Electric Energy and Power Consumption by Light-Duty Plug-In Electric Vehicles

Di Wu, *Student Member, IEEE*, Dionysios C. Aliprantis, *Senior Member, IEEE*, and Konstantina Gkritza

***Abstract*—This paper proposes methodologies to estimate the electric energy and power consumption by light-duty plug-in electric vehicles (PEVs). Using the travel patterns of light-duty vehicles in the U.S. obtained from the 2009 National Household Travel Survey, the PEVs' energy and power consumption are estimated for two uncontrolled charging scenarios.**

***Index Terms*—Land vehicles, load forecasting, probability, road vehicle electric propulsion, stochastic approximation.**

NOMENCLATURE

a	All-electric range.
c_{fr}	Fraction of daily vehicle miles traveled (VMT) in all-electric mode.
d	Charge-depleting range.
$E(\mathbf{x})$	Expected value of random variable (RV) $\mathbf{x}$.
f_x	Probability density function of RV $\mathbf{x}$.
F_x	Cumulative distribution function of RV $\mathbf{x}$.
h_{e}	Portion of h_{tr} from the electrical traction subsystem.
h_{tr}	Tractive energy per mile at the wheels.
m	Daily VMT.
m_{a}	Daily VMT in all-electric mode.
m_{cd}	Daily VMT in charge-depleting mode.
$M_N(t)$	Sample mean of power consumption at time t over a sample size N.
W_n	Daily energy consumption of a fleet of n PEVs.
$\mathbf{x}$	Random variable.
$\mathbf{x}(t)$	Stochastic process.
$\hat{x}$	Estimate of a random variable's expected value.
$Y_n(t)$	Power consumption at time t of a fleet of n PEVs.
$\delta(x)$	Dirac delta function.
ϵ	Daily electric energy consumption of a PEV.
η	Wall-to-wheels efficiency.
ξ	Fraction of tractive energy derived from electricity.
$\sigma(\mathbf{x})$	Standard deviation of RV $\mathbf{x}$.

Manuscript received November 17, 2009; revised November 21, 2009 and March 22, 2010; accepted May 31, 2010. Date of publication July 26, 2010; date of current version April 22, 2011. This material is based upon work supported by the National Science Foundation under Grant No. 0835989. Paper no. TPWRS-00890-2009.

D. Wu and D. C. Aliprantis are with the Department of Electrical and Computer Engineering, Iowa State University, Ames, IA 50011 USA (e-mail: dwu@iastate.edu; dali@iastate.edu).

K. Gkritza is with the Department of Civil, Construction, and Environmental Engineering, Iowa State University, Ames, IA 50011 USA (e-mail: nadia@iastate.edu).

Digital Object Identifier 10.1109/TPWRS.2010.2052375

I. INTRODUCTION

PLUG-IN electric vehicles (PEVs) have been identified as a vital technology to reduce carbon emissions and dependence on petroleum [1]. An expectation has been set for one million PEVs on U.S. roads alone by 2015. PEVs—either plug-in hybrid electric vehicles (PHEVs) or pure electric vehicles (EVs)—adopt similar drivetrain configurations as hybrid electric vehicles (HEVs) [2], but are characterized by larger battery capacity and the capability of being recharged from the electric grid. Therefore, a portion of the energy obtained from gasoline can be replaced by electricity from the power system.

The emerging fleet of PEVs will introduce a considerable amount of additional load on the power system. Several studies have been devoted to this topic during the last few years, at both national and regional scales [3]–[10]. In most of these, all PEVs in a fleet are assigned the same all-electric range (AER)[1] and the corresponding amount of usable energy in their batteries. The daily electric energy consumption is then estimated assuming that the charging frequency is once per day. Power consumption is typically estimated based on the results of the energy calculations.

Previous work has adopted assumptions that lead to inaccurate results. First, some PEVs will be incapable of being always driven in all-electric mode, but rather they will be operated in blended mode, requiring occasional support from their internal combustion engine [11]. Second, the electric energy consumption is often estimated without considering vehicle travel patterns. For example, in [5]–[7] and [10], all vehicles leave home with fully charged batteries and return home with the entire usable energy exhausted. However, some PEVs may not travel at all on a day, or will travel less than their electric range, thus consuming only a fraction of their battery energy. Therefore, this leads to an overestimation of electric energy consumption. Third, when estimating power consumption, some studies use models that represent situations unlikely to occur. In [3], off-peak electricity is consumed by the entire PEV fleet, whereas in reality, some vehicles may be traveling, and some will be unable to receive any more energy from the grid because their batteries

[1]AER is defined as the distance from the beginning of a driving cycle with initially fully charged battery to the exact point at which the internal combustion engine turns on [11].

will be fully charged. In [6], all PEVs begin charging simultaneously at 5 p.m. or 10 p.m. In the uncontrolled charging scenarios of [7], all PEVs leave home evenly between 8 a.m. and 9 a.m., and return home between 6 p.m. and 9 p.m. Obviously, these simplifying assumptions do not account for real-world travel patterns, so the validity of the results obtained is questionable.

Herein, a more accurate methodology to estimate the electric energy and power consumption of light-duty PEVs is set forth. The analysis is based on the actual U.S. travel patterns, as captured by the 2009 National Household Travel Survey (NHTS). The formulation is probabilistic and makes use of the NHTS statistical data to represent the travel patterns of the U.S. light-duty vehicle (LDV) fleet.[2] LDV travel accounts for 92% of the highway vehicle miles traveled (VMT) [13], 76% of the energy consumed by highway travel modes [14], and 74% of the carbon dioxide emissions from on-road sources [15].

The remainder of this paper is structured as follows: Section II discusses travel patterns and the NHTS database. Section III describes the basics of PEV operation. In Section IV, an analytical methodology to estimate PEV electric energy consumption is presented. Section V illustrates a simulation-based methodology for calculating PEV power and energy consumption. In Section VI, some concluding remarks are offered.

II. Travel Patterns

A fundamental underlying assumption of this analysis is that the driving behavior of PEV owners will be similar to the behavior of drivers of conventional nonelectric vehicles. In other words, it is assumed that PEVs will not affect daily travel patterns and lifestyles in any significant fashion: people will have the same travel demands as before, and will use their vehicles (either PEVs or not) to run the same everyday errands. It could be argued that this assumption is not entirely correct, because PEV owners may drive differently than the average driver. This change could be attributed to either a PEV (being a different type of vehicle) impacting the travel patterns, or to specific attributes of PEV owners, such as increased environmental awareness or income level [16]. At least initially, when PEVs enter the market, this argument could be valid. However, as the penetration of PEVs increases, then the PEV driver will "converge" to the average driver.

The 2009 NHTS collects information on the travel behavior of a national representative sample of U.S. households, such as mode of transportation, trip origin and purpose, and trip distance. The database files can be found online at [17]. For this analysis, information contained in the "travel day trip" database file (DAYPUBLL) and the "vehicle" database file (VEHPUBLL) is needed. The survey consists of 150 147 households and 294 408 LDVs. Table I shows the distribution of the LDV fleet by vehicle class, in urban or rural areas in the U.S.

It was observed that vehicle travel patterns vary by household area (urban or rural) and day of the week (weekday or weekend). Therefore, the vehicle travel pattern is examined separately for the following four cases: 1) trip in an urban area on a weekday ("urban weekday"), 2) trip in an urban area during the weekend ("urban weekend"), 3) trip in a rural area on a weekday ("rural weekday"), and 4) trip in a rural area during the weekend ("rural weekend"). These four area/day cases are represented by 141 011; 56 677; 68 979; and 27 741 LDVs, respectively. Because the NHTS data set contains trips spread throughout a year, and because herein these trips are not further distinguished with respect to the date they occurred on, the results obtained should be interpreted as statistics of energy and power consumption for an arbitrary urban/rural weekday/weekend of the year.

TABLE I
Distribution of LDV Fleet by Vehicle Class and Area Type

	Car	Van	SUV	Pickup truck
Urban	56.9%	9.2%	19.6%	14.3%
Rural	42.9%	8.0%	19.1%	30.0%
All	53.0%	8.9%	19.4%	18.7%

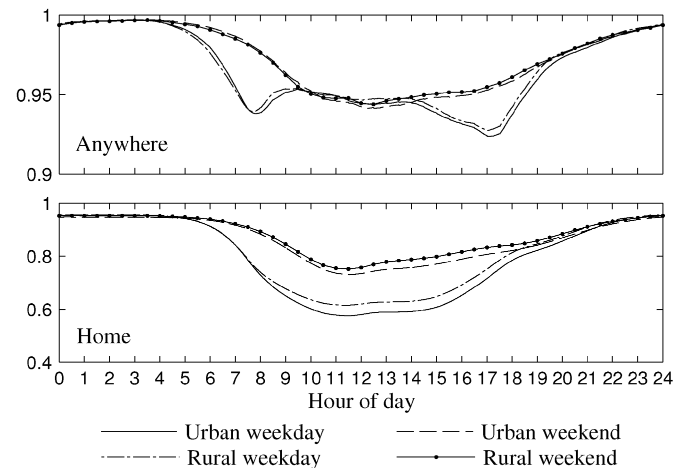


Fig. 1. Probability of a random LDV to be parked. (Top) Parked anywhere (including at home). (Bottom) Parked at home.

It should be noted that not all LDVs travel on a given day. The probability that a random LDV (in an urban or a rural area) travels (on a random weekday or weekend) can be estimated by using the information included in the DAYPUBLL and VEHPUBLL files. The derived vehicle travel probabilities are in the range 45%–65%. Previous reports have not taken this fact explicitly into account, and have assumed that all PEVs travel every day, resulting in an overestimation of the energy and power consumption [4].

The parking start/end times and location (e.g., home, work, shopping mall, etc.) for every vehicle throughout the day can be extracted from the vehicle database. This kind of information is required for the determination of the charging profile. The probability of a vehicle to be parked anywhere (including at home) or be parked at home is shown in Fig. 1. These plots provide valuable insights to comprehend the outcome of the power consumption estimation, which will be carried out in Section V.

III. Basics of PEV Operation

There is still uncertainty regarding the size and configuration of future PEVs. The market will contain an array of models with different drivetrain topologies and electric ranges. Some PEVs may be pure EVs, without an internal combustion engine. Others may be designed to operate initially in EV mode, and

[2]The U.S. fleet of light-duty vehicles consists of cars and light trucks, including minivans, sport utility vehicles (SUVs), and trucks with gross vehicle weight less than 8500 pounds [12].

then switch to a charge-sustaining mode (e.g., series PHEVs). However, a clearly defined switch from one mode of operation to the other is not the only possible operation strategy. PEVs can be also operated in blended mode, where the internal combustion engine occasionally assists the electric motor in supplying the tractive energy (e.g., a parallel PHEV with a relatively weak electric traction motor).

Therefore, the operation of PEVs can be classified into the charge-depleting (CD) mode and the charge-sustaining (CS) mode [11]. In CD mode, the vehicle is gradually depleting the energy stored in the batteries, with either a fraction of or the entire tractive energy coming from the battery pack. The total distance that a PEV can travel in CD mode with its batteries initially fully charged is defined as its "charge-depleting range" (CDR). After all the usable battery energy is exhausted, the operation of the PEV enters CS mode, where it is operated similarly to a conventional HEV, with all tractive energy derived from the fuel. Several of the previous studies treat CD operation the same as all-electric (i.e., EV) operation. In those, the designation "PHEV-x" simply represents a PHEV that, starting with a fully charged battery, can travel x miles in EV mode without consuming any fuel in the tank. In order to encompass all possible operating strategies, this analysis is performed based on the more comprehensive concepts of CD operation and CDR.

To represent the uncertainty regarding future PEVs, a probabilistic formulation is provided, with all parameters expressed as random variables (RVs). Herein, RVs are denoted by boldface symbols; for instance, the daily VMT $(\mathbf{m})$ or the tractive energy per mile at the wheels $(\mathbf{h}_{\rm tr})$ of a random PEV.

The tractive energy per mile that is provided by the battery in CD mode $(h_{\rm e})$ is a fraction (ξ) of the total tractive energy per mile $(h_{\rm tr})$ required to overcome aerodynamic drag, rolling resistance, and vehicle inertia [9], [11]: $h_{\rm e} = \xi h_{\rm tr}$. The tractive energy depends on several parameters, such as vehicle weight, aerodynamic drag coefficient, personal driving habits, geographic location, driving cycle, weather conditions, road conditions, and others. In this study, $\mathbf{h}_{\rm tr}$ is assumed to have a normal distribution with mean value determined by the vehicle class—0.21 kWh/mile for cars, 0.33 kWh/mile for vans, 0.37 kWh/mile for SUVs, and 0.40 kWh/mile for pickup trucks[3]—and standard deviation equal to 10% of the mean.

In order to capture the entire spectrum of possible PEV operation—from "light" parallel to pure EV, it is assumed that $\boldsymbol{\xi}$ is an RV with the following PDF:

$$f_{\xi}(x) = \begin{cases} 1, & \text{for } 0.2 \leq x < 1 \\ 0.2\delta(x-1), & \text{for } x = 1. \end{cases} \tag{1}$$

In other words, it is assumed that 20% of PEVs will be operated as pure EVs in CD mode. Furthermore, it is assumed that $\boldsymbol{\xi}$ is independent of $\mathbf{h}_{\rm tr}$, leading to

$$E(\mathbf{h}_{\rm e}) = E(\boldsymbol{\xi})E(\mathbf{h}_{\rm tr}). \tag{2}$$

[3]These numerical values were derived using information found in [9], [18], and [19].

This is a safe assumption to make as long as future PEV drivetrain topologies will be independent of vehicle class. However, if, for instance, smaller vehicles will tend to be correlated with higher ξ, while larger vehicles with smaller ξ, this assumption will have to be revisited. Nevertheless, the above assumptions are warranted by lack of better information presently.

IV. Electric Energy Consumption

This section presents an analytical methodology to estimate the energy consumption of PEVs, under the assumption that charging occurs once per day (after all trips are completed). A methodology to estimate the energy when multiple daily charges in-between trips are possible is presented in Section V.

For a random PEV in an urban (or rural) area, on a random weekday (or weekend), the daily electric energy consumption $(\boldsymbol{\epsilon})$ depends on the product of two RVs, namely $\mathbf{h}_{\rm e}$ and $\mathbf{m}_{\rm cd}$ (daily VMT in CD mode):

$$\boldsymbol{\epsilon} = \frac{1}{\eta}\mathbf{h}_{\rm e}\mathbf{m}_{\rm cd} \tag{3}$$

where $\eta = 67.2\%$ accounts for the overall wall-to-wheels efficiency, and is assumed to be constant.[4] The VMT in CD mode depend on both the travel patterns and the CDR. When assuming that the charging frequency is once per day and that the PEV starts with a fully charged battery, $m_{\rm cd}$ can be expressed as a function of VMT (m) and CDR (d):

$$m_{\rm cd} = \begin{cases} m, & \text{for } m \leq d \\ d, & \text{for } m > d. \end{cases} \tag{4}$$

If $\mathbf{h}_{\rm e}$ is assumed to be independent of $\mathbf{m}$ and $\mathbf{d}$, then $\mathbf{h}_{\rm e}$ is independent of $\mathbf{m}_{\rm cd}$. Again, this simplifying assumption—namely, that drivetrain topology, vehicle class, VMT, and CDR are all mutually independent—is required to proceed with the analysis due to insufficient data (but it is recognized that it might not portray reality accurately). Under these assumptions, the expected value of $\boldsymbol{\epsilon}$ is

$$E(\boldsymbol{\epsilon}) = \frac{1}{\eta}E(\mathbf{h}_{\rm e})E(\mathbf{m}_{\rm cd}). \tag{5}$$

A. Previous Work

In previous studies, it is often assumed that PEVs are operated as pure EVs within their CD range $(\xi = 1)$. As a result, the CDR (d) obtains the meaning of an AER (a), and $\mathbf{h}_{\rm e}$ becomes synonymous to $\mathbf{h}_{\rm tr}$. In this case, (5) becomes

$$E(\boldsymbol{\epsilon}) = \frac{1}{\eta}E(\mathbf{h}_{\rm tr})E(\mathbf{m}_{\rm a}) \tag{6}$$

where $\mathbf{m}_{\rm a}$ is the daily VMT in all-electric mode, as expressed in (4) with d replaced by a. In [5]–[7] and [10], it is assumed

[4]It is assumed that the efficiencies of charger, battery (roundtrip), on-board power electronics, traction motor, and mechanical transmission plus accessory loads (e.g., air-conditioning, on-board electronics) are: 95% [9], 92% [20], 95% [9], [21], 92% [21], and 88% [22], respectively; this results in an overall efficiency from the wall outlet to the wheels of 67.2%. In particular, the selected value for efficiency of mechanical transmission and accessory loads (88%) represents the overall efficiency of a fleet of PEVs that consists of: hybrid electric vehicles with gearbox and mechanical driveline, and pure EVs or series PEVs that drive the wheels and power the accessory loads directly.

further that $m_{\rm a} = a$. In other words, it is assumed that all PEVs are operated as pure EVs until they completely deplete their batteries by being driven at least as far as their all-electric range on a daily basis. Hence, (6) becomes

$$E(\boldsymbol{\epsilon}) = \frac{1}{\eta}E(\mathbf{h}_{\rm tr})a. \tag{7}$$

This estimation is simple and facilitates calculations, but it is inaccurate because the effect of travel patterns on the energy consumption is ignored. The estimated energy consumption becomes equal to the entire usable energy, irrespective of how a PEV travels.

In fact, the expected value of daily VMT powered from electricity is only a fraction of the expected daily VMT. In order to include effects of travel patterns on the electric energy consumption, [18] defined a "battery usage factor" as a function of AER based on the 1995 Nationwide Personal Travel Survey data.[5] This can be expressed as

$$c_{\rm fr}(a) = \frac{E(\mathbf{m}_{\rm a})}{E(\mathbf{m})} = \frac{\int_0^a x f_m(x)dx + a\int_a^\infty f_m(x)dx}{\int_0^\infty x f_m(x)dx}. \tag{8}$$

Replacing $E(\mathbf{m}_{\rm a})$ by $c_{\rm fr}(a)E(\mathbf{m})$ in (6) yields

$$E(\boldsymbol{\epsilon}) = \frac{1}{\eta}E(\mathbf{h}_{\rm tr})c_{\rm fr}(a)E(\mathbf{m}). \tag{9}$$

Such an estimation was performed in [3] and [4].

Although (9) is more accurate than (6) and (7), blended mode operation ($\xi < 1$) is still not considered. Moreover, rather than being assigned a unique value a, the CDR (instead of the AER) should be represented by a random variable. In order to take these facts into account, an improved estimation method is proposed in the next subsection.

B. Proposed Method

Substituting (2) into (5) yields the more general formula

$$E(\boldsymbol{\epsilon}) = \frac{1}{\eta}E(\boldsymbol{\xi})E(\mathbf{h}_{\rm tr})E(\mathbf{m}_{\rm cd}). \tag{10}$$

One can proceed with calculations of the three expected values in the right-hand side of (10) as follows.

1) The first term, $E(\boldsymbol{\xi})$, is the mean value of the distribution of the PEV drivetrain electrification parameter (see Section III), which is equal to 0.68 for the proposed PDF (1).
2) The second term is $E(\mathbf{h}_{\rm tr}) = \sum_{k=1}^4 r_k E(\mathbf{h}_{{\rm tr},k})$, where r_k are the ratios of different vehicle classes (Table I), and $E(\mathbf{h}_{{\rm tr},k})$ are given in Section III. The results are provided in Table II.
3) The calculation of the third term, $E(\mathbf{m}_{\rm cd})$, requires knowledge of the PDF of $\mathbf{m}_{\rm cd}(f_{m_{\rm cd}})$. Given that $\mathbf{m}$ and $\mathbf{d}$ are assumed independent, the corresponding CDF can be expressed in terms of probabilities as

$$\begin{aligned} F_{m_{\rm cd}}(x) &= P[\mathbf{m}_{\rm cd} \le x] = P[\mathbf{d} \le x] + P[\mathbf{m} \le x, \mathbf{d} > x] \\ &= P[\mathbf{d} \le x] + (P[\mathbf{m} \le x] - P[\mathbf{m} \le x, \mathbf{d} \le x]). \end{aligned} \tag{11}$$

Differentiating (11) yields, after manipulations

$$f_{m_{\rm cd}}(x) = f_m(x)\int_x^\infty f_d(v)dv + f_d(x)\int_x^\infty f_m(u)du. \tag{12}$$

The above equation highlights the interplay between travel patterns and technological advances when determining $E(\mathbf{m}_{\rm cd})$. The PDF f_m can be readily extracted from the 2009 NHTS data. For f_d, two distinct cases are considered, namely two log-normal distributed RVs, $f_{d,1}$ and $f_{d,2}$, with $(E(\mathbf{d}), \sigma(\mathbf{d}))$ equal to (40, 10) and (70, 20), respectively.[6] These two hypothetical cases are devised to highlight the effect on energy consumption of possible future technological improvements (which could enable longer CDRs).

The electric energy consumption estimation results are provided in Table II. The following observations confirm *a priori* expectations: 1) vehicles in rural areas consume more energy than vehicles in urban areas; 2) during the weekends, the energy consumption is smaller.

The formulation using RVs also allows calculation of the standard deviation of the daily energy consumption. This is found by

$$\begin{aligned} \sigma(\boldsymbol{\epsilon}) &= \sqrt{E(\boldsymbol{\epsilon}^2) - E^2(\boldsymbol{\epsilon})} \\ &= \sqrt{E(\boldsymbol{\xi}^2)E\left(\mathbf{h}_{\rm tr}^2\right)E\left(\mathbf{m}_{\rm cd}^2\right)/\eta^2 - E^2(\boldsymbol{\epsilon})} \end{aligned} \tag{13}$$

where RV independence has been assumed. Moreover, $E(\boldsymbol{\xi}^2) = \int_0^1 x^2 f_\xi(x)dx$, $E(\mathbf{m}_{\rm cd}^2) = \int_0^\infty x^2 f_{m_{\rm cd}}(x)dx$, and $E(\mathbf{h}_{\rm tr}^2) = \sum_{k=1}^4 r_k E(\mathbf{h}_{{\rm tr},k}^2) = \sum_{k=1}^4 r_k[E^2(\mathbf{h}_{{\rm tr},k}) + \sigma^2(\mathbf{h}_{{\rm tr},k})]$. These calculations are straightforward to perform once the PDFs have been defined.

The results are provided in Table II. The standard deviations are large compared to the expected values. Hence, the daily electric energy consumption of an individual PEV cannot be precisely predicted. However, the results can be utilized to estimate the overall energy consumption of a PEV fleet. Assuming there are n PEVs, the total daily energy consumption, $\mathbf{W}_n = \sum_{i=1}^n \boldsymbol{\epsilon}_i$, is also a random variable. If the $\boldsymbol{\epsilon}_i$'s are assumed independent, then the covariance of any two $\boldsymbol{\epsilon}_i$ and $\boldsymbol{\epsilon}_j$ is zero.[7] Hence, for identically independently distributed $\boldsymbol{\epsilon}_i$'s, $E(\mathbf{W}_n) = nE(\boldsymbol{\epsilon})$, $\sigma(\mathbf{W}_n) = \sqrt{n}\sigma(\boldsymbol{\epsilon})$, and the coefficient of variation $\sigma(\mathbf{W}_n)/E(\mathbf{W}_n)$ is proportional to $1/\sqrt{n}$. For a fleet size of one million "urban-weekday" PEVs with $E(\mathbf{d}) = 40$ miles, the energy consumption has $E(\mathbf{W}_n) = 4,160$ MWh and $\sigma(\mathbf{W}_n) = 5.36$ MWh. In addition, according to the central limit theorem, $\mathbf{W}_n$ will have an approximately normal distribution with the above parameters. Note that the estimated electric energy consumption is at the outlet, excluding transmission and distribution losses.

[5]In [23], a "utility factor" is similarly defined, except that the concept of CDR is used rather than AER. This factor represents the fraction of daily VMT in CD mode.

[6]The log-normal PDF has the convenient property of $(0, +\infty)$ support. The parameters (40, 10) and (70, 20) represent the expected value and standard deviation of the lognormal distribution (i.e., they do not represent the parameters of the RV's natural logarithm).

[7]In reality, the covariance will not be zero because of external factors, such as the weather or gasoline prices, which can affect travel demand. However, this is not taken into account in this study.

TABLE II
DAILY ENERGY CONSUMPTION ESTIMATION RESULTS (PER PEV)

	$E(\mathbf{h}_{\text{tr}})$ kWh/mile	$E(\mathbf{m}_{\text{cd}})$ miles		$E(\boldsymbol{\epsilon})$ kWh		$\sigma(\boldsymbol{\epsilon})$ kWh	
		$f_{d,1}$	$f_{d,2}$	$f_{d,1}$	$f_{d,2}$	$f_{d,1}$	$f_{d,2}$
Urban weekday	0.28	14.70	17.89	4.16	5.06	5.36	7.31
Urban weekend	0.28	11.41	14.10	3.23	3.99	4.98	6.92
Rural weekday	0.31	15.70	20.24	4.88	6.29	6.43	9.10
Rural weekend	0.31	11.92	15.29	3.70	4.75	5.87	8.28

C. Sensitivity Analysis

Equation (10) can be used to gauge the estimation error due to uncertainty in knowing the true values of the parameters' expected values; namely, the drivetrain electrification coefficient, the tractive energy, and—indirectly via the VMT in CD mode—the charge-depleting range. As a matter of fact, any RV distribution that can be devised about PEVs at this point in time represents only a "best guess." (Similarly, the assumed value of η might be incorrect.) Hence, the true mean values can be related to their estimates as $E(\mathbf{x}) = \hat{x} + \Delta x$. (Also, formally, $\eta = \hat{\eta} + \Delta\eta$.) Using a Taylor series expansion of (10), the following first-order approximation of the relationship between relative estimation errors can be obtained:

$$\frac{\Delta\epsilon}{\hat{\epsilon}} \approx \frac{\Delta\xi}{\hat{\xi}} + \frac{\Delta h_{\text{tr}}}{\hat{h}_{\text{tr}}} + \frac{\Delta m_{\text{cd}}}{\hat{m}_{\text{cd}}} - \frac{\Delta\eta}{\hat{\eta}} \tag{14}$$

where $\hat{\epsilon} = \hat{\xi}\hat{h}_{\text{tr}}\hat{m}_{\text{cd}}/\hat{\eta}$.

Also, instead of considering only two distinct cases for f_d, namely, $f_{d,1}$ and $f_{d,2}$, it is possible to compute the variation of $E(\mathbf{m}_{\text{cd}})$ as a function of $E(\mathbf{d})$ and $\sigma(\mathbf{d})$. This is depicted in Fig. 2. It can be observed that the miles driven in CD mode (hence, the absorbed electrical energy) will generally increase with $E(\mathbf{d})$, whereas $\sigma(\mathbf{d})$ has a secondary effect on the result.[8] It is also interesting to note that the energy consumption will increase only incrementally after approximately $E(\mathbf{d}) = 80$ miles. Increasing the CDR even further might be beneficial to the marketability of PEVs, but it will not provide significant benefits to the average driver [24]. The intersection of this surface with the $\sigma(\mathbf{d}) = 0$ plane is identical to $c_{\text{fr}}(d)E(\mathbf{m})$ [using (8) with $d = a$]. This plot reveals that the estimation of the miles driven in CD mode using the unique value $d = E(\mathbf{d})$ (rather than modeling the CDR as a distributed RV) does indeed introduce some error; it leads to an overestimation by 5%–15%.

Finally, one might question the choice of the log-normal distribution for f_d, lacking a clear physical justification. However, it has been found that other probabilistic models, such as the gamma, the Weibull, and even the uniform distribution, provide remarkably similar results to the ones shown in Table II and Fig. 2.

V. ELECTRIC POWER CONSUMPTION

A. Previous Work

The estimation of electric power consumption by PEVs is more complicated than computing the total energy consumption, because of the inherent difficulty in predicting when a PEV will be plugged in, and the duration of its connection to the grid. Previous studies have thus estimated power consumption based on estimates of electric energy consumption, obtained first using either (6) or (9), by simply assuming a constant power draw during a predefined time period [6], [7]. To account for all PEVs on the road, the total power is increased proportionally.

[8]In fact, it can be shown that the gradient vector of this function always points towards increasing $E(\mathbf{d})$ and decreasing $\sigma(\mathbf{d})$.

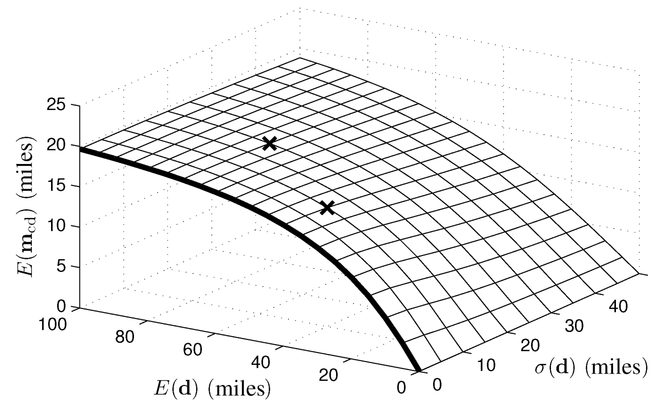


Fig. 2. $E(\mathbf{m}_{\text{cd}})$ versus $E(\mathbf{d})$ and $\sigma(\mathbf{d})$ for an urban weekday. [Note: The two "×" symbols correspond to $f_{d,1}$ and $f_{d,2}$.]

Alternative charging scenarios that include some sort of time-of-day dependence have been devised, such as uncontrolled charging, delayed charging, and off-peak charging [3], [6], [7]. These can be further classified in accordance with the location of charging into: charging only at home, delayed charging only at home, charging only at home and work, charging at any place, etc. In previous work, these scenarios have been analyzed using similar simplifications.

Clearly, this type of methodology leads to unrealistic results. First, it is unreasonable to expect that all PEVs begin charging simultaneously. Some may be parked with their batteries fully charged already, and some may be traveling. Second, charging may occur in-between trips, that is, the charging frequency does not need to be limited to once per day. In general, this method overestimates the peak value of power consumption [6], [7].

B. Proposed Methodology

For an estimation of power consumption, the travel patterns should be taken into account. The proposed methodology consists of simulating daily trips using the 2009 NHTS data. The following two scenarios are simulated:

a) uncontrolled charging any time the vehicle is parked at home;
b) uncontrolled "opportunistic" charging at any location (home, shopping mall, work, etc.).

These scenarios might not be completely representative of the actual behavior of PEV drivers; for instance, it might be unrealistic to expect that drivers would decide to charge their car every single time they return home. Nevertheless, they represent two possible futures characterized by extreme cases of public charging infrastructure investment (from minimum to maximum). In particular, scenario b) provides an upper bound for PEV energy consumption. Other scenarios, such as controlled charging (where time of charging is influenced by an electricity price or other signal) or exchanging batteries at

TABLE III
CHARGING CIRCUITS

Charging circuit	Charger size (kW)	Ratio
120 V, 15 A (Level 1)	1.4	1/3
120 V, 20 A (Level 1)	2	1/3
240 V, 30 A (Level 2)	6	1/3

battery stations, are not considered; these can be addressed in future work.

The charging circuit significantly affects the power consumption curve. Two ac charging levels have been recently standardized, with a third dc level currently under development [25]. For a normal household circuit breaker and wiring installation, typical options for charging circuits [18] are shown in Table III, where "charger size" denotes the nominal power consumption at the wall outlet. It is assumed that a PEV is always charged with a constant power draw—equal to the charger size. Even though this does not correspond to an actual battery charging profile [26], it has been found that this simplification does not affect the results significantly. The results provided herein will account for the cases where 1) all PEVs utilize a single charger type, and 2) PEVs are randomly assigned a home charger type based on an (arbitrarily) predetermined ratio, also shown in Table III. For scenario b), it is assumed that the public charging infrastructure involves only 6-kW chargers (i.e., the most expensive option).

The proposed methodology proceeds as follows. For each of the four area/day cases considered, a random vehicle (along with its travel pattern) is selected from the corresponding set of vehicles in the NHTS. These sets contain all vehicles, even those that do not travel on a given day. The selected vehicle is probabilistically assigned a tractive energy based on its type as per Section III. Thus, the interdependency between vehicle type and its travel pattern is now captured. (These two RVs were assumed independent in the analysis of Section IV.) In addition, the vehicle is virtually converted into a PEV by being assigned values of ξ and d based on the distributions given in previous sections. Then its power consumption throughout the day is observed using a computer simulation. To initialize the simulations, it is assumed that all vehicles start their first trip of the day with fully charged batteries, where "first trip" is defined as the first trip that takes place after 4 a.m. Each simulation starts at the instant where the vehicle first departs, and ends after 24 h, even if its battery is not fully charged at this point in time. In essence, this method generates instances of the stochastic process $\mathbf{x}(t)$ that describes the daily power consumption of a random PEV.

For a fleet of n PEVs charging independently of each other, the overall power consumption is $\mathbf{Y}_n(t) = \sum_{i=1}^{n} \mathbf{x}_i(t)$, with $E(\mathbf{Y}_n(t)) = nE(\mathbf{x}(t))$[9] and $\sigma(\mathbf{Y}_n(t)) = \sqrt{n}\sigma(\mathbf{x}(t))$. The coefficient of variation $\sigma(\mathbf{Y}_n(t))/E(\mathbf{Y}_n(t))$ is equal to $\sigma(\mathbf{x}(t))/\sqrt{n}E(\mathbf{x}(t))$. For large n, the central limit theorem suggests that the distribution of $\mathbf{Y}_n(t)$ will be approximately Gaussian.

According to the law of large numbers, the expected power draw per PEV, $E(\mathbf{x}(t))$, can be approximated by finding the sample mean of the power consumed by a large number N of PEVs, $\mathbf{M}_N(\mathbf{x}(t)) = (1/N) \sum_{i=1}^{N} \mathbf{x}_i(t)$. This is essentially the procedure followed herein. It is illustrated using a hypothetical vehicle with parameters $\xi = 0.8$, $h_{\mathrm{tr}} = 0.25$ kWh/mile, and $d = 40$ miles. The usable energy initially contained in the fully charged battery is $E_0 = (0.8)(0.25)(40)/\eta_1 = 8/\eta_1$ kWh, where η_1 is the battery-to-wheels efficiency. At $t_0 =$ 09:57, the vehicle departs from home with E_0 stored in the battery. After traveling a total of $m_1 = 24.7$ miles, the vehicle returns home at $t_1 =$ 11:49, and begins charging at once. The usable energy that remains in the battery at t_1 can be calculated by

$$E_1 = \begin{cases} E_0 - (\xi h_{\mathrm{tr}} m_1)/\eta_1, & \text{for } E_0 - (\xi h_{\mathrm{tr}} m_1)/\eta_1 > 0 \\ 0, & \text{for } E_0 - (\xi h_{\mathrm{tr}} m_1)/\eta_1 \leq 0. \end{cases} \tag{15}$$

In this case, $E_1 = 3.06/\eta_1$ kWh, and an amount of energy $(E_0 - E_1)/\eta_2 = \xi h_{\mathrm{tr}} m_1/\eta = 7.35$ kWh is required from the outlet to fully recharge the battery, where η_2 is the wall-to-battery efficiency. If a 2-kW charger is used, a complete recharge takes 3 h and 40 min, so it concludes at $t_2 = 15:29$. Of course, the simulations permit vehicles to begin their next trip before their batteries become fully charged. These subsequent trips (if any) are simulated in the same manner. By repeating a simulation for every PEV included in the survey, the sample mean $\mathbf{M}_N(\mathbf{x}(t)) \approx E(\mathbf{x}(t))$ is found.

Furthermore, the simulations can be used to find $\sigma(\mathbf{x}(t))$, and thus to calculate a confidence interval for the power consumption estimation. For the simple case where all PEVs have a single charger type, rated at c kW, a random PEV's charging at time t is a Bernoulli trial: $\mathbf{x}(t) \in \{0, c\}$. So, if $p(t)$ is the probability of it being charged, $E(\mathbf{x}(t)) = cp(t)$, and $\sigma^2(\mathbf{x}(t)) = c^2 p(t)(1 - p(t))$. If there exists a mix of K distinct charger ratings c_k, with $k = 1, \ldots, K$, and if $p_k(t)$ is the probability of a random PEV being charged at a rate c_k, then $E(\mathbf{x}(t)) = \sum_{k=1}^{K} c_k p_k(t)$ and $\sigma^2(\mathbf{x}(t)) = \sum_{k=1}^{K} c_k^2 p_k(t) - (\sum_{k=1}^{K} c_k p_k(t))^2$. The probability $p_k(t)$ that appears in the above expressions can be obtained from the simulations.

It should be noted that the distribution of vehicles by class in the survey is slightly different from the actual nationwide distribution. Therefore, to improve the accuracy of the estimate, the power consumption is adjusted by appropriate weight factors (included in the NHTS), which are calculated for each of the four cases considered.

Simulation results for the two scenarios are shown in Fig. 3. These curves depict the expected daily power consumption per PEV on U.S. roads, measured at the "outlet." (The curves account for all registered household light-duty PEVs, even those that are not driven on a given day.) The following observations can be made.

- The load profiles are somewhat different from the ones that have been presented in previous studies [6], [7], which tend to overestimate the peak of the power consumption. The two main reasons for this are: 1) ignoring the travel probability (see Section II), and 2) assuming that PEVs can only charge after ca. 18:00, whereas some PEVs might be plugged in during the morning and early afternoon hours.
- During the workweek in scenario a), the power peaks around 18:00, while people are returning home from work (cf. Fig. 1). At that time, the number of PEVs being charged

[9] The reader is cautioned that this notation does not imply an averaging process over time, but rather an averaging of all possible outcomes of an experiment conducted at a specific point in time.

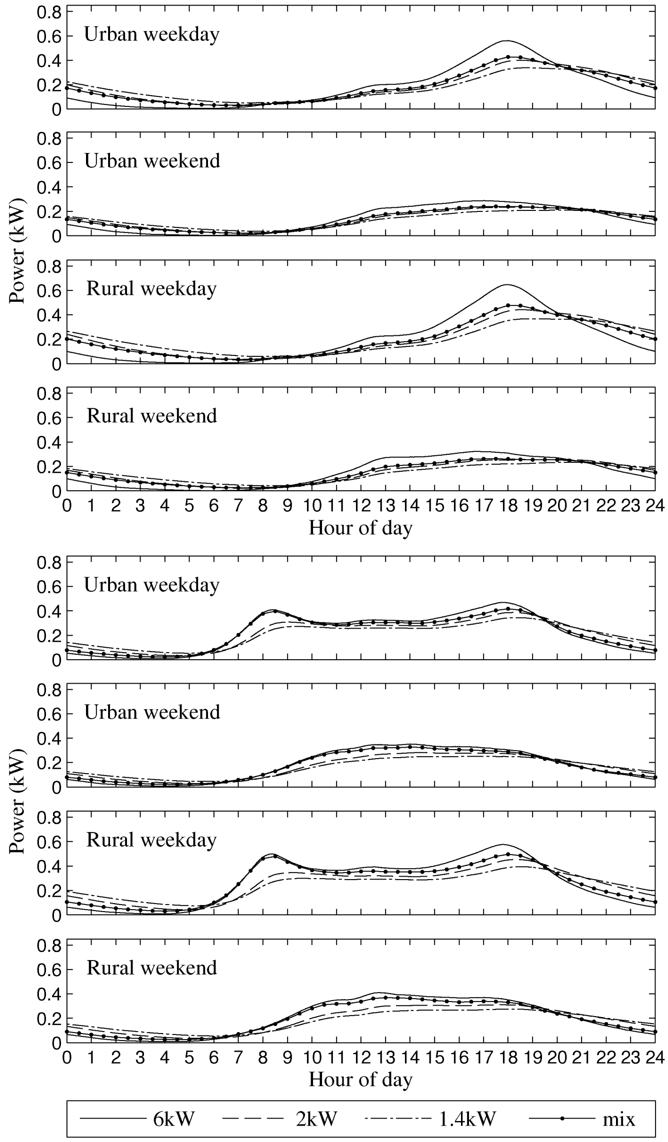


Fig. 3. Average power consumption per PEV with $f_{d,1}$. (Top) Scenario a). (Bottom) Scenario b).

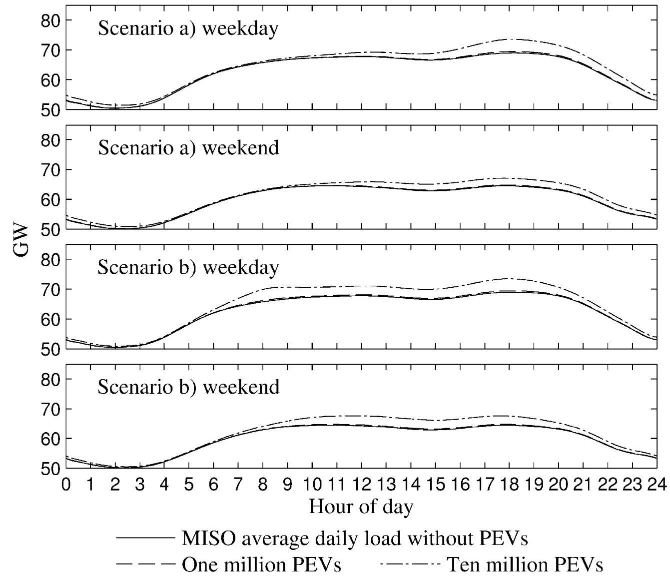


Fig. 4. PEV fleet power load superimposed on MISO load curve. [The horizontal axis shows the hour of day in the central time zone.]

reaches a maximum. In contrast, in scenario b), three peaks are apparent—around 8:00, noon, and 18:00—coincident with people arriving at work, driving to and from lunch, and returning home from work. Interestingly, even though charging can occur anywhere vehicles can park, the 18:00 peak value is similar.

- During weekends, the load profiles are smoother and have lower peak values than on weekdays.
- The variation with respect to charger size is quite significant. Smaller charger sizes tend to reduce the peak value of power consumption, but spread the load to longer time periods. It should be noted that the peaks of the power curves are not proportional to charger size (e.g., the 6-kW peak is not equal to three times the 2-kW peak). It is interesting to observe that the expected peak of power consumption per PEV is always less than 1 kW (even with the 6-kW chargers).
- The difference between the power curves with $f_{d,1}$ and $f_{d,2}$ (not shown due to space limitations) is not significant. This occurs because apparently a 40-mile average CDR can satisfy most daily travel requirements (cf. Fig. 2). On the other hand, if the average CDR is reduced below 40 miles, simulations predict a significant decrease in power consumption.

To assess the impact of a large PEV fleet on a power system, the computed PEV load is added to the Midwest ISO (MISO) load profile, as shown in Fig. 4. The $f_{d,1}$ CDR PDF is used and a mix of chargers is assumed, as previously described. The PEVs' power consumption is converted from the outlet to the substation level, assuming that distribution losses are 5%. The solid load curves represent the average weekday and weekend load as reported by MISO [27] in 2009. The number of LDVs in the MISO footprint today is approximately 28 million [28], with ca. 75% of these in urban areas [17]. About 17% are in the eastern time zone, and the remaining are in the central time zone. Notably, the impact on power consumption of one million PEVs on MISO's system would be relatively small. Further increases will require additional peaking capacity to be installed, because the peak PEV load will be more or less synchronous with the peak of the MISO load curve. Therefore, some form of time-dependent pricing scheme would be greatly beneficial in shifting the PEV load to off-peak periods.

Lastly, the daily electric energy consumption can be obtained by numerically integrating the power consumption curve. These results are provided in Table IV, which also contains the results of the analytical computation of Section IV-B (column labeled "Table II") for convenience. The following can be observed.

- Energy consumption increases with charger size. This could signify a potentially undesirable situation where chargers are inadequately powerful to completely recharge some PEVs overnight.
- Investments in public charging infrastructure will lead to an increase in electric energy consumption.
- The results of the analytical calculation method of Section IV-B are consistent with the simulation results.

TABLE IV
ENERGY ESTIMATION BY INTEGRATING POWER (IN kWh/PEV)

		Table II	Scenario a)				Scenario b)			
			6 kW	2 kW	1.4 kW	mix	6 kW	2 kW	1.4 kW	mix
$f_{d,1}$	U. w/day	4.16	4.24	4.13	4.09	4.15	5.39	5.12	4.94	5.30
	U. w/end	3.23	3.22	3.14	3.10	3.16	4.23	3.92	3.80	4.13
	R. w/day	4.88	4.82	4.66	4.59	4.69	6.53	6.07	5.84	6.42
	R. w/end	3.70	3.57	3.43	3.41	3.47	4.86	4.46	4.27	4.72
$f_{d,2}$	U. w/day	5.06	4.93	4.80	4.72	4.82	5.72	5.46	5.25	5.64
	U. w/end	3.99	3.77	3.67	3.59	3.68	4.57	4.35	4.18	4.46
	R. w/day	6.29	5.87	5.75	5.60	5.74	7.06	6.65	6.37	6.92
	R. w/end	4.75	4.32	4.15	4.10	4.19	5.36	4.99	4.79	5.17

However, the latter can reveal interesting interactions between charger size, travel patterns, and CDR.

VI. CONCLUSIONS

In this paper, a theoretical framework for assessing light-duty PEVs as a power system load has been set forth. The most authoritative source of national travel patterns (i.e., the 2009 NHTS database) was utilized to obtain a PEV load forecast. Uncontrolled PEV charging will almost certainly increase the power system's peak load in the U.S.

This work can become the starting point for incorporating vehicle travel patterns in studies such as: quantifying the effect that time-dependent pricing of electricity can have on PEV load leveling; analyzing the impact of the additional PEV load on locational marginal prices; estimating PEV impacts on greenhouse gas emissions; studying localized effects on power grids by introducing the spatial distribution of vehicles; and examining the potential of PEVs to act as distributed generation sources using vehicle-to-grid technologies.

ACKNOWLEDGMENT

The authors would like to thank Ms. S. Liss at the Federal Highway Administration and Ms. C. Rentziou at Iowa State University for the assistance provided.

REFERENCES

[1] Technology Roadmap: Electric and Plug-In Hybrid Electric Vehicles, International Energy Agency (IEA), Jan. 2009, Tech. Rep.

[2] C. C. Chan, "The state of the art of electric, hybrid, and fuel cell vehicles," *Proc. IEEE*, vol. 95, no. 4, pp. 704–718, Apr. 2007.

[3] P. Denholm and W. Short, An Evaluation of Utility System Impacts and Benefits of Optimally Dispatched Plug-In Hybrid Electric Vehicles, National Renewable Energy Laboratory, Golden, CO, Tech. Rep. NREL/TP-620-40293, Oct. 2006.

[4] K. Parks, P. Denholm, and T. Markel, Costs and Emissions Associated With Plug-In Hybrid Electric Vehicle Charging in the Xcel Energy Colorado Service Territory, National Renewable Energy Laboratory, Golden, CO, Tech. Rep. NREL/TP-640-41410, May 2007.

[5] M. Kintner-Meyer, K. Schneider, and R. Pratt, "Impacts assessment of plug-in hybrid vehicles on electric utilities and regional U.S. power grids. Part 1: Technical analysis," *J. EUEC*, vol. 1, no. 4, 2007. [Online]. Available: http://www.euec.com/content/EUEC-2007.aspx.

[6] S. W. Hadley and A. Tsvetkova, Potential Impacts of Plug-In Hybrid Electric Vehicles on Regional Power Generation, Oak Ridge National Laboratory, Oak Ridge, TN, Tech. Rep. ORNL/TM-2007/150, Jan. 2008.

[7] S. Letendre and R. A. Watts, "Effects of plug-in hybrid electric vehicles on the Vermont electric transmission system," in *Proc. Transportation Research Board 88th Annu. Meeting*, Washington, DC, Jan. 2009.

[8] Alternate Route: Electrifying the Transportation Sector. Potential Impacts of Plug-In Hybrid Electric Vehicles on New York State's Electricity System, New York Independent System Operator, Jun. 2009, Tech. Rep.

[9] S. Meliopoulos, J. Meisel, G. Cokkinides, and T. Overbye, Power System Level Impacts of Plug-In Hybrid Vehicles, Power Systems Engineering Research Center (PSERC), Oct. 2009, Tech. Rep.

[10] A. Hajimiragha, C. A. Cañizares, M. W. Fowler, and A. Elkamel, "Optimal transition to plug-in hybrid electric vehicles in Ontario, Canada, considering the electricity-grid limitations," *IEEE Trans. Ind. Electron.*, vol. 57, no. 2, pp. 690–701, Feb. 2010.

[11] M. Duoba, R. Carlson, and D. Bocci, "Calculating results and performance parameters for PHEVs," presented at the SAE World Congr. Exhib., Detroit, MI, Apr. 2009, 2009-01-1328.

[12] Energy Information Administration, Fuel Economy of the Light-Duty Vehicle Fleet. [Online]. Available: http://www.eia.doe.gov/oiaf/aeo/otheranalysis/aeo_2005analysispapers/feldvf.html.

[13] U.S. Department of Transportation, Federal Highway Administration, Highway Statistics 2006. Table VM-1. [Online]. Available: http://www.fhwa.dot.gov/policy/ohim/hs06/htm/vm1.htm.

[14] U.S. Department of Transportation, Bureau of Transportation Statistics, National Transportation Statistics. Table 4-6. [Online]. Available: http://www.bts.gov/publications/national_transportation_statistics/html/table_04_06.html.

[15] U.S. Department of Transportation, Bureau of Transportation Statistics, Transportation Statistics Annual Report 2008. Table 1-1-1. [Online]. Available: http://www.bts.gov/publications/transportation_statistics_annual_report/2008/html/chapter_01/table_01_01_01.html.

[16] L. Turcksin, S. Van Moll, C. Macharis, N. Sergeant, and J. Van Mierlo, "How green is the car purchase decision? A review," in *Proc. 10th Int. Conf. Application Advances Technology Transportation*, Athens, Greece, May 27–31, 2008.

[17] U.S. Department of Transportation, Federal Highway Administration, National Household Travel Survey (NHTS). [Online]. Available: http://nhts.ornl.gov/download.shtml.

[18] Comparing the Benefits and Impacts of Hybrid Electric Vehicle Options. Electric Power Research Institute, Palo Alto, CA, Tech. Rep. 1000349, Jul. 2001.

[19] Comparing the Benefits and Impacts of Hybrid Electric Vehicle Options for Compact Sedan and Sport Utility Vehicles. Electric Power Research Institute, Palo Alto, CA, Tech. Rep. 1006892, Jul. 2002.

[20] N. Shidore, T. Bohn, M. Duoba, H. Lohse-Busch, and P. Sharer, "PHEV 'All electric range' and fuel economy in charge sustaining mode for low SOC operation of the JCS VL41M Li-ion battery using battery HIL," in *Proc. 23rd Int. Electric Vehicle Symp. (EVS23)*, Anaheim, CA, Dec. 2007.

[21] T. A. Burress, C. L. Coomer, S. L. Campbell, A. A. Wereszczak, J. P. Cunningham, L. D. Marlino, L. E. Seiber, and H. T. Lin, Evaluation of the 2008 LEXUS LS 600 h Hybrid Synergy Drive System, Oak Ridge National Laboratory (ORNL), Oak Ridge, TN, Tech. Rep. ORNL/TM-2008/185, Jan. 2009.

[22] U.S. Department of Energy, Office of Energy Efficiency and Renewable Energy, and U.S. Environmental Protection Agency, Advanced Technologies & Energy Efficiency. [Online]. Available: http://www.fueleconomy.gov/feg/atv.shtml.

[23] *Utility Factor Definitions for Plug-In Hybrid Electric Vehicles Using 2001 U.S. DOT National Household Travel Survey Data*, Society of Automotive Engineers (SAE) Std. J2841, Mar. 2009.

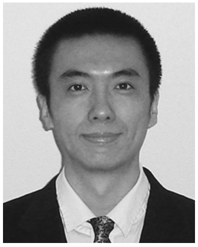
[24] A. Moawad, G. Singh, S. Hagspiel, M. Fellah, and A. Rousseau, "Impact of real world drive cycles on PHEV fuel efficiency and cost for different powertrain and battery characteristics," in *Proc. 24th Int. Electric Vehicle Symp. (EVS24)*, Stavanger, Norway, May 2009.

[25] *SAE Electric Vehicle and Plug in Hybrid Electric Vehicle Conductive Charge Coupler*, Society of Automotive Engineers (SAE) Std. J1772, Jan. 2010.

[26] D. Danilov and P. H. L. Notten, "Adaptive battery management systems for the new generation of electrical vehicles," in *Proc. IEEE Vehicle Power Propulsion Conf. (VPPC)*, Dearborn, MI, Sep. 2009, pp. 317–320.

[27] MidwestISO MarketInformation.[Online]. Available: http://www.midwestmarket.org/home/Market%20Reports?type=rt_ex&list=month.

[28] U.S. Department of Transportation, Bureau of Transportation Statistics, State Transportation Statistics. [Online]. Available: http://www.bts.gov/publications/state_transportation_statistics/.



Di Wu (S'08) received the B.S. and M.S. degrees in electrical engineering from Shanghai Jiao Tong University, Shanghai, China, in 2003 and 2006, respectively. He is currently pursuing the Ph.D. degree in the Department of Electrical and Computer Engineering at Iowa State University, Ames.

His research interests include power electronics, with applications in hybrid-electric vehicles and wind energy conversion systems.

Dionysios C. Aliprantis (SM'09) received the Diploma in electrical and computer engineering from the National Technical University of Athens, Athens, Greece, in 1999 and the Ph.D. degree from Purdue University, West Lafayette, IN, in 2003.

He is currently a Litton Industries Assistant Professor of Electrical and Computer Engineering at Iowa State University, Ames. His interests include the modeling and simulation of electric machines and power systems, power electronics and controls, and renewable energy applications.

Konstantina Gkritza received the Diploma in civil engineering from the National Technical University of Athens, Athens, Greece, in 2001; the M.S. degree in civil engineering from the Virginia Polytechnic Institute and State University, Falls Church, in 2003; and the Ph.D. degree from Purdue University, West Lafayette, IN, in 2006.

She is currently an Assistant Professor of civil engineering at Iowa State University, Ames. Her research interests lie in the application of economic concepts and statistical methods to problems and decisions in the transportation field.