Statistical Development of a Duty Cycle for Plug-in Vehicles in a North American Urban Setting Using Fleet Information

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Abstract—Development of a daily duty cycle based on real-world driving behavior and parking times is a critical requirement in the optimal design of power-train components of a plug-in vehicle. Standard driving cycles cannot completely emulate the real-world power demand of a vehicle and its downtimes in particular. To address these shortcomings, a large database of one year of measured data collected from a fleet of 76 cars in the city of Winnipeg, MB, Canada is obtained and is then used to develop a new duty cycle. This paper describes a methodology for statistical analysis of the fleet data, including while a vehicle is parked. Due to the intrinsic differences in vehicle usage profiles during weekdays and weekends, two 24-h duty cycles with suitable windows of opportunity for charging are developed for weekday and weekend driving patterns. The uniqueness of the proposed statistical methodology and the resulting duty cycles contribute to addressing the present shortcomings of standard driving cycles.

Index Terms—Battery storage, driving cycle, duty cycle, electric vehicle, plug-in hybrid vehicles, renewable energy.

I. INTRODUCTION

ELECTRIFICATION of transportation for light-duty vehicles is a prominent step toward sustainable transportation [1], [3]. It can also contribute to efficient integration and use of existing and emerging renewable energy resources. Plug-in vehicles (i.e., pure electric or plug-in hybrids) have a strong potential to reduce petroleum consumption by shifting energy demand away from fossil fuels to electrical energy that is domestically produced using renewable sources. A plug-in vehicle allows its battery storage to recharge via connection to a utility grid while the vehicle is parked. Therefore, it covers a wide range of vehicles using electricity as a source of propulsion either partially, such as in a plug-in hybrid electric vehicle (PHEV), or entirely, such as in a battery electric vehicle (BEV). When used in conjunction with a distributed high-capacity-storage electric utility, it will also help accommodate the variable and unpredictable nature of renewable sources. It is envisioned that by increasing the share of renewable energies for electric power generation and optimizing rechargeable energy storage battery units in plug-in vehicles, major concerns with regard to peak oil, greenhouse gases leading to climate change, energy security, and emissions, can be simultaneously addressed [4]. Due to high cost and large weight per unit energy capacity of current battery cells, the technology pathway for plug-in PHEVs to lower the battery size and cost includes providing additional daily charging opportunities during periods when the 48 vehicles are parked and opportunities for charging exist [3]–[7].

Complete assessment of the potential power and energy 50 demand in plug-in vehicles is required to simulate and optimize their energy-storage systems [8]. Optimal sizing of the electric 52 drive-train components, choice of battery chemistry and storage size, development of controllers tuned and optimized to vehicle 54 driving patterns, as well as realistic opportunity charging sce- 55 narios, all require detailed information on the vehicle’s usage 56 profile. Obviously, recharging scenarios and grid impacts can be 57 better analyzed with detailed information on parking durations, 58 as well as time and location of parking events in drivers’ 59 daily routines. Real-world driving patterns provide insight into 60 speed and acceleration characteristics. However, only stan- 61 dard driving schedules conducted on dynamometers or well- 62 documented tracks have been accepted as a systematic approach 63 to mimic real-life situations. Standard certification driving 64 cycles such as the Urban Dynamometer Driving Schedule 65 (UDDS) or Highway Fuel Economy Test have been convention- 66 ally used in conjunction with controlled chassis dynamometer 67 testing to represent average driving behavior of the drivers in 68 real-world fuel economy and emission certification of the vehicles. 69

It is important to note that the standard certification cycles are 70 still unable to handle extreme acceleration or deceleration rates 71 that fall beyond capabilities of laboratory equipment and are 72 bound to limited cycle durations, i.e., usually less than 20 min, 73 to keep test costs low [5], [12]. For instance, the FTP72 driving 74 cycle, which dates back to early 1970s, was primarily developed 75 to measure exhaust emissions of typical light-duty vehicle 76 operations in the Los Angeles urban area [13]. To address the 77 shortcomings of the FTP72 cycle in representing more aggres- 78 sive speeds and accelerations, a Unified Cycle was developed 79 in 1992 based on collected data, known as LA92. However, 80 there are still many concerns about the problems inherent in the 81 existing driving cycles, which lead to underestimation of cruise, 82 acceleration, or stop-and-go activities in different brackets of 83
velocities [14]. It is therefore concluded that such cycles cannot completely emulate the real-world daily power demand of a vehicle. More importantly, they do not provide information on parking times as opportunities for charging in the case of emerging plug-in vehicles. In addition, it is important to base duty cycles on larger data sets to reduce statistical errors.

An extensive literature survey conducted revealed no reference to the development of a daily driving cycle, taking into account power and energy demands as major requirements for representing the real-world data. Most studies have focused on developing urban driving cycles using snippets extracted from recorded speed–time traces to estimate vehicular emissions and fuel consumption in different cosmopolitan areas [15], [19]. The objective of these studies is to represent the driving information in a collected data set using a single driving cycle. Some other studies discuss the effectiveness of the methodologies used in developing driving cycles to represent the inherent characteristics of driving behavior in the collected data [20], [21].

A few recent studies exist that have assessed the performance of hybrid electric vehicles (HEVs) in real-world operation. For example, data collected for a fleet in the St. Louis, MO, metropolitan area were used in the simulation of energy usage in a PHEV, but no single driving pattern was extracted from the collected data [22]. Fuzzy logic pattern recognition techniques have also been used to perform driving and duty cycle analyses on data collected for a fleet of HEVs [23]. Another effort to modify standard cycles for better representing real-world behavior introduced a driver model in connection with European standard cycles into simulations [24]. A methodology that generates a driving cycle has also been reported based on the assumption of constant acceleration and deceleration rates, along with consideration of the speed limits in different road segments in representative areas [25]. It can therefore be concluded that there does not exist a single widely accepted duty cycle in the literature to appropriately represent typical daily activities of the vehicles and to address the energy and power demands of the PHEVs and BEVs.

The study presented in this paper addresses the gap in the literature by developing a statistical methodology and constructing the needed duty cycles based on a database of over 44 million Global Positioning System (GPS) data points recorded over the course of one year in Winnipeg, MB, Canada. Depending on the context, the terms “driving cycle” and “duty cycle” may convey different meanings. In this paper, a “driving cycle” refers to a history of daily driving periods represented by a speed-versus-time curve. A “duty cycle” refers to a profile of daily usage of power by the vehicle, which is typically represented by a 24-h history of driving and parking events. Note that, in the case of an HEV, only a driving cycle is sufficient to calculate vehicle’s power demand, whereas in the case of a plug-in vehicle, parking times also become vital as they may be used for charging from the electric grid, and therefore, they should be included in the daily profile. Parking times are also important to utilities servicing jurisdictions with large vehicular loads, as they can be used to predict and control the load on the grid.

The objective of the present study is to first develop a new driving cycle most closely mirroring the characteristics of urban driving, including real-world energy and power demands. Once this is achieved, this study aims to incorporate a pattern representing most probable downtimes of the vehicles to charge during their daily usage profile. A comprehensive daily duty cycle is a crucial component for optimal design of plug-in vehicular drive-trains. This study improves the conventional methods of driving cycle generation [26], [28]. The present study also establishes a set of performance measures required to assess a driving cycle suited for electric/plug-in hybrid vehicles. The methodology used in the precedent study for simulation of a plug-in vehicle is enhanced by including 25 parameters to characterize different velocity brackets in a driving cycle [29]. The uniqueness of this study is proposing a methodology that addresses the particular requirements associated with the design of plug-in vehicles in construction of a 24-h duty cycle.

Following the introduction, in Section II, duty cycle requirements to be fulfilled for enhanced simulation and optimization of plug-in vehicles are discussed. Data collection, driving cycle generation, and characterization are described in Section III. Parking data analysis for weekdays and week-ends is presented in Section IV. The resulting 24-h duty cycles are given in Section V, and driving characteristics are critically compared with those of the standard cycle for urban driving, i.e., the UDDS. Conclusions are presented in Section VI.

II. DUTY CYCLE REQUIREMENTS FOR PLUG-IN VEHICLES

The total distance that a plug-in vehicle can electrically drive is an important measure for the vehicle’s performance. For instance, PHEVs are usually classified according to their all-electric range (AER), which is defined as the total miles electrically driven after a full recharge before the engine turns on for the first time [30]. A fully recharged PHEV operates in charge-depleting mode until the battery is depleted to a target state-of-charge (SOC), at which point, the vehicle switches to charge-sustaining mode, using the internal combustion engine to maintain the target SOC [3]. Fig. 1 shows the typical variation in the SOC of the battery in the operating modes of a PHEV.

Obviously, the instantaneous power demand resulting from the driving style of the driver is critical in the definition of the AER. The standard cycle UDDS is usually used to measure AER. The standard cycle UDDS is usually used to measure 100
TABLE I

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Database average</th>
<th>Final duty cycles</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>weekday</td>
<td>weekend</td>
</tr>
<tr>
<td>1 Average speed of the entire driving cycle in km/h</td>
<td>31.4</td>
<td>35.3</td>
</tr>
<tr>
<td>2 Average running speed in km/h</td>
<td>39.8</td>
<td>43.9</td>
</tr>
<tr>
<td>3 Total daily distance traveled in km</td>
<td>32.2</td>
<td>33.9</td>
</tr>
<tr>
<td>4 Average acceleration of all acceleration phases in m/s²</td>
<td>0.6</td>
<td>0.6</td>
</tr>
<tr>
<td>5 Average deceleration of all deceleration phases in m/s²</td>
<td>-0.6</td>
<td>-0.6</td>
</tr>
<tr>
<td>6 Average number of change in acceleration rate (+/-) in one driving period</td>
<td>6.5</td>
<td>7.2</td>
</tr>
<tr>
<td>7 Average daily power demand in kW</td>
<td>7.9</td>
<td>8.3</td>
</tr>
<tr>
<td>8 Maximum power demand in kW</td>
<td>59.3</td>
<td>72.2</td>
</tr>
<tr>
<td>9 Total daily energy demand in MJ</td>
<td>17.3</td>
<td>17.7</td>
</tr>
<tr>
<td>10 Average daily breaking power in kW</td>
<td>-5.3</td>
<td>-5.4</td>
</tr>
<tr>
<td>11 Root mean square of acceleration in m/s²</td>
<td>0.8</td>
<td>0.8</td>
</tr>
<tr>
<td>12 Average length of a driving period in km</td>
<td>0.9</td>
<td>1.2</td>
</tr>
<tr>
<td>13 Time percentage of idling (zero velocity) in %</td>
<td>21.8</td>
<td>20.7</td>
</tr>
<tr>
<td>14 Time percentage of acceleration: acceleration&gt;0.1 m/s² in %</td>
<td>31.4</td>
<td>31.3</td>
</tr>
<tr>
<td>15 Time percentage of Cruising (acceleration [-0.1, 0.1] m/s², speed&gt;5 m/s) in %</td>
<td>14.9</td>
<td>16.7</td>
</tr>
<tr>
<td>16 Time percentage of deceleration: acceleration &lt;0.1 m/s² in %</td>
<td>31.2</td>
<td>30.9</td>
</tr>
<tr>
<td>17 Time percentage of creeping (acceleration [-0.1, 0.1] m/s², speed&lt;5 m/s) in %</td>
<td>0.6</td>
<td>0.5</td>
</tr>
<tr>
<td>18 Time percentage of driving at very low speed bracket [0 20] km/h in %</td>
<td>94.5</td>
<td>90.6</td>
</tr>
<tr>
<td>19 Average speed in very low speed bracket [0 20] km/h</td>
<td>6.6</td>
<td>10.3</td>
</tr>
<tr>
<td>20 Time percentage of driving at low speed bracket [20 50] km/h in %</td>
<td>58.9</td>
<td>59.6</td>
</tr>
<tr>
<td>21 Average speed in low speed bracket [20 50] km/h</td>
<td>18.9</td>
<td>20.8</td>
</tr>
<tr>
<td>22 Time percentage of driving at moderate speed bracket [50 80] km/h in %</td>
<td>36.7</td>
<td>36.9</td>
</tr>
<tr>
<td>23 Average speed in moderate speed bracket [50 80] km/h</td>
<td>32.9</td>
<td>30.2</td>
</tr>
<tr>
<td>24 Time percentage of driving at high speed bracket [80 100] km/h in %</td>
<td>9.9</td>
<td>10.0</td>
</tr>
<tr>
<td>25 Average speed in high speed bracket [80 100] km/h</td>
<td>16.3</td>
<td>15.0</td>
</tr>
</tbody>
</table>

184 the AER for classifying PHEVs. Therefore, a PHEV x expected
185 to travel x miles on battery, in the real world, would perform
186 quite differently, depending on the driving habits of the driver.
187 The mentioned difficulty in providing a realistic performance
188 measure to the end users is also valid in the case of an HEV.
189 The dominant mode of operation in an HEV battery is charge
190 sustaining, and its fuel efficiency is characterized by a higher
191 mile per gallon rate when compared with conventional vehicles.
192 Again, using the standard cycle is misleading as, in reality, fuel
193 consumption would be higher, depending on the aggressiveness
194 of the driver.
195 In this study, real-world driving data are collected over a
196 sufficiently long period to reduce statistical errors. In addition,
197 the characterizing parameters of the driving cycles used to
198 generate the standard driving cycles are extended to cover
199 average driver’s daily energy demand and maximum power
200 demand (positive in acceleration and negative in deceleration)
201 for light-duty vehicles (with a dominant share in urban traffic).
202 The information on parking events such as the frequency of
203 occurrence and the ratio of parking to driving times in an
204 average daily driving profile is also included to construct an
205 average 24-h duty cycle.
206 The characterizing parameters considered in this paper are
207 those defining power requirements at different driving modes,
208 as listed in Table I. Except for its considerably cold winter
209 temperatures, Winnipeg, with a population of 700 000, is a
210 typical North American urban setting where driving culture,
211 population, and traffic behavior are similar to many other cities
212 across the United States and Canada. Although the particular
duty cycles developed in this study may be applied to many
213 other similarly populated cities, the methodology described in
214 the next section is general and can be used to develop duty
215 cycles for any other urban area of interest.

III. METHODOLOGY OF DEVELOPMENT

The proposed methodology comprises two stages: 1) de-
veloping a driving cycle based on a large set of data points
220 collected and 2) incorporating results of a statistical analysis
221 on daily parking times to construct a 24-h duty cycle. An
222 enhanced statistical approach is developed using 25 parame-
ters to characterize the driving cycle by selecting candidates
223 from the database that have the closest match to the average
224 of the parameters. The candidate cycle is then incrementally
225 enhanced by replacing its microtrips with those extracted from
the same traffic group to minimize a figure of merit defined
227 based on average values of the characterizing parameters. The
229 processed parking data are then categorized in various groups
230 and included in the daily usage profile.
231 There are two general methodologies to develop a driving cycle.
232 One is based on creating a pool of trip segments extracted
233 from recorded speed–time traces of vehicles, followed by cat-
234 egorizing them into several driving modes and finally patching
235 snippets selected based on desired selection criteria together
236 to develop a representative driving cycle with a predetermined
duration [14]. In the other method, the single most representa-
tive speed–time trace is selected among a large number of
The dataset used in this study is schematically shown in Fig. 2. Fleet users were excluded from this study. The methodology is divided into two groups of weekday and weekend cycles. Commercial recorded driving cycles of participating vehicles are divided blockage due to tall buildings in the downtown area or during trips due to lack of connection to the positioning satellites or GPS loss-of-signal in the beginning of some times. The sources of error in collection of data for this study can be attributed to GPS loss-of-signal in the beginning of some times. The acting forces are the aerodynamic drag derivative of momentum in the moving direction. The time. The parameters in Table I were selected to ensure that the resulting cycle could be used to optimize a large array of drive-train topologies from conventional electric power to purely electric and with all possible topologies in between when using 322 combinations of propulsion systems.

The cycles that have the closest set of characterizing parameters to the average values in the weekday and weekend groups are selected and will be referred to as the candidate cycles hereinafter. The power and energy demand needed to meet the instantaneous speed of vehicle are calculated based on a longitudinal model for the dynamics of the vehicle, as follows:

\[ P = m \frac{dv}{dt} \]

where \( P \) is the power demand, \( m \) is the mass of the vehicle, \( v \) is the velocity, and \( m \frac{dv}{dt} \) is the rate of change of momentum. The power demand is calculated as the sum of the propulsion power, the braking power, and the accessory power.

The characterizing parameters of each individual cycle are measured and assigned to each individual cycle as follows:

\[ \sigma = \left( \sum_{i=1}^{N} \left( \frac{x_i - \bar{x}}{\sigma_i} \right)^2 \right) / N \]

where \( \sigma \) is the figure of merit, and \( N \) is the number of characterizing parameters, which is 25 in this study. Table I shows the list of the characterizing parameters \( x_i \), and their average values \( \bar{x} \), for both the weekday and weekend cycles are then calculated, as given in Table I.

The objective of analyzing parking data, which constitute the potential charging times for plug-in vehicles, is twofold: 1) to optimize the battery size for an individual vehicle based on several realistic charging scenarios and 2) to estimate the hourly distributed load on the electric grid of the municipality for preparation of adequate infrastructure to keep pace with increasing popularity of plug-in vehicles in the future. The former is important from a vehicle manufacturer’s perspective, and the latter is crucial for the electric utility to locate high-voltage feeders and redesign required infrastructure to charge vehicles in urban areas.

A. Selecting the Candidate Driving Cycles

A set of 25 parameters, as listed in Table I, is used to characterize each of the driving cycles in the pool of recorded data. In addition to the parameters describing kinematics of a 305 cycle, average power demand and average breaking power are also used. This is to extend the set of performance measures for driving cycles in line with the objectives of this study for plug-in vehicle design.

Characteristic parameters of each individual cycle are measured against their corresponding average values, and a figure of merit is calculated and assigned to each individual cycle as follows:

\[ \sigma = \left( \sum_{i=1}^{N} \left( \frac{x_i - \bar{x}}{\sigma_i} \right)^2 \right) / N \]

where \( \sigma \) is the figure of merit, and \( N \) is the number of characterizing parameters, which is 25 in this study. Table I shows the list of the characterizing parameters \( x_i \), and their average values \( \bar{x} \), for both the weekday and weekend cycles are then calculated, as given in Table I.

The parameters in Table I were selected to ensure that the resulting cycle could be used to optimize a large array of drive-train topologies from conventional electric power to purely electric and with all possible topologies in between when using 322 combinations of propulsion systems.

The cycles that have the closest set of characterizing parameters to the average values in the weekday and weekend groups are selected and will be referred to as the candidate cycles hereinafter. The power and energy demand needed to meet the instantaneous speed of vehicle are calculated based on a longitudinal model for the dynamics of the vehicle, as given in (2) and (3) [31]. The power demand is calculated by integrating net forces acting in the direction of motion over a time. The acting forces are the aerodynamic drag \( F_D \), the time derivative of momentum in the moving direction \( m \frac{dv}{dt} \), the derivative of momentum in the moving direction \( m \frac{dv}{dt} \), and the derivative of momentum in the moving direction \( m \frac{dv}{dt} \).
The microtrips are then classified according to their traffic into “microtrips.” A microtrip is defined as a snippet of the given in Table I. The average values for the enhanced candidate cycles are also on a methodology shown in Fig. 3. A maximum 5% deviation the database. The candidate cycles are then enhanced based figure of merit using microtrips of other cycles available in cycles, further processing is done with a view to improve their and 0.295, respectively. To enhance the quality of the candidate merit for weekday and weekend candidate cycles are 0.197 until the best figure of merit $\sigma$ is obtained. Classification of microtrips is an important step in the cycle-enhancement method that describes their physical characteristics in terms of driving patterns and traffic conditions. Congested traffic such as stop-and-go patterns is characterized by low average speed and mild acceleration (e.g., driving pattern in main commuting streets during rush hours). Urban traffic is designated by its moderate average speed and wider range of acceleration typically governed by stop signs and traffic lights in normal urban driving. Finally, the distinct feature of highway traffic is high average speed and moderate acceleration rates. The variations in the speed and acceleration can change the power demand accordingly, and hence, the time percentages spent in various speed and acceleration ranges provide important information about power demand in different traffic categories defined in Table III.

An alternative approach to developing a driving cycle is to use random selection methods to select the appropriate number of classified microtrips required to construct a representative cycle matching well with the average characterizing parameters with the lowest figure of merit. Random combination of microtrips has been used by other researchers as a means to construct representative driving cycles. Another approach to improve the current methodology would be to give a weighting factor to the terms in the definition of the figure of merit [see (1)] to adjust sensitivity of the final result to bias characterizing parameters in accordance with their importance in the final

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\rho$</td>
<td>1.2 kg/m³</td>
</tr>
<tr>
<td>$A_f$</td>
<td>2.5 m²</td>
</tr>
<tr>
<td>$C_D$</td>
<td>0.3</td>
</tr>
<tr>
<td>$V_W$</td>
<td>0 m/s</td>
</tr>
<tr>
<td>$m$</td>
<td>1550 kg</td>
</tr>
<tr>
<td>$\theta$</td>
<td>0</td>
</tr>
</tbody>
</table>

Table II: Parameters Used in Power and Energy Calculation

The governing equations are given as follows:

$$P = \left( m \frac{dv}{dt} + F_D + F_F + F_G \right) v$$

$$E = \int \left( m \frac{dv}{dt} + F_D + F_F + F_G \right) \cdot v \cdot dt$$

Where

$$F_D = \rho A_f C_D (v + v_w) \cdot \frac{v + v_w}{100} \cdot mg \cdot \cos \theta / 100$$

$$F_F = mg \sin \theta$$

$\rho$ is the air density, $A_f$ is the vehicle frontal area, $C_D$ is the aerodynamic drag coefficient, $V_W$ is the head-wind speed, $m$ is the mass of the vehicle, $g$ is the gravitational constant (9.8 m/s²), and $\theta$ is the grade angle of the road. In this paper, typical values for a midsize sedan, as given in Table II, are used in the energy and power calculations.

This assumption is in line with the dominance of sedans in urban transportation fleet, which is also mirrored in the fleet of participant vehicles in the data-collection phase. Positive values of power demand indicate the power to be provided by the propulsion system at the wheels. The total daily energy demand is calculated 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 by conventional breaking systems or partially recovered in regenerative breaking systems.

### B. Enhancement of the Candidate Driving Cycles

It is clear that the two candidate driving cycles do not necessarily match all the average values uniformly well, although they have the best figures of merit for single daily cycles in the database. In this paper, for instance, figures of merit for weekday and weekend candidate cycles are 0.197 and 0.295, respectively. To enhance the quality of the candidate cycles, further processing is done with a view to improve their figure of merit using microtrips of other cycles available in the database. The candidate cycles are then enhanced based on a methodology shown in Fig. 3. A maximum 5% deviation from average daily energy demand for final driving cycles is allowed in the construction of the enhanced candidate cycles.

The average values for the enhanced candidate cycles are also given in Table I.

The recorded speed–time traces from the database are split into “microtrips.” A microtrip is defined as a snippet of the speed–time trace that begins and ends at idle states: zero speed. The microtrips are then classified according to their traffic groups characterized by average speed and acceleration, as given in Table III. Here, each microtrip of the candidate cycle is iteratively exchanged with microtrips of the same traffic group until the best figure of merit $\sigma$ is obtained.

<table>
<thead>
<tr>
<th>Traffic category</th>
<th>Average speed</th>
<th>Acceleration</th>
</tr>
</thead>
<tbody>
<tr>
<td>Congested</td>
<td>Low: [0.5] km/h</td>
<td>Mild: [-0.1,0.1] m/s²</td>
</tr>
<tr>
<td>Urban</td>
<td>Moderate: [5.40] km/h</td>
<td>Harsh: [-3.0,3.0] m/s²</td>
</tr>
<tr>
<td>Highway</td>
<td>High: [40,100] km/h</td>
<td>Moderate: [-1.0,1.0] m/s²</td>
</tr>
</tbody>
</table>

Fig. 3. Methodology of enhancing the candidate cycles.

Table III: Microtrip Clustering Criteria
duty cycle. In this paper, all weighting factors are considered equal to 1. Evidently, energy needed and power demand for traveling the same distance in different traffic modes are not equal. It is also well understood that the aggressiveness of the driver in accelerating and decelerating the vehicle increases power consumption. However, it should be noted that replacing microtrips of the candidate cycle with microtrips of the same traffic mode, but potentially from different driving styles, is not misleading from an energy perspective. This is due to the fact that all parameters defining aggressiveness, energy level, and power consumption are already included in the 25 characterizing parameters used in this study, and the replacements increasing the figure of merit to larger values are not considered. Implementing alternative enhancement methodologies mentioned earlier and their performance assessment are left for further work. Fig. 4 shows the enhanced weekday and weekend candidate driving cycles. The metric units are used throughout the study.

The speed in the driving cycles shown in Fig. 4 is given in kilometers per hour; however, for more convenience, both English and metric versions of the driving cycles in digital format are made available to the public [36].

Durations of the weekday and weekend cycles are 3484 and 3616 s, respectively. The maximum velocity is higher in the weekend cycle, i.e., 114 km/h, whereas in the weekday cycle, the maximum velocity is 89.6 km/h. The enhancement process does not necessarily finish by yielding a figure of merit equal to zero, but a considerable improvement can be expected as, in this study, the initial values were improved by approximately 40%. The figure of merit for the enhanced weekday and weekend driving cycles are 0.15 and 0.2, respectively. The two patterns are different in nature. Stop-and-go events characterized by larger acceleration or deceleration rates at low speeds are more probable in the weekday pattern. However, high-speed events are more probable in the weekend pattern. The driving pattern on the weekend is slightly more aggressive due to higher acceleration and deceleration rates, which results in higher power demand for weekend driving patterns.

The power–time profiles corresponding to the two driving cycles are also presented in Fig. 6. To obtain these profiles, a vehicle with the specifications listed in Table II is considered to have driven the two cycles. Evidently, variations and abrupt changes in power demand are more considerable in the stop-and-go driving mode that is dominant in congested and urban traffics in the weekday driving cycle. This mode of driving considerably contributes to air pollution in downtown areas of large metropolitan areas, and it is particularly important to be covered by electric propulsion in the case of HEVs.
IV. PARKING ANALYSIS

Vehicle parking at home, the workplace, commercial locations, and on the street constitutes a critically important element of a modern duty cycle that can address a multitude of drive-train topologies, storage technologies, and controllers. Developing models to analyze the parking behavior in an urban area for city planning may require detailed information on the parameters affecting parking behavior during the day, such as travel demands, district-based knowledge on cost of parking, nature of activities in the area of interest, and supply and demand on an hourly basis. However, from the charging perspective only, relatively long parking times provide potential charging times to increase the SOC of an onboard energy storage device. A typical duration for a full charge under normal charging conditions (110 V and 15 A) for current competitive battery technologies used in electric vehicles, namely, lithium ion and nickel metal hydride, is approximately 6 h; the minimum duration for partial charging is presently not known with a high confidence level. Therefore, it is expected that most plug-in electric vehicles will be charged mainly overnight. If a relatively long parking time (e.g., more than 3 h) during the day is considered as a realistic scenario for a reasonable share of the urban fleet, it is possible to downsize the battery storage capacity and reduce the capital cost of a plug-in vehicle or, in the case of a PHEV with a fixed size of battery storage, drive more miles on electricity to improve cost effectiveness.

In addition, fast charging schemes using level 2 (120 V and 30 A) and direct dc chargers will facilitate full charging in shorter charging durations, i.e., as low as 20 min, depending on the battery technology and dc charging infrastructure.

It is also important to highlight that identification of parking locations for charging opportunities is critical; this aspect has been of strong interest to utilities, as they need to address both power and energy demand for electric mobility, with power having a large impact on grid infrastructure costs. Charging at residential areas, parking lots at work places, and large shopping malls is of interest; however, parking in streets or less-frequently open areas is not emphasized due to the large infrastructure cost required to achieve this type of opportunity charging. In the development of a duty cycle in this work, parking events are described for all categories over a 24-h period to provide data for any combination of future charging scenarios. Inherent in this study is the assumption that plug-in vehicle owners will not be significantly modifying their parking behaviors, although they may change their parking stall to access a plug.

An extensive literature survey reveals that a few studies have focused on the potential charging aspect of parking times as a part of daily activities of vehicles; none seem to have incorporated this into a duty cycle. This aspect is of critical importance to address energy drivers in transportation and allow the displacement of fossil fuels with new renewable energy generation. The analysis conducted by the Argonne National Laboratory (ANL) shows that, in the United States, 66% of the vehicles driven to work are parked more than 3 h before noon, potentially allowing a second charge before the electric utility peak demand begins [37]. It was also observed that vehicles were parked for a short time for shopping purposes, and parking was often during peak electric demand [36].

In this paper, GPS-based data loggers provide information on location, type of parking, and duration of parking events. The type of parking can be determined from the driver’s behavior, where it is relatively simple to determine where the person lives and works; commercial parking locations are found by digitizing commercial parking lots in Winnipeg. Street parking is deduced from a car staying on the street. Note that studies dedicated to record the instantaneous speed of the vehicle for certification purposes, such as that leading to the FTP72 standard cycle and its enhanced cycles, do not provide information on parking times. Here, probable parking times and average duration for each parking event, as well as the standard deviation of the data points, are included to adequately reflect a daily driving and parking profile for electric vehicle design of drive-train topologies.

Parking times of less than half an hour are arbitrarily classified in our study as short; the distribution of such parking events shows that, in early mornings and afternoons, this type of parking is the most likely. It is important to note that stop times of less than 2 min, happening at stop signs or traffic lights, are excluded from short parking. The results of short parking times are not presented here as it is assumed that, in the real world, these occasional parking events are not favored by drivers for charging. However, a cumulative parking time...
representing short parking times per day will be included in the final duty cycles. The results of studying parking periods that exceed 30 min are shown in Fig. 7.

Fig. 7(a) and (b) shows mean values and standard deviations of parking durations by hour of day for weekdays and weekends, respectively.

Two distinct patterns in daily parking behavior can be recognized, namely, a mean value less than or equal to the standard deviation and a mean value larger than the standard deviation. Long parking duration with a mean value larger than the standard deviation happens between 8 P.M. and 6 A.M., showing that the majority of drivers tend to park their vehicles for a long time. However, when the standard deviation is greater than the mean value of parking duration, the data show an increase in daily trips, happening between 10 A.M. and 4 P.M., and the average of the mean values is about 4 h. Peaks in probability of parking events in terms of hour of day, as shown in Fig. 7(c), reflect the difference in nature of activities between weekdays and weekends. While there is only one peak in the weekend curve happening at 7 P.M., there are three peaks occurring at 7 A.M., 12 P.M., and 5 P.M. during weekdays.

On weekdays, 67% of the vehicles park for more than 3 h between 6 A.M. and 9 A.M., whereas between 9 A.M. and 12 P.M., only 33% of the vehicles park for more than 3 h. This can be justified as many commuters drive to work and park their car during working hours at their working place early in the morning. However, after 9 A.M., vehicles moving in the streets tend to park for a limited duration, i.e., typically less than 3 h, which is necessary for activities such as shopping. The analysis shows that, while overnight charging is the first choice for charging the battery, second charging is most likely to happen in the morning around 9 A.M. or in the afternoon around 5 P.M. Taking the higher electricity price in peak hours in many jurisdictions, a more realistic scenario for charging would be overnight followed by early mornings. However, the distribution of charging load on the electric grid overnight or during the day would be different, which indicates a need to redesign the location of feeders in the city. This aspect of charging electric cars is beyond the scope of this study and will be published in separate articles of various charging opportunities and power levels.

V. Assembly of the Driving Cycles

Analysis was performed on the raw GPS data in conjunction with the digitized maps of the roads and commercial parking locations to characterize the driving and parking behavior of the vehicles under the one-year span of the survey in the city of Winnipeg. Using the method shown in Fig. 2, two 24-h vehicle usage profiles representing a daily duty cycle were developed for both weekdays and weekends. The parking patterns obtained from the analysis of parking times, as well as cumulative short parking events, are included in the daily duty cycles for weekdays and weekends. In creating this, the average distance traveled in driving events is considered to separate the final driving cycle into parts, and then, parking events are inserted in between in the most probable way. The resulting cycles are shown in Fig. 8 and are meant to represent the 44 million data points into a condensed duty cycle for studies pertaining to plug-in hybrids, including optimization of power trains [29]. In Fig. 8, D stands for driving, P stands for parking periods, P1 stands for home, P2 stands for work, P3 stands for parking, P4 stands for short stops, and P5 stands for street parking. The driving cycles are on a 1-h basis, and the duty cycles, with long parking times included, are on a 24-h basis and are both combined into the same figure. The parking durations on a 24-h scale designated by color codes are also shown on a 1-h driving scale for the sake of clarity. The parking events that potentially can be used for charging are P1, P2, or P3 when the vehicle is most probably parked in a parking spot with access to level-1 or level-2 charging. The parking events that happen on the street or short parking durations are considered not suitable for charging.

Some characteristics of the enhanced driving cycle are compared with those of the standard cycle UDDS, and the results are presented in Fig. 9. The comparison indicates that more aggressive characteristics are associated with the real-world
cycle, whereas, on average, the two cycles may be considered interchangeable.

Evidently, the vehicles with the opportunity to charge limited to overnight have more time to be fully charged under slow charging mode on the weekends. This is particularly important for PEVs with larger battery storage capacity. Deriving a grid load based on this driving cycle has merit but requires the understanding of its limitations for utilities; however, it is beyond the scope of this work.

The data files of the duty cycles and the collected raw data are available to the public on the World Wide Web through a unique Digital Object Identifier number [36]. Forty-four million speed–time data points, stamped with date and time, and collected over the course of one year are made available. The latitude and longitude of the position of the vehicles recorded on a secondly basis are masked by mapping the starting point of every trip to (0,0) to respect the confidentiality agreement with the participants in the data-collection phase. However, personal information about the participants is used to label the parking locations as home or work. Labeled parking locations, as well as the duration of parking events needed for further analyses with different charging scenarios in the case of plug-in electric vehicles, are included in the data files. The parking events that are less than 30 min in duration are labeled short stops. Parking events happening along the street are not potentially suitable for charging. The locations of the parking events longer than 30 min in duration are marked home, work, shop, and street. The effectiveness of the methodology presented in this study, even with far fewer data points (about 1 million data points, which is equal to about 2% of the data points used in this study), for simulation-based optimization of a PHEV was shown in [29].

VI. Conclusion

A new approach to the development of a duty cycle that addresses the requirements associated with the design of electric vehicles—e.g., HEV, PHEV, BEV, and extended-range vehicles, has been proposed and implemented on a 24-h timescale. It provides a complete data set for optimization of battery size for on-road vehicles in a typical North American urban setting. For example, power and energy demand in the daily operation of a sedan is directly related to the rate of acceleration and deceleration and time spent in different traffic modes; charging scenarios depend on parking times and duration. The driving behavior of a fleet of 76 participants in a one-year voluntary data-collection program in the city of Winnipeg is analyzed to develop a driving cycle and is composed of two 24-h duty cycles for weekdays and weekends. This cycle provides information about the time and duration of driving in different traffic categories, as well as information on parking times when the vehicle is not in use. Further vehicle simulation tools can use the daily duty cycles developed to optimally design propulsion systems, drive-train configurations, and storage components for PEV technologies under real-world driving conditions. Furthermore, this information can be used to analyze the impact of daytime charging by a fleet of plug-in electric vehicles on the electric utility grid that may create a peak demand during the day to be met by the local utility grid.

The target use of the developed cycle is to provide a duty cycle that can be used to optimally address energy drivers simultaneously facing transportation by displacing fossil fuels with new renewable energy generations with the direct consequences of increasing the renewable energy ratio of various jurisdictions.

To achieve this goal, 25 parameters characterizing a driving cycle for further PEV simulations are recognized, and two candidate daily cycles having the closest match to the average 680 of the parameters are selected. The candidate cycles are then incrementally enhanced by replacing their microtrips with those extracted from the same traffic group, minimizing a figure of merit defined based on the characterizing parameters. Finally, the processed parking data are included to complete two 24-h duty cycles. The final result is therefore reflecting more accurately a realistic driving pattern than driving cycles resulting from methodologies that patch snippets of driving data from different drivers or occasions to make a driving cycle. Although the data collected represent driving behavior in the city of Winnipeg, MB, Canada, the methodology presented here can be extended to any other urban area of interest.

There exist a few directions to continue the research on or using the collected data. Other methods for development of a driving cycle may include a stochastic approach for selecting and patching snippets of speed–time traces using a probability matrix [14], [21], which might be enhanced to incorporate power and energy requirements of the vehicle. Future work may also concentrate on one specific driving pattern, for instance, a commuter, to develop a dedicated driving cycle best mirroring that particular driving pattern. The driving cycle may also be used for a wide range of applications, such as energy assessment of the vehicles in daily use in urban transportation, analysis of charging scenarios in PHEVs and PEVs, vehicle-to-grid analysis, and statistical assessment of driving cycle variability on hybrid drive-train design. Finding other applications, particularly from a social driving behavior perspective, can also be viewed as an important extension of the work.

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REFERENCES

A. Esteves-Booth, T. Muneer, H. Kirby, J. Kubie, and J. Hunter, “The IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY


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Statistical Development of a Duty Cycle for Plug-in Vehicles in a North American Urban Setting
Using Fleet Information

Soheil Shahidinejad, Eric Bibeau, and Shaahin Filizadeh, Member, IEEE

Abstract—Development of a daily duty cycle based on real-world driving behavior and parking times is a critical requirement in the optimal design of power-train components of a plug-in vehicle. Standard driving cycles cannot completely emulate the real-world power demand of a vehicle and its downtimes in particular. To address these shortcomings, a large database of one year of measured data collected from a fleet of 76 cars in the city of Winnipeg, MB, Canada is obtained and is then used to develop a new duty cycle. This paper describes a methodology for statistical analysis of the fleet data, including while a vehicle is parked. Due to the intrinsic differences in vehicle usage profiles during weekdays and weekends, two 24-h duty cycles with suitable windows of opportunity for charging are developed for weekday and weekend driving patterns. The uniqueness of the proposed statistical methodology and the resulting duty cycles contribute to addressing the present shortcomings of standard driving cycles.

Index Terms—Battery storage, driving cycle, duty cycle, electric vehicle, plug-in hybrid vehicles, renewable energy.

I. INTRODUCTION

ELECTRIFICATION of transportation for light-duty vehicles is a prominent step toward sustainable transportation [1], [3]. It can also contribute to efficient integration and use of existing and emerging renewable energy resources. Plug-in vehicles (i.e., pure electric or plug-in hybrids) have a strong potential to reduce petroleum consumption by shifting energy demand away from fossil fuels to electrical energy that is domestically produced using renewable sources. A plug-in vehicle allows its battery storage to recharge via connection to a utility grid while the vehicle is parked. Due to the intrinsic differences in vehicle usage profiles during weekdays and weekends, two 24-h duty cycles with suitable windows of opportunity for charging are developed for weekday and weekend driving patterns. The uniqueness of the proposed statistical methodology and the resulting duty cycles contribute to addressing the present shortcomings of standard driving cycles.

The variable and unpredictable nature of renewable sources. It is envisioned that by increasing the share of renewable energies for electric power generation and optimizing rechargeable energy storage battery units in plug-in vehicles, major concerns with regard to peak oil, greenhouse gases leading to climate change, energy security, and emissions, can be simultaneously addressed [4]. Due to high cost and large weight per unit energy capacity of current battery cells, the technology pathway for plug-in PHEVs to lower the battery size and cost includes providing additional daily charging opportunities during periods when the 48 vehicles are parked and opportunities for charging exist [3]–[7].

Complete assessment of the potential power and energy demand in plug-in vehicles is required to simulate and optimize their energy-storage systems [8]. Optimal sizing of the electric drive-train components, choice of battery chemistry and storage size, development of controllers tuned and optimized to vehicle driving patterns, as well as realistic opportunity charging scenarios, all require detailed information on the vehicle’s usage profile. Obviously, recharging scenarios and grid impacts can be better analyzed with detailed information on parking durations, as well as time and location of parking events in drivers’ daily routines. Real-world driving patterns provide insight into speed and acceleration characteristics. However, only standard driving schedules conducted on dynamometers or well-documented tracks have been accepted as a systematic approach to mimic real-life situations. Standard certification driving cycles such as the Urban Dynamometer Driving Schedule (UDDS) or Highway Fuel Economy Test have been conventionally used in conjunction with controlled chassis dynamometer testing to represent average driving behavior of the drivers in fuel economy and emission certification of the vehicles.

It is important to note that the standard certification cycles are still unable to handle extreme acceleration or deceleration rates that fall beyond capabilities of laboratory equipment and are bound to limited cycle durations, i.e., usually less than 20 min, to keep test costs low [5], [12]. For instance, the FTP72 driving cycle, which dates back to early 1970s, was primarily developed to measure exhaust emissions of typical light-duty vehicle operations in the Los Angeles urban area [13]. To address the shortcomings of the FTP72 cycle in representing more aggressive speeds and accelerations, a Unified Cycle was developed in 1992 based on collected data, known as LA92. However, there are still many concerns about the problems inherent in the existing driving cycles, which lead to underestimation of cruise, acceleration, or stop-and-go activities in different brackets of...
An extensive literature survey conducted revealed no reference to the development of a daily driving cycle, taking into account power and energy demands as major requirements for representing the real-world data. Most studies have focused on developing urban driving cycles using snippets extracted from recorded speed–time traces to estimate vehicular emissions and fuel consumption in different cosmopolitan areas [15], [19]. The objective of these studies is to represent the driving information in a collected data set using a single driving cycle. Some other studies discuss the effectiveness of the methodologies used in developing driving cycles to represent the inherent characteristics of driving behavior in the collected data [20], [21]. A few recent studies exist that have assessed the performance of hybrid electric vehicles (HEVs) in real-world operation. For example, data collected for a fleet in the St. Louis, MO, metropolitan area were used in the simulation of energy usage in a PHEV, but no single driving pattern was extracted from the collected data [22]. Fuzzy logic pattern recognition techniques have also been used to perform driving and duty cycle analyses on data collected for a fleet of HEVs [23]. The methodology used in the precedent study for simulation of a plug-in vehicle is enhanced by including 25 parameters to characterize different velocity brackets in a driving cycle [24]. The uniqueness of this study is proposing a methodology that addresses the particular requirements associated with the design of plug-in vehicles in construction of a 24-h duty cycle.

Following the introduction, in Section II, duty cycle requirements to be fulfilled for enhanced simulation and optimization of plug-in vehicles are discussed. Data collection, methods of driving cycle generation [26], [28], and the European standard cycles into simulations [24]. A methodology that generates a driving cycle has also been reported based on the assumption of constant acceleration and deceleration rates, along with consideration of the speed limits in different road segments in representative areas [25]. It can therefore be concluded that there does not exist a single widely accepted duty cycle in the literature to appropriately represent typical daily activities of the vehicles and to address the energy and power demands of the PHEVs and BEVs. The study presented in this paper addresses the gap in the literature by developing a statistical methodology and constructing the needed duty cycles based on a database of over 44 million Global Positioning System (GPS) data points recorded over the course of one year in Winnipeg, MB, Canada.

Depending on the context, the terms “driving cycle” and “duty cycle” may convey different meanings. In this paper, a “driving cycle” refers to a history of daily driving periods represented by a speed-versus-time curve. A “duty cycle” refers to a profile of daily usage of power by the vehicle, which is typically represented by a 24-h history of driving and parking events. Note that, in the case of an HEV, only a driving cycle is sufficient to calculate vehicle’s power demand, whereas in the case of a plug-in vehicle, parking times also become vital as they may be used for charging from the electric grid, and therefore, they should be included in the daily profile. Parking times are also important to utilities servicing jurisdictions with large vehicular loads, as they can be used to predict and control the load on the grid.

The objective of the present study is to first develop a new driving cycle most closely mirroring the characteristics of urban driving, including real-world energy and power demands. Once this is achieved, this study aims to incorporate a pattern representing most probable downtimes of the vehicles to charge during their daily usage profile. A comprehensive daily duty cycle is a crucial component for optimal design of plug-in vehicular drive-trains. This study improves the conventional methods of driving cycle generation [26], [28]. The present study also establishes a set of performance measures required to assess a driving cycle suited for electric/plug-in hybrid vehicles. The methodology used in the precedent study for simulation of a plug-in vehicle is enhanced by including 25 parameters to characterize different velocity brackets in a driving cycle [24]. The uniqueness of this study is proposing a methodology that addresses the particular requirements associated with the design of plug-in vehicles in construction of a 24-h duty cycle.

Following the introduction, in Section II, duty cycle requirements to be fulfilled for enhanced simulation and optimization of plug-in vehicles are discussed. Data collection, methods of driving cycle generation, and characterization are described in Section III. Parking data analysis for weekdays and weekend ends is presented in Section IV. The resulting 24-h duty cycles are given in Section V, and driving characteristics are critically compared with those of the standard cycle for urban driving, i.e., the UDDS. Conclusions are presented in Section VI.

II. DUTY CYCLE REQUIREMENTS FOR PLUG-IN VEHICLES

The total distance that a plug-in vehicle can electrically drive is an important measure for the vehicle’s performance assessment. For instance, PHEVs are usually classified according to their all-electric range (AER), which is defined as the total miles electrically driven after a full recharge before the engine turns on for the first time [30]. A fully recharged PHEV operates in charge-depleting mode until the battery is depleted to a target state-of-charge (SOC), at which point, the vehicle switches to charge-sustaining mode, using the internal combustion engine to maintain the target SOC [3]. Fig. 1 shows the typical variation in the SOC of the battery in the operating modes of a PHEV.

Obviously, the instantaneous power demand resulting from the driving style of the driver is critical in the definition of the AER. The standard cycle UDDS is usually used to measure
TABLE I
CHARACTERIZING PARAMETERS AND THEIR VALUES

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Database average</th>
<th>Final duty cycles</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Average speed of the entire driving cycle in km/h</td>
<td>31.4</td>
<td>32.6</td>
</tr>
<tr>
<td>2 Average running speed in km/h</td>
<td>39.8</td>
<td>40.3</td>
</tr>
<tr>
<td>3 Total daily distance traveled in km</td>
<td>32.2</td>
<td>33.1</td>
</tr>
<tr>
<td>4 Average acceleration of all acceleration phases in m/s^2</td>
<td>0.6</td>
<td>0.55</td>
</tr>
<tr>
<td>5 Average deceleration of all deceleration phases in m/s^2</td>
<td>-0.6</td>
<td>-0.59</td>
</tr>
<tr>
<td>6 Average number of change in acceleration rate (+/-) in one driving period</td>
<td>6.5</td>
<td>7.83</td>
</tr>
<tr>
<td>7 Average daily power demand in kW</td>
<td>7.9</td>
<td>8.92</td>
</tr>
<tr>
<td>8 Maximum power demand in kW</td>
<td>59.3</td>
<td>49.45</td>
</tr>
<tr>
<td>9 Total daily energy demand in MJ</td>
<td>17.3</td>
<td>16.41</td>
</tr>
<tr>
<td>10 Average daily breaking power in kW</td>
<td>-5.3</td>
<td>-5.47</td>
</tr>
<tr>
<td>11 Root mean square of acceleration in m/s^2</td>
<td>0.8</td>
<td>0.66</td>
</tr>
<tr>
<td>12 Average length of a driving period in km</td>
<td>0.9</td>
<td>0.75</td>
</tr>
<tr>
<td>13 Time percentage of idling (zero velocity) in %</td>
<td>21.8</td>
<td>19.1</td>
</tr>
<tr>
<td>14 Time percentage of acceleration: acceleration&gt;0.1 m/s^2 in %</td>
<td>31.4</td>
<td>36.5</td>
</tr>
<tr>
<td>15 Time percentage of cruising (acceleration [-0.1,0.1] m/s^2, speed&gt;5 m/s) in %</td>
<td>14.9</td>
<td>9.8</td>
</tr>
<tr>
<td>16 Time percentage of deceleration: acceleration &lt;-0.1 m/s^2 in %</td>
<td>31.2</td>
<td>34.4</td>
</tr>
<tr>
<td>17 Time percentage of creeping (acceleration [-0.1,0.1] m/s^2, speed&lt;5 m/s) in %</td>
<td>0.6</td>
<td>0.32</td>
</tr>
<tr>
<td>18 Time percentage of driving at very low speed bracket [0 20] km/h in %</td>
<td>94.5</td>
<td>85.3</td>
</tr>
<tr>
<td>19 Average speed in very low speed bracket [0 20] km/h</td>
<td>6.6</td>
<td>7.3</td>
</tr>
<tr>
<td>20 Time percentage of driving at low speed bracket [20 50] km/h in %</td>
<td>58.9</td>
<td>62.0</td>
</tr>
<tr>
<td>21 Average speed in low speed bracket [20 50] km/h</td>
<td>18.9</td>
<td>19.2</td>
</tr>
<tr>
<td>22 Time percentage of driving at moderate speed bracket [50 80] km/h in %</td>
<td>36.7</td>
<td>37.4</td>
</tr>
<tr>
<td>23 Average speed in moderate speed bracket [50 80] km/h</td>
<td>32.9</td>
<td>34.9</td>
</tr>
<tr>
<td>24 Time percentage of driving at high speed bracket [80 100] km/h in %</td>
<td>9.9</td>
<td>8.9</td>
</tr>
<tr>
<td>25 Average speed in high speed bracket [80 100] km/h</td>
<td>16.3</td>
<td>15.0</td>
</tr>
</tbody>
</table>

The AER for classifying PHEVs. Therefore, a PHEV expected to travel x miles on battery, in the real world, would perform quite differently, depending on the driving habits of the driver. The mentioned difficulty in providing a realistic performance measure to the end users is also valid in the case of an HEV. The dominant mode of operation in an HEV battery is charge sustaining, and its fuel efficiency is characterized by a higher mile per gallon rate when compared with conventional vehicles. Again, using the standard cycle is misleading as, in reality, fuel consumption would be higher, depending on the aggressiveness of the driver.

In this study, real-world driving data are collected over a sufficiently long period to reduce statistical errors. In addition, the characterizing parameters of the driving cycles used to generate the standard driving cycles are extended to cover average driver’s daily energy demand and maximum power demand (positive in acceleration and negative in deceleration) for light-duty vehicles (with a dominant share in urban traffic). The information on parking events such as the frequency of occurrence and the ratio of parking to driving times in an average daily driving profile is also included to construct an average 24-h duty cycle.

The characterizing parameters considered in this paper are those defining power requirements at different driving modes, as listed in Table I. Except for its considerably cold winter temperatures, Winnipeg, with a population of 700 000, is a typical North American urban setting where driving culture, population, and traffic behavior are similar to many other cities across the United States and Canada. Although the particular duty cycles developed in this study may be applied to many other similarly populated cities, the methodology described in the next section is general and can be used to develop duty cycles for any other urban area of interest.

III. METHODOLOGY OF DEVELOPMENT OF A DRIVING CYCLE

The proposed methodology comprises two stages: 1) developing a driving cycle based on a large set of data points collected and 2) incorporating results of a statistical analysis on daily parking times to construct a 24-h duty cycle. An enhanced statistical approach is developed using 25 parameters to characterize the driving cycle by selecting candidates from the database that have the closest match to the average of the parameters. The candidate cycle is then incrementally enhanced by replacing its microtrips with those extracted from the same traffic group to minimize a figure of merit defined based on average values of the characterizing parameters. The processed parking data are then categorized in various groups and included in the daily usage profile.

There are two general methodologies to develop a driving cycle. One is based on creating a pool of trip segments extracted from recorded speed–time traces of vehicles, followed by categorizing them into several driving modes and finally patching snippets selected based on desired selection criteria together to develop a representative driving cycle with a predetermined duration [14]. In the other method, the single most representative speed–time trace is selected among a large number of
speed–time traces recorded from real-world driving. A set of 241 characterizing parameters describing the driving cycle is used 242 to select this representative cycle, and modifications are made 243 to the selected cycle to meet certain constraints of important 244 aspects of a cycle to address the concerns in plug-in 245 vehicle design and optimization, as mentioned previously. 246 Therefore, the second methodology is used in this study to 247 develop a cycle realistically mirroring the characteristics of 248 urban driving. This study adopts an adequately long-term app 249roach to data collection from a fleet of instrumented vehicles 250 to reduce the risk of unreal driving behavior resulting from 251 any influence of the onboard instruments that may potentially 252 bias drivers’ driving behavior. Over a one-year timescale, the 253 vehicle owners presumably drive on their ordinary travel routes, 254 whereas onboard instruments automatically timestamp the ve 255hicle’s location and speed on a secondly basis. 256

In the present study, data from 76 participant vehicles over a 259 one-year period starting from May 2008 to June 2009 collected 260 by the University of Winnipeg are used. The participants have 261 been selected from different income brackets, education levels, 262 and gender and from different areas of the city to create a 263 statistical population best representing the drivers in the area. 264 The fleet of participating vehicles consists of sedans, both ful 265 and midsize (67%), and sport utility vehicles and pickup trucks 266 (33%). Recorded raw data are used to create a database for 267 further analysis to identify daily driving cycles and parking 268 times. The sources of error in collection of data for this study 269 can be attributed to GPS loss-of-signal in the beginning of some 270 trips due to lack of connection to the positioning satellites or 271 blockage due to tall buildings in the downtown area or during 272 the days with significant cloud coverage. 273

The database includes trip number, date, time, position, 274 actual speed, and maximum allowable speed (according to the 275 traffic signs at a vehicle’s location), on a secondly basis. The 276 recorded driving cycles of participating vehicles are divided 277 into two groups of weekday and weekend cycles. Commercial 278 fleet users were excluded from this study. The methodology 279 used in this study is schematically shown in Fig. 2. 280

It comprises three major steps to find a candidate cycle, 281 enhancing the candidate cycle for best representativeness, and, 282 finally, including results of parking data analysis into the 283 driving cycle to create a 24-h duty cycle.

In this paper, two daily driving cycles, i.e., one representing 284 weekdays and one for weekends, are selected among the avail 285 able recorded cycles to avoid lower resolution resulting from 286 mixing their different parking and driving patterns. The two 287 candidate driving cycles best match the average weekday and 288 weekend behavior of the fleet in terms of a set of characterizing 289 parameters given in Table I.

The objective of analyzing parking data, which constitute 291 the potential charging times for plug-in vehicles, is twofold: 292 1) to optimize the battery size for an individual vehicle based 293 on several realistic charging scenarios and 2) to estimate the 294 hourly distributed load on the electric grid of the municipality 295 for preparation of adequate infrastructure to keep pace with 296 increasing popularity of plug-in vehicles in the future. The 297 former is important from a vehicle manufacturer’s perspective, 298 and the latter is crucial for the electric utility to locate high 299 voltage feeders and redesign required infrastructure to charge 300 vehicles in urban areas.

A. Selecting the Candidate Driving Cycles

A set of 25 parameters, as listed in Table I, is used to 303 characterize each of the driving cycles in the pool of recorded 304 data. In addition to the parameters describing kinematics of a 305 cycle, average power demand and average breaking power are 306 also used. This is to extend the set of performance measures 307 for driving cycles in line with the objectives of this study for 308 plug-in vehicle design.

Characteristic parameters of each individual cycle are mea 310 sured against their corresponding average values, and a figure 311 of merit is calculated and assigned to each individual cycle as 312 follows:

$$\sigma = \left( \frac{1}{N} \sum_{i=1}^{N} \left( \frac{x_i - \bar{x}}{\sigma} \right)^2 \right)^{1/2}$$

where $\sigma$ is the figure of merit, and $N$ is the number of char 314 acterizing parameters, which is 25 in this study. Table I shows 315 the list of the characterizing parameters $x_i$, and their average 316 values $\bar{x}$ for both the weekday and weekend cycles are then 317 calculated, as given in Table I.

The parameters in Table I were selected to ensure that the 319 resulting cycle could be used to optimize a large array of 320 drive-train topologies from conventional gas powered to purely 321 electric and with all possible topologies in between when using 322 combinations of propulsion systems.

The cycles that have the closest set of characterizing pa 324 rameters to the average values in the weekday and weekend 325 groups are selected and will be referred to as the candidate 326 cycles hereinafter. The power and energy demand needed to 327 meet the instantaneous speed of vehicle are calculated based 328 on a longitudinal model for the dynamics of the vehicle, as 329 given in (2) and (3) [31]. The power demand is calculated by 330 integrating net forces acting in the direction of motion over 331 time. The acting forces are the aerodynamic drag $F_D$, the time 332 derivative of momentum in the moving direction $mdv/dt$, the 333
334 rolling friction $F_D$, and the road grade force $F_G$ [32], [33]. The
335 governing equations are given as follows:

\[
P = \left( m \frac{dv}{dt} + F_D + F_F + F_G \right) v \quad (2)
\]

\[
E = \int_0^t \left( m \frac{dv}{dt} + F_D + F_F + F_G \right) \cdot v \cdot dt \quad (3)
\]

336 where

\[
F_D = \rho A_f C_D (v + v_w)^2 / 2 \quad (4)
\]

\[
F_F = (1 + v/100) \cdot m g \cdot \cos \theta / 100 \quad (5)
\]

\[
F_G = m g \sin \theta \quad (6)
\]

337 $\rho$ is the air density, $A_f$ is the vehicle frontal area, $C_D$ is
338 the aerodynamic drag coefficient, $V_w$ is the head-wind speed, $m$
339 is the mass of the vehicle, $g$ is the gravitational constant
340 $(9.8 \text{ m/s}^2)$, and $\theta$ is the grade angle of the road. In this paper,
341 typical values for a midsize sedan, as given in Table II, are used
342 in the energy and power calculations.

343 This assumption is in line with the dominance of sedans in
344 urban transportation fleet, which is also mirrored in the fleet of
345 participants in the data-collection phase. Positive values
346 of power demand indicate the power to be provided by the
347 propulsion system at the wheels. The total daily energy demand
348 is calculated by integrating the positive values of the power
349 demand over time divided by the number of data-collection
350 days. Negative values of power demand represent the power
351 to be dissipated as heat by conventional breaking systems or
352 partially recovered in regenerative braking systems.

353 B. Enhancement of the Candidate Driving Cycles

354 It is clear that the two candidate driving cycles do not
355 necessarily match all the average values uniformly well, al-
356 though they have the best figures of merit for single daily
357 cycles in the database. In this paper, for instance, figures of
358 merit for weekday and weekend candidate cycles are 0.197
359 and 0.295, respectively. To enhance the quality of the candidate
360 cycles, further processing is done with a view to improve their
361 figure of merit using microtrips of other cycles available in
362 the database. The candidate cycles are then enhanced based
363 on a methodology shown in Fig. 3. A maximum 5% deviation
364 from average daily energy demand for final driving cycles is
365 allowed in the construction of the enhanced candidate cycles.
366 The average values for the enhanced candidate cycles are also
367 given in Table I.

368 The recorded speed–time traces from the database are split
369 into “microtrips.” A microtrip is defined as a snippet of the
370 speed–time trace that begins and ends at idle states: zero speed.
371 The microtrips are then classified according to their traffic
372 groups characterized by average speed and acceleration, as 373
374 given in Table III. Here, each microtrip of the candidate cycle is 375
376 iteratively exchanged with microtrips of the same traffic group 377
378 until the best figure of merit $\sigma$ is obtained.

379 Classification of microtrips is an important step in the 376
379 cycle-enhancement method that describes their physical char-377
380 acteristics in terms of driving patterns and traffic conditions. 381
377 Congested traffic such as stop-and-go patterns is characterized 378
381 by low average speed and mild acceleration (e.g., driving pat-380
382tern in main commuting streets during rush hours). Urban traffic 383
381 is designated by its moderate average speed and wider range 382
380 of acceleration typically governed by stop signs and traffic 383
381 lights in normal urban driving. Finally, the distinct feature of 384
381 highway traffic is high average speed and moderate acceleration 385
382 rates. The variations in the speed and acceleration can change 386
381 the power demand accordingly, and hence, the time percent-
387 ages spent in various speed and acceleration ranges provide 388
387 important information about power demand in different traffic 389
390 categories defined in Table III.

391 Speed–acceleration frequency distribution (SAFD) plots pro-
392 vide the needed information about the time proportions of 392
391 individual driving modes [34]. The use of microtrips of the 393
391 same traffic group serves to maintain the matching of the SAFD 394
390 of the two candidate cycles to that of the SAFD of all recorded 395
391 cycles.

396 An alternative approach to developing a driving cycle is to 397
396 use random selection methods to select the appropriate number 398
397 of classified microtrips required to construct a representative 399
396 cycle matching well with the average characterizing parame-
397 ters with the lowest figure of merit. Random combination of 400
398 microtrips has been used by other researchers as a means to 400
398 construct representative driving cycles [35]. Another approach 401
398 to improve the current methodology would be to give a weight-
399 ing factor to the terms in the definition of the figure of merit [see 402
399 (1)] to adjust sensitivity of the final result to bias characterizing 400
399 parameters in accordance with their importance in the final 401

### TABLE II

<table>
<thead>
<tr>
<th>Parameter</th>
<th>$\rho$</th>
<th>$A_f$</th>
<th>$C_D$</th>
<th>$V_w$</th>
<th>$m$</th>
<th>$\theta$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value</td>
<td>1.2 kg/m$^3$</td>
<td>2.5 m$^2$</td>
<td>0.3</td>
<td>0 m/s</td>
<td>1550 kg</td>
<td>0</td>
</tr>
</tbody>
</table>

### TABLE III

<table>
<thead>
<tr>
<th>Traffic category</th>
<th>Average speed</th>
<th>Acceleration</th>
</tr>
</thead>
<tbody>
<tr>
<td>Congested</td>
<td>Low: [0-5] km/h</td>
<td>Mild: [-0.1,0.1] m/s$^2$</td>
</tr>
<tr>
<td>Urban</td>
<td>Moderate: [5,40] km/h</td>
<td>Harsh: [-3,0.3] m/s$^2$</td>
</tr>
<tr>
<td>Highway</td>
<td>High: [40,100] km/h</td>
<td>Moderate: [-1,0] m/s$^2$</td>
</tr>
</tbody>
</table>

Fig. 3. Methodology of enhancing the candidate cycles.
In this paper, all weighting factors are considered equal to 1. Evidently, energy needed and power demand for traveling the same distance in different traffic modes are not equal. It is also well understood that the aggressiveness of the driver in accelerating and decelerating the vehicle increases power consumption. However, it should be noted that replacing microtrips of the candidate cycle with microtrips of the same traffic mode, but potentially from different driving styles, is not misleading from an energy perspective. This is due to the fact that all parameters defining aggressiveness, energy level, and power consumption are already included in the 25 characterizing parameters used in this study, and the replacements increasing the figure of merit to larger values are not considered. Implementing alternative enhancement methodologies mentioned earlier and their performance assessment are left for further work. Fig. 4 shows the enhanced weekday and weekend candidate driving cycles. The metric units are used throughout the study. The speed in the driving cycles shown in Fig. 4 is given in kilometers per hour; however, for more convenience, both English and metric versions of the driving cycles in digital format are made available to the public [36]. Durations of the weekday and weekend cycles are 3484 and 3616 s, respectively. The maximum velocity is higher in the weekend cycle, i.e., 114 km/h, whereas in the weekday cycle, the maximum velocity is 89.6 km/h. The enhancement process does not necessarily finish by yielding a figure of merit equal to zero, but a considerable improvement can be expected as, in this study, the initial values were improved by approximately 40%. The figure of merit for the enhanced weekday and weekend driving cycles are 0.15 and 0.2, respectively. The driving pattern on the weekend is slightly more aggressive due to higher acceleration and deceleration rates, which results in higher power demand for weekend driving patterns. The power–time profiles corresponding to the two driving cycles are also presented in Fig. 6. To obtain these profiles, a vehicle with the specifications listed in Table II is considered to have driven the two cycles. Evidently, variations and abrupt changes in power demand are more considerable in the stop-and-go driving mode that is dominant in congested and urban traffics in the weekday driving cycle. This mode of driving considerably contributes to air pollution in downtown areas of large metropolitan areas, and it is particularly important to be covered by electric propulsion in the case of HEVs.
Vehicle parking at home, the workplace, commercial locations, and on the street constitutes a critically important element of a modern duty cycle that can address a multitude of drive-train topologies, storage technologies, and controllers. Developing models to analyze the parking behavior in an urban area for city planning may require detailed information on the parameters affecting parking behavior during the day, such as travel demands, district-based knowledge on cost of parking, nature of activities in the area of interest, and supply and demand on an hourly basis. However, from the charging perspective only, relatively long parking times provide potential charging times to increase the SOC of an onboard energy storage device. A typical duration for a full charge under normal charging conditions (110 V and 15 A) for current competitive battery technologies used in electric vehicles, namely, lithium ion and nickel metal hydride, is approximately 6 h; the minimum duration for partial charging is presently not known with a high confidence level. Therefore, it is expected that most plug-in electric vehicles will be charged mainly overnight. If a relatively long parking time (e.g., more than 3 h) during the day is considered as a realistic scenario for a reasonable share of the urban fleet, it is possible to downsize the battery storage capacity and reduce the capital cost of a plug-in vehicle or, in the case of a PHEV with a fixed size of battery storage, drive more miles on electricity to improve cost effectiveness. In addition, fast charging schemes using level 2 (120 V and 30 A) and direct dc chargers will facilitate full charging in shorter charging durations, i.e., as low as 20 min, depending on the battery technology and dc charging infrastructure.

It is also important to highlight that identification of parking locations for charging opportunities is critical; this aspect has been of strong interest to utilities, as they need to address both power and energy demand for electric mobility, with power having a large impact on grid infrastructure costs. Charging at residential areas, parking lots at work places, and large shopping malls is of interest; however, parking in streets or less-frequently open areas is not emphasized due to the large infrastructure cost required to achieve this type of opportunity charging. In the development of a duty cycle in this work, parking events are described for all categories over a 24-h period to provide data for any combination of future charging scenarios. Inherent in this study is the assumption that plug-in vehicle owners will not be significantly modifying their parking behaviors, although they may change their parking stall to access a plug.

An extensive literature survey reveals that a few studies have focused on the potential charging aspect of parking times as a part of daily activities of vehicles; none seem to have incorporated this into a duty cycle. This aspect is of critical importance to address energy drivers in transportation and allow the displacement of fossil fuels with new renewable energy generation. The analysis conducted by the Argonne National Laboratory (ANL) shows that, in the United States, 66% of the vehicles driven to work are parked more than 3 h before noon, potentially allowing a second charge before the electric utility peak demand begins [37]. It was also observed that vehicles were parked for a short time for shopping purposes, and parking was often during peak electric demand [36].

In this paper, GPS-based data loggers provide information on location, type of parking, and duration of parking events. The type of parking can be determined from the driver’s behavior, where it is relatively simple to determine where the person lives and works; commercial parking locations are found by digitizing commercial parking lots in Winnipeg. Street parking is deduced from a car staying on the street. Note that studies dedicated to record the instantaneous speed of the vehicle for certification purposes, such as that leading to the FTP72 standard cycle and its enhanced cycles, do not provide information on parking times. Here, probable parking times and duration for each parking event, as well as the standard deviation of the data points, are included to adequately reflect a daily driving and parking profile for electric vehicle design of drive-train topologies.

Parking times of less than half an hour are arbitrarily classified in our study as short; the distribution of such parking events shows that, in early mornings and afternoons, this type of parking is the most likely. It is important to note that stop times of less than 2 min, happening at stop signs or traffic lights, are excluded from short parking. The results of short parking times are not presented here as it is assumed that, in the real world, these occasional parking events are not favored by drivers for charging. However, a cumulative parking time...
representing short parking times per day will be included in the final duty cycles. The results of studying parking periods that exceed 30 min are shown in Fig. 7.

Fig. 7(a) and (b) shows mean values and standard deviations of parking durations by hour of day for weekdays and weekends, respectively.

Two distinct patterns in daily parking behavior can be recognized, namely, a mean value less than or equal to the standard deviation and a mean value larger than the standard deviation. Long parking duration with a mean value larger than the standard deviation happens between 8 P.M. and 6 A.M., showing that the majority of drivers tend to park their vehicles for a long time. However, when the standard deviation is greater than the mean value of parking duration, the data show an increase in daily trips, happening between 10 A.M. and 4 P.M., and the average of the mean values is about 4 h. Peaks in probability of parking events in terms of hour of day, as shown in Fig. 7(c), reflect the difference in nature of activities between weekdays and weekends. While there is only one peak in the weekend curve happening at 7 P.M., there are three peaks occurring at 7 A.M., 12 P.M., and 5 P.M. during weekdays.

On weekdays, 67% of the vehicles park for more than 3 h between 6 A.M. and 9 A.M., whereas between 9 A.M. and 12 P.M., only 33% of the vehicles park for more than 3 h. This can be justified as many commuters drive to work and park their car during working hours at their workplace early in the morning. However, after 9 A.M., vehicles moving in the streets tend to park for a limited duration, i.e., typically less than 3 h, which is necessary for activities such as shopping. The analysis shows that, while overnight charging is the first choice for charging the battery, second charging is most likely to happen in the morning around 9 A.M. or in the afternoon around 5 P.M. Taking the higher electricity price in peak hours in many jurisdictions, a more realistic scenario for charging would be overnight followed by early mornings. However, the distribution of charging load on the electric grid overnight or during the day would be different, which indicates a need to redesign the location of feeders in the city. This aspect of charging electric cars is beyond the scope of this study and will be published in separate articles of various charging opportunities and power levels.

V. ASSEMBLY OF THE DRIVING CYCLES

Analysis was performed on the raw GPS data in conjunction with the digitized maps of the roads and commercial parking locations to characterize the driving and parking behavior of the vehicles under the one-year span of the survey in the city of Winnipeg. Using the method shown in Fig. 2, two 24-h vehicle usage profiles representing a daily duty cycle were developed for both weekdays and weekends. The parking patterns obtained from the analysis of parking times, as well as cumulative short parking events, are included in the daily duty cycles for weekdays and weekends. In creating this, the average distance traveled in driving events is considered to separate the final driving cycle into parts, and then, parking events are inserted in between in the most probable way. The resulting cycles are shown in Fig. 8 and are meant to represent the 44 million data points into a condensed duty cycle for studies pertaining to plug-in hybrids, including optimization of power trains [29]. In Fig. 8, D stands for driving, P stands for parking periods, P1 stands for home, P2 stands for work, P3 stands for commercial, P4 stands for short stops, and P5 stands for street parking. The driving cycles are on a 1-h basis, and the duty cycles, with long parking times included, are on a 24-h basis and are both combined into the same figure. The parking durations on a 24-h scale designated by color codes are also shown on a 1-h driving scale for the sake of clarity. The parking events that potentially can be used for charging are P1, P2, or P3 when the vehicle is most probably parked in a parking spot with access to level-1 or level-2 charging. The parking events that happen on the street or short parking durations are considered not suitable for charging.

Some characteristics of the enhanced driving cycle are compared with those of the standard cycle UDDS, and the results are presented in Fig. 9. The comparison indicates that more aggressive characteristics are associated with the real-world
cycle, whereas, on average, the two cycles may be considered interchangeable.

Evidently, the vehicles with the opportunity to charge limited to overnight have more time to be fully charged under slow charging mode on the weekends. This is particularly important for PEVs with larger battery storage capacity. Deriving a grid load based on this driving cycle has merit but requires the understanding of its limitations for utilities; however, it is beyond the scope of this work.

The data files of the duty cycles and the collected raw data are available to the public on the World Wide Web through a unique Digital Object Identifier number [36]. Forty-four million speed–time data points, stamped with date and time, and collected over the course of one year are made available. The latitude and longitude of the position of the vehicles recorded on a secondly basis are masked by mapping the starting point of every trip to (0,0) to respect the confidentiality agreement with the participants in the data-collection phase. However, personal information about the participants is used to label the parking locations as home or work. Labeled parking locations, as well as the duration of parking events needed for further analyses with different charging scenarios in the case of plug-in electric vehicles, are included in the data files. The parking events that are less than 30 min in duration are labeled short stops. Parking events happening along the street are not potentially suitable for charging. The locations of the parking events longer than 30 min in duration are marked home, work, shop, and street. The effectiveness of the methodology presented in this study, even with far fewer data points (about 1 million data points, which is equal to about 2% of the data points used in this study), for simulation-based optimization of a PHEV was shown in [29].

VI. CONCLUSION

A new approach to the development of a duty cycle that addresses the requirements associated with the design of electric vehicles—e.g., HEV, PHEV, BEV, and extended-range vehicles, has been proposed and implemented on a 24-h timescale. It provides a complete data set for optimization of battery size for on-road vehicles in a typical North American urban setting. For example, power and energy demand in the daily operation of a sedan is directly related to the rate of acceleration and deceleration and time spent in different traffic modes; charging scenarios depend on parking times and duration. The driving behavior of a fleet of 76 participants in a one-year voluntary data-collection program in the city of Winnipeg is analyzed to develop a driving cycle and is composed of two 24-h duty cycles for weekdays and weekends. This cycle provides information about the time and duration of driving in different traffic categories, as well as information on parking times when the vehicle is not in use. Further vehicle simulation tools can use the daily duty cycles developed to optimally design propulsion systems, drive-train configurations, and storage components for PEV technologies under real-world driving conditions. Furthermore, this information can be used to analyze the impact of daytime charging by a fleet of plug-in electric vehicles on the electric utility grid that may create a peak demand during the day to be met by the local utility grid.

The target use of the developed cycle is to provide a duty cycle that can be used to optimally address energy drivers simultaneously facing transportation by displacing fossil fuels with new renewable energy generations with the direct consequences of increasing the renewable energy ratio of various jurisdictions.

To achieve this goal, 25 parameters characterizing a driving cycle for further PEV simulations are recognized, and two candidate daily cycles having the closest match to the average 680 of the parameters are selected. The candidate cycles are then incrementally enhanced by replacing their microtrips with those extracted from the same traffic group, minimizing a figure of merit defined based on the characterizing parameters. Finally, the processed parking data are included to complete two 24-h duty cycles. The final result is therefore reflecting more accurately a realistic driving pattern than driving cycles resulting from methodologies that patch snippets of driving data from different drivers or occasions to make a driving cycle. Although the data collected represent driving behavior in the city of Winnipeg, MB, Canada, the methodology presented here can be extended to any other urban area of interest.

There exist a few directions to continue the research on using the collected data. Other methods for development of a driving cycle may include a stochastic approach for selecting and patching snippets of speed–time traces using a probability matrix [14], [21], which might be enhanced to incorporate power and energy requirements of the vehicle. Future work may also concentrate on one specific driving pattern, for instance, a commuter, to develop a dedicated driving cycle that mirrors that particular driving pattern. The driving cycle may also be used for a wide range of applications, such as energy assessment of the vehicles in daily use in urban transportation, analysis of charging scenarios in PHEVs and PEVs, vehicle-to-grid analysis, and statistical assessment of driving cycle variability on hybrid drive-train design. Finding other applications, particularly from a social driving behavior perspective, can also be viewed as an important extension of the work.

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REFERENCES


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