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Stochastic Modeling of Battery Electric Vehicle Driver Behavior: Impact of Charging Infrastructure Deployment on the Feasibility of Battery Electric Vehicles

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Abstract

A stochastic modeling approach is proposed to characterize battery electric vehicle (BEV) drivers' behavior. The approach uses longitudinal travel data and thus allows more realistic analysis of the impact of the charging infrastructure on BEV feasibility. BEV feasibility is defined as the probability that the ratio of the distance traveled between charges to the BEV range is kept within a comfort level (i.e., drivers are comfortable with driving the BEV when the battery's state of charge is above a certain level). When the ratio exceeds the comfort level, travel adaptation is needed–-use of a substitute vehicle, choice of an alternative transportation mode, or cancellation of a trip. The proposed stochastic models are applied to quantify BEV feasibility at different charging infrastructure deployment levels with the use of GPS-based longitudinal travel data collected in the Seattle, Washington, metropolitan area. In the Seattle case study, the range of comfort level was found to be critical. If BEV drivers were comfortable with using all the nominal range, about 10% of the drivers needed no or little travel adaptation (i.e., they made changes on less than 0.5% of travel days), and almost 50% of the drivers needed travel adaptation on up to 5% of the sampled days. These percentages dropped by half when the drivers were only comfortable with using up to 80% of the range. In addition, offering opportunities for one within-day recharge can significantly increase BEV feasibility, provided that the drivers were willing to make some travel adaptation (e.g., up to 5% of drivers in the analysis).

Keywords

Battery electric vehicle, Range anxiety, Charging infrastructure, GPS-based longitudinal travel data

Disciplines

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Comments

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Abstract

This paper proposes a stochastic modeling approach to characterize battery electric vehicle (BEV) drivers' behavior using longitudinal travel data, thus allowing more realistic analysis of the charging infrastructure impact on BEV feasibility. BEV feasibility is defined as the probability that the ratio of distance traveled between charges and the BEV range is kept within a comfort level (i.e., drivers are comfortable with driving the BEV when the battery's state of charge is above a certain level). When the ratio exceeds the comfort level, travel adaption is needed—using a substitute vehicle, choosing an alternative transportation mode, or canceling a trip. To account for day-to-day variations, travel distances—in terms of daily vehicle miles traveled or trip lengths—are represented by gamma distributions. The actual range of a BEV, influenced by traffic conditions and atmospheric and environmental factors, is regarded as a Weibull-distributed random variable. By assuming trip lengths following a gamma distribution and the number of trips between charges following a Poisson distribution, the between-charge travel distances are characterized by a Poisson-gamma distribution. Building on these probability distributions, BEV feasibility can be evaluated for a heterogeneous driving population.

The proposed stochastic models are applied to quantify BEV feasibility at different charging infrastructure deployment levels, using GPS-based longitudinal travel data collected in the Seattle metropolitan area. In the Seattle case study, the range of comfort level is found to be critical. If BEV drivers are comfortable with using all the nominal range, about 10% of the drivers need no or very little travel adaption (i.e., make changes on less than 0.5% travel days), and almost 50% of the drivers need travel adaption on up to 5% of the sampled days. These percentages drop by half when the drivers are only comfortable with using up to 80% of the range. It is also found that, offering within-one-day recharge opportunities can significantly increase BEV feasibility, provided that drivers are willing to make some travel adaption (e.g., up to 5% in the analysis).

Keywords—Battery electric vehicle; Range anxiety; Charging infrastructure; GPS-based longitudinal travel data.

1 Introduction

Electric powertrains could deliver better performance, higher efficiency, and zero tailpipe emissions. The successful deployment of battery electric vehicles (BEVs) has the potential to reduce oil dependence, improve urban air quality, and reduce greenhouse gas emissions. The limited range and the associated range anxiety are considered as critical barriers for consumer adoption of BEVs (*1, 2*). Opportunities to charge at workplaces and convenient public locations in addition to at home can extend the electric range without additional battery capacity. Thus, an adequate charging infrastructure is considered a technological option for reducing the market barriers to BEVs. To better design the charging infrastructure, forecast market acceptance, and quantify the societal benefits of BEVs, it is essential to understand travelers' driving, charging, and travel adaption behavior. Advances in sensing and communications technologies allow for tracking individual vehicles and for collecting fine-grained spatial and temporal travel data. Despite privacy issues and data ownership concerns, more and more spatial and longitudinal travel datasets from urban travel surveys are made available to researchers through secured accesses (e.g., the Transportation Secure Data Center). Examining travelers' habitual driving behavior using conventional gasoline vehicles can help to develop realistic driver behavioral models, analyze the competiveness of electric powertrain technology, and design a charger network that can best serve BEV customers.

Drivers' travel itineraries, including trip distances, routes, and dwell time at destinations, largely determine whether a BEV is a feasible substitute for the conventional gasoline vehicle. In general, travelers prefer little or no change to their travel plans and being able to charge the vehicle without much inconvenience. However, within-day and day-to-day variations exist in their travel activities. Several studies pointed out that, in plug-in electric vehicle (PEV) energy analysis, it is import to account for not only the average but also the variation in daily travel activities (*3, 4*). Lin and Greene (*5*) showed that ignoring the daily vehicle mile traveled (DVMT) variation would underestimate fuel consumption and overestimate electricity consumption of plug-in hybrid electric vehicles (PHEVs). This effect is more significant when the average DVMT is close to the vehicle's charge-depleting range.

The objective of this study is to stochastically model BEV driving and charging behavior with longitudinal travel data, thus allowing more realistic analysis of the charging infrastructure impact on BEV feasibility in the real-world driving context. In particular, day-to-day variation of a particular driver's activities is represented by gamma-distributed travel distances in terms of DVMTs or trip lengths. User heterogeneity in the traveling population is represented by different shape and rate parameters of the corresponding distributions for different drivers. On the other hand, since driving style, traffic conditions, and atmospheric and environmental effects influence the actual range of the vehicle, BEV range is represented by a Weibull-distributed random variable. Thus, BEV feasibility can be quantified based on driver's travel distance and the vehicle range constraint by the battery capacity. In addition, increased charging infrastructure adequacy offers more within-day recharge opportunities, can potentially reduce the distance traveled between two consecutive charges, and thus increase BEV feasibility. This effect is captured by assuming that the number of trips between charges follows a Poisson distribution. Together with the assumption of gamma-distributed trip lengths, the distance traveled between two charges is represented by a compound Poisson-gamma distribution. The proposed stochastic model allows for quantifying the impact of charging infrastructure deployment levels on BEV feasibility, market penetrations, and the resulting social benefits.

The next section defines the research problem, followed by stochastic formulation of driver behavioral models and BEV feasibility in Sect. 3. After that, a GPS-based longitudinal travel survey dataset is used to calibrate the proposed models and analyze BEV feasibility for the sample population. Finally, conclusions and caveats of the study are discussed in Sect. 5.

2 Problem statement

This paper formulates probabilistic distributions to describe driving and charging behavior from longitudinal travel data and quantifies BEV feasibility for the heterogeneous driving population.

2.1 Driving and charging behavior

Variations in driving distances play an important role in infrastructure planning, market analysis, and energy consumption estimation for alternative fuel and limited-range vehicles. Global positioning system (GPS)-based travel survey data capture real-world travel activities and thus provide a basis for establishing realistic driving behavioral models. In the recent literature, longitudinal vehicle data, collected from conventional gasoline vehicles, have been used to analyze daily driving patterns and infer the market niche for electric vehicles in selected areas, including Winnipeg, Canada (*6*), and the Atlanta, Georgia, greater metropolitan area (*7*). Because of the limited number of BEVs on the road today, charging behavior modeling suffers from the lack of real-world data. One of the most significant efforts in collecting such data is the EV Project launched in 2009. Partnered with automotive companies, charger suppliers, and DOE national laboratories, the EV Project collects data from PEV drivers who qualify and volunteer to participate. The resulting database is expected to characterize vehicle use in diverse topographic and climatic conditions and to evaluate the effectiveness of the charge infrastructure (*8*). Table 1 summarizes the metrics of BEV (i.e., Nissan Leaf) driving and charging behavior observed early in the EV Project based on a nonrepresentative sample.

Table 1 Summary Statistics of BEV Driving and Charging Behavior Observed Early in the EV Project (*8*)

	Mean	Median	Maximum
Trip distance (mi)	6.9	4.0	100.6
DVMT (mi)	30.3	26.8	227.7
Number of trips between charging events	4.2	3	-
Number of charges per day	1.05	0.99	3.22
Trip distance driven between charging events (mi)	28.8	27.1	101

2.2 BEV feasibility

To better understand market barriers, optimize the BEV range, and explore solutions to reduce range anxiety, a quantifiable measure of BEV feasibility is needed. In this paper, *BEV feasibility* is defined as the probability $\tau(\theta)$ that the ratio of distance traveled between charges (c) and the BEV range (r) is kept within an acceptable level (θ).

$$\tau(\theta) = P\left(\frac{c}{r} \leq \theta\right) , \tag{1}$$

where

$\tau(\theta)$ = BEV feasibility at θ level
c = distance traveled between charges
r = BEV's range
θ = the threshold below which drivers are comfortable using BEV for the planned travel

The threshold θ indicates how comfortable drivers are with BEV range. Because of limited away-from-home charging opportunities and range anxiety, early adopters tend to use BEVs for short trips. For example, a BEV-100 driver might be comfortable with using the vehicle for trips as long as 80 miles, indicating that θ equals 0.8. When drivers are familiar with the vehicle performance and are provided with adequate charging opportunities, they might be willing to use the vehicle for longer trips and return home with a nearly empty battery, that is, θ is close to 1.

The proposed BEV feasibility measure can incorporate stochastic driver behavior by incorporating randomly distributed c and r variables. If only night charging at home is considered and c becomes the daily travel distance, the probability that a BEV is feasible (at θ level) for a traveler can be translated to number of days per year or per vehicle's lifetime that a BEV can provide a sufficient range for his/her daily travel. For example, if a vehicle is used on 200 days out of 365 days (*9*), 95% BEV feasibility means that, on average, there are 10 days every year that the BEV cannot be used to fulfill the traveler's travel need. A substitute vehicle, emergency roadside services, or making a detour for charging is needed to compensate the insufficient range. In fact, BEV manufacturers have begun to provide complimentary roadside assistance and rental cars as a means to ease range anxiety.

3 Methodology

In this section, stochastic models are proposed to describe BEV driver behavior and evaluate BEV feasibility. When a BEV is charged only at home, presumably overnight, BEV feasibility at a certain comfort level is dictated by gamma distributed DVMTs and Weibull-distributed vehicle ranges (Sect. 3.1). When within-day charging is considered, the distance between charges is represented by a compound Poisson-gamma distribution. BEV feasibility is determined by trips distances, number of trips and away-from-home charging opportunities (Sect. 3.2).

3.1 BEV feasible with home charging only

At an early market stage, BEV drivers will charge their vehicles after returning home in the evening. For current Nissan Leaf users (as shown in Table 1), the average distance driven between charge events is close to the average DVMT. Therefore, by assuming that a BEV is charged once per day at home to its full capacity, BEV feasibility is defined as the probability that the ratio of daily VMT and the BEV range is within the driver's comfort threshold.

3.1.1 DVMT distribution

DVMT varies among drivers and over time for a particular driver. Variations in DVMT need to be accounted for when analyzing range requirements for meeting daily travel demand and identifying potential market for limited-range vehicles. In the literature, different types of parametric probability distributions have been assumed to characterize DVMT variations as a means to inform the design of electric vehicles and other limited-range vehicles. For example, Traut et al. (*2*) use the exponential family of distributions to fit the multiday travel data of 133 vehicles in Minnesota and assume a Weibull distribution to characterize the daily driving distance variation among drivers. Greene (*10*) assumed and estimated the gamma distribution's parameters using maximum likelihood estimation and odometer data of 2290 households over a period of 36 months. Later, Lin et al. (*11*) validated the gamma distribution assumption and found acceptable accuracy in the context of PHEV energy analysis using longitudinal GPS travel survey data collected from the Seattle metropolitan area over an 18-month period. In this paper, the DVMT of driver *i* is assumed to follow a gamma distribution, that is, $d \sim gamma(\alpha_i, \mu_i)$. The probability density function (PDF) can be written as:

$$f_D(d) = \frac{{\mu_i}^{\alpha_i} d^{\alpha_i - 1} e^{-\mu_i d}}{\Gamma(\alpha_i)}, \text{ for } d > 0, \mu_i > 0, \text{ and } \alpha_i > 0 \quad (2)$$

where

$f_D(d)$ = PDF of daily vehicle miles traveled

α_i = shape parameter for driver *i*

μ_i = rate parameter for driver *i*

By convention, the uppercase letters are used to represent random variables (e.g., *D* denotes random daily VMT), whereas lowercase letters (e.g., *d*) denote the observations generated from the corresponding probability distributions, so called random variates (*12*). The cumulative distribution function (CDF) of the gamma distribution is written as follows:

$$F_D(d) = 1 - \frac{\Gamma(\alpha_i, \mu_i d)}{\Gamma(\alpha_i)} \quad (3)$$

$\Gamma(s, x) = \int_x^\infty t^{s-1} e^{-t} dt$ is the incomplete gamma function.

Figure 1 illustrates the PDF and CDF of an example gamma distribution, characterizing one driver's DVMT distribution. The shape and rate parameters define the mean and mode of the driver's DVMT.

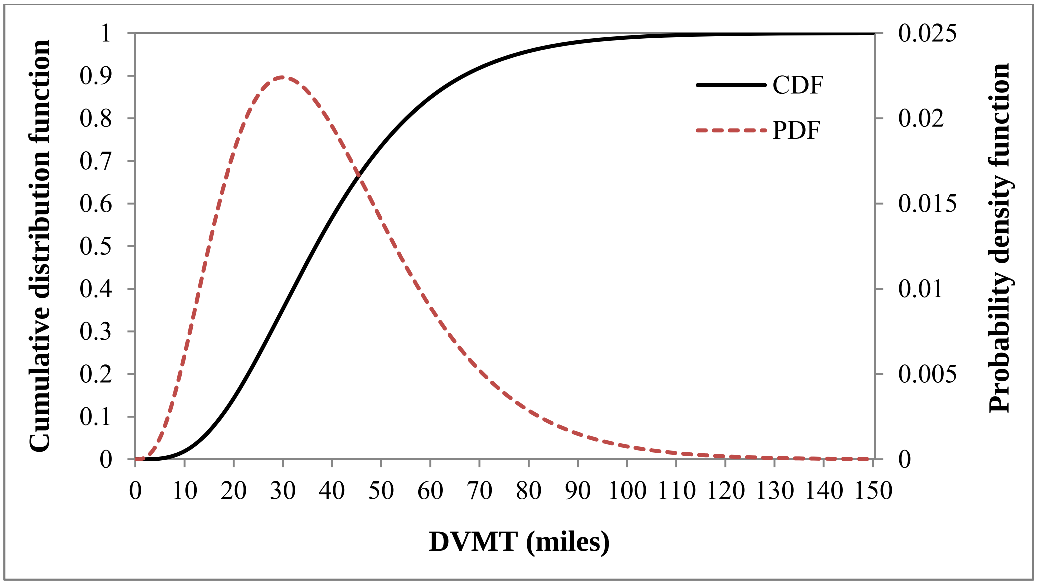


Figure 1. Gamma distribution of DVMTs. In this example, shape parameter $\alpha = 4$ and rate parameter $\mu = 0.1$. The mean and mode of the distribution are 40 and 30 miles, respectively.

3.1.2 BEV range distribution

Driving style, traffic conditions, and atmospheric and environmental effects would affect the actual distance that a BEV could travel on a particular day. Thus, the driving range is represented by a Weibull-distributed random variable, that is,

$$f_R(r) = \beta\lambda^\beta r^{\beta-1}e^{-(\lambda r)^\beta}, \text{ for } r > 0, \lambda > 0, \text{ and } \beta > 1 \ , \tag{4}$$

where

$f_R(r)$ = the PDF of the BEV range
β = shape parameter
λ = rate parameter

Figure 2 demonstrates the distributions of DVMTs and BEV ranges. In this example, a driver travels 40 miles per day on average (representative of an average American driver) and drives a BEV with an average driving range of 76 miles (representative of a Nissan Leaf).

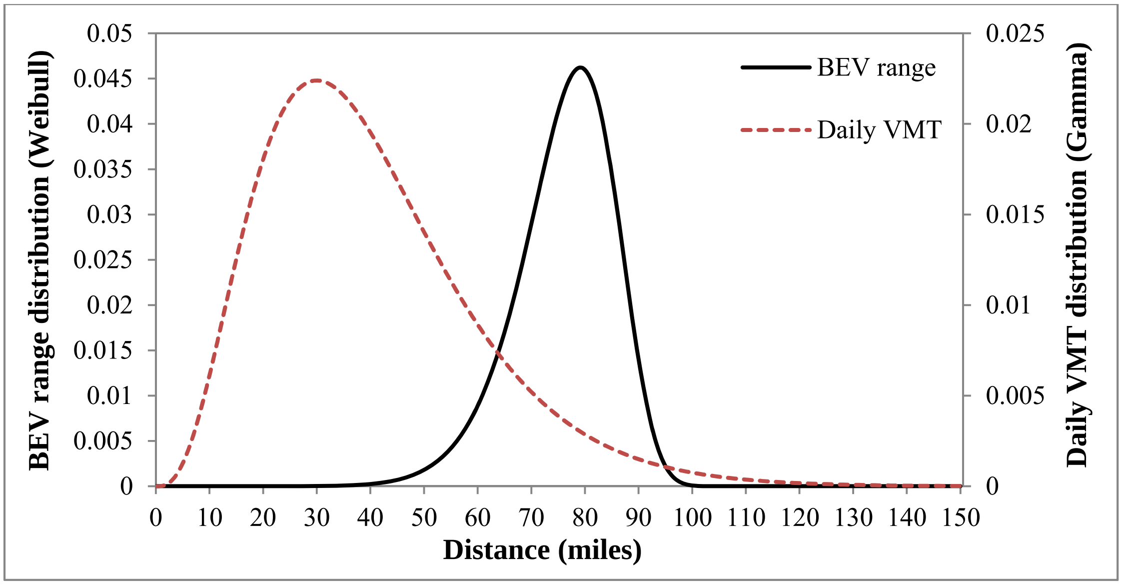


Figure 2. Gamma distribution of DVMT and Weibull distribution of BEV range. In this example, gamma distribution is specified the same as in Figure 1; Weibull distribution's shape parameter $\beta = 10$ and rate parameter $\lambda = 0.0125$. The mean and standard deviation of the BEV ranges are 76 and 9.2 miles, respectively.

3.1.3 Quantify BEV feasibility

As explained earlier, we assume that DVMT (D) and BEV range (R) are independent random variables following gamma and Weibull distributions, respectively. The CDF of the ratio, denoted by random variable $X = D/R$, can be express as (*13*)[1]:

$$F_X(x) = \frac{{\mu_i}^{\alpha_i} x^{\alpha_i}}{\lambda^{\alpha_i}\Gamma(\alpha_i)} \sum_{k=0}^{\infty} \frac{1}{k!(k+\alpha_i)} \Gamma\left(\frac{\alpha_i+\beta+k}{\beta}\right)\left(-\frac{\mu_i x}{\lambda}\right)^k, \text{ for } \beta > 1 \ , \quad (5)$$

where

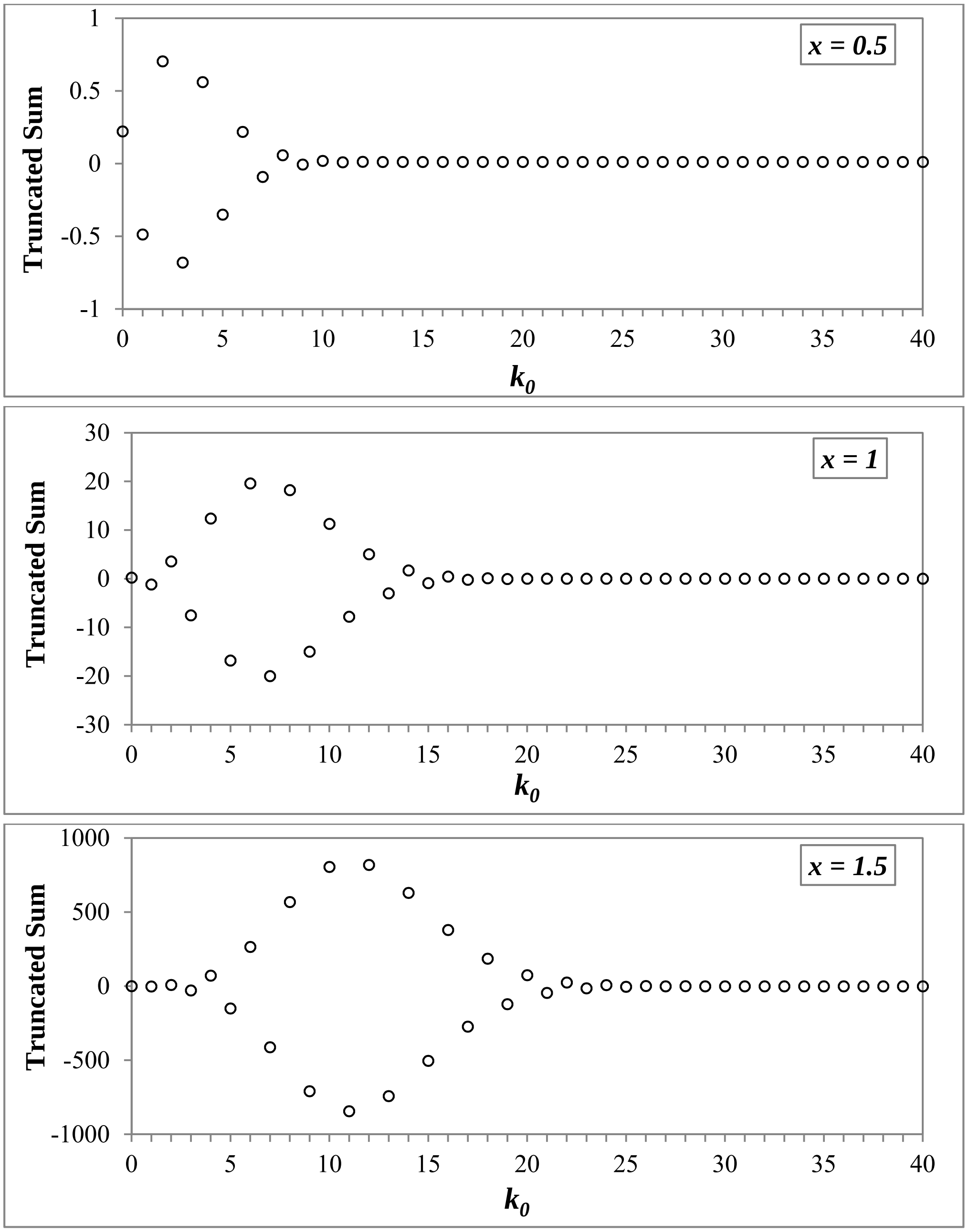
$F_X(x)$ = the CDF, describing the probability of random variable X takes on a value less than or equal to x.

By definition, BEV feasibility at θ level can be written as:

$$\tau(\theta) = F_X(\theta) \ . \quad (6)$$

The closed form representation of the BEV feasibility can greatly reduce the computational burden, when evaluating the measure for a large population and integrating the behavioral model in the infrastructure optimization framework. Note that, although it is written in a closed-form equation, the CDF includes the sum of an infinite series. As the plots in Figure 3 show, the truncated sum, $\sum_{k=0}^{k_0} \frac{1}{k!(k+\alpha_i)} \Gamma\left(\frac{\alpha_i+\beta+k}{\beta}\right)\left(-\frac{\mu_i x}{\lambda}\right)^k$, converges quickly even for $x = 2$. Therefore, only a few terms are needed to approximate the sum of the infinite series.

[1] There is a mistake in the equation derived by Nadarajah and Kotz (2006). The corrected formula is used in the current paper.


x = 0.5
Truncated Sum
k_0
x = 1
Truncated Sum
k_0
x = 1.5
Truncated Sum
k_0

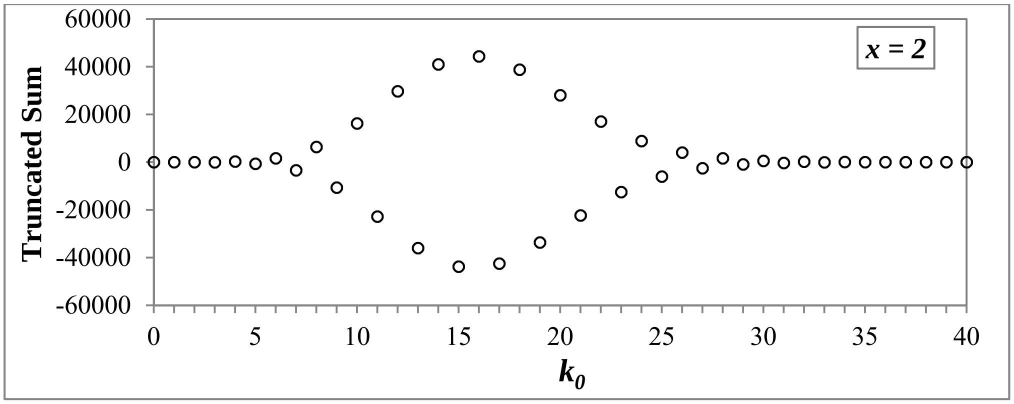


Figure 3. The truncated sum of the infinite series in Equation (5) verse k_0 for $\alpha = 4, \mu = 0.1, \beta = 10, \lambda = 0.0125$, and $x = 0.5, 1, 1.5, 2$.

The PDF and CDF of the D/R ratio are plotted in Figure 4. In this particular example, the probability of the DVMT being less than the driving range of the BEV is 93%. It means that, for 93% of the travel days, the BEV can be used to fulfill the driver's travel need. If the driver prefers returning home with at least 20% of the driving range left, namely a comfort threshold of 0.8, the BEV feasibility drops to 84%.

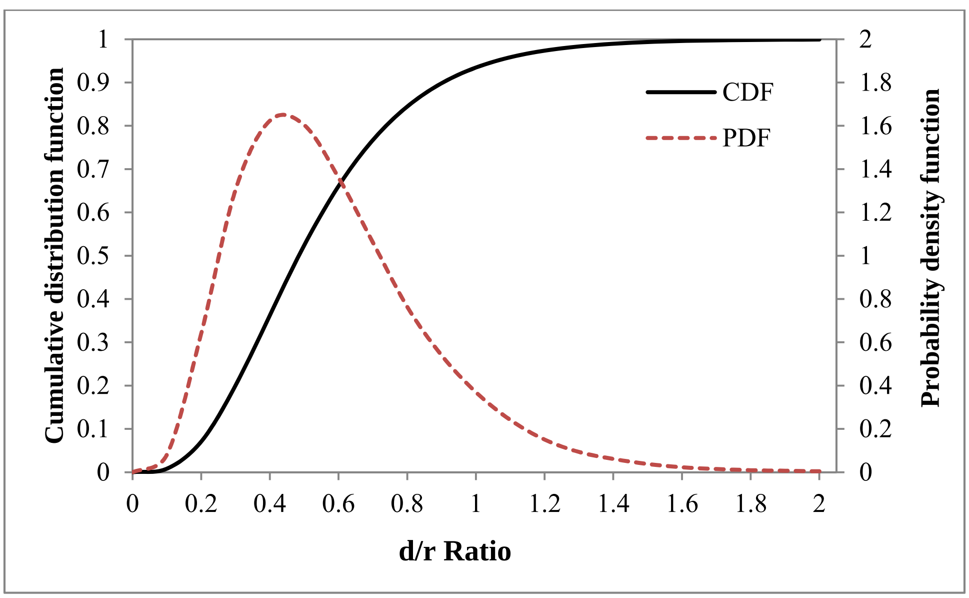


Figure 4. The ratio of gamma distributed DVMTs and Weibull-distributed BEV ranges. In this example, Weibull distribution's shape parameter $\beta = 10$ and rate parameter $\lambda = 0.0125$; gamma distribution's shape parameter $\alpha = 4$ and rate parameter $\mu = 0.1$.

3.2 BEV feasibility considering within-day charging

In the previous section, the number of trips between two charges equals the daily trip frequency, as the BEV is assumed to be charged once per day at home. When away-from-home chargers are available, drivers might charge their vehicles during the day, which reduces travel distance between charges. As a result, miles traveled between two consecutive charges would be less than DVMT. Assuming that the number of trips between charges follows a Poisson distribution and that trip length follows a gamma distribution, the distance traveled between charges can be represented by a compound Poisson-gamma distribution (*14*). By implicitly reflecting charging decision making in the distribution of miles traveled between charges, the impact of charging infrastructure deployment level on BEV feasibility can be quantified.

3.2.1 Distribution of distance traveled between charges

Assume the trip length follows a gamma distribution:

$$f_L(l) = \frac{\mu^{\alpha} l^{\alpha-1} e^{-\mu l}}{\Gamma(\alpha)}, \text{ for } l > 0, \mu > 0, \text{ and } \alpha > 0 \ . \tag{7}$$

The number of trips between two consequent charges, say N_c, follows a Poisson distribution with mean ρ_c, that is,

$$P(N_c = i) = e^{-\rho_c} \frac{{\rho_c}^i}{i!} \ . \tag{8}$$

For example, based on Smart and Schey (2012), on average Nissan Leaf users drove 4.2 trips between charging events, namely $\rho_c = 4.2$.

Therefore, the miles traveled between two charges, namely C, follows the Poisson-gamma distribution.

$$C = \sum_{i=1}^{N_c} L_i \tag{9}$$

The PDF of the compound Poisson-gamma can be written as

$$f_C(c) = e^{-\rho}\delta(c) + \frac{e^{-\rho-\mu c} r_\alpha(\rho\mu^\alpha c^\alpha)}{c} \ . \tag{10}$$

$\delta(c)$ is the Dirac delta function, and

$$r_\alpha(y) = \sum_{i=1}^{\infty} \frac{y^i}{i!\Gamma(i\alpha)} \ . \tag{11}$$

Note that the truncated sum $\sum_{i=1}^{i_0} \frac{y^i}{i!\Gamma(i\alpha)}$ converges quickly. As shown by Withers and Nadarajah (*15*), only a few terms are needed to converge for y to be as large as 10. In the current paper, for the largest possible value that y might take, the truncated sum converges within 20 terms. Thus, the infinite series in Equation (11) can be approximated using the truncated sum of the first 20 terms. Figure 5 shows some example Poisson-gamma distributions of distance traveled between two charges, with varying parameter ρ. With an increasing coverage of the public charging infrastructure, the number of trips between two consecutive charges can be reduced. This leads to a smaller ρ and a higher probability of keeping the distance traveled between two charges within the BEV range. Consequently, BEV is feasible for more drivers on more travel days.

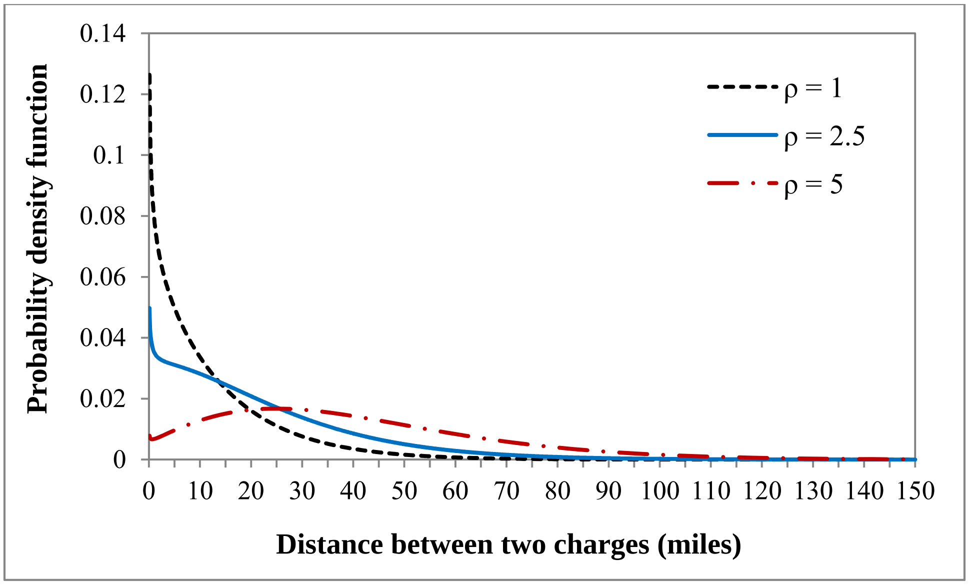


Figure 5. Poisson-gamma distribution of distance traveled between two charges. In this example, shape parameter $\boldsymbol{\alpha = 0.8}$, rate parameter $\boldsymbol{\mu = 0.1}$, and $\boldsymbol{\rho_c = 1, 2.5, 5}$.

3.2.2 Quantify BEV feasibility

Unlike the case discussed in Sect. 3.1.3, there is no closed-form distribution for the ratio of a Poisson-gamma–distributed random variable and a Weibull-distributed random variable. To quantify BEV feasibility considering within-day recharge, the driving range is assumed as a fixed value, namely the mean BEV range, $\bar{R}$. The state of charge of the battery is assumed to reach at least $\theta\bar{R}$ after recharge. The charging time is not explicitly accounted for in this study. When one within-day charge is considered, the BEVs can be charged during the longest time that a vehicle is parked (e.g., at the work place) or using a fast charger (e.g., at a restaurant). Accordingly, the BEV feasibility can be computed using the CDF of the compound Poisson-gamma distribution, as follows.

$$\tau(\theta) = P(c \leq \theta\bar{R}) = \int_0^{\theta\bar{R}} f_C(x)dx \tag{12}$$

4 Results and discussions

The proposed probabilistic BEV driver behavioral models are calibrated using longitudinal GPS travel data. BEV feasibility is quantified for the sample fleet, considering different comfort buffers and charging infrastructure deployment levels.

4.1 GPS-based longitudinal travel survey data

The trip lengths and DVMTs used in this study are extracted from the GPS tracking data collected for the Traffic Choices Study in the Seattle metropolitan area (*16*). The Traffic Choices Study recorded driving activities of 275 volunteer households in the Seattle metropolitan area over an 18-month period (from November 2004 to April 2006). To record and transmit data on a regular basis, the GPS devices instrumented on the participant vehicles are turned on/off when turning on/off the ignition. This allows for continuous collection of vehicles' travel distances, which is an essential requirement for estimating DVMT and trip length distributions.

Travel activities of 382 vehicles with recorded travel for more than half a year (i.e., the number of recorded days is greater than or equal to 183) are extracted from the Traffic Choices Study database. Summary statistics listed in Table 2 are calculated for the sample population; that is, each data point in the sample corresponds to a driver. The DVMT, trip length, and number of trips of a particular driver are averaged over multiple travel days. For example, among the 382 drivers, the maximum average DVMT is 91.61 miles, though in the dataset the maximum one-day travel distance is over 800 miles.

Table 2 Seattle Travel Survey Data Summary Statistics

	Mean	Standard deviation	Minimum	Maximum
Average DVMT (miles)	31.88	12.51	5.13	91.61
Average trip length (miles)	6.35	2.24	1.56	16.02
Average number of trips	5.07	1.32	1.80	9.50

In this paper, we assume that the motorists' travel behavior remains unchanged when switching to BEV technologies. Though drivers who adopted BEVs might change their travel behavior, such travel adaption is usually associated with an added cost or certain inconvenience. At the current stage, there is no clear evidence on how BEV drivers will adapt to the limited vehicle range and long charging time. Therefore, assuming no behavior adaption might be a practical and relevant approach for market assessment and policy discussion.

4.2 BEV feasibility with home charging only

The shape and scale parameters of 382 drivers' DVMT distributions have been calibrated (*11*). BEV feasibility at different comfort levels (i.e., $\theta = 0.6$, 0.8, and 1) are compared in Figure 6. When θ equals 1, that is, BEV is considered feasible as long as the DVMT is less than the driving range, 10% of the drivers needs little adaption (less than 0.5% of travel days) to use the BEV for all travel days. When θ is decreased to 0.6, reflecting early adopters' range anxiety, only 2% of the drivers can use a BEV on almost all travel days. A comfort level of 0.8 could reflect a moderate degree of range anxiety. It might also address the fact that some drivers opt for charging the battery to its 80% capacity either for battery protection or constrained time for charging.

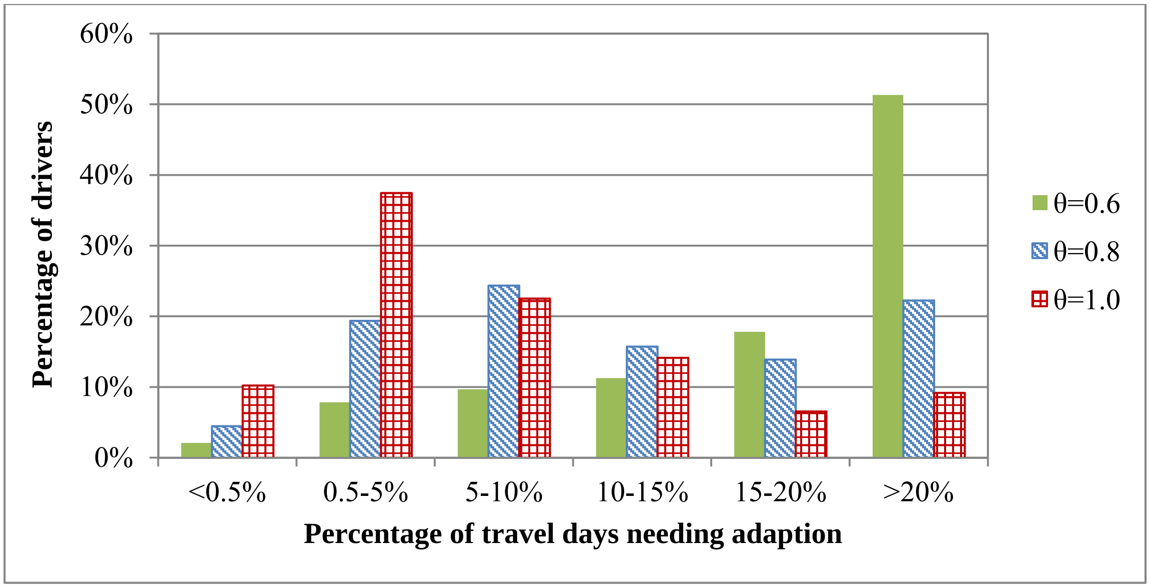


Figure 6. BEV feasibility of the sample fleet assuming home charging only.

If up to 5% travel adaption is acceptable, almost half of the fleet could switch to a BEV, assuming drivers are comfortable with using all the nominal range (i.e., $\theta = 1$). This percentage drops by half, to about a quarter of the fleet, when the comfort level is 0.8. Moreover, if drivers are comfortable with using up to only 60% of the range, the percentage of drivers who can tolerate 5% travel-day adaption drops significantly to about 10%. Note that, among all the participating households, more than half of the households own multiple vehicles. If a household owns one BEV and one conventional vehicle, for a travel day with anticipated long trips, the drivers in the household could switch their vehicles to accommodate the travel. Therefore, in a multi-vehicle household, if a driver of a BEV also has access to a conventional vehicle, making travel adaption for 5% of travel days would not be too difficult.

4.3 BEV feasibility considering within-day charging

The shape and scale parameters of 382 drivers' trip length distributions, as well as the average trip frequencies, are estimated using the GPS data set. BEV feasibility is evaluated for three scenarios: (1) The "no within-day charge" scenario assumes no within-day charges, as in the previous section that assumes home charging only. The number of trips between charges equals to the daily trip frequency. The Poisson-gamma distribution of each driver's between-charge travel distance is characterized by three parameters defined in Equations (7) and (8). This distribution serves as the baseline. (2) The "one within-day charge" scenario is designed to reflect the fact that, when the charging infrastructure improves, more within-day charge opportunities will be available. Each driver is assumed to recharge the battery once, somewhere away from home, which reduces the average number of trips between charges by half. (3) The "charge everywhere" scenario represents the "ideal" situation where the driver can charge the vehicle wherever he/she stops. The number of trips between charges is reduced to 1. The comfort level is assumed to be 0.8 in all three scenarios.

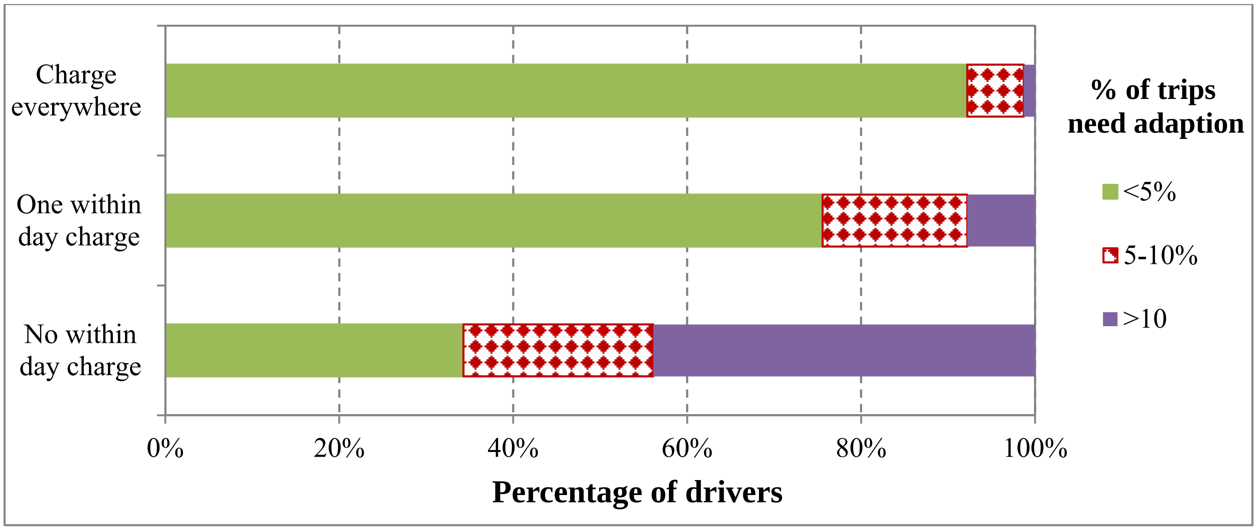


Figure 7. BEV feasibility of the sample fleet considering a within-day charge ($\theta = 0.8$).

The stacked bar chart in Figure 7 shows that, without away-from-home charging, about one-third of the drivers can use BEVs for most of their travels (i.e., more than 95%, shown in green solid bars). By offering one within-day recharge opportunity for each driver, this percentage is increased to about 75%. When chargers are available "everywhere," 99% of the drivers can use BEVs to fulfill 90% of their travel needs.

5 Conclusions

Aimed at linking charging infrastructure deployment and BEV range limitation, this study proposes, formulates, and applies a stochastic metric, called BEV feasibility, defined as the probability that the ratio of distance traveled between charges and the nominal range of the BEV is kept within an acceptable level. Travel distances, in terms of daily vehicle miles traveled or trip lengths, are represented by gamma distributions. The actual range of a BEV, influenced by traffic conditions and atmospheric and environmental factors, is regarded as a Weibull-distributed random variable. The between-charge travel distances are characterized by a Poisson-gamma distribution. The BEV feasibility metric is then applied to the GPS-based longitudinal travel dataset collected in the Seattle metropolitan area for understanding the BEV feasibility at different charging infrastructure deployment levels.

The main caveat of the study is that the charging decision is modeled implicitly via the assumption of some PDFs. Explicit formulation of charging decisions in response to gasoline and electricity prices, location and user-friendliness of chargers, and trip chains is desirable in future research. The empirical findings from this study are based on one region's data and might not be applicable for other regions. More regional studies using the proposed metric are thus recommended.

Despite these shortcomings, the study demonstrates a new method by explicitly modeling the range comfort level and recognizing the stochastic nature of travel distance, trip frequency, and BEV range. In the Seattle case study, the range comfort level is found to be critical. If BEV drivers are comfortable with using all the nominal range, about 10% of the vehicles need no or very little travel adaption (i.e., make changes on less that 0.5% travel days), and almost 50% of the vehicles need travel adaption on up to 5% of the sampled days. But if they are comfortable with using up to only 60% of the range, the percentage of drivers who can tolerate a 5% travel day adaption drops significantly to about 10%. This suggests that BEV feasibility can be improved by raising consumers' range comfort level. For example, provided with roadside assistance or informed of nearby chargers, BEV drivers might be more comfortable with using all the driving range. It is also found that, offering within-day recharge opportunities can significantly increase BEV feasibility, provided that drivers are willing to make some travel adaption, e.g., up to 5% in the analysis. If no adaption is made (i.e., less that 0.5% in the analysis), even with chargers everywhere, BEVs might not be considered feasible by the majority of the drivers.

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