distribution) for the EV to drive at a specific speed with a particular acceleration rate on a route with a certain grade.

Fig. 11 presents three examples of above data analysis results. The two numbers in the brackets in the figure represent mean and standard deviation respectively. Fig. 11a shows the relationship between the EV power and velocity under the condition that the acceleration is within the range of $0\text{--}2 \text{ ft/s}^2$ and roadway grade changes from 0% to 2%. So each red point with square mark in this figure represents the average power value required for the EV to drive at a specific speed with the acceleration rate between 0 and 2 ft/s^2 and grade between 0% and 2%. Similarly, Fig. 11b shows the relationship between EV power and acceleration for the condition that the velocity is within the range of 15–20 mph and roadway grade changes from 0% to 3%; and Fig. 11c shows the relationship of power vs. roadway grade for the condition that vehicle velocity is between 25 and 30 mph and acceleration is within the range of $0\text{--}2 \text{ ft/s}^2$. Note these ranges could be smaller which would provide more precise description of these relationships if more data were available.

Note the average value of power (i.e. the "y" coordinates for the red square point in Fig. 11) is derived from a group of data points corresponding to the power values required for the EV driving under a certain condition with a specific range of

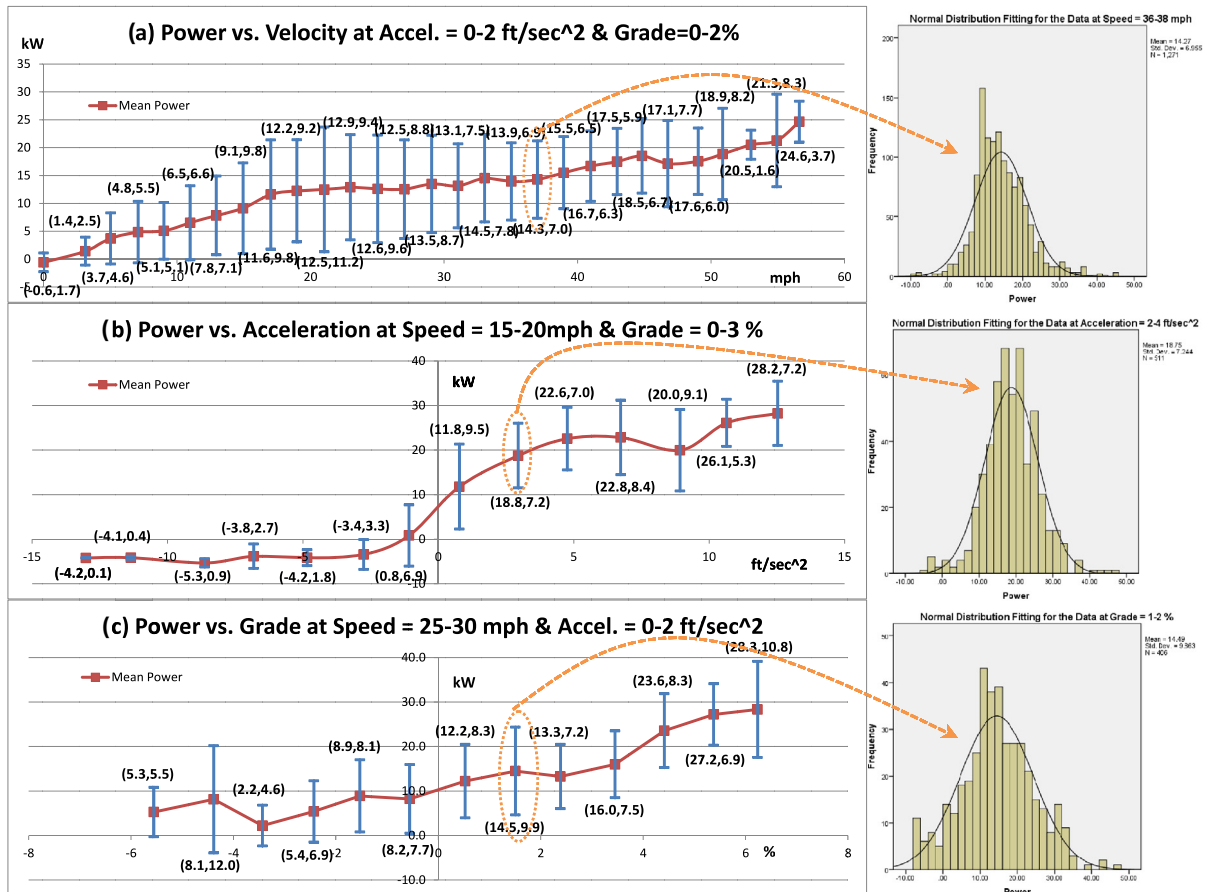


Fig. 11. Mean power distribution with a fixed acceleration and grade (numbers within brackets represent mean and standard deviation respectively).

velocity, acceleration, and grade. We then statistically analyzed each group of these power data by using a distribution to fit the data. The histograms in Fig. 11 suggest that the EV's power within a specific range of velocity, acceleration, and grade could be described as a normal (or log-normal) distribution; and the distributions vary for different ranges as indicating by the different values of the mean and variance (see the numbers in the brackets). As shown in Fig. 11, the mean values of each distribution (indicated by red square points) are changing for different values of "x" coordinates, and the ranges for each distribution (indicated by blue bars) are different for different conditions too. Note the ranges for each data point are calculated using mean minus (for lower bound) or plus (for upper bound) standard deviation. There are many plots which are similar to those presented here. Due to space limitations, we only present three represented examples.

Using distributions to describe the power data which is corresponding to a specific range of velocity, acceleration, and roadway grade is very important for EVs' energy consumption estimation. As shown in Fig. 11, from the distribution, we can directly estimate the mean value of the power and its variance required for an EV to drive at a specific range of speed, acceleration and grade. This essentially presents a data-driven method that can be used to estimate EVs' instantaneous power and energy consumption. But this method requires a large amount of data in order to find the accurate relationships among EV's power, velocity, acceleration, and roadway grade. So this method could be very time-consuming and computationally expensive therefore may not be suitable for real-time applications. To overcome these disadvantages, we propose an analytical EV power estimation model which will be described in the following section.

An energy consumption estimation model for electric vehicles

As discussed above, directly using distributions to estimate EVs' instantaneous power and energy consumption could be challenging partly because these distributions have relatively large variances which could generate estimation errors, and partly because this method is time-consuming and computationally expensive in terms of data collection and analysis. Therefore, an analytical model of power estimation is proposed here.

Power estimation model

According to the fundamental theory of vehicle dynamics (and also it has been observed in our data analysis), we know that EV's instantaneous power is determined by vehicle speed, acceleration and roadway grade. Therefore the proposed model essentially is an analytic description of the relationship among EVs' power, velocity, acceleration, and grade.

First of all, according to basic physics, the required tractive effort for an EV driving on certain conditions is determined by three major resistances as described by the following equation:

$$F = ma + R_a + R_{rl} + R_g \quad (1)$$

where F is tractive effort (in N or lb); m is vehicle mass (in kg or slug); a is acceleration (in m/s^2 ; or; ft/s^2), and R_a , R_{rl} , and R_g are aerodynamic, rolling, and grade resistances respectively (in N or lb).

Given that vehicle velocity is v (in m/s ; or; ft/s), acceleration is a (in m/s^2 ; or; ft/s^2), and roadway grade is θ (in degree), R_a , R_{rl} , and R_g can be calculated by the following equation:

$$\begin{cases} R_a = kv^2 = \frac{\rho}{2} C_D A_f v^2 \\ R_{rl} = f_{rl} mg \\ R_g = mg \sin \theta \end{cases} \quad (2)$$

where k is aerodynamic resistance constant, which is determined by air density ρ (in kg/m^3 or slug/ft^3), frontal area of the vehicle A_f (in m^2 or ft^2), and coefficient of drag C_D (no unit); f_{rl} is rolling resistance constant (no unit); and g is gravity acceleration ($g = 9.81 \text{ m/s}^2$ or 32.2 ft/s^2).

Combining Eqs. (1) and (2), we can get:

$$F = ma + kv^2 + f_{rl} mg + mg \sin \theta \quad (3)$$

The above equation can be applied for both ICE and electric vehicles. To generate above tractive force, the required power (p , in watt) for a vehicle traveling at v can be estimated using the following equation:

$$p = F \cdot v = (ma + kv^2 + f_{rl} mg + mg \sin \theta) v \quad (4)$$

p actually is the output power, which is provided by the input power (P , in watt). For ICE vehicles, P is generated by combustion of the fuel; but for EVs, P is generated by an electric motor. EVs are much more efficient than ICE vehicles because electrical power losses for an electric motor are small. If we assume the motor efficiency is η , we have the following relationship between the input power and output power:

$$p = \eta \cdot P \quad (5)$$

If we ignore the electricity used for climate control and other vehicle accessories, the majority of electrical power loss would be copper loss for the high-current region (for a DC motor) or iron loss (for an AC motor). In general, the power losses could be described as a product of the square of the current (I) and the resistance of the conductor (r) (Tanaka et al., 2008). Therefore, the motor efficiency η can be calculated by:

$$\eta = (P - I^2 r) / P \quad (6)$$

where I (in ampere) represents the current, and r (in Ω) represents the resistance of the conductor.

From Eqs. ((4)–(6)), EVs' instantaneous power can be estimated by:

$$P = I^2 r + Fv \quad (7)$$

On the other hand, the force F is generated by the torque of the motor, which can be simplified as a product of the Armature constant (K_a), magnetic flux (Φ_d), and current (I):

$$F = \frac{\tau}{R} = \frac{K_a \cdot \Phi_d \cdot I}{R} \quad (8)$$

where τ (in Nm or lb ft) is the torque; R (in m or ft) is the radius of the tire; K_a is the armature constant; Φ_d (in webe) is the magnetic flux; and I (in A) is the current. Note for DC and AC motors, Φ_d is different. For a DC motor, Φ_d is the direct-axis air-gap flux per pole; and for an AC motor, Φ_d is the rms value of the direct-axis air-gap flux per pole.

To simplify Eq. (8), we define:

$$K = K_a \cdot \Phi_d \quad (9)$$

Then Eq. (8) becomes:

$$F = \frac{K \cdot I}{R} \quad (10)$$

Finally, combining Eqs. (3), (7) and (10), an EV's instantaneous power can be estimated by:

$$P = \frac{r \cdot R^2}{K^2} \left(ma + kv^2 + f_{rl}mg + mg \sin \theta \right)^2 + v \left(kv^2 + f_{rl}mg + mg \sin \theta \right) + mav \quad (11)$$

Eq. (11) can be simplified as the following equation:

$$P = P_m + P_t + P_g \quad (12)$$

where $P_m = \frac{rR^2}{K^2} \left(ma + kv^2 + f_{rl}mg + mg \sin \theta \right)^2$ is the power losses by the motor; $P_t = v(kv^2 + f_{rl}mg + mg \sin \theta)$ is the power losses because of travel resistance; and $P_g = mav$ is the possible gained energy from acceleration (or deceleration).

Model evaluation

The above model has been evaluated using our test vehicle. We have specifically focused on the following two questions: (1) can the model accurately estimate instantaneous power; and (2) can the model accurately estimate the energy consumption of a trip?

Instantaneous power estimation

To estimate EVs' instantaneous power, we first need to determine the values of the parameters in Eq. (11) including vehicle weight (m), rolling resistance coefficient (f_{rl}), aerodynamic resistance coefficient (k), product of armature constant and magnetic flux (K), equivalent resistance of motor (r), radius of tire (R), and transmission efficiency (η). Note most of these parameters including vehicle weight, armature constant, magnetic flux, motor resistance, and radius of tire are physical features of the test vehicle therefore can be directly measured from the vehicle. Other parameters such as rolling resistance coefficient, aerodynamic resistance coefficient, and transmission efficiency are difficult to directly measure so they were estimated based on other related research. Table 1 provides the suggested values for these parameters used in the model.

Based on the values in Table 1, we then used Eq. (11) to estimate EV's instantaneous power given the information of EV's velocity, acceleration, and roadway grade. Vehicle's velocity and acceleration at each time step were directly measured by the data collection system, and grade information was manually collected from Google earth as we mentioned before. With these input values, Eq. (11) is used to calculate EV power at each time step. We then compared this estimated power with the value directly measured by our data collection system. Fig. 12 presents an example based on a trip on December 03, 2012. Because of too many data points (one data point per second), only twenty minutes' data (from 8:40:00 am to 9:00:00 am) are presented here. As we can see from the figure, the purple line with triangle markers, which represents estimated EV power, closely follows the red line with square markers, which is the measured EV power. This indicates that the proposed simple estimation model can accurately estimate EVs' instantaneous power. We also include vehicle velocity (green line) and acceleration (blue line) as the background information of the figure. Interestingly, we can see that the change of power closely follows the trend of the change of acceleration.

Trip energy consumption estimation

In addition, we are interested if the developed model can accurately estimate the overall energy consumption (i.e. electricity usage) for a trip. The total electricity usage (E) for a trip is computed by integrating the power over the trip time (T) as described by Eq. (13):

$$E = \int_0^T P(t)dt \quad (13)$$

Based on above integration, we computed the energy usage for over 40 trips made during May, 2013. Fig. 13 compares the measured and estimated energy for each trip. It is clear that the proposed model can successfully estimate trip energy usage.

Table 1
Suggested values for the parameters in Eq. (11).

Parameters	Values
Vehicle weight (including driver), m [kg]	1266
Rolling resistance coefficient, f_{rl}	0.006*
Aerodynamic resistance coefficient, $k = \frac{\rho}{2} C_D A_f$ [kg/m]	1.30**
Product of armature constant and magnetic flux, $K = K_a \cdot \Phi d$ [V s]	10.08
Resistance of motor (in general), r [Ω]	0.11
Radius of tire, R [m]	0.50
Transmission efficiency, η [%]	95

* Value suggested by The Engineering Toolbox, (2013a).

** Values calculated by assuming $\rho = 1.2$ kg/m³, $A_f = 2.666$ m², and $C_D = 0.8$. ρ and C_D values are suggested by The Engineering Toolbox (2013b); and A_f value is suggested by Ecomodder (2013).

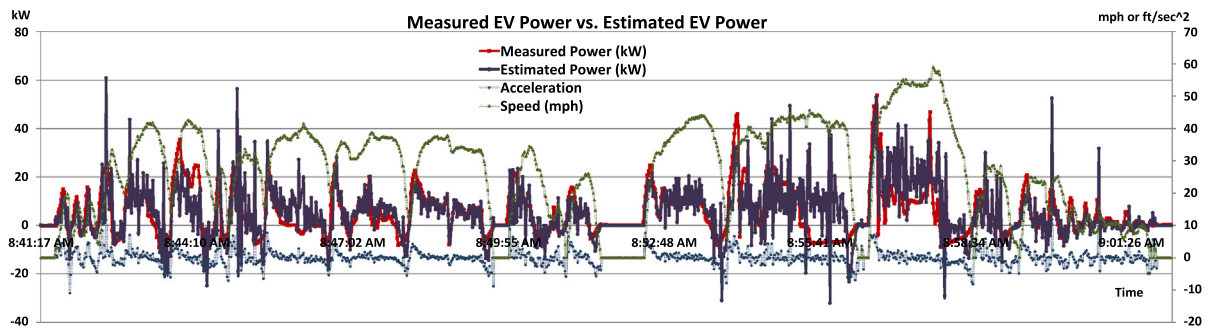


Fig. 12. Measured power vs. estimated power.

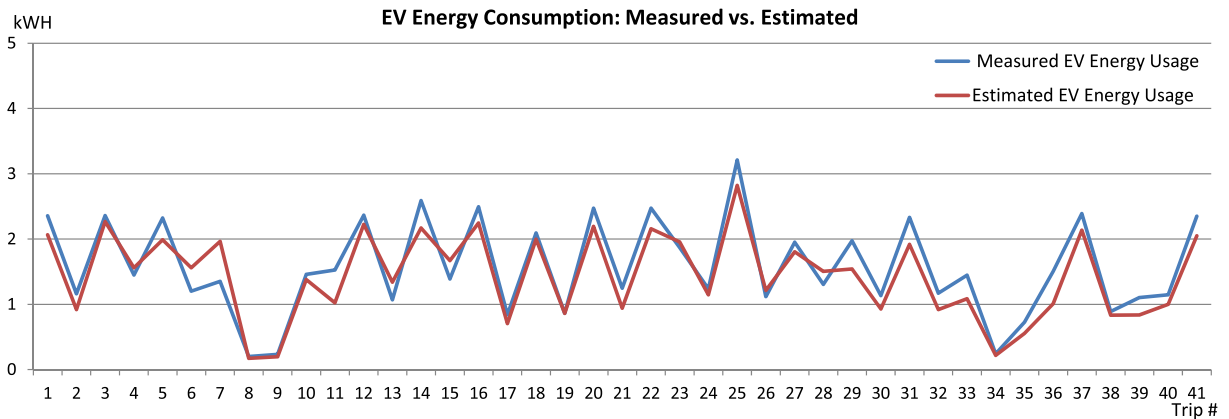


Fig. 13. Estimated EV energy consumption vs. measured EV energy consumption for 41 trip.

We also calculated mean absolute error (MAE). The average MAE for all trips shown in Fig. 13 is 15.6%. Further calibration of the parameters presented in Table 1 may improve the accuracy for our model.

We would like to point out that the proposed model is developed based on very fundamental theories in physics. Similar ideas have been adopted by much other research, e.g. Larminie and Lowry (2003) and Tanaka et al. (2008). Therefore, it is hard to claim any original contribution of this model simply from the theoretical point of view. But the proposed model nicely describes EV's instantaneous power by three parts including the losses by the motor, the losses by travel resistance, and possible gains from acceleration; this could be helpful for EV power estimation. Furthermore, a comprehensive evaluation of this model based on a real EV will be beneficial for future references.

The proposed model is specifically designed so it is personalized and data driven. The model itself requires the depth knowledge of the vehicle and its systems. But this kind of information can be derived based on the historical and real-time in-use vehicle's data collected by the data collection system developed in this research. A data driven methodology will be developed in future research to derive and calibrate the parameters required to run the model. Doing so can also improve the accuracy of the estimation of the proposed model.

More importantly, the purpose of developing such a simple analytical model is for real-time applications. Different with many other models which take into account too many factors therefore are difficult to be used for real-time applications, the proposed model is simple and ideal for real-time applications. One potential application is to apply the proposed model to determine a time-dependent optimal velocity profile for an EV to minimize the electricity usage along a chosen route (Wu et al., 2014). Such application can be further applied in the forthcoming autonomous technology. By incorporating the optimal speed control into a self-driving car, together with connected vehicle technologies (US DOT, 2013) that provide real-time traffic information, we can significantly reduce energy consumption for EVs. This might be a promising way to relieve future energy crises when EVs become a major mode of daily transportation.

Concluding remarks

This paper first presented a system which can collect in-use EV data including battery state of charge, pack current, pack voltage, pack power, vehicle velocity, acceleration, and vehicle position (latitude, longitude, and elevation). This system then has been installed in an EV conversion vehicle built in this research as a test vehicle. Approximately 5 months of EV data have

been collected and these data have been used to analyze both EV performance and driver behaviors. The analysis shows that the EV is more efficient when driving on in-city routes than driving on freeway routes. As a result, this particular EV driver prefers in-city routes over freeway routes. Another important finding was that by providing timely information on energy usage, this EV driver consciously adjusted his driving behavior to reduce energy consumption. This could be an indication of information-induced behavior for EV drivers.

To understand EV's energy consumption, we analyzed the relationships between the EV's power and vehicle velocity, acceleration, and roadway grade. The power vs. velocity plot shows that driving at higher speed requires more power; the power vs. acceleration plot confirms that the EV is consuming energy when accelerating but re-generating electricity when decelerating; and the power vs. grade plot indicates that with the increase of roadway grade, the required instantaneous power is increasing too. But these plots only describe very rough relationships between EV's instantaneous power and velocity, acceleration, and roadway grade. To gain a better understanding of the relationships among power, velocity, acceleration, and roadway grade, we conducted a deeper investigation of the data by further subdividing the data into specific ranges of velocity, acceleration, and roadway grade and then statistically analyzing the subdivided data. The results show that the EV's power within a specific range of velocity, acceleration, and grade could be described as a normal or log-normal distribution; and for different ranges of velocity, acceleration, and grade, the mean and variance values of these distributions are different. Knowing the distribution of the power data which is corresponding to a specific range of velocity, acceleration, and grade is very important for EV energy consumption estimation. Using these distributions, the mean and variance of the EV power usage can be directly estimated based on vehicle's condition indicating by a specific range of speed, acceleration and grade values. This essentially presents an empirical method to estimate EVs' power.

However the empirical method is both time-consuming and computationally expensive. Therefore this research further proposed an analytical model which can estimate EVs' instantaneous power in real time. The model is based on the fundamental theory of vehicle dynamics and the basic relationships among power, force, torque, voltage, and current. This model was evaluated using the test vehicle. The results indicate that this model can successfully estimate EVs' instantaneous power and trip energy consumption.

In conclusion, this research provides a comprehensive review of EV energy use. It demonstrates the feasibility of collecting such data and the potential insights that can be gained from analysis of the data. The energy estimation model presented appears to work well and has potential as both a research tool and resource for EV users. However, the data set in this research is limited since it contains data from only one driver, one vehicle, which is not one of current commercially produced vehicles, and includes limited freeway driving. This research should be expanded to include many different drivers and current commercially produced vehicles to gain more data to improve the estimation model and validate the preliminary conclusions presented in this paper.

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