The Impact of Reliable Range Estimation on Battery Electric Vehicle Feasibility

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Abstract

Range limitation is a significant obstacle to market acceptance of battery electric vehicles (BEV). Range anxiety is exacerbated when drivers could not reliably predict the remaining battery range or when their journeys were unexpectedly extended. This paper quantifies the impact of reliable range estimation on BEV feasibility using GPS-tracked travel survey data, collected over an 18-month period (from November 2004 to April 2006) in the Seattle metropolitan area. BEV feasibility is quantified as the number of days when travel adaption is needed if a driver replaces a conventional gasoline vehicle (CGV) with a BEV. The distribution of BEV range is estimated based on the real-world fuel efficiency data. A driver is assumed to choose between using a BEV or a substitute gasoline vehicle, based on the cumulative prospect theory (CPT). BEV is considered feasible for a particular driver if he/she needs to use a substitute vehicle on less than 0.5% of the travel days. By varying the values of some CPT parameter, the percentage of BEV feasible vehicles could change from less than 5% to 25%. The numerical results also show that with a 50% reduction in the standard deviation and 50% increase in the mean of the BEV range distribution BEV feasibility increases from less than 5% of the sampled drivers to 30%.

Keywords

Battery electric vehicles (BEV); Range anxiety; Cumulative prospect theory (CPT); Daily vehicle miles traveled (DVMT)
1. Introduction

Petroleum comprises 92% of the U.S. transportation energy use in 2017 (Davis et al. 2018). One of the pathways to sustainable petroleum displacement is a transition to high-efficiency and low-emission powertrain technologies, such as battery electric vehicles (BEVs). Constrained by the limited driving range and insufficient charging opportunities, drivers might need to change their travel routines when switching from a conventional gasoline vehicle to a BEV. The fear that the vehicle has insufficient range to reach the destination, known as range anxiety, has been shown to be a significant obstacle to market acceptance of BEVs. In an internet survey administered to electric vehicle technology enthusiasts and potential buyers, Egbue and Long (2012) found that range limitation is considered to be the biggest concern. Graham-Rowe et al. (2012) observed that, in a plug-in electric vehicle trial focusing on mainstream consumers in the United Kingdom, range anxiety was exacerbated when drivers could not predict the remaining battery range or when their journeys were unexpectedly extended. Therefore, a BEV may become infeasible on a given day due to both the expected value and uncertainty of the daily vehicle miles traveled (DVMT) and the effective BEV range. Due to the relatively high cost of the batteries at present, increasing the driving range by installing a larger battery pack will significantly drive up the sales price. A cost-effective alternative is to better utilize the battery capacity by providing drivers with a more reliable range estimation.

Daily travel variation has been widely studied in the literature pertaining to travel demand modeling (e.g., Pas and Sundar 1995, Elango et al. 2007) and energy analysis of alternative fuel vehicles (e.g., Gonder et al. 2007, Smith et al. 2011, Pearre et al. 2011, Dong and Lin 2012, Khan and Kockelman 2012, Lin et al. 2012, Greaves et al. 2014, Wu et al. 2014, Li et al. 2016, Tamor et al. 2013, Tamor et al. 2015). Recently, attention to DVMT variation is largely driven by interest
in alternative fuel vehicles, such as battery electric vehicles and fuel cell vehicles. Unlike conventional gasoline vehicles, which have a long driving range and easy access to refueling stations, alternative fuel vehicles often face the challenge of limited driving range, inadequate refueling or recharging infrastructure, or both. The key to quantifying the inconvenience associated with refueling or recharging is to reasonably characterize how often a driver needs to travel beyond the vehicle range. Therefore, daily distance variation tends to matter more for alternative fuel vehicles than for gasoline vehicles. Due to the lack of longitudinal data, single-day survey data were used to quantify daily travel variation in early studies (Kiselewich and Hamilton 1982). More recently, GPS-instrumented conventional gasoline vehicles have been used to track participants’ daily travel activities. One-day (e.g., Gonder et al. 2007, Dong and Lin 2012) or multiday vehicle data (e.g., Smith et al. 2011, Pearre et al. 2011, Khan and Kockelman 2012, Lin et al. 2012, Greaves et al. 2014, Wu et al. 2014, 2015, Wu 2018) have been used to assess the market potential and energy efficiency of plug-in electric vehicles.

The actual distance that a plug-in electric vehicle can travel with a fully charged battery varies greatly in real-world driving due to a number of factors, including driving style, traffic conditions, terrain, ambient temperature, and the use of climate control and other auxiliary systems. Based on the fuel economy data of plug-in hybrid electric vehicles collected by the EV Project (i.e., data collected from a set of privately owned Chevrolet Volts), Smart et al. (2014) observed wide variation in charge depleting (CD) range distributions, based on the actual miles driven from a fully charged to an empty battery. By analyzing the in-use energy consumption data collected from 600 BMW ActiveE electric vehicles for approximately one year, Rodgers et al. (2014) found that auxiliary loads (e.g., heating, defrosting) consumed 10% to 50% of the total energy and contributed to more variation than driving energy consumption. Direct measurement
of the actual BEV range is difficult, because the vehicle battery is rarely completely depleted in real-world use. One alternative approach is to estimate the range based on trip-level fuel economy measurements, such as the FleetCarma data used in this paper.

Due to the abovementioned variability in both DVMTs and BEV ranges, early adopters of BEVs tend to use the vehicle only for short trips and usually return home with a high state of charge (SOC), which means low utilization of the battery. Based on a GPS-based longitudinal travel data collected in the Seattle metropolitan area, Dong and Lin (2014) found that, if at most 5% of travel adaption was acceptable, almost half of the fleet could switch to a BEV with an average range of 76 miles (122 km) when drivers were comfortable with using all the nominal range. However, this percentage dropped significantly to about 10% if they were only comfortable with using up to 60% of the range. To encourage higher utilization of the battery, one solution is to provide public charging infrastructure that can be seen as “BEV rescue” in case the actual travel distance exceeds the vehicle range. As revealed by a study from the Tokyo Electric Power Company (TEPCO), Tokyo BEV drivers significantly increased their battery utilization after the installation of some public chargers that were actually not used extensively (World Bank, 2011). Another complimentary solution is to predict the BEV range more precisely and provide reliable information to the driver. Franke et al. (2012) conducted a field test in Berlin, Germany, to study the range experience of BEV drivers. In this study, converted MINI Cooper EVs with a driving range of 250 km were leased to 40 sampled customers for a six-month period. Travel diary surveys and face-to-face interviews were conducted prior to receiving the BEV, three months later, and upon returning the BEV. The authors suggested that providing drivers with a reliable usable range might be more effective than simply increasing the driving range.
The impact of stochastic driving range on charging infrastructure planning has been studied in Davidov and Pantoš (2017). However, little has been done to quantify the impact of range variation on BEV acceptance. When driving a BEV, there is no significant perceivable benefit if the distance of a daily trip falls below the BEV range, but if the distance exceeds the range by surprise and the driver is restrained on the road or forced to detour for a public charger, the loss is perceivably large. As a result, the daily travel distance planned by drivers would be far below the expected value of the BEV range, leading to underutilization of the battery. The more the distance or range varies (unexpectedly), the worse the battery utilization. Precise prediction of the effective battery range can be achieved by combining real-time battery SOC modeling, on-road fuel economy modeling, and connected vehicle technologies (especially vehicle-to-infrastructure). These technologies are currently being developed and improved. The results of the analysis in this study can be used to show the benefit of such technologies for improving battery utilization and promoting BEV consumer acceptance through more reliable range estimation.

The objective of this study is to quantify the impact of reliable BEV range estimation on BEV feasibility for the mass-market consumers. An innovative approach is proposed to describe BEV feasibility based on the cumulative prospect theory (CPT). Current BEV drivers are the early adopters whose behavior might not be representative of the mass market. For this reason, GPS-tracked travel survey data of conventional gasoline vehicle (CGV) drivers are used in this study. These drivers are considered as prospective BEV buyers who might purchase a BEV if it can satisfactorily fulfil their daily travel needs. In fact, using travel survey data collected from CGVs to predict plug-in electric vehicle consumer acceptance has been widely used in recent literature to represent the behavior of the mass market (e.g., Pearre et al. 2011, Zhang et al. 2011, Khan and Kockelman 2012, Wu et al. 2014, 2015 and Wu 2018). Two sources of variability that influence
the travel decisions of prospective BEV drivers are considered in this paper: (1) DVMT variation and (2) BEV range variation. On each travel day, a driver decides whether to use the BEV or not based on his/her daily travel distances, access to substitute vehicles, and other factors. Over an 18-month period, BEV feasibility for a particular driver is quantified as the number of days when travel adaption is needed, that is, when one needs to change the original travel plans, use a substitute vehicle, or use a different travel mode. The main contributions of the paper are: (1) estimate BEV range variation using real world vehicle data; (2) quantify BEV feasibility based on cumulative prospect theory; (3) examine the tradeoff between range extension and reliable range prediction for the mass market.

2. BEV Range Distribution

2.1. Data description

The Nissan Leaf, a popular BEV model, is used to represent BEVs in this paper. The U.S. Environmental Protection Agency (EPA) energy efficiency rating for the 2011/2012 Leaf is 340 watt-hours (Wh) per mile (211 Wh per km), which is associated with a 73 mile (117 km) range with 100% charge. FleetCarma estimated the BEV ranges in the real world based on the collected BEV travel data, which includes daily trip records of six Nissan Leafs (2011 and 2012 models) in three states (California, Texas, and Maine) for approximately seven months. Each trip includes information regarding trip start time, trip end time, vehicle idle time, travel time, driving distance, electricity consumption, and ambient temperature. Individual trip-based electricity consumption rates, in terms of electricity consumption per mile, can be calculated from this information. The range of the BEV can be derived as the ratio of battery capacity to electricity consumption rate. However, the trip-based energy consumption rate depends on a variety of factors such as trip
distance, idle time, and auxiliary loads. For example, electricity consumption rates of short-distance trips with long idle times will be high and sensitive to small errors. To decide whether to drive a BEV on a particular day or not, a robust range estimation approach is needed to calculate average electricity consumption rate based on all trips in a day. The average electricity consumption rate in a day is calculated as the ratio of the total daily electricity consumption to the total daily travel distance, and the BEV range is calculated as its battery capacity divided by the average electricity consumption rate. As a result, we can derive daily travel-based range estimates for each day. Table 1 summarizes the statistics for daily travel-based range estimates of the six Nissan Leaf during a period of seven months.

Table 1 Summary Statistics for BEV Range Estimates Based on FleetCarma Data

<table>
<thead>
<tr>
<th>Number of observations</th>
<th>1,260</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Range</td>
<td>90 miles (145 km)</td>
</tr>
<tr>
<td>Standard deviation of the range</td>
<td>18.0 miles (29.0 km)</td>
</tr>
<tr>
<td>Coefficient of variation</td>
<td>0.200</td>
</tr>
<tr>
<td>EPA rated range</td>
<td>73 miles (114 km)</td>
</tr>
</tbody>
</table>

As seen in Table 1, the Leaf has a large range variation. Caution should be taken when comparing the estimated ranges with the EPA rated range. First, the EPA uses a single full-depletion test to determine range and AC energy consumption for multiple drive-cycle types. A vehicle’s total usable battery energy is used to determine the electric range. In real-world driving, the battery is seldom depleted from full to empty. Instead, in this paper, the energy efficiency of a BEV is estimated based on one day’s driving distance and a partially depleted battery. Second, the EPA rating is determined using test cycles. A 20% to 30% discrepancy has been reported when comparing the test cycle energy consumption and in-use fuel efficiency for gasoline vehicles and
plug-in electric vehicles (e.g., Mock et al. 2013, Williams et al. 2011). Third, the real-world BEV range distribution is estimated based on a limited dataset of ten BEVs in three states, and thus the observation of longer average ranges than those used for the EPA rating cannot be generalized.

Furthermore, the standard deviations of the observed BEV ranges reflect the variability across drivers, different ambient temperatures and driving conditions, and so forth. An experienced BEV driver, who is familiar with the vehicle’s performance and traffic and weather conditions to some extent, might have a better knowledge of range variability and perceive a smaller variation. However, prospective BEV buyers are likely to perceive range variability at a scale similar to what is listed in Table 1. In addition, a related observation from the FleetCarma data is that the minimum SOC observed for each driver over the seven-month period are within the range of 11 to 30 miles, and the lowest 1 percentile of the SOC falls in the range between 24 and 46 miles. This indicates that current BEV drivers tend to reserve a buffer that is comparable to or greater than the standard deviation.

2.2. Distribution estimation

The daily travel-based electricity consumption rates are used to estimate the distribution of BEV ranges. The plausible probability density distribution forms, Weibull, gamma, lognormal, and normal, were considered to fit the data, respectively, as shown in Table 2.

<table>
<thead>
<tr>
<th>Function</th>
<th>Probability density function</th>
<th>Parameters</th>
<th>Mean</th>
<th>Mode</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gamma</td>
<td>$p(x) = \frac{1}{\theta^k \cdot \Gamma(k)} x^{k-1} \cdot e^{-\frac{x}{\theta}}$</td>
<td>$k &gt; 0$ – shape, $\theta &gt; 0$ – scale</td>
<td>$k \theta$</td>
<td>$(k-1)\theta$, for $k \geq 1$</td>
</tr>
</tbody>
</table>

Table 2 Plausible Function Forms of BEV Range Distribution
The maximum likelihood estimation method was used to estimate the parameters of the distribution functions listed in Table 2. The fitted curves and the histogram of the data are plotted in Figure 1.

![Histogram and theoretical densities](image)

Figure 1 Estimated range distributions of 2011/2012 Nissan Leaf

The estimated parameters and the corresponding log likelihood (LL) values are listed in Table 3. Based on the LL values, it is seen that normal distribution fits the data best and is used in the subsequent analysis.
Table 3 Probability Distribution Estimation Results of Normalized Nissan Leaf Ranges

<table>
<thead>
<tr>
<th></th>
<th>Gamma</th>
<th>Weibull</th>
<th>Lognormal</th>
<th>Normal</th>
</tr>
</thead>
<tbody>
<tr>
<td>shape/(log)mean</td>
<td>18.74</td>
<td>5.38</td>
<td>4.47</td>
<td>90.04</td>
</tr>
<tr>
<td>rate/(log)standard deviation</td>
<td>0.21</td>
<td>96.90</td>
<td>0.26</td>
<td>17.95</td>
</tr>
<tr>
<td>log likelihood</td>
<td>-5589.1</td>
<td>-5455.9</td>
<td>-5736.4</td>
<td>-5426.2</td>
</tr>
</tbody>
</table>

Furthermore, Table 4 illustrates how different temperature levels affect the range distribution. For example, at low temperature (i.e. below 10 °C) the mean range is reduced by about 8% and the standard deviation is reduced by about 22%, compared to the cases of moderate temperature (i.e. 10–25 °C).

Table 4 BEV Range Distributions at Different Temperature Levels

<table>
<thead>
<tr>
<th></th>
<th>Number of Observations</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Normal Distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>All data</td>
<td>1260</td>
<td>90.0</td>
<td>18.0</td>
<td>(90.0, 18.0^2)</td>
</tr>
<tr>
<td>Low (&lt;10 °C)</td>
<td>49</td>
<td>82.7</td>
<td>13.9</td>
<td>(82.7, 13.8^2)</td>
</tr>
<tr>
<td>Moderate (10–25 °C)</td>
<td>1053</td>
<td>89.4</td>
<td>17.8</td>
<td>(89.4, 17.8^2)</td>
</tr>
<tr>
<td>High (&gt;=25 °C)</td>
<td>158</td>
<td>96.4</td>
<td>18.7</td>
<td>(96.4, 18.6^2)</td>
</tr>
</tbody>
</table>

3. Method

Although range anxiety has been well observed and extensively discussed in the transportation energy and alternative powertrain research communities, rigorous behavioral models are lacking. In this study, we adopt the cumulative prospect theory (CPT) to describe drivers’ decisions on whether to use a BEV or a substitute gasoline vehicle on a travel day.
3.1. Overview

Since the distances that a BEV can travel with a full charge vary greatly under real-world driving conditions, the BEV range is considered as a random variable. Based on the estimation results from Section 2.2, a normal distribution is used to describe the BEV range distribution. Similarly, DVMTs vary from one day to another for the same driver and vary among different drivers. Thus, DVMTs of different drivers were extracted from the GPS tracking data collected for the Traffic Choices Study in the Seattle metropolitan area (PSRC, 2008). The Traffic Choices Study recorded driving activities of about 275 volunteer households in the Seattle metropolitan area from November 2004 to April 2006. After removing the erroneous data (as outliers), travel activities of 402 household vehicles are used in this paper. As illustrated in Figure 2, if a driver needs to drive 75 miles on a particular day, the probability of completing this travel\(^1\) is represented by the shaded area. For early adopters, BEVs are usually used for shorter trips due to limited away-from-home charging opportunities and range anxiety. That is to say, a driver is confident of using the BEV only when the probability of completing the trip is close to 1.

\(^1\) We assume that the battery is fully charged when leaving home and there is no other charging opportunity before returning home.
Figure 2 DVMT and BEV range distributions. The probability of completing a DVMT of 75 miles using a BEV is illustrated by the shaded area.

Because the BEV range is considered to follow a normal distribution, $r \sim N(\mu, \sigma^2)$, for driver $i$ the probability that a BEV is feasible for daily travel on day $j$ is calculated as the probability that the randomly distributed BEV range is greater than or equal to the DVMT of that day for driver $i$, $d_{ij}$, that is,

$$p_{i,j} = P(r \geq d_{ij}) = 1 - \phi \left( \frac{d_{ij} - \mu}{\sigma} \right)$$  \hspace{1cm} (1)

where

$p_{i,j} =$ the probability of driver $i$ completing the DVMT using a BEV on day $j$

$\phi(\cdot) =$ the cumulative distribution function of standard normal distribution

$d_{ij} =$ the DVMT of driver $i$ on day $j$

$\mu =$ the mean of the BEV range distribution
\( \sigma = \) the standard deviation of the BEV range distribution

### 3.2. Cumulative prospect theory

To decide whether or not to use a BEV on a particular travel day the driver might consider a series of factors such as travel distance, urgency, cost, hassle, travel schedule, and knowledge about the refueling network. CPT is adopted to model the decision making process. CPT was originally framed in the context of the lottery and has been used to model other choices between risky alternatives. In particular, CPT has been applied in route choice (Avineri and Bovy, 2008; de Luca and Di Pace, 2015; Gao et al., 2010; Wang and Xu, 2011; Xu et al., 2011; Yang and Jiang, 2014; Zhou et al., 2014), commuter departure time choice (Senbil and Kitamura, 2004; Schwanen and Ettema, 2009), public-transport users’ mode choice at transfer stations (Ceder et al., 2013), use of the high-occupancy-vehicle lane (Chow et al., 2010), classification of the risk attitude of travelers (Yang et al., 2015), and congestion pricing (Liu et al., 2010). The above-mentioned studies all found success in using CPT to describe people’s limited rationality and risk attitudes when making decisions.

As illustrated in Figure 3, CPT proposes that people overweight small probabilities and underweight moderate and high probabilities (Tversky and Kahneman, 1992). In addition, with proper specification of the value function prospect theory can describe the behavior that individuals are more sensitive to losses than gains. Thus, CPT rationale is appropriate to describe the range anxiety phenomenon associated with limited-range vehicles.
Figure 3 Decision weighting functions of CPT

Given a DVMT, a sample driver who knows his/her DVMT well may have the following two options if he/she drives a BEV:

Option 1: use a substitute vehicle on the travel day. The cost of driving a conventional gasoline vehicle to complete the daily trips includes the fuel cost and the additional cost associated with vehicle substitution.

\[ C_{ij}^{CGV} = C_{i}^{sub} + P^g \cdot \frac{d_{ij}}{mpg} \]  \hspace{1cm} (2)

where

\( C_{ij}^{CGV} \) = the cost of using a conventional gasoline vehicle for driver \( i \) on travel day \( j \)

\( C_{i}^{sub} \) = the cost of using a substitute vehicle for driver \( i \) (this cost is applied to all travel days)

\( P^g \) = the gasoline price, assumed to be $3.5 per gallon
\[ mpg = \text{the gasoline vehicle’s fuel efficiency, assumed to be 27.5 miles per gallon (NHTSA 2011)} \]

The vehicle substitution cost indicates the ease with which a backup vehicle can be obtained when the expected daily distance exceeds the expected vehicle range. This cost depends on household vehicle flexibility and can range from $15 to $50, where the lower bound reflects the cost of using an easily available vehicle in the household by considering vehicle depreciation and fuel cost and the upper bound reflects the cost of a delivered rental vehicle (Lin 2012). In this paper, the vehicle substitution cost is determined using a linear interpolation based on the vehicle substitution ratio of each household. The substitution ratio is defined as the number of vehicles per worker in each household. When the vehicle-worker ratio is less than one, the maximum value is applied. This implies that the driver is most likely to rent a vehicle. On the other hand, when the vehicle-worker ratio is greater than three, the minimum substitution cost is applied because the driver can probably find a substitute vehicle in his/her household easily. If the vehicle substitution ratio is between 1 and 3, the substitution cost for driver \( i \), \( C_{i}^{\text{sub}} \), is obtained by linear interpolation, as follows:

\[
C_{i}^{\text{sub}} = C_{\text{max}}^{\text{sub}} - 17.5 \cdot (R_{i} - 1), \text{ if } 1 \leq R_{i} \leq 3
\]

where

\( C_{\text{max}}^{\text{sub}} = \text{the maximum vehicle substitution cost, assumed to be $50} \)

\( R_{i} = \text{the vehicle substitution ratio of driver } i \text{'s household} \)

Option 2: use a BEV on the travel day. As illustrated in Figure 2, for a given DVMT there is a certain probability of completing all-day travel using the BEV. When the BEV has a sufficient
range to complete all-day travel, the cost is determined by the electricity price, miles driven, and electricity consumption rate, as follows:

\[
C_{ij}^{BEV} = P^e \cdot r^e \cdot d_{ij}
\]  

where

\( C_{ij}^{BEV} \) = the cost of using the BEV for driver \( i \) on travel day \( j \)

\( P^e \) = the electricity price, assumed to be $0.11 per kWh (EIA, 2015)

\( r^e \) = the electricity consumption rate, assumed to be 0.3 kWh/mile

\( d_{ij} \) = the total travel distance of driver \( i \) on travel day \( j \)

On the other hand, it is also possible that the range is insufficient to complete all trips planned for that day. In this case, a large penalty will be applied, considering the additional costs of the roadside service, taxi fare to cover the remaining trip, and the loss of productivity of the driver. Because the battery range is uncertain, the remaining distance to the destination after the battery is depleted is unknown. To simplify the problem, a threshold is defined: \( d_0 = (\mu - 2\sigma)/2 \), where \( \mu \) and \( \sigma \) are the mean and standard deviation of a BEV’s range. The probability that the range will be less than \( d_0 \) is fairly small. Based on this threshold, \( d_0 \), two scenarios are considered. First, if the DVMT, i.e., \( d_{ij} \), is less than \( d_0 \), it implies that the remaining distance to the destination \( (d_{ij} - d_0) \) would be very small\(^2\). In this case, the taxi fare is ignored because one may walk to the destination. Second, if \( d_{ij} \geq d_0 \), the taxi fare is calculated based on the remaining distance, \( d_{ij} - d_0 \). This conservative estimate is appropriate because the failure of a BEV on the way to the

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\(^2\) Based on the FleetCarma data, \( d_0 = 29 \) miles. Therefore, \( d_{ij} - d_0 \) is small if the DVMT \( d_{ij} \) is not very large
destination would have a significant economic and psychological impact on a traveler. Therefore, travelers tend to be conservative in estimating the range of a BEV. The cost associated with the emergency situation can be calculated as follows.

\[
C_{ij}^{\text{penalty}} = \begin{cases} 
C_{RS} + C^h + C^{BEV}, & \text{if } d_{ij} < d_0 \\
C_{RS} + C^h + C^{BEV} + \beta_{\text{taxi}}(d_{ij} - d_0), & \text{if } d_{ij} \geq d_0 
\end{cases}
\]

where

\[C_{ij}^{\text{penalty}} = \text{the total cost associated with the emergency situation when the BEV fails to complete driver } i \text{'s all-day travel on day } j\]

\[d_0 = (\mu - 2\sigma)/2, \text{ the threshold to determine whether a taxi ride is needed or not}\]

\[C_{RS} = \text{the roadside service cost, assumed to be$62 for each service call based on rates of fuel delivery services by rental car companies (USA Today 2010)}\]

\[C^h = \text{the hassle and loss of productivity experienced by the driver due to the trip interruption, assume to be$100}\]

\[C^{BEV} = \text{the electricity cost associated with depleting a 24 kWh battery pack. Because the electricity price is assumed to be$0.11 per kWh, the estimated electricity cost is$2.64 and thus can be ignored.}\]

\[\beta_{\text{taxi}} = \text{the taxi rate, assumed to be$2.51 per mile based on the data published on the taxi fare finder website (2015)}\]

The outcomes of the two options are mapped as gains or losses relative to some reference point. Because prospect theory was originally proposed to deal with choices between alternatives
framed as lotteries and gambles, $0 may be the common reference point. Avineri and Bovy (2008) pointed out that when applying CPT in describing travel choices, one of the modeling challenges is the lack of consensus regarding reference point values. In this study we use the cost of driving a conventional gasoline vehicle to complete the daily trips as the reference point. Accordingly, the gains and losses associated with driver choices can be quantified for each travel day. For Option 2, there are two outcomes: completion (associated with a gain of $\chi_c$) and incompletion (associated with a loss of $\chi_n$), with the corresponding probabilities of $p_c$ and $p_n$, respectively. Therefore, a BEV driver can use a value function, $v(\cdot)$, and a probability weighting function, $\pi(p)$, to evaluate the CPT value of this option, as follows:

$$\text{CPT} = \pi(p_c)v(\chi_c) + \pi(p_n)v(\chi_n)$$  \hspace{1cm} (6)

Using the forms and the parameter estimates in Kahneman and Tversky (1992), we can calculate the respective cumulative weighted prospect values of Options 1 and 2, respectively. The following value function is applied:

$$v(\chi) = \begin{cases} \chi^\alpha & \text{if } \chi \geq 0 \\ -\lambda(-\chi)^\beta & \text{if } \chi < 0 \end{cases}$$  \hspace{1cm} (7)

The parameter $\lambda$ describes the degree of loss aversion and was estimated to be 2.25 by Tversky and Kahneman (1992). Parameters $\alpha$ and $\beta$ measure the degree of diminishing sensitivity and were estimated to be 0.88. These parameter values have been confirmed by other studies (e.g., Benartzi and Thaler 1995) and used in travel choice analysis by Avineri and Bovy (2008), Yang and Jiang (2014), and Zhou et al. (2014). The weighting functions proposed by Tversky and Kahneman (1992) for gains and losses are as follows:
\[ \pi^+(p) = \frac{p^\gamma}{[p^\gamma + (1-p)^\gamma]^{1/\gamma}} \]  

(8)

\[ \pi^-(p) = \frac{p^\delta}{[p^\delta + (1-p)^\delta]^{1/\delta}} \]  

(9)

Based on the experimental results, Tversky and Kahneman (1992) estimated \( \gamma \) to be 0.61 and \( \delta \) to be 0.69. Later, reasonably close values were estimated from several empirical studies (e.g., Camerer and Ho 1994, Wu and Gonzalez 1996, Abdellaoui 2000, Bleichrodt and Pinto 2000). Due to the limited number of BEVs on the road today and the absence of BEV driver behavioral data, the calibration of these parameters is outside the scope of this paper.

3.3. Quantification of BEV feasibility

BEV feasibility is defined as the percentage of the sample population who would view a BEV as a viable option for their everyday travel, allowing for minimal travel adaption. For example, a 10% BEV feasibility at the 99.5% level means that 10% of the sample population, if they switched to a BEV, could use the BEV to fulfil 99.5% of their travel needs. In other words, these drivers only need to use a substitute vehicle less than two days per year. To quantify BEV feasibility, each driver’s DVMTs are used to determine the driver’s vehicle choice decision based on his/her CPT.

Given the probability of completing the trip, the weights, \( \pi^+(p) \) and \( \pi^-(p) \), can be calculated based on Equations (9) and (10), respectively. For a driver on a particular day, there are two possible outcomes for Option 2: completion (associated with a gain of \( \chi_c \)) or incompletion (associated with a loss of \( \chi_n \)). With a probability of \( p_c \), the driver can complete all-day travel using the BEV. The savings (or gain) compared to the reference point can be computed as
\[ \chi_c = C^{CGV} - C^{BEV} \]  \hspace{1cm} (10)

On the other hand, with a probability of \((1 - p_c)\), the driver cannot complete all-day travel using the BEV. The loss compared to the reference point can be computed as

\[ \chi_n = C^{penalty} - C^{CGV} \]  \hspace{1cm} (11)

The cumulative prospect value of Option 2 can then be calculated using Equation (7). Because the reference point is the cost of driving a conventional gasoline vehicle to complete the daily trips, the cumulative prospect value of Option 1 is always 0. Therefore, when the CPT of Option 2 is greater than 0, the driver will use the BEV on that day; otherwise, the driver will use a substitute vehicle.

4. Results and Discussion

Assuming that all the drivers charge their BEVs at home overnight, the BEV feasibility for each sample driver is based on his/her DVMTs and the BEV range distribution. The assumed range distribution captures variability across drivers, time of year, and driving conditions. It represents the perceived range variability for a potential BEV buyer. For an experienced BEV driver, however, the perceived range variability might be smaller, as he/she learns the impact of temperature, traffic, and driving style on the vehicle range over time. On each travel day, a driver chooses between using a BEV or a substitute conventional gasoline vehicle based on the cumulative prospect values, as computed in Equation (6). A BEV is considered feasible for a particular driver if he/she needs to use a substitute vehicle or make another travel adaption for only two days or less per year (i.e. BEV is feasible for at least 99.5% of the time).

Since the parameters in the value function \((\alpha, \beta)\) and weighting function \((\gamma, \delta)\) control the shape of the function and influence the CPT values, a series of sensitivity analysis were conducted.
with regard to the parameter values. As shown in Figure 4, the percentage of BEV feasible vehicles are not sensitive to $\alpha$, $\gamma$ and $\delta$ when they vary from 0.25 to 0.95. The value of $\beta$, however, influences BEV feasibility significantly—a smaller $\beta$ resulting in less negative valuation of a particular loss compared to a larger $\beta$. Thus, travelers are more likely to use a BEV when $\beta$ is small, making BEV feasible for more travelers. In particular, by changing the value of $\beta$ from the default value of 0.88 to 0.25, BEV feasible vehicles can increase from 5% to 25% of the sample population.

![Figure 4 Percent of BEV feasible vehicles varying with CPT parameters](image)

Note: when changing the value of one parameter, other three remain the default values.

To examine the impact of mean range and range uncertainty on BEV feasibility, various scenarios were tested as follows.

First, assume that the mean of the BEV range remains unchanged, that is, the size of the battery pack remains the same, but the standard deviation of the range varies from 60% to 140% of the baseline value. Figure 5 reports the BEV feasibility at various levels, from a 0.5% chance of travel adaption (i.e., a driver needs to use a substitute vehicle on less than 0.5% of the travel days, or less than two days per year) to over 20% chance of travel adaption (i.e. a driver needs to
use a substitute on more than 73 days per year). In the base case, a BEV is feasible for about 4.5% of drivers if they are willing to use a substitute vehicle on up to two days per year. When the standard deviation of the BEV range is reduced to 60% of the baseline level, a BEV is considered feasible for only about 10% of the sample population at the same level, i.e., a 0.5% chance of travel adaption. In addition, range uncertainty reduction also reduces the fraction of drivers who may be extremely unlikely to buy a BEV (i.e., those who would need to make a lot of travel adoptions if they use a BEV as the primary vehicle). As reported in Figure 4, the share of drivers who need more than 20% chance of travel adaption (i.e., more than 6 days per month on average, and equivalently over 73 days per year) decreases from about 14% to less than 6%, as a result of the 40% reduction in standard deviation of the BEV range.

Figure 5 Impact of varying standard deviation of ranges on BEV feasibility

Second, to examine the impact of range extension on the BEV feasibility, the mean value of the range distribution varies from 60% to 140% of the baseline value, while the standard deviation remains unchanged. As shown in Figure 6, when the mean range is increased by 40%, a
BEV is considered feasible for about 18% of the sample population. Such an increase in the mean BEV range is generally achieved by installing a larger battery pack.

![Figure 6 Impact of mean range on BEV feasibility](image)

Furthermore, to study the tradeoff between the mean extension and variance reduction of BEV range, Figure 7 plots a series of contour lines: the standard deviation and mean of the range can increase or decrease at the same time to keep BEV feasible for 10%, 20%, 30%, and 40% of the sample population, respectively. As reported in Figures 5 and 6, only 4.5% of the sample population sees a 99.5% BEV feasibility (i.e., only two days per year on which a travel adaption is needed) based on the current normal-distributed BEV range, that is, \( N(90, 17.95^2) \). To make BEV feasible at 99.5% level, for 10% of the sample population, one can extend the range by 15% and keep the same standard deviation, or reduce the variance by 40% and keep the same mean range. To increase the potential BEV market share to 30%, one can extend the range by 50% while reducing the standard deviation by half.
Figure 7 Contours of standard deviation and mean of ranges for a certain fraction of the sample population who achieve 99.5% BEV feasibility

5. Conclusions

Vehicle range uncertainty is observed in the real-world BEV usage data and appears to be significant. Range uncertainty can cause underutilization of the battery, as evidenced by BEV surveys (Smart and Schey 2012). Underutilization of the battery reduces consumer benefits and reflects a barrier to market acceptance. This paper presents a CPT-based approach to quantify the impact of reliable range estimation on BEV feasibility. The sensitivity analysis reveals that BEV feasibility is sensitive to parameter $\beta$ in the value function, but not sensitive to other parameters. By varying the value of $\beta$, the percentage of BEV feasible vehicles changes from less than 5% to 25%. The numerical results show that with a 50% reduction in the standard deviation and 50% increase in the mean of the BEV range distribution BEV feasibility increases from less than 5% of the sampled drivers to 30%. The findings from this study have some important policy implications.
First, range extension and variance reduction strategies can complement each other in promoting market acceptance of BEVs. There has been a long debate on whether the investment should be made to support battery technology research and development to reduce battery cost or to deploy more charging stations. Both increasing the battery size and expanding charging infrastructure coverage would contribute to a range extension for BEVs. Less attention has been paid to reduce the variability of the real-world BEV ranges. The results of this paper show that a large variation in the driving range will lower the usage of BEVs and discourage consumer acceptance. To reduce the range variability in the real-world driving context, enhanced powertrain control algorithms and battery management systems are desired.

Second, innovation in precise range prediction is desired. Improving individual range prediction is valuable fundamentally in the same way as improving consumer information in general (Helberger, 2013) and particularly reducing information uncertainty (Gal and Rucker 2018, Greene 2011, Lin and Green 2011b). Based on the generally accepted value of informing consumers, more accurate prediction of driving range can increase perceived utility of BEVs, that is, consumers are more confident in using all or most of the battery capacity and more likely to adopt a BEV. Several vehicle physics, battery performance, and statistical models have been proposed to predict the remaining driving range of electric vehicles (e.g., Hayes et al. 2011, Oliva et al. 2013 and Peterson et al. 2010). Further improvement in range prediction can be achieved through connected vehicle technologies, GPS with terrain maps, real-time traffic and weather information, and personal driving pattern records. Comprehensive models that account for range uncertainty due to multiple sources are yet to be developed for precisely predicting personalized trip-level BEV range.
Third, effective training and education might help to relieve some range anxiety. One type of intervention for BEV users would be to use a travel diary or online tools to track their daily travel behavior (e.g., the My MPG tool available at fueleconomy.gov). In the BEV driver behavior study conducted by Franke et al. (2012), participants reported that using a travel dairy improved their confidence in using BEVs, as they discovered, for the first time, that a BEV can be used for a high percentage of their trips. Furthermore, introducing BEVs to a car sharing or car rental fleet could expose more drivers to the new technology (e.g., Zoepf and Keith 2016).

There are many factors influencing real-world battery range and traveler decisions. This paper shows that reducing variability in the real-world driving ranges has the potential to promote BEV consumer acceptance. Taking advantage of widely available real-time data and recent advances in information and communication technologies, more accurate and robust range prediction algorithms can be designed in the future research to provide real-time range information. For example, Rahimi-Eichi and Chow (2014) proposed a big data analytics-based framework to estimate the remaining driving range of electric vehicles based on historical and real-time data from multiple sources.

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References


42. Puget Sound Regional Council (PSRC), Traffic Choices Study - Summary Report, 2008.


