Modeling charging behavior of battery electric vehicle drivers: A cumulative prospect theory based approach

Liang Hu  
*Iowa State University*

Jing Dong  
*Iowa State University, jingdong@iastate.edu*

Zhenhong Lin  
*Oak Ridge National Laboratory*

Follow this and additional works at: [https://lib.dr.iastate.edu/ccee_pubs](https://lib.dr.iastate.edu/ccee_pubs)

Part of the Civil Engineering Commons, and the Transportation Engineering Commons

The complete bibliographic information for this item can be found at [https://lib.dr.iastate.edu/ccee_pubs/293](https://lib.dr.iastate.edu/ccee_pubs/293). For information on how to cite this item, please visit [http://lib.dr.iastate.edu/howtocite.html](http://lib.dr.iastate.edu/howtocite.html).
Modeling charging behavior of battery electric vehicle drivers: A cumulative prospect theory based approach

Abstract
The behavior of drivers in charging a battery electric vehicle (BEV) can be influenced by psychological factors such as personality and risk preference. This paper proposes a cumulative prospect theory (CPT) based modeling framework to describe the charging behavior of BEV drivers. CPT captures an individual's attitude and preference toward risk in the decision-making process. A BEV mass-market scenario is constructed using the 2017 National Household Travel Survey (NHTS) data. This paper applies the CPT-based charging behavior model to study the battery state-of-charge (SOC) when drivers decide to charge their vehicles, charging timing and location choices, and charging power demand profile under the mass-market scenario. In addition, sensitivity analyses are used to examine the drivers’ risk attitudes and public charger network coverage. BEV drivers who display a higher degree of risk-seeking tend to charge vehicles at a lower SOC. Some home charging shifts to workplace and public charging as the public charger network expands, but home charging still plays the most significant role in BEV use. The power demand from public chargers increases significantly with BEV expansion and has a larger impact on the power grid. The time-of-use (TOU) electricity rate can shift peak power demand to off-peak periods from midnight to early morning.

Keywords
Battery electric vehicle, Charging behavior, Cumulative prospect theory, 2017 National Household Travel Survey (NHTS), Power grid

Disciplines
Civil Engineering | Transportation Engineering

Comments
This is a manuscript of an article published as Hu, Liang, Jing Dong, and Zhenhong Lin. "Modeling charging behavior of battery electric vehicle drivers: A cumulative prospect theory based approach." Transportation Research Part C: Emerging Technologies 102 (2019): 474-489. DOI: 10.1016/j.trc.2019.03.027. Posted with permission.

Creative Commons License
This work is licensed under a Creative Commons Attribution-NonCommercial-No Derivative Works 4.0 International License.
Modeling Charging Behavior of Battery Electric Vehicle Drivers: A Cumulative Prospect Theory Based Approach

Liang Hu\(^1\) (lianghu@iastate.edu), Jing Dong\(^*\)\(^1\) (jingdong@iastate.edu), Zhenhong Lin\(^2\) (linz@ornl.gov)

\(^1\)Iowa State University, \(^2\)Oak Ridge National Laboratory

\(^*\)Corresponding author

This manuscript has been authored by UT-Battelle, LLC under Contract No. DE-AC05-00OR22725 with the U.S. Department of Energy. The United States Government retains and the publisher, by accepting the article for publication, acknowledges that the United States Government retains a non-exclusive, paid-up, irrevocable, world-wide license to publish or reproduce the published form of this manuscript, or allow others to do so, for United States Government purposes. The Department of Energy will provide public access to these results of federally sponsored research in accordance with the DOE Public Access Plan (http://energy.gov/downloads/doe-public-access-plan).

Abstract

The behavior of drivers in charging a battery electric vehicle (BEV) can be influenced by psychological factors such as personality and risk preference. This paper proposes a cumulative prospect theory (CPT) based modeling framework to describe the charging behavior of BEV drivers. CPT captures an individual’s attitude and preference toward risk in the decision-making process. A BEV mass-market scenario is constructed using the 2017 National Household Travel Survey (NHTS) data. This paper applies the CPT-based charging behavior model to study the battery state-of-charge (SOC) when drivers decide to charge their vehicles, charging timing and location choices, and charging power demand profile under the mass-market scenario. In addition, sensitivity analyses are used to examine the drivers’ risk attitudes and public charger network coverage. BEV drivers who display a higher degree of risk-seeking tend to charge vehicles at a lower SOC. Some home charging shifts to workplace and public charging as the public charger network expands, but home charging still plays the most significant role in BEV use. The power demand from public chargers increases significantly with BEV expansion and has a larger impact on the power grid. The time-of-use (TOU) electricity rate can shift peak power demand to off-peak periods from midnight to early morning.

Keywords

Battery electric vehicle; Charging behavior; Cumulative prospect theory; 2017 National household travel survey (NHTS); Power grid
1. Introduction

Promoting the use of battery electric vehicles (BEV) is regarded as an effective way to reduce emissions and dependence on petroleum. Due to the limited battery range and insufficient charging infrastructure, BEV drivers need to pay attention to their battery state-of-charge (SOC) and make proper charging plans to avoid driving with low SOC and experiencing the “range anxiety” phenomenon (Neubauer and Wood, 2014). Better understanding of BEV drivers’ charging behavior, such as determining the SOC when charging occurs, and choices of charging time and location (home, workplace, or public), will provide guidance to BEV use, charging infrastructure planning, and power grid capacity expansion.

The charging decisions of electric vehicle (EV) drivers have been modeled using simple and deterministic rules. For example, Kang and Recker (2009), Darabi and Ferdowsi (2011), and Kongthong and Dechanupapritta (2014) assumed that only home charging took place. Dong and Lin (2012) quantified the benefit and cost of a charge and assumed drivers decided to charge only if the benefit-to-cost ratio was larger than one. Hu et al. (2018) and Yang et al. (2016) assumed BEV taxi drivers would go to charging stations only if the SOC drops below a certain level. These papers help us understand the travel and charging patterns of EVs in the early adopter stage. However, these assumptions may not reflect realistic behaviors because charging behavior is not always deterministic and can be influenced by various factors. To overcome these limitations, random utility theory (RUT) was introduced to describe drivers’ decision-making about charging while operating under uncertain conditions and randomness. For example, Daina et al. (2017) developed a joint random utility model of charging and activity-travel timing choices that takes various utilities across individuals into account. To incorporate heterogeneity among decision-makers, mixed logit choice models with random coefficients were developed to describe the decision to charge at the end of each trip (Zoepf et al., 2013), fast charging station choices (Sun et al., 2016), and charge timing choices (Langbroek et al., 2017).

One of the basic assumptions of RUT is that individuals are rational decision-makers who maximize utility relative to their choices. However, the assumption that decision-makers are rational has long been challenged (Kahneman and Tversky, 1979; Durbach and Stewart, 2012; Ilin and Rogova, 2017). In transportation research, irrational behaviors have been observed and

To take the limited rationality in decision-making into account, cumulative prospect theory (CPT) was introduced. CPT is a behavioral science theory that describes the extent of decision-makers’ attitudes and preference toward risk (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992). The theory proposes that decision-makers (1) are risk-averse when outcomes are framed as gains relative to a reference point, and risk-seeking when outcomes are framed as losses; (2) are more sensitive to losses than gains; and (3) tend to apply too much weight to unlikely outcomes and too little weight to likely outcomes. CPT has been applied in many transportation research fields, such as 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; Zhang et al., 2018; 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). These studies all found success in using CPT to describe people’s limited rationality and risk attitudes when making decisions. Among these works, Schwanen and Ettema (2009), Gao et al. (2010), Xu et al. (2011), Wang and Xu (2011), and Yang and Jiang (2014) compared CPT with utility theory expectations and showed that CPT is a better approach to modeling travelers’ behavior.

When driving a BEV, there are no significant perceivable gains if the trip distance falls below the BEV range, but if the distance unexpectedly exceeds the range and the driver is caught on the road or forced to detour to reach a public charger, the losses are perceivably large. Moreover, BEV drivers tend to recharge at high battery SOC to avoid range anxiety. Therefore, the charging behavior of BEV drivers is in accordance with the rationale of CPT. This paper proposes an innovative modeling framework for the charging behavior of BEV drivers based on CPT.

By applying the CPT-based charging behavior model, this paper examines the collective effects of nationwide BEV charging under a mature market. A BEV mass-market scenario is constructed based on the 2017 National Household Travel Survey (NHTS). By aggregating individuals’ charging behavior, we can examine the distribution of battery SOC at the start of charging.
events, charging timing and location choices, and charging power demand profile. Sensitivity analyses are conducted to explore the influences of BEV drivers’ attitudes toward risk on charging behavior and the influences of the public charger network coverage on the power grid.

2. Methodology

CPT describes an individual’s decision-making process when confronted with uncertain outcomes and risks. The charging behavior modeling framework consists of two phases—editing and evaluation—as shown in Figure 1. Based on the dwell and trip characteristics of a BEV, the editing phase confirms the outcomes of charging or not charging by the cost functions. The outcomes are converted to values (either gains or losses) relative to a reference point. Then the model considers the distribution of outcomes and estimates the corresponding probabilities. Weighting functions convert these probabilities into decision weights. In the evaluation phase, the prospects of charging or not charging are computed, and BEV drivers make charging decisions based on these prospects. The battery SOC and travel distance to the next charger are updated based on the charging decision. The following sections describe the modeling framework in detail. All the parameters of the modeling framework and their values are listed in Appendix A.
2.1. Cost functions

BEV drivers make a charging decision when a charger is available at the dwell location. The decision could be affected by the current SOC (the remaining range over full battery range, in %), charger power, charging cost, distance to the next charger, dwell time, dwell location, etc. The charging decision has a direct impact on the remaining range at the next charger (Equation 1).

\[ r_n = r_c + r_i - d \]  

where

- \( r_n \) is the remaining range at the next charger (mi);
- \( r_c \) is the current remaining range (mi);
$r_i$ is the range increase (mi); and

d is the travel distance to the next charger (mi).

If the driver decides to charge the vehicle, the range increase is calculated as in Equation 2; otherwise, it is 0. Note that range increase should not surpass BEV’s full range.

$$r_i = \min\left( r_f - r_c - \frac{t_d \times P}{e_r} \right)$$

where

$r_f$ is BEV’s full range (mi);

$t_d$ is dwell time (h);

$P$ is charger power (kW); and

$e_r$ is electricity consumption rate (kWh/mi), assumed 0.3 kWh/mi (U.S. EPA, 2017).

The remaining range at the next charger will result in different outcomes. Franke and Krems (2013) conducted a survey on 40 drivers of electric MINI Coopers which have a 104-mile range under normal driving conditions. They found that these drivers feel comfortable when the battery SOC is above 20%–25%. However, when SOC drops below that comfort range, the drivers become anxious about using up electricity. This range anxiety phenomenon leads to unpleasant driving experiences. Therefore, this paper considers 20 miles as the comfortable range threshold ($r_a$).

If a driver decides to charge the vehicle and arrive at the next charger with 20 miles or more range remaining, the costs for the driver consist of the charging hassle cost ($c_h$), charging service cost ($c_s$), and electricity cost ($c_e$). Kurani et al. (2009) and Axsen and Kurani (2009) found that BEV drivers perceived that recharging was not worth the hassle under certain circumstances. The value of time (VOT) is assumed as $13.6/h for personal local travel and $25.4/h for business local travel (U.S. DOT, 2016). Plugging and unplugging may take around 2 min (Dong and Lin, 2012; Wu et al., 2015; Wu et al., 2014), so we assume the charging hassle cost is $0.45 if the trip is out of personal purpose and $0.85 if the trip is out of business purpose. In addition, users typically pay a one-time service fee or a monthly membership fee to get access to public fast
chargers. The charging service cost \( c_s \) is assumed as $5 per charge (Francfort, 2015). The driver also needs to pay for the electricity, as calculated in Equation 3.

\[
c_e = r_i \times e_r \times e_c
\]

where

\( e_c \) is the electricity price, assumed as $0.12/kWh (U.S. EIA, 2017).

If the driver has not arrived at the next charger but the remaining range drops below the comfortable point, \( r_a \), there is a psychological cost for the driver as he/she becomes increasingly anxious as the remaining range decreases. Thus, we assume the psychological cost increases linearly to the penalty cost \( c_p \) as the remaining range drops to 0. \( c_p \) equals $109, which is the U.S. national average car towing cost (Moor, 2016).

Even though the driver has charged the vehicle, it is still possible that the vehicle will run out of electricity during the trip. When this happens, the driver has to pay for towing and travel to the destination by other means, such as taking a taxi.

Therefore, the outcomes of charging can be represented by the cost function \( C_1(r_n) \) as below.

\[
C_1(r_n) = \begin{cases} 
-c_h - c_s - c_e, & r_n \geq r_a \\
-c_h - c_s - c_e - \frac{r_a - r_n}{r_a} \times c_p, & 0 \leq r_n < r_a \\
-c_h - c_s - c_e - c_p - c_t \times |r_n|, & r_n < 0 
\end{cases}
\]

where

\( c_t \) is the taxi rate ($/mi), assumed $2.51/mi based on the data published on TaxiFareFinder (2018).

In contrast, the outcomes of not charging are represented by the cost function \( C_2(r_n) \) as shown in Equation 5. There is no charging cost, but the driver runs a higher risk of feeling range anxiety or becoming stranded.

\[
C_2(r_n) = \begin{cases} 
0, & r_n \geq r_a \\
-\frac{r_a - r_n}{r_a} \times c_p, & 0 \leq r_n < r_a \\
-c_p - c_t \times |r_n|, & r_n < 0 
\end{cases}
\]
2.2. Reference point and value function

The outcomes at the next charging opportunity are determined by the cost functions $C_1(r_n)$ and $C_2(r_n)$. The outcomes are framed as gains or losses when compared to a reference point ($c_0$).

The reference point is defined as the cost of driving to the next charger, as shown in Equation 6.

The value function, shown in Equation 7 and Figure 2, considers gains and losses separately, and converts the outcomes to values for the decision-maker.

\[
c_0 = -d \times e_r \times e_c \tag{6}
\]

\[
V(c) = \begin{cases} 
(c - c_0)^\alpha, & c \geq c_0 \\
-\lambda(c_0 - c)^\beta, & c < c_0 
\end{cases} \tag{7}
\]

where

$\alpha$ and $\beta$ are the risk preference parameters ($0 < \alpha, \beta < 1$);

and $\lambda$ is the loss aversion parameter ($\lambda > 1$).

The value function exhibits risk-aversion over gains and risk-seeking over losses. Larger values of $\alpha$ and $\beta$ indicate that people are more sensitive to risk. $\lambda$ is larger than 1, which suggests that people are more sensitive to losses than gains. Larger values of $\lambda$ represent the increasing degree of sensitivity.

![Figure 2. Value function.](image-url)
2.3. Estimating probabilities of outcomes

The outcomes encountered by BEV drivers are uncertain, because the remaining range at the next charger, denoted by $r_n^k$, is not deterministic. The real world BEV electricity consumption can be affected by ambient temperature (Wang et al., 2017), driving speed (Wager et al., 2016; Yi and Shirk, 2018), road gradient (Liu et al., 2017b), and use of air-conditioning (Liu et al., 2017a). Assume $r_n^k$ follows the normal distribution

$$r_n^k \sim N(r_n, (cv \times r_n)^2) \tag{8}$$

where $cv$ is the coefficient of variation.

We use $r_n$ estimated by Equation 1 as the mean for the normal distribution, and $cv \times r_n$ as the standard deviation. $cv$ is 0.234 based on a FleetCarma dataset which includes travel activities of 436 2013/2014 Nissan Leafs in three U.S. states (California, Texas, and Maine) for about 7 months. The distance and electricity consumption of each trip are available. 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. The range is calculated as the battery capacity divided by the average electricity consumption rate. It was found that the mean and standard deviations of the LEAF’s range are 96 mi and 22.5 mi, respectively, so the coefficient of variation is 0.234.

Note that $r_n^k$ follows a continuous distribution. To apply CPT, we convert the normal distribution into a discrete distribution that generates 10 possible outcomes of the remaining range at the next charger with the associated probabilities. First, we construct a confidence interval $(\theta)$ with a level of confidence of $p\%$.

$$a = r_n - cv \times r_n \times \phi^{-1}(0.5 + 0.5 \times p\%) \tag{9}$$

$$b = r_n + cv \times r_n \times \phi^{-1}(0.5 + 0.5 \times p\%) \tag{10}$$

$$\theta = [a, b] \tag{11}$$

where
\( \phi(\cdot) \) is the cumulative distribution function of standard normal distribution.

Convert the normal distribution to a truncated normal distribution that lies within the confidence interval \( \Theta \). Divide \( \Theta \) into 10 equal intervals, denoted by \( \Delta_1, \Delta_2, \ldots, \Delta_{10} \). \( r^k_n \) serves as the median of interval \( \Delta_k \) \((k = 1, 2, \ldots, 10)\), and the corresponding probability \( p_k \) is the probability that the remaining range falls in \( \Delta_k \). Note that \( p_k \) is also the probability of the outcome \( c_k \) associated with \( r^k_n \).

2.4. Weighting functions

CPT states that an event with a small possibility of occurring will generally be overestimated by decision-makers, whereas an event with a larger possibility of occurring will be underestimated, as illustrated in Figure 3. The cumulative decision weights \( \pi(p) \) are defined in Equations 12 and 13 (Tversky and Kahneman, 1992). They are calculated based on the weighting functions \( w(p) \), as seen in Equations 14 and 15, where the probabilities of gains and losses take different parameters, \( \gamma \) and \( \delta \). The parameters \( \gamma \) and \( \delta \) indicate the extent of influence from overweighting and underweighting, and \( 0 < \gamma, \delta < 1 \). The smaller \( \gamma \) and \( \delta \) result in a more curved weighting function.

\[
\pi^+_i(p_i) = w^+(p_i + \cdots + p_n) - w^+(p_{i+1} + \cdots + p_n) \quad \text{for } 0 \leq i < n \quad \text{and} \quad \pi^+_n(p_n) = w^+(p_n) \quad (12)
\]

\[
\pi^-_j(p_j) = w^-(p_{-m} + \cdots + p_j) - w^-(p_{-m} + \cdots + p_{j-1}) \quad \text{for } -m \leq j < 0 \quad \text{and} \quad \pi^-_{-m}(p_{-m}) = w^-(p_{-m}) \quad (13)
\]

\[
w^+(p_i) = \frac{p_i^\gamma}{[p_i^\gamma + (1-p_i)^\gamma]^{1/\gamma}} \quad (14)
\]

\[
w^-(p_j) = \frac{p_j^\delta}{[p_j^\delta + (1-p_j)^\delta]^{1/\delta}} \quad (15)
\]
2.5. Charging decision

BEV drivers make their charging decisions based on cumulative prospect values. The cumulative prospect values of charging and not charging are calculated based on Equation 16.

\[
U(c, p) = \sum_{i=0}^{n} \pi_i^+(p_i)V(c_i) + \sum_{j=-m}^{-1} \pi_j^-(p_j)V(c_j)
\]  \hfill (16)

The probability of making the charging decision \( p_c \) is calculated as follows:

\[
p_c = \frac{e^{U_1}}{e^{U_1} + e^{U_2}}
\]  \hfill (17)

where

\( U_1 \) is cumulative prospect value of charging the vehicle; and

\( U_2 \) is cumulative prospect value of not charging the vehicle.

Note that the charging probability \( p_c \) is calculated based on the next charging opportunity. When making charging decisions BEV drivers may think beyond the next charging opportunity and consider the itinerary of the travel day to plan for charging. Therefore, the threshold probability of charging \( p_t \) is determined based on the remaining travel distance and the number of charging opportunities before arriving at the last destination at the end of the day, as shown in Equation 18. If \( p_c \) is greater than \( p_t \), the driver decides to charge; otherwise, the driver will not charge.
\[ p_t = \frac{1}{1 + e^{-\frac{h}{\ell}}} \] (18)

where

- \( h \) is the number of later charging opportunities before arriving at the last destination of the day;
- \( l \) is the travel distance from the current stop to the last destination of the day (mi); and
- \( \varepsilon \) is the scale parameter.

Since the last destination of the day is usually home, \( \frac{h}{\ell} \) indicates the charging opportunities per mile before returning home. When the charger coverage in the remaining itinerary is high, the threshold probability \( p_t \) is large and drivers are less likely to charge vehicles at the current stop.

The scale parameter \( \varepsilon \) is used to adjust the impact of itinerary on the threshold probability, which is often seen in CPT applications (Jou and Chen, 2013; Lou and Cheng, 2016; Schwanen and Ettema, 2009; Zhang et al., 2018).

The CPT parameters indicate different risk attitudes among individuals. The driver’s socioeconomic characteristics (e.g., income, gender, age, and education), BEV experience, charger familiarity, etc., have effects on the parameters. Calibration of these parameters is beyond the scope of this paper. This paper adopts the values calibrated by Tversky and Kahneman (1992): \( \alpha = 0.88, \beta = 0.88, \lambda = 2.25, \gamma = 0.61, \) and \( \delta = 0.69 \) in the following analysis.

In addition, sensitivity analyses are conducted to examine the impact of the parameters on charging behavior.

3. BEV Mass-market Scenario based on 2017 National Household Travel Survey

This paper builds a BEV mass-market scenario based on the 2017 National Household Travel Survey (NHTS). The scenario shows how to examine charging behavior in the long term under a mature BEV market with factors such as high BEV penetration, long range, and adequate charging infrastructure with more fast chargers available.

3.1. BEVs in 2017 NHTS

The 2017 NHTS is an inventory of the U.S. residents’ travel behavior during a travel day, including trips made by all modes of transportation (U.S. DOT, FHWA, 2017). The VEHICLE
file of the NHTS consists of 242,160 passenger vehicles (i.e., cars, SUVs, vans, or pickup trucks) owned by the respondents. The 2017 NHTS introduced a new field—HFUEL in the VEHICLE file—to indicate the type of powertrain. For example, HFUEL = 3 means that the vehicle is a BEV. There are 607 BEVs in the raw data. However, some respondents mistakenly reported their plug-in hybrid electric vehicles (PHEV), such as the Chevrolet Volt, Ford Fusion Hybrid, and Toyota Camry Hybrid, as BEVs. After removing these PHEVs, there are 392 BEVs remaining, as listed in Table 1. The BEV market penetration is a mere 0.16%. This survey showed that the Nissan Leaf (182 in total) and Tesla are the most popular models among BEV drivers in the U.S. The ranges of most BEV models are less than 100 miles.

The average travel distance during the travel day of non-Tesla BEVs ($\mu_{BEV}$) is 28.1 miles, while the average travel distance of gasoline vehicles ($\mu_{GV}$) is 34.7 miles. We compare the two means using the t-test. The alternative hypothesis is that the non-Tesla BEVs have a shorter average travel distance than gasoline vehicles; that is $H_a: \mu_{BEV} < \mu_{GV}$. The t-test shows that the p-value is 0, indicating the BEVs’ average daily travel distance is significantly shorter than that of gasoline vehicles. The average travel distance of Teslas ($\mu_{Tesla}$) is 41.2 mile. A t-test is conducted with the alternative hypothesis of $H_a: \mu_{Tesla} > \mu_{GV}$. The test shows that the Teslas’ average daily travel distance is not significantly longer than gasoline vehicles (p-value is 0.0802). Since the BEV samples in the 2017 NHTS are inappropriate for studying charging behavior in a mature market, we constructed a BEV mass-market scenario using the 2017 NHTS with the assumption that some gasoline vehicles will be replaced by BEVs without changing their current travel patterns.

Table 1. BEVs in 2017 NHTS.

<table>
<thead>
<tr>
<th>BEV make and model</th>
<th>Number of vehicles</th>
<th>EPA rated range (in miles)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tesla</td>
<td>121</td>
<td>249*</td>
</tr>
<tr>
<td>2013/14/15 Nissan LEAF</td>
<td>117</td>
<td>84</td>
</tr>
<tr>
<td>2011/12 Nissan LEAF</td>
<td>45</td>
<td>73</td>
</tr>
<tr>
<td>Fiat 500e</td>
<td>27</td>
<td>87</td>
</tr>
<tr>
<td>2016/17 Nissan LEAF</td>
<td>20</td>
<td>107</td>
</tr>
<tr>
<td>Chevrolet Spark EV</td>
<td>17</td>
<td>82</td>
</tr>
<tr>
<td>Volkswagen e-Golf</td>
<td>14</td>
<td>83</td>
</tr>
<tr>
<td>Smart Fortwo electric drive</td>
<td>11</td>
<td>68</td>
</tr>
<tr>
<td>Ford Focus Electric</td>
<td>6</td>
<td>76</td>
</tr>
<tr>
<td>Toyota RAV4 EV</td>
<td>5</td>
<td>103</td>
</tr>
<tr>
<td>Kia Soul EV</td>
<td>5</td>
<td>93</td>
</tr>
<tr>
<td>Honda Fit EV</td>
<td>3</td>
<td>82</td>
</tr>
</tbody>
</table>
The model of Tesla is not available. Use 249 miles in this paper.

3.2. Vehicle travel activities

The TRIP file of the 2017 NHTS recorded the trips of each person in the household during a travel day. The following filtering criteria were applied to select the personally operated vehicle (POV) trips on the travel day.

- TRPTRANS = 3, 4, 5, or 6 (the POV is a car, SUV, van, or a pickup truck);
- DRVR_FLG = 1 (identical POV trips are counted once).

The trip characteristics are listed in Table 2. The dwell time at a destination is derived from the time intervals between two continuous trips. After removing vehicles with incorrect or missing fields, there are 153,776 vehicles left. Based on the trip and dwell characteristics, we can determine the vehicle travel activities during the day, as illustrated in Figure 4.

Table 2. Selected trip characteristic fields from the TRIP file.

<table>
<thead>
<tr>
<th>Field</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>HOUSEID</td>
<td>Household identifier.</td>
</tr>
<tr>
<td>VEHID</td>
<td>Vehicle identifier.</td>
</tr>
<tr>
<td>STRTTIME</td>
<td>Trip start time.</td>
</tr>
<tr>
<td>ENDTIME</td>
<td>Trip end time.</td>
</tr>
<tr>
<td>WHYFROM</td>
<td>Trip origin. Convert the values of 1 or 2 to ‘home’, 3 or 4 to ‘work’, and ≥5 to ‘public’.</td>
</tr>
<tr>
<td>WHYTRP1S</td>
<td>Trip destination. Convert the values of 1 to ‘home’, 10 to ‘work’, and ≥20 as ‘public’.</td>
</tr>
<tr>
<td>VMT_MILE</td>
<td>Trip distance for POV trips (mi).</td>
</tr>
<tr>
<td>DWELTIME</td>
<td>Time spent at the destination.</td>
</tr>
</tbody>
</table>

Figure 4. Travel activities of a sample vehicle during the day.
3.3. Charger network coverage and charger power

Wide BEV adoption is constrained by insufficient charger network coverage and low-speed chargers. Charger network coverage can be represented by the probability that a charger is available at the destination (Dong and Lin, 2012; Kontou et al., 2019). If a charger is available, BEV drivers may take advantage of the dwell time at the destination to charge their vehicles without interfering with their travel plans (Dong et al., 2014; Hu et al., 2018). In this study, charger availability \( X \) is drawn from a Bernoulli distribution with probability \( p_a \). \( X = 1 \) means a charger is available; otherwise, \( X = 0 \).

\[
\text{Pr}(X = 1) = 1 - \text{Pr}(X = 0) = p_a, \quad 0 \leq p_a \leq 1
\]  

(19)

Homes, workplaces, and public locations offer different probabilities of having available chargers. For example, in Figure 4, this vehicle has charging opportunities at home, the workplace, and the grocery store. At each charger site, we calculate the travel distance to the next charging opportunity and apply the CPT model to determine the driver’s charging decision.

Charger power also varies at different charging locations. Regular residential chargers are Level 2 of 3.3 kW and some are Level 2 of 6.6 kW (Francfort, 2015). The power of Level 2 chargers could increase to 19.2 kW (SAE, 2016). Direct current (DC) fast chargers of 50 kW have been introduced to the market and are gaining popularity (Saxton, 2013). The EV Project showed that current BEV drivers use AC Level 2 chargers (3.3 kW and 6.6 kW) most frequently (83% of all charging events), while 11% of charges are being performed using DC fast chargers (Smart and Scoffield, 2014). This paper considers Level 2 chargers with higher power and DC fast chargers in the mass-market scenario.

3.4. The BEV mass-market scenario

The Market Acceptance of Advanced Automotive Technologies (MA3T) model developed by Oak Ridge National Laboratory is a simulation tool for the U.S. vehicle market (Lin, 2014; Lin and Greene, 2011; Xie and Lin, 2017). MA3T uses a nested multinomial logit model to predict customer acceptance of advanced vehicle technologies, including BEVs. Under the “Developed” scenario that supposes a further expansion of charging infrastructure with higher power, the model predicts that by 2030 the BEV market share is 17%, among which 58.7% are BEVs with a 100-mi range (BEV-100), 41.1% are BEV-200, and 0.3% are BEV-300 (Xie et al., 2018).
Accordingly, we selected 242,160 $\times$ 17\% = 43,540 vehicles from the 2017 NHTS as the BEV samples to build the mass-market scenario. The average weight is 869 (U.S. DOT, FHWA, 2017), indicating that a vehicle sample in the NHTS can represent 869 vehicles nationwide. Thus, the selected 43,540 vehicles can represent 37,836,260 BEVs in the country. The BEV range is assumed to be 100, 200, or 300 miles, and the shares are in accordance with the MA3T model predictions. Moreover, in the mass-market scenario there is an adequate charging infrastructure with more fast chargers available. It is assumed that BEV drivers all install chargers at home and out-of-home charging coverage is 0.5 at workplaces and in public locations (Tehrani et al., 2013). The scenario parameters are listed in Table 3.

Table 3. Parameters of BEV mass-market scenario.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>BEV range (mi)</td>
<td>100, 200, or 300</td>
</tr>
<tr>
<td>Home charger network coverage</td>
<td>1.0</td>
</tr>
<tr>
<td>Work charger network coverage</td>
<td>0.5</td>
</tr>
<tr>
<td>Public charger network coverage</td>
<td>0.5</td>
</tr>
<tr>
<td>Home charger power (kW)</td>
<td>6.6</td>
</tr>
<tr>
<td>Work charger power (kW)</td>
<td>19.2</td>
</tr>
<tr>
<td>Public charger power (kW)</td>
<td>50</td>
</tr>
<tr>
<td>BEV market share</td>
<td>17%</td>
</tr>
</tbody>
</table>

The EV Project showed that the SOC is nearly always above 78\% at the end of overnight home charging for Nissan Leaf drivers (Smart and Schey, 2012). Nissan also offers the option of stopping the charging once the SOC reaches 80\% to preserve battery life when full range charging is not necessary (Nissan, 2011). Since over 90\% of vehicles in the 2017 NHTS started their travel day at home, this paper assumes the battery SOC at the beginning of the first trip during the day is uniformly distributed between 78\% and 100\%.

3.5. Simulation

This paper simulates the BEV mass-market scenario using the TRIP data in the 2017 NHTS and the CPT charging behavior model. For each sampled BEV, we first determined its travel activities during the day using the data fields listed in Table 2, including trip origin and destination, trip start time and end time, trip distance, and dwell time at the destination. As illustrated in Figure 4, a BEV travels 6 times that day and has 3 charging opportunities at work, in public (grocery store), and at home. When the driver arrives at the workplace, the BEV’s remaining range $r_c$ is updated, and the dwell time at the workplace $t_d$ can potentially be used for
charging with an increase of $r_i$ miles. The travel distance to the next public charging opportunity
grocery store) $d$ is the total distance of trips 2, 3, and 4. With these travel data as inputs, we
apply the CPT charging behavior model to determine the driver’s charging decision. If the driver
decides to charge, the BEV’s remaining range is updated when the charging session ends. By
aggregating the individual’s charging decisions, the collective effects of nationwide BEV
charging under the mass-market scenario can be examined. When running the simulation, we
have adjusted the dollar values of different years in the CPT model to the values of 2017 based
on the inflation rates published by the U.S. Department of Labor (2019).

4. Results

4.1. Charging behavior under the mass-market scenario

4.1.1. Battery SOC at the start of charging events

The battery SOC at which BEV drivers decide to charge is an important aspect of charging
behavior. On one hand, drivers may want to charge at a higher SOC to avoid range anxiety; on
the other hand, drivers may think charging is not worth the hassle. Therefore, BEV drivers
charge their vehicles at a wide range of starting SOC levels. The EV Project showed that the
majority of charging events started with a 20~80% SOC and the most frequent starting SOC
levels are within 50~60% (Smart and Schey, 2012). Zou et al. (2016) found that about three-
quarters of the BEV taxi drivers in Beijing, China did not resort to charging until the SOC
dropped below 50% and most charging events started with a 40~50% SOC.

Figure 5 examines the distribution of battery SOC at the beginning of charging events under the
mass-market scenario. On average, BEV drivers start charging at a 41% SOC. Most charge
events start with a SOC between 40% and 50%. Seventy-three percent of all charge events occur
when the SOC drops below 50%. BEV drivers do not often decide to charge at either very high
or very low levels of SOC. Only 2.5% of charging events start with an 80% SOC or even higher,
and only 7.5% of charging falls below the anxiety range of 20 miles. Compared with the EV
Project observations in which most charges occurred at 50~60% SOC, drivers tend to charge at a
lower SOC in the mass-market scenario. BEV drivers will be more confident with using the more
of the battery range when the charging infrastructure is well established.
Figure 5. Distribution of battery SOC at the start of charging events.

The battery SOC before charging varied by charger location. The average starting SOC levels at home, workplace, and public chargers are 40.6%, 47.8%, and 39.1%, respectively. The average SOC at workplace chargers is higher, mainly because the drivers have not traveled a long distance when they first arrive at the workplace in the morning. The initial SOC is slightly lower for home and public charging. This is due to the higher cost associated with using public chargers.

4.1.2. Charge timing and location choices

BEV drivers may charge vehicles at different times of the day in different places. Figure 6 shows that the amount of vehicles undergoing charging and the proportions of charging location usage fluctuate during the day. In the morning, fewer BEVs choose to recharge, because either the vehicles have not consumed enough electricity to need a charge or the vehicles are in use. In the afternoon, the number of vehicles being charged starts to rise. The increasing rate is especially dramatic from 3 to 6 p.m. when people typically return home from work or other places. The number of charging vehicles peaks at 6 to 7 p.m.

The charging location also changes considerably during the day. From 6 to 9 a.m., over 50% of the charging vehicles are using workplace chargers. In the afternoon, the use of public and home chargers rises and the workplace chargers are used less. The public chargers are mainly used in the daytime. The proportion of publicly charging vehicles is highest around noon, when drivers take advantage of lunchtime to recharge. Home chargers play the dominant role in BEV charging. Although the proportion of home charging drops dramatically in the morning, drivers
prefer home charging during other times of the day, even if work and public chargers provide higher power. At night, almost all charging vehicles use home chargers.

Figure 6. Number of vehicles in charging and the proportions by charging locations.

4.1.3. Charging power demand

Some of the concerns with mass adoption of BEVs relate to whether the current electrical grid capacity can accommodate the additional load (Green et al., 2011; Hardman et al., 2018; Liu, 2012; Moon et al., 2018). Figure 7 shows the charging power demand during the daytime and where the demand comes from. The load profile generally follows a trend similar to the number of charging vehicles during the day. In the morning, the power demand is the lowest and mainly comes from workplace chargers. Demand is at a moderate level from noon to 4 p.m. Note that during this time period, the power demand mainly comes from public chargers. Although home charging is more frequent than public charging, a considerable share of the power demand during the daytime comes from public chargers. After working hours, since the majority of charging vehicles use home chargers, the load from home charging again accounts for the largest share. The load peak occurs between 5 and 8 p.m.

In summary, the three important characteristics of the BEV demands on charging power are (1) daytime load is higher than nighttime load; (2) daytime load mainly comes from workplace and public chargers, while nighttime load mainly comes from home chargers; and (3) the load contribution from workplace chargers peaks in the early morning, while the load contributed by public chargers peaks at noon.
4.2. Impacts of driver risk attitude on charging behavior

The CPT model describes how people’s attitudes toward risk affect the decision-making process. The parameters $\alpha$ and $\beta$ in the value function (i.e., Equation 7) represent the risk preference of decision makers. Higher values of $\alpha$ and $\beta$ indicate that decision makers have a greater degree of risk aversion; while lower values indicate a greater degree of risk seeking. $\lambda$ is the loss aversion parameter. Lower values of $\lambda$ represent the decreasing degree of sensitivity to losses over gains.

Figure 8 shows the impacts of risk preference parameters $\alpha$ and $\beta$ on battery SOC at the start of charging and on the proportions of charges that begin with a 20-mile range (or less) remaining. Let $\alpha = \beta$, indicating the same risk preference for gains and losses (Schwanen and Ettema, 2009). By changing the values from 0.05 to 0.95, Figure 8 shows that drivers’ risk preferences have a significant impact on charging behavior. As $\alpha$ and $\beta$ increase, drivers become more risk averse, and the average starting SOC increases steadily. Meanwhile, the proportion of the charges with less than 20 miles SOC remaining decreases. The drivers who are more risk averse tend to charge vehicles at a higher SOC in order to avoid range anxiety. In contrast, when drivers are extreme risk seekers, the starting SOC (on average) is 33.4% and over 20% of all charges start with 20 miles or less remaining.
(a) Impact on average SOC at the start of charging events

Figure 8. Impacts of BEV drivers’ risk preference on charging behavior.

(b) Impact on the proportion of the charges with 20-mi range or less remaining

$\lambda$ has relatively weaker impacts on charging behavior compared to $\alpha$ and $\beta$ in the value function. In Figure 9, the values of $\lambda$ vary from 1.25 to 5.75. Higher values of $\lambda$ indicate an increasing degree of sensitivity to losses. As BEV drivers become more sensitive to losses than gains, the drivers exhibit stronger range anxiety, and the average battery SOC at the start of charging increases slightly. In the meantime, the proportion of the charges with 20 miles or less remaining is nearly unchanged.

(a) Impact on average starting SOC

(b) Impact on the proportion of the charges with 20-mi range or less remaining

Figure 9. Impacts of BEV drivers’ loss aversion attitude on charging behavior.

4.3. Impacts of irrational behavior on charging power demand

The CPT parameters $\alpha$, $\beta$, $\lambda$, $\gamma$, and $\delta$ control the degree of irrationality of decision makers. If these parameters all equal 1, BEV drivers are assumed to be rational when making charging decisions; that is, the drivers are neither risk averse nor risk seeking, losses and gains are
weighted the same, and unlikely and likely outcomes are weighted the same. Figure 10 compares
the charging power demand with the CPT model and the rational driver assumption. It is seen
that the peak power demand with the rational driver assumption is underestimated by 4%. This
could lead to insufficient expansion of grid capacity in the future. Figure 10 also compares the
charging power demand if BEV drivers are highly risk averse (i.e., $\alpha, \beta = 0.95$) or highly risk
seeking (i.e., $\alpha, \beta = 0.05$). The power demands of extremely risk-averse drivers are higher during
evening peak hours than is shown in the CPT model, because these drivers are more worried
about using up the battery range. By contrast, the strong risk-seeking drivers are less worried and
tend to have lower charging demands. In summary, the CPT model, which captures the irrational
behavior of BEV drivers, is more appropriate to guide grid capacity expansion choices. In
addition, BEV drivers with different levels of irrationality have different effects on charging
power demand.

![Figure 10. Charging power demand under the BEV mass-market scenario with drivers of different levels of irrationality.](image)

4.4. Impacts of public charger network coverage on charging behavior

Public chargers provide charging opportunities when needed during the day. Higher public
charger coverage also makes drivers more confident about accessing the greater range of charger
potential (Nicholas and Tal, 2017). Figure 11 shows how public charger coverage affects
charging location choices and power demand. It is seen that as the public charger coverage
increases, drivers are more likely to use public chargers. About 20% of vehicles charge at public
locations when the charger coverage exceeds 0.6. However, home charging still plays the
dominant role and accounts for 63% of all charging events even if public charging opportunities are everywhere.

![Graph](image)

(a) Impact on charging location  
(b) Impact on charging power demand

Figure 11. Impacts of public charger network coverage on charging location and charging power demand.

The charging power demand from public chargers increases significantly with the expansion of public charger network. Under the mass-market scenario where public charger coverage is assumed as 0.5, 36% of power demand comes from public chargers. Just 20% of charges done at public locations could potentially account for up to 40% of total electricity demand. In addition, expanding the grid capacity for public chargers is necessary as fast chargers will have a greater impact on the grid. Currently, the largest share of the power demand still comes from homes. Thus, providing enough grid capacity in residential areas and maintaining reliable home charging service are important to expanded BEV use.

4.5. Impacts of time-of-use (TOU) electricity rate on charging power demand

The electricity price is assumed as constant in the previous sections. The time-of-use electricity rates, which vary with the changes in grid loads, have been implemented in some areas and will impact BEV drivers’ charging behavior. Cao et al. (2016) defined 11 a.m. to 2 p.m. and 7 p.m. to 11 p.m. as the mid-peak period, 2 p.m. to 9 p.m. as the on-peak period, and 11 p.m. to 11 a.m. as the off-peak period. The on-peak rate is about 1.5 times of the mid-peak rate; the mid-peak rate is about twice of the off-peak rate (Cao et al., 2012; Cao et al., 2016; Crow, 2014). This TOU
pricing is showed as the TOU 1 in Figure 12, where $e_c$ is used as the mid-peak electricity price. The TOU 2, which increases the on-peak rate and reduces the off-peak rate, is used to explore drivers’ response given a larger gap between on-peak and off-peak rates. Moreover, TOU pricing could also be determined by the charging power demands of BEVs. In Figure 7, the day’s power demand is highest from 4 to 9 p.m. and drops to the lowest level from 12 a.m. Thus, we can adjust TOU pricing accordingly, which might reduce additional peak demand. The TOU 3 and TOU 4 represent the pricing adjusted by the power demand of BEVs and have the same rates with the TOU 1 and TOU 2, respectively.

To take advantage of the off-peak electricity price, delayed charging is allowed for vehicles that satisfy the conditions that (1) home is the last destination of the day and (2) vehicles can be fully charged before the next trip. The charging start time will be postponed until a period of cheaper charging cost arrives. When BEV drivers return home and make their charging decisions, the cheaper electricity cost may change their charging choice and the power demand profile.

<table>
<thead>
<tr>
<th>TOU 1</th>
<th>Off-peak $0.06$</th>
<th>Mid-peak $0.12$</th>
<th>On-peak $0.18$</th>
<th>Mid-peak $0.12$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0:00</td>
<td>11:00</td>
<td>14:00</td>
<td>19:00</td>
<td>23:00</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>TOU 2</th>
<th>Off-peak $0.03$</th>
<th>Mid-peak $0.12$</th>
<th>On-peak $0.24$</th>
<th>Mid-peak $0.12$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0:00</td>
<td>11:00</td>
<td>14:00</td>
<td>19:00</td>
<td>23:00</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>TOU 3</th>
<th>Off-peak $0.06$</th>
<th>Mid-peak $0.12$</th>
<th>On-peak $0.18$</th>
<th>Mid-peak $0.12$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0:00</td>
<td>11:00</td>
<td>16:00</td>
<td>21:00</td>
<td>24:00</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>TOU 4</th>
<th>Off-peak $0.03$</th>
<th>Mid-peak $0.12$</th>
<th>On-peak $0.24$</th>
<th>Mid-peak $0.12$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0:00</td>
<td>11:00</td>
<td>16:00</td>
<td>21:00</td>
<td>24:00</td>
</tr>
</tbody>
</table>

Figure 12. Time-of-use electricity rates (unit: $/kWh$).

Figure 13 compares the charging power demand with the constant rate and the four TOU rates under the BEV mass-market scenario. With TOU rates and delayed charging, the demand
profiles become much flatter. The peak power demand decreases dramatically, especially with the TOU 4 that cuts the peak demand at 6 to 7 p.m. by almost 50%. The evening peak loads shift to the off-peak period when the demand is very low with the constant rate. With more vehicles being fully charged overnight, the TOU-rate charging demand declines gradually until 7 a.m., but is still significantly higher than the constant-rate demand. Therefore, TOU rates with delayed charging help distribute the charging power demand more evenly throughout the day and have fewer negative impacts on the grid.

By adjusting TOU pricing based on the charging demands of BEVs, TOU 3 and 4 are able to reduce peak demand by more than TOU 1 and 2 are. The TOU 2 and 4 options, with a larger gap between on-peak and off-peak rates, reduce peak demand slightly and shift more peak demand to off-peak hours than do TOU 1 and 3. Therefore, the negative impacts of charging on the grid could be mitigated by adjusting TOU pricing based on the constant-rate power demand of BEVs.

Overall, cheaper charging costs may affect BEV drivers’ charging decisions. The TOU electricity rate with delayed charging dramatically shifts the peak charging power demand to off-peak hours, especially from midnight to early morning.

![Figure 13. Charging power demand under the BEV mass-market scenario with different electricity rates.](image)

5. Conclusions and Discussions

This paper proposes a CPT-based modeling framework to describe the charging behavior of BEV drivers. The cost functions are introduced to convert the amount of range remaining at the
next charger into the outcomes in the CPT model. BEV drivers decide to charge their vehicles according to the cumulative prospect values. Based on the 2017 NHTS, a BEV mass-market scenario is constructed to represent a mature BEV market in the long term—high market penetration of BEVs, long range, and extensive charging infrastructure. Under the mass-market scenario, this paper applies the CPT model to study charging behavior and its collective effects on the power grid, including battery SOC at the start of charging events, charging timing and location, and charging power demand. In addition, sensitivity analyses with regard to the risk attitude parameters in the CPT model were conducted. Risk preference parameters $\alpha$ and $\beta$ have significant impacts on charging behavior, while the loss aversion parameter $\lambda$ does not. The results show that as BEV drivers display a higher degree of risk-seeking, they tend to charge vehicles at lower SOC levels and a higher proportion of charges start with less than 20 miles of remaining range.

The key findings are as follows. On average, BEV drivers charge their vehicles at 41% SOC. Most charges start with 40~50% SOC. Seventy-three percent of charging events start with less than 50% SOC and 7.5% engage in risky charging with less than 20 miles range remaining. BEV drivers are less likely to charge in the morning, and this type of charging mainly occurs at workplaces. The number of BEVs being charged and the electricity demand reach their peaks in the early evening. The public fast chargers contribute the most significant share of power demand during the daytime. During nighttime, the charging load mainly comes from home charging. Furthermore, we examined the collective effects of public charger network coverage on charging behavior and the power grid. Some of the home charging shifts to charging at the workplace and public spots as the public charger network expands, but home charging still plays the dominant role in BEV charging and contributes the largest share to the power load. The power demand from the public chargers increases significantly with their expansion and has large effects on the grid. Finally, the TOU electricity rate and delayed charging greatly change the charging load profile under the BEV mass-market scenario. The peak charging power demands dramatically shift to off-peak hours from midnight to early morning. If we adjust the TOU pricing based on the charging demand under the constant rate, the charging loads could be distributed more evenly during the day and have fewer negative impacts on the grid. In addition, the proposed model can be used to provide insights to BEV use, charging infrastructure planning, and capacity expansion of the power grid.
One limitation of this research is the lack of behavioral data for calibrating the CPT model parameters. The model uses the experimental parameters set by Tversky and Kahneman (1992). In practice, the model parameters could vary across individuals due to different personalities and risk attitudes. Parameter calibration could be done in the future when charging behavior data are collected from a mature BEV market. Another limitation stems from the assumptions made for the mass-market scenario. This paper makes reasonable assumptions based on previous studies regarding BEV market penetration and charger coverage in a mature market. However, BEV adoption and charging infrastructure development might take place faster than predicted.

**Acknowledgement**

This research is funded by the Vehicle Technologies Office of the U.S. Department of Energy. The authors are solely responsible for the content and views expressed.

**Appendix A**

Table A.1. The CPT-based charging behavior modeling framework parameters.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Dollar year</th>
<th>Source</th>
<th>Adjusted value used in simulation</th>
</tr>
</thead>
<tbody>
<tr>
<td>$e_r$</td>
<td>0.3 kWh/mi</td>
<td>—</td>
<td>U.S. EPA (2017)</td>
<td>—</td>
</tr>
<tr>
<td>$r_a$</td>
<td>20 miles</td>
<td>—</td>
<td>Franke and Krems (2013)</td>
<td>—</td>
</tr>
<tr>
<td>$c_h$</td>
<td>$0.45 for personal local travel; $0.85 for business local travel</td>
<td>2016 U.S. DOT (2016); Dong and Lin (2012); Wu et al. (2015); Wu et al. (2014)</td>
<td>$0.46 for personal local travel; $0.87 for business local travel</td>
<td></td>
</tr>
<tr>
<td>$c_s$</td>
<td>$5</td>
<td>2015</td>
<td>Francfort (2015)</td>
<td>$5.14</td>
</tr>
<tr>
<td>$e_c$</td>
<td>$0.12/kWh</td>
<td>2017</td>
<td>U.S. EIA (2017)</td>
<td>$0.12/kWh</td>
</tr>
<tr>
<td>$c_p$</td>
<td>$109</td>
<td>2016</td>
<td>Moor (2016)</td>
<td>$111.29</td>
</tr>
<tr>
<td>$c_t$</td>
<td>$2.51/mile</td>
<td>2018</td>
<td>TaxiFareFinder (2018)</td>
<td>$2.46/mile</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>0.88</td>
<td>—</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>$\beta$</td>
<td>0.88</td>
<td>—</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>2.25</td>
<td>—</td>
<td>Tversky and Kahneman (1992)</td>
<td>—</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>0.61</td>
<td>—</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>$\delta$</td>
<td>0.69</td>
<td>—</td>
<td>—</td>
<td>—</td>
</tr>
</tbody>
</table>
References


