Characterization of urban commuter driving profiles to optimize battery size in light-duty plug-in electric vehicles

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A R T I C L E   I N F O

Keywords:
Driving cycle
Plug-in hybrid vehicles
Electric vehicle
Urban driving

A B S T R A C T

Electrification of light duty vehicles using plug-in electric vehicles in conjunction with new generation of renewable energy to match the new electrical load addresses global concerns of greenhouse gas emissions and is being considered as a way to reduce environmental damage from the transportation sector. A database was gathered over a year from a fleet of 76 vehicles in Winnipeg, Canada and is used to develop a daily driving profile approximating actual driving power demand and parking times for charging these vehicles. The data are utilized to construct a commuter driving cycle based on the parameters defining functionality of a light duty vehicle. The cycle is then used in an energy-based simulation to optimize battery size for a commuter sedan car. Overnight only versus overnight and day charging scenarios are then compared. It is found that the battery storage size can be decreased by up to 40% without loss of functionality with a 2.4 h daily charge.

1. Introduction

Battery electric vehicles (BEV) and plug-in hybrid electric vehicles (PHEV)¹ are seen as having potential for reducing oil dependency and greenhouse gas emissions in transportation use. Design of plug-in powertrains requires optimizing the battery storage capacity considering the possibility of recharging from the electric grid between trips. Optimal battery capacity leads to a lighter weight, lower cost and more efficient PEV but it requires information on the driving profile of an average driver and parking times of the vehicle. Duty cycles provide comprehensive histories of vehicle over a typical 24-h span, including parking times and associated idling times, while a driving cycle refers only to driving history of a vehicle.

Standard cycles such as FTPs, LA92, UDDS and US06 are adjusted to the limitations of the lab testing equipment, but they cannot completely emulate real world driving (Lin and Niemeier, 2003). More importantly for designing of PEVs, standard cycles do not provide information on vehicle parking times nor do they include a wide array of routes driven by commuters.

Using global positioning system (GPS) based data loggers is now widely practiced to track and record driving events, determine trip purpose, traffic congestion levels and develop driving cycles (Dai et al., 2008). The steps to construct a driving cycle include data collection, segmenting data into meaningful snippets or micro-trips, constructing cycles from the snippets, and evaluating the constructed cycle. Different methods for classifying micro-trips to create the duty cycle can be used: calculations of micro-trip probability and frequency (Tong et al., 2005); classifications of urban, suburban and freeway driving based on acceleration and speed ranges (Andre et al., 1995); and quasi-random micro-trip selection methods (Lin and Niemeier, 2002).

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¹ For simplicity we use PEV to refer to both BEV and PHEV throughout.
We examine the habits characterizing a commuter’s driving pattern, create a large database of driving and parking times, and develop a duty cycle based on functionality of vehicle use. It should be possible to implement the methodologies developed for Winnipeg in Canada, a city with a population of 0.7 million, for other urban settings with appropriate data on vehicle driving patterns. The data was collected at a time when only two plug-in electric vehicles were operating in Winnipeg. Therefore GPS data was gathered using gasoline vehicles assuming that driver behavior is the same irrespective of the power source of a vehicle.

2. Data collection and analysis

The data logger used is a GPS receiver that records position, speed, date and time at one-second intervals (Persen Technologies Inc., 2010). Speed data is calculated by the logger from the position records with a minimum precision of 0.37 km/h. In addition to positional and speed data, the logger also numbers vehicle trips sequentially and records the speed limit.

Social factors that likely influence the driving patterns of the volunteers are considered as much as possible to ensure that the sample is a good representation of the population at large. A snowball sampling method is used to select 76 volunteers with the required characteristics reflecting different income brackets, sex, education levels and occupations. Fig. 1 describes characteristics of the fleet. To minimize any bias that may arise because of the presence of a data logger in the vehicle, data was collected over a year; this yields more than 44 million data points.

![Fig. 1. Drivers' characteristics: (a) gender, (b) age, (c) household income, (d) vehicle types, (e) employment and (f) level of education.](image-url)
The quality of GPS data can vary because of signal interference and multi-bounce associated with natural and artificial barriers, e.g., tall buildings and trees. To improve the quality of raw data, post-processing is required. To filter out erroneous data and reconstruct missing values, trips recorded as separate trips due to a brief 12 V power interruption to the device, supplied by a cigarette lighter, are pasted together. A threshold of two minutes is used to determine whether a two-trip fragment is part of the same trip, or whether there are separate trips (Schönfelder et al., 2002). The second step is to locate the true start point of new trips missed due to lags in the GPS acquiring satellite signals, and to link the end point of the previous trip. By determining the straight-line distance between the recorded trip start and an adjusted trip start, the approximate distance missing from the record can be estimated. This gap is filled by randomly selecting and pasting micro-trips—snippets of data points bounded by zero speed at both ends—from the previous trip together until the gap distance is reached. Finally, the reconstructed data is re-processed through the first filter to ensure elimination of the gaps between trips.

Using manual and automated techniques, origins and destinations of the trips are identified as home, work, known commercial parking lots, and other. In manual identification, a density analysis of the parking instances for each driver is performed on an ortho-photo of the city. Denser clustering of parking instances is assumed at homes, verified by the volunteer’s home address. The second densest cluster of parking is at work for the volunteers working full time. The automated method identifies parking locations nearby buildings with known types. The locations identified are then categorized as school, shopping centre or hospital, and city zones as commercial, industrial or residential.

3. Duty cycle construction methodology

Various driving characteristics such as idling, high traffic congestion, free moving, creep and high-speed roadways necessitate data reduction and clustering. The daily trips divided into micro-trips are classified according to their ranges of speed and acceleration into certain traffic groups. A random selection method is adopted to select the number of classified micro-trips required to recreate an average trip. The number of trips per cycle, the hours of day that the vehicle is being used, and the second-by-second speed trace of the vehicle within each trip are obtained after data reduction and determination of driving patterns. One hundred candidate driving cycles are then generated using the constructed trips, and a cycle, WPG03, is retained as the most representative duty cycle.

To cluster driving data, patterns are divided into three broad categories according to their cumulative trip counts by hours of the day: isolated commuting, work-related driving, and social or recreational driving in accordance with US Department of Transportation (2004). Trip origins and destinations are then mapped to help isolate specific trip types, such as from home to work, or home to shopping centre. Finally, individual trips are divided into micro-trips and then clustered based on their specific power value into eight micro-trip types (MTT). Specific power, \( P_s \), is a measure of power demand per unit mass of a vehicle and is calculated as (US Environmental Protection Agency, 1995):

\[
P_s = 2 \nu a_{pos}
\]

where \( \nu \) is instantaneous speed and \( a_{pos} \) is positive acceleration. Negative accelerations do not contribute to overall engine power demand. MTT types are numbered from one to eight corresponding to brackets of total specific power: 0, 0–9, 10–99, 100–199, 200–299, 300–399, 400–599 and 800–2000 m\(^2\)s\(^{-3}\). In general, MTT types four, five and six are associated with urban and suburban driving in freely moving traffic and with higher speeds and greater distances than types one, two and three, while types seven and eight are associated with freeway or highway driving.

Driving patterns are found by a cumulative count of an individual’s trip in terms of hour of day. Distribution of the trips defined by purpose of trip over a typical 24-h period is analyzed. The type of driver selected to represent urban driving conditions is a commuter—commuters account for 44% of the drivers, while social or recreational and work related activities accounted for 28% and 12% of the remainder, respectively.

Trips per day is calculated as the number of vehicle trips recorded over the year divided by the number of recording days—the frequency of the numbers of trips made per day is given in Fig. 2. The median, mean and standard deviation for the data are 4.0, 5.0, and 2.9. Hence four trips per commuter cycle are considered in the construction of the cycle. Fig. 3 shows the 24-h driving pattern for a weekday commuter with four distinct peaks at 08:00, 12:00, 16:00 and 17:00 h. To produce commuter duty cycles, different MTTs matching commuter patterns are randomly selected from the database and pasted together in a randomized order to recreate the number of trips for commuters, making the final driving cycle.

The number of micro-trips selected for each trip is calculated as the number of micro-trips divided by the number of trips in the commuter cycle. The percentage of each MTT multiplied by the micro-trips expected per trip is used to select the types of micro-trips needed. For simplicity, a random selection method is used to determine the order of the micro-trips within each reconstructed trip. This is hypothesized to have limited influence on the result, because the total power demand per trip remains the same no matter how the micro-trips are ordered. Four constructed trips are combined to make a single commuter duty cycle. Zero speed, representing idling or parking events, is entered between trips.

One hundred candidate duty cycles are constructed and for each the specific power average, speed and cumulative distance is calculated. The cycle having the closest values to the averages for all duty cycles is selected as the representative cycle. The commuter duty cycle is 55 min in duration, comprising four trips and covers a distance of 25 km. Trip 1 is the morning commute to work, trip 2 is a noon-hour trip, trip 3 is an evening commute from work, and trip 4 is an evening
errand as seen in Fig. 4. Statistics for the entire cycle, given in Table 1, indicate that the distance, duration, speed and idling percentage for the cycle correlate well with values for actual commuters.

4. Database specifications

The data was collected subject to a confidentiality agreement with the volunteer drivers. The origin of each trip is mapped to a neutral (0, 0) origin and all displacements of the trip are calculated with respect to this. A digital map of the city is used to mark parking events. Identification of parking types can be misleading as a parking event in a commercial zone can be either interpreted as parking at work by the staff or as parking for shopping. Guided by location, trip purpose and infrastructure, an attempt was made to classify all parking events as home, work, shop and street. The objective of the classification is to provide descriptions of parking habits and to determine the potential charging locations within the city.

Fig. 2. Frequency of the number of trips made per day.

Fig. 3. Percentage of driving over a 24-h period for commuters.

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2 The raw data is made available for public use in Smith and Blair (2010): The database provides the numbers of trips, date, time in UTC, latitude, longitude, maximum local driving speed in km/h according to traffic signs, vehicle speed in km/h, type of data according to whether it is raw or fixed and location and duration of parking events. Motionless periods less than 2 min are considered as idling. Parking events less than 30 min, potentially not suitable for opportunity charging, are isolated.

3 An alternative method to derive a representing duty cycle is presented by (Shahidinejad et al., 2010) based on the same data.
5. Battery size optimization

Even though battery technology is likely to continue to improve, batteries may remain the most expensive propulsion component. The challenge is then to find the minimum battery capacity that would respond well to the demands of an urban commuter.

The battery technologies for wide adoption in PEVs are still evolving as lower capital costs are being sought. PEVs economically perform best, in terms of overall cost per kilometer, when the battery size relates more closely to the charging patterns of the driver. Since the goals of reducing costs and overall fuel consumption are fairly well-aligned in the context of drivers who can charge frequently, economic interest may lead to the development of solutions for commuters having regular driving patterns.

To find the optimum battery capacity based on two chemistries for a BEV using cycle WPG03, vehicle mobility is simulated using a one-dimensional dynamic model. Power demand is calculated by integrating the net forces acting in the direction of a moving vehicle, namely the opposing aerodynamic drag ($F_D$), the opposing rolling friction ($F_F$) and the time derivative of momentum in the moving direction ($m\frac{dv}{dt}$) times the vehicle’s velocity over time. The governing equations are (Ehsani et al., 2004):

$$E = \int_0^1 \left( m\frac{dv}{dt} + F_D + F_F \right) v \cdot dt$$  \hspace{1cm} (2)

$$P = \left( m\frac{dv}{dt} + F_D + F_F \right) v$$  \hspace{1cm} (3)

$$F_D = \frac{1}{2} \rho A_f C_D v^2$$  \hspace{1cm} (4)

$$F_F = (0.01 + 0.0001v)mg$$  \hspace{1cm} (5)

where $\rho$, is the air density equal to $1.2 \text{ kg/m}^3$ in standard conditions and, $g$, is the gravitational constant of $9.8 \text{ m/s}^2$. The average values for different sedan cars are used in the energy and power calculations. The vehicle frontal area ($A_f$), aerodynamic drag coefficient ($C_D$), and the mass of the vehicle platform ($m$) are set equal to $2.3 \text{ m}^2$, $0.28$ and $1000 \text{ kg}$. These values are in line with the dominant sedan cars in the urban transportation fleets and are mirrored in the fleet of the vehicles used in the testing. Positive values of power demand indicate the power that the propulsion system must provide at the wheels. Daily energy demand is estimated by integrating the positive values of the power demand over time divided by the number of data
collection days. Negative values of power demand represent the power to be dissipated as heat during breaking, or partially recovered during regenerative braking.

The vehicle is assumed to be used 300 days per year, with the opportunity to be charged either overnight at home, or both overnight and during the day at the work place. Ni–MH and Li–Ion battery modules are selected as the chemistries. Variations in the state of charge are adjusted to obtain 1500 life cycles or a minimum of five years operation for each battery type. The batteries are considered to operate in charge depletion mode and their technologies are compared on the basis of cost per kilometer. The weight of a passenger is assumed to be 80 kg. The battery pack weight depending on its type is added to the vehicle platform weight. Each battery module is assumed to be one kilogram. The specifications for the battery modules used in the simulation are given in Table 2. Additional weights of metal frame, cooling device and AC/DC converter are assumed equal for the chemistries, approximately 25 kg, and are included in the platform weight.

The results for the home-only charging scenario, Fig. 5, show that 404 modules of the Ni–MH battery, 18.9 kWh in capacity, are needed to power the simulated PEV up to maximum 68.8 kW over the commuter cycle, WPG03. Using 222 modules of Li–Ion battery, 14.4 kWh in capacity, 60.5 kW is provided. As seen in Fig. 5a the capital costs of Ni–MH and Li–Ion batteries in the home-only charging scenario will be $6868 and $14,385. Under the home and work charging scenario, a vehicle can be charged for 6 h, 09:00 to 12:00 and 13:00 to 16:00, which helps to downsize the battery capacity to 136 modules, 8.8 kWh, with Li–Ion or 237 modules, 11.1 kWh, with Ni–MH. This implies that additional day charging can downsize the battery capacity by 39% in the Li–Ion case and 41% in for Ni–MH. As seen in Fig. 5b, the capital costs for Ni–MH and Li–Ion batteries in home and work charging will be $3281 and $8812. Fig. 5 also shows that increasing number of modules not only increases the capital cost but also the efficiency of battery storage decreases as the swing in state of charge does not change significantly when the battery capacity is increased: larger battery packs make the vehicle heavier and less efficient. The average charging time required for full charging based on a downsized battery using home and work charging is 2.4 h. Given that the day time charging can be more expensive than overnight charging for peak or mid-peak in time-of-use pricing systems, it is also possible to calculate the overall cost per kilometer of driving including variable pricing.

The price of charging is based on time of use; we consider off-peak at 4.4 ¢/kWh from 21:00 to 07:00, mid-peak, at 8.0 cents/kWh from 11:00 to 17:00, and peak at 9.3 ¢/kWh from 07:00 to 11:00, and 17:00 to 21:00. Using the optimum size of battery storage the overall cost per kilometer is calculated ignoring depreciation, interest costs, and inflation. The average distance per day for the commuter cycle is 15.1 km. Regarding the home-only charging scenario, the overall cost per kilometer are 21.1 ¢ and 41.1 ¢ for Ni–MH and Li–Ion chemistries, and 10.6 ¢ and 25.9 ¢ for in home and work charging. The average gas price in Canada in 2009 was 101.8 ¢ per liter, and assuming the average gas consumption in city driving for a sedan car is 0.1 liter per kilometer, the cost per kilometer of a conventional sedan car would be 10.2 ¢. This implies that PEVs may become attractive options, and price competitive, if the optimum battery capacity is adopted by urban drivers who can charge frequently.

### Table 2

<table>
<thead>
<tr>
<th>Battery chemistry</th>
<th>Ni–MH</th>
<th>Li–Ion</th>
</tr>
</thead>
<tbody>
<tr>
<td>Capacity per module (Wh)</td>
<td>46.8</td>
<td>64.8</td>
</tr>
<tr>
<td>Swing in state of charge (%)</td>
<td>60</td>
<td>70</td>
</tr>
<tr>
<td>Charge/discharge efficiency (%)</td>
<td>80</td>
<td>95</td>
</tr>
<tr>
<td>Cost per module ($)</td>
<td>17</td>
<td>64.8</td>
</tr>
</tbody>
</table>

#### Fig. 5.

Capital cost for Li–Ion and Ni–MH battery chemistries (a) home-only charging scenario, and (b) home and work charging scenario.

#### 6. Conclusion

In constructing a duty cycle using data collected in Winnipeg the emphasis has been on commuters. A cycle representing weekday commuting in the city and, including vehicle down-times suitable for charging, is developed aimed at exploring optimal PEV battery optimization and powertrain design. The results of simulations show that the Ni–MH battery technology,
along with home and work charging, currently provides the lowest cost per kilometer for an urban commuter. Since commuting represents more than a third of the urban driving in the city, electrification of transportation for commuters could considerably decrease air pollution in cities where drivers perceive it as economical. Our results also show the battery storage size for an urban commuter can be reduced by approximately 40% without loss of functionality by opportunity charging during the day.

Acknowledgement

Data collection and analysis was supported by a grant from the AUTO21 Network of Centers of Excellence, Project number DF302-DBS. The authors would like to thank Arne Elias from the Centre for Sustainable Transportation at the University of Winnipeg and Frank Franczyc from Persen Technologies Inc. Discussions with Emerging Energy Systems at Manitoba Hydro and Tom Molinski are acknowledged.

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