

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 PHEVs to lower the battery size and cost includes providing additional daily charging opportunities during periods when the 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

Manuscript received April 13, 2010; revised June 21, 2010; accepted July 16, 2010. This work was supported by the AUTO21 Network of Centers of Excellence under Project DF302-DBS. The review of this paper was coordinated by Dr. A. Khaligh.

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Digital Object Identifier 10.1109/TVT.2010.2061243

84 velocities [14]. It is therefore concluded that such cycles cannot
85 completely emulate the real-world daily power demand of a
86 vehicle. More importantly, they do not provide information
87 on parking times as opportunities for charging in the case of
88 emerging plug-in vehicles. In addition, it is important to base
89 duty cycles on larger data sets to reduce statistical errors.

90 An extensive literature survey conducted revealed no refer-
91 ence to the development of a daily driving cycle, taking into
92 account power and energy demands as major requirements for
93 representing the real-world data. Most studies have focused on
94 developing urban driving cycles using snippets extracted from
95 recorded speed–time traces to estimate vehicular emissions and
96 fuel consumption in different cosmopolitan areas [15], [19].
97 The objective of these studies is to represent the driving infor-
98 mation in a collected data set using a single driving cycle. Some
99 other studies discuss the effectiveness of the methodologies
100 used in developing driving cycles to represent the inherent char-
101 acteristics of driving behavior in the collected data [20], [21].

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

121 The study presented in this paper addresses the gap in the
122 literature by developing a statistical methodology and con-
123 structing the needed duty cycles based on a database of over
124 44 million Global Positioning System (GPS) data points
125 recorded over the course of one year in Winnipeg, MB, Canada.
126 Depending on the context, the terms “driving cycle” and
127 “duty cycle” may convey different meanings. In this paper,
128 a “driving cycle” refers to a history of daily driving periods
129 represented by a speed-versus-time curve. A “duty cycle” refers
130 to a profile of daily usage of power by the vehicle, which is
131 typically represented by a 24-h history of driving and parking
132 events. Note that, in the case of an HEV, only a driving cycle
133 is sufficient to calculate vehicle’s power demand, whereas in
134 the case of a plug-in vehicle, parking times also become vital
135 as they may be used for charging from the electric grid, and
136 therefore, they should be included in the daily profile. Parking
137 times are also important to utilities servicing jurisdictions with
138 large vehicular loads, as they can be used to predict and control
139 the load on the grid.

140 The objective of the present study is to first develop a
141 new driving cycle most closely mirroring the characteristics of

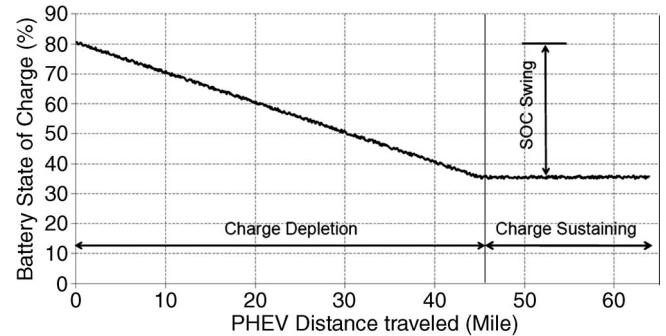


Fig. 1. Typical variation in the SOC of a PHEV battery.

urban driving, including real-world energy and power demands. 142
Once this is achieved, this study aims to incorporate a pattern 143
representing most probable downtimes of the vehicles to charge 144
during their daily usage profile. A comprehensive daily duty 145
cycle is a crucial component for optimal design of plug-in 146
vehicular drive-trains. This study improves the conventional 147
methods of driving cycle generation [26], [28]. The present 148
study also establishes a set of performance measures required to 149
assess a driving cycle suited for electric/plug-in hybrid vehicles. 150
The methodology used in the precedent study for simulation 151
of a plug-in vehicle is enhanced by including 25 parameters 152
to characterize different velocity brackets in a driving cycle 153
[29]. The uniqueness of this study is proposing a methodol- 154
ogy that addresses the particular requirements associated with 155
the design of plug-in vehicles in construction of a 24-h duty 156
cycle. 157

Following the introduction, in Section II, duty cycle re- 158
quirements to be fulfilled for enhanced simulation and opti- 159
mization of plug-in vehicles are discussed. Data collection, 160
driving cycle generation, and characterization are described 161
in Section III. Parking data analysis for weekdays and week- 162
ends is presented in Section IV. The resulting 24-h duty 163
cycles are given in Section V, and driving characteristics 164
are critically compared with those of the standard cycle for 165
urban driving, i.e., the UDSS. Conclusions are presented 166
in Section VI. 167

II. DUTY CYCLE REQUIREMENTS FOR PLUG-IN VEHICLES 168

The total distance that a plug-in vehicle can electrically 169
drive is an important measure for the vehicle’s performance 170
assessment. For instance, PHEVs are usually classified ac- 171
cording to their all-electric range (AER), which is defined as 172
the total miles electrically driven after a full recharge before 173
the engine turns on for the first time [30]. A fully recharged 174
PHEV operates in charge-depleting mode until the battery is 175
depleted to a target state-of-charge (SOC), at which point, the 176
vehicle switches to charge-sustaining mode, using the internal 177
combustion engine to maintain the target SOC [3]. Fig. 1 shows 178
the typical variation in the SOC of the battery in the operating 179
modes of a PHEV. 180

Obviously, the instantaneous power demand resulting from 181
the driving style of the driver is critical in the definition of the 182
AER. The standard cycle UDSS is usually used to measure 183

TABLE I
CHARACTERIZING PARAMETERS AND THEIR VALUES

Parameter	Database average		Final duty cycles	
	weekday	weekend	Weekday	weekend
1 Average speed of the entire driving cycle in km/h	31.4	35.3	32.6	35.0
2 Average running speed in km/h	39.8	43.9	40.3	43.4
3 Total daily distance traveled in km	32.2	33.9	31.6	35.2
4 Average acceleration of all acceleration phases in m/s ²	0.6	0.6	0.55	0.59
5 Average deceleration of all deceleration phases in m/s ²	-0.6	-0.6	-0.59	-0.6
6 Average number of change in acceleration rate (+/-) in one driving period	6.5	7.2	7.83	7.9
7 Average daily power demand in kW	7.9	8.3	8.92	9.3
8 Maximum power demand in kW	59.3	72.2	49.45	60.0
9 Total daily energy demand in Mj	17.3	17.7	16.41	18.2
10 Average daily breaking power in kW	-5.3	-5.4	-5.47	-6.0
11 Root mean square of acceleration in m/s ²	0.8	0.8	0.66	0.69
12 Average length of a driving period in km	0.9	1.2	0.75	1.03
13 Time percentage of Idling (zero velocity) in %	21.8	20.7	19.1	19.31
14 Time percentage of acceleration: acceleration > 0.1 m/s ² in %	31.4	31.3	36.5	35.1
15 Time percentage of Cruising (acceleration [-0.1, 0.1] m/s ² , speed > 5 m/s) in %	14.9	16.7	9.8	10.5
16 Time percentage of deceleration: acceleration < -0.1 m/s ² in %	31.2	30.9	34.4	34.9
17 Time percentage of creeping (acceleration [-0.1, 0.1] m/s ² , speed < 5 m/s) in %	0.6	0.5	0.32	0.14
18 Time percentage of driving at very low speed bracket [0 20] km/h in %	94.5	90.6	85.3	90.5
19 Average speed in very low speed bracket [0 20] km/h	6.6	10.3	7.3	6.5
20 Time percentage of driving at low speed bracket [20 50] km/h in %	58.9	59.6	62.0	61.0
21 Average speed in low speed bracket [20 50] km/h	18.9	20.8	19.2	28.1
22 Time percentage of driving at moderate speed bracket [50 80] km/h in %	36.7	36.9	37.4	36.4
23 Average speed in moderate speed bracket [50 80] km/h	32.9	30.2	34.9	29.0
24 Time percentage of driving at high speed bracket [80 100] km/h in %	9.9	10.0	8.9	10.6
25 Average speed in high speed bracket [80 100] km/h	16.3	15.0	16.9	15.1

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. 216

217 III. METHODOLOGY OF DEVELOPMENT 217 218 OF A DRIVING CYCLE 218

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

232 There are two general methodologies to develop a driving
 233 cycle. One is based on creating a pool of trip segments extracted
 234 from recorded speed-time traces of vehicles, followed by cat-
 235 egorizing them into several driving modes and finally patching
 236 snippets selected based on desired selection criteria together
 237 to develop a representative driving cycle with a predetermined
 238 duration [14]. In the other method, the single most represen-
 239 tive speed-time trace is selected among a large number of

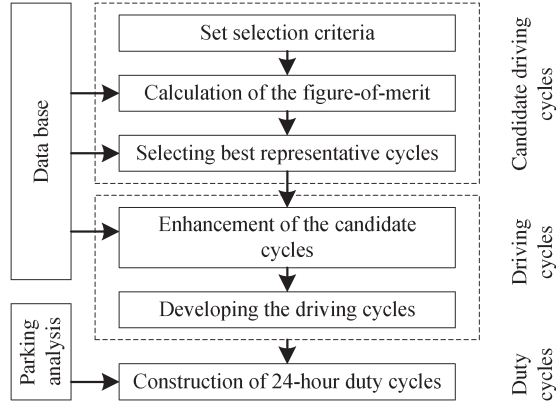


Fig. 2. Methodology of developing a 24-h duty cycle.

240 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 import-
 244 ance [17].

245 In this paper, emphasis is placed on the energy and power-
 246 demand aspects of a cycle to address the concerns in plug-
 247 in vehicle design and optimization, as mentioned previously.
 248 Therefore, the second methodology is used in this study to
 249 develop a cycle realistically mirroring the characteristics of
 250 urban driving. This study adopts an adequately long-term ap-
 251 proach to data collection from a fleet of instrumented vehicles
 252 to reduce the risk of unreal driving behavior resulting from
 253 any influence of the onboard instruments that may potentially
 254 bias drivers’ driving behavior. Over a one-year timescale, the
 255 vehicle owners presumably drive on their ordinary travel routes,
 256 whereas onboard instruments automatically timestamp the ve-
 257 hicle’s location and speed on a secondly basis.

258 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 full-
 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.

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

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

A. Selecting the Candidate Driving Cycles

302 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 braking 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.

309 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:
 313

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

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

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

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

TABLE II
VALUES OF PARAMETERS USED IN POWER AND ENERGY CALCULATION

Parameter	ρ	A_f	C_D	V_W	m	θ
Value	1.2 kg/m ³	2.5 m ²	0.3	0 m/s	1550 kg	0

334 rolling friction F_F , 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

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

$$F_F = (1 + v/100) \cdot mg \cdot \cos \theta / 100 \quad (5)$$

$$F_G = mg \sin \theta \quad (6)$$

337 ρ 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,
339 m is the mass of the vehicle, g is the gravitational constant
340 (9.8 m/s²), and θ 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 participant vehicles 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 breaking 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

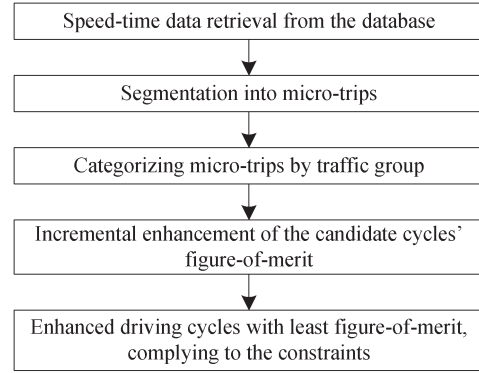


Fig. 3. Methodology of enhancing the candidate cycles.

TABLE III
MICROTRIP CLUSTERING CRITERIA

Traffic category	Average speed	Acceleration
Congested	Low: [0 5] km/h	Mild: [-0.1,0.1] m/s ²
Urban	Moderate: [5,40] km/h	Harsh: [-3.0,3.0] m/s ²
Highway	High: [40 100] km/h	Moderate: [-1.0,1.0] m/s ²

groups characterized by average speed and acceleration, as
372 given in Table III. Here, each microtrip of the candidate cycle is
373 iteratively exchanged with microtrips of the same traffic group
374 until the best figure of merit σ is obtained. 375

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

Speed-acceleration frequency distribution (SAFD) plots pro-
391 vide the needed information about the time proportions of
392 individual driving modes [34]. The use of microtrips of the
393 same traffic group serves to maintain the matching of the SAFD
394 of the two candidate cycles to that of the SAFD of all recorded
395 cycles. 396

An alternative approach to developing a driving cycle is to
397 use random selection methods to select the appropriate number
398 of classified microtrips required to construct a representative
399 cycle matching well with the average characterizing parame-
400 ters with the lowest figure of merit. Random combination of
401 microtrips has been used by other researchers as a means to
402 construct representative driving cycles [35]. Another approach
403 to improve the current methodology would be to give a weight-
404 ing factor to the terms in the definition of the figure of merit [see
405 (1)] to adjust sensitivity of the final result to bias characterizing
406 parameters in accordance with their importance in the final
407

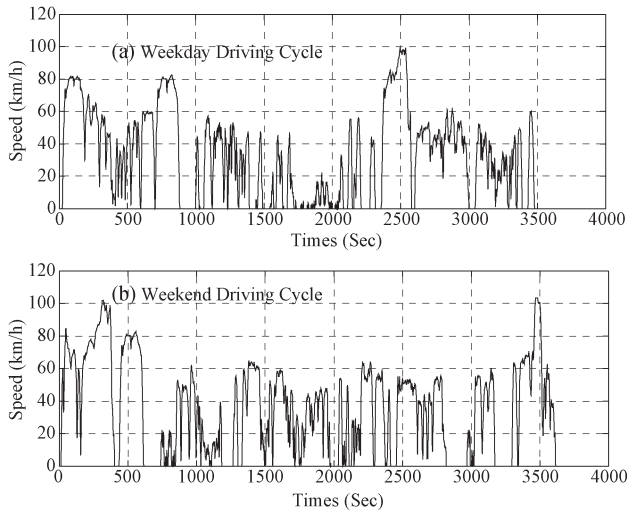


Fig. 4. Enhanced candidate driving cycles. (Top) Weekday. (Bottom) Weekend.

408 duty cycle. In this paper, all weighting factors are considered
 409 equal to 1. Evidently, energy needed and power demand for
 410 traveling the same distance in different traffic modes are not
 411 equal. It is also well understood that the aggressiveness of the
 412 driver in accelerating and decelerating the vehicle increases
 413 power consumption. However, it should be noted that replacing
 414 microtrips of the candidate cycle with microtrips of the same
 415 traffic mode, but potentially from different driving styles, is
 416 not misleading from an energy perspective. This is due to the
 417 fact that all parameters defining aggressiveness, energy level,
 418 and power consumption are already included in the 25 char-
 419 acterizing parameters used in this study, and the replacements
 420 increasing the figure of merit to larger values are not con-
 421 sidered. Implementing alternative enhancement methodologies
 422 mentioned earlier and their performance assessment are left for
 423 further work. Fig. 4 shows the enhanced weekday and weekend
 424 candidate driving cycles. The metric units are used throughout
 425 the study.

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

430 Durations of the weekday and weekend cycles are 3484 and
 431 3616 s, respectively. The maximum velocity is higher in the
 432 weekend cycle, i.e., 114 km/h, whereas in the weekday cycle,
 433 the maximum velocity is 89.6 km/h. The enhancement process
 434 does not necessarily finish by yielding a figure of merit equal to
 435 zero, but a considerable improvement can be expected as, in this
 436 study, the initial values were improved by approximately 40%.
 437 The figure of merit for the enhanced weekday and weekend
 438 driving cycles are 0.15 and 0.2, respectively. Fig. 5 shows
 439 the SAFD plot for weekday and weekend enhanced candidate
 440 driving cycles.

441 The two patterns are different in nature. Stop-and-go events
 442 characterized by larger acceleration or deceleration rates at low
 443 speeds are more probable in the weekday pattern. However,
 444 high-speed events are more probable in the weekend pattern.
 445 The driving pattern on the weekend is slightly more aggressive

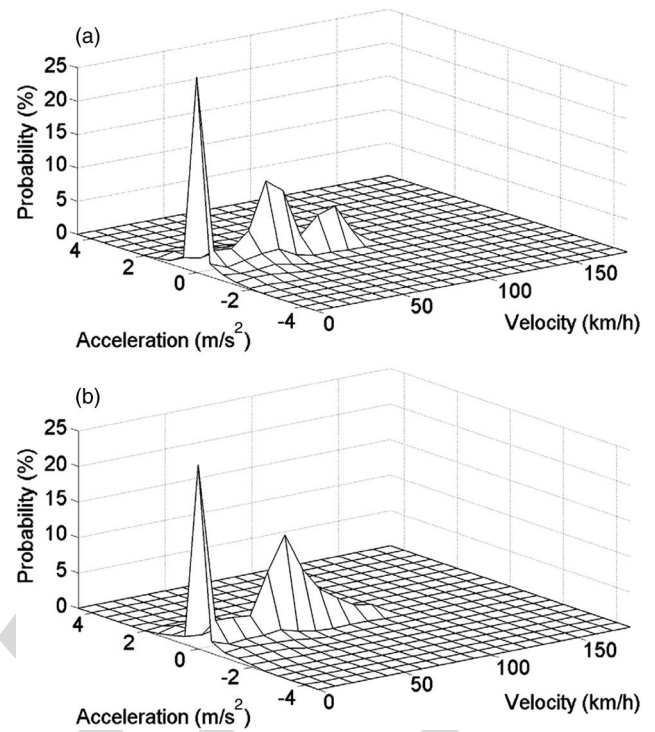


Fig. 5. SAFD plots for the enhanced candidate driving cycles. (a) Weekday. (b) Weekend.

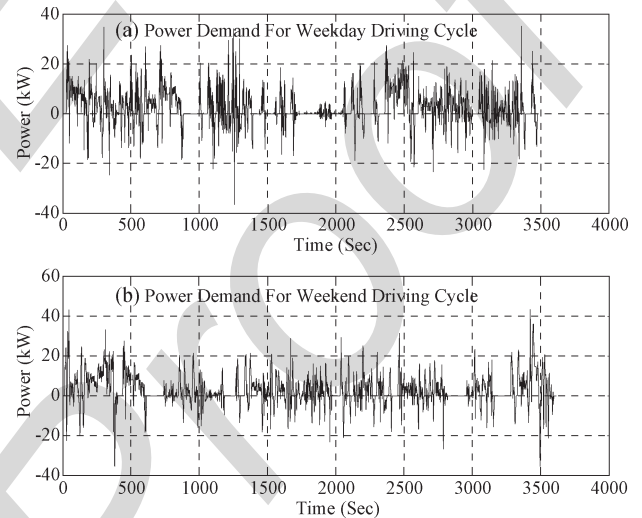


Fig. 6. Power-time traces for the enhanced candidate driving cycles. (a) Weekday. (b) Weekend.

446 due to higher acceleration and deceleration rates, which results
 447 in higher power demand for weekend driving patterns.

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

IV. PARKING ANALYSIS

459 Vehicle parking at home, the workplace, commercial lo-
 460 cations, and on the street constitutes a critically important
 461 element of a modern duty cycle that can address a multitude
 462 of drive-train topologies, storage technologies, and controllers.
 463 Developing models to analyze the parking behavior in an urban
 464 area for city planning may require detailed information on the
 465 parameters affecting parking behavior during the day, such as
 466 travel demands, district-based knowledge on cost of parking,
 467 nature of activities in the area of interest, and supply and
 468 demand on an hourly basis. However, from the charging per-
 469 spective only, relatively long parking times provide potential
 470 charging times to increase the SOC of an onboard energy
 471 storage device. A typical duration for a full charge under normal
 472 charging conditions (110 V and 15 A) for current competitive
 473 battery technologies used in electric vehicles, namely, lithium
 474 ion and nickel metal hydride, is approximately 6 h; the mini-
 475 mum duration for partial charging is presently not known with
 476 a high confidence level. Therefore, it is expected that most
 477 plug-in electric vehicles will be charged mainly overnight. If
 478 a relatively long parking time (e.g., more than 3 h) during the
 479 day is considered as a realistic scenario for a reasonable share
 480 of the urban fleet, it is possible to downsize the battery storage
 481 capacity and reduce the capital cost of a plug-in vehicle or,
 482 in the case of a PHEV with a fixed size of battery storage,
 483 drive more miles on electricity to improve cost effectiveness.
 484 In addition, fast charging schemes using level 2 (120 V and
 485 30 A) and direct dc chargers will facilitate full charging in
 486 shorter charging durations, i.e., as low as 20 min, depending
 487 on the battery technology and dc charging infrastructure.

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

504 An extensive literature survey reveals that a few studies
 505 have focused on the potential charging aspect of parking times
 506 as a part of daily activities of vehicles; none seem to have
 507 incorporated this into a duty cycle. This aspect is of critical
 508 importance to address energy drivers in transportation and
 509 allow the displacement of fossil fuels with new renewable
 510 energy generation. The analysis conducted by the Argonne
 511 National Laboratory (ANL) shows that, in the United States,
 512 66% of the vehicles driven to work are parked more than
 513 3 h before noon, potentially allowing a second charge before
 514 the electric utility peak demand begins [37]. It was also ob-
 515 served that vehicles were parked for a short time for shop-

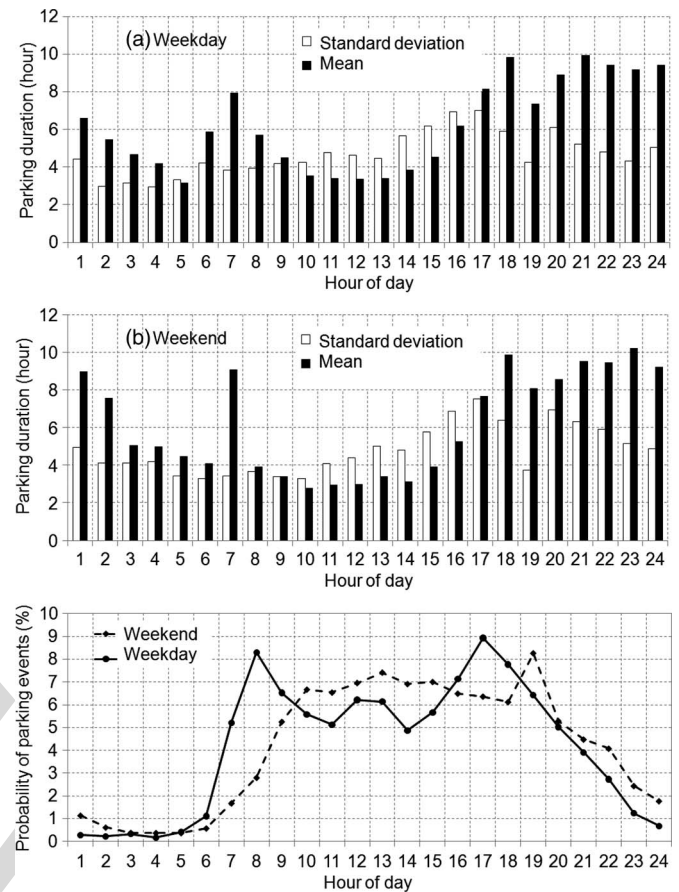


Fig. 7. Mean and standard deviation of parking duration by hour of day. (a) Weekdays. (b) Weekends. (c) Probability of parking events by hour of day for both weekdays and weekends.

ping purposes, and parking was often during peak electric 516 demand [36]. 517

In this paper, GPS-based data loggers provide information 518 on location, type of parking, and duration of parking events. 519 The type of parking can be determined from the driver's 520 behavior, where it is relatively simple to determine where 521 the person lives and works; commercial parking locations 522 are found by digitizing commercial parking lots in Winnipeg. 523 Street parking is deduced from a car staying on the street. Note 524 that studies dedicated to record the instantaneous speed of the 525 vehicle for certification purposes, such as that leading to the 526 FTP72 standard cycle and its enhanced cycles, do not provide 527 information on parking times. Here, probable parking times 528 and average duration for each parking event, as well as the 529 standard deviation of the data points, are included to adequately 530 reflect a daily driving and parking profile for electric vehicle 531 design of drive-train topologies. 532

Parking times of less than half an hour are arbitrarily clas- 533 sified in our study as short; the distribution of such parking 534 events shows that, in early mornings and afternoons, this type 535 of parking is the most likely. It is important to note that stop 536 times of less than 2 min, happening at stop signs or traffic 537 lights, are excluded from short parking. The results of short 538 parking times are not presented here as it is assumed that, in 539 the real world, these occasional parking events are not favored 540 by drivers for charging. However, a cumulative parking time 541

542 representing short parking times per day will be included in the
543 final duty cycles. The results of studying parking periods that
544 exceed 30 min are shown in Fig. 7.

545 Fig. 7(a) and (b) shows mean values and standard deviations
546 of parking durations by hour of day for weekdays and week-
547 ends, respectively.

548 Two distinct patterns in daily parking behavior can be recog-
549 nized, namely, a mean value less than or equal to the standard
550 deviation and a mean value larger than the standard deviation.
551 Long parking duration with a mean value larger than the stan-
552 dard deviation happens between 8 P.M. and 6 A.M., showing
553 that the majority of drivers tend to park their vehicles for a long
554 time. However, when the standard deviation is greater than the
555 mean value of parking duration, the data show an increase in
556 daily trips, happening between 10 A.M. and 4 P.M., and the
557 average of the mean values is about 4 h. Peaks in probability
558 of parking events in terms of hour of day, as shown in Fig. 7(c),
559 reflect the difference in nature of activities between weekdays
560 and weekends. While there is only one peak in the weekend
561 curve happening at 7 P.M., there are three peaks occurring at
562 7 A.M., 12 P.M., and 5 P.M. during weekdays.

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

583 V. ASSEMBLY OF THE DRIVING CYCLES

584 Analysis was performed on the raw GPS data in conjunction
585 with the digitized maps of the roads and commercial parking
586 locations to characterize the driving and parking behavior of
587 the vehicles under the one-year span of the survey in the
588 city of Winnipeg. Using the method shown in Fig. 2, two
589 24-h vehicle usage profiles representing a daily duty cycle
590 were developed for both weekdays and weekends. The parking
591 patterns obtained from the analysis of parking times, as well as
592 cumulative short parking events, are included in the daily duty
593 cycles for weekdays and weekends. In creating this, the average
594 distance traveled in driving events is considered to separate
595 the final driving cycle into parts, and then, parking events are
596 inserted in between in the most probable way. The resulting
597 cycles are shown in Fig. 8 and are meant to represent the

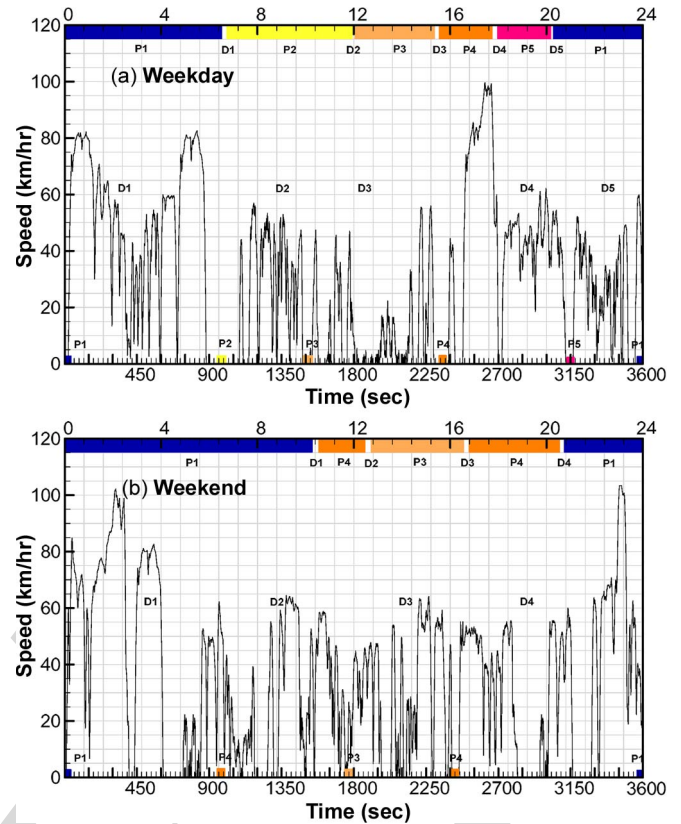


Fig. 8. Resulting 24-h duty cycles. (a) Weekdays. (b) Weekends.

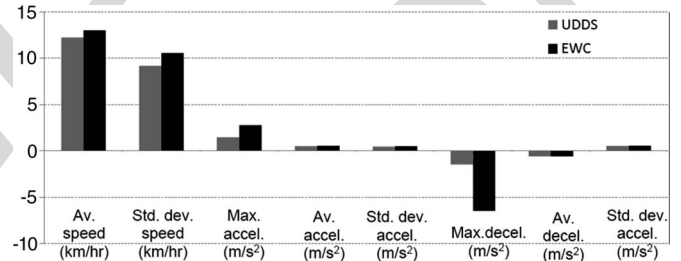


Fig. 9. Comparison between the standard cycle UDSS and the enhanced weekday cycle (EWC).

44 million data points into a condensed duty cycle for studies
598 pertaining to plug-in hybrids, including optimization of power
599 trains [29]. In Fig. 8, D stands for driving, P stands for parking
600 periods, P1 stands for home, P2 stands for work, P3 stands
601 for commercial, P4 stands for short stops, and P5 stands for
602 street parking. The driving cycles are on a 1-h basis, and the
603 duty cycles, with long parking times included, are on a 24-h
604 basis and are both combined into the same figure. The parking
605 durations on a 24-h scale designated by color codes are also
606 shown on a 1-h driving scale for the sake of clarity. The parking
607 events that potentially can be used for charging are P1, P2, or P3
608 when the vehicle is most probably parked in a parking spot with
609 access to level-1 or level-2 charging. The parking events that
610 happen on the street or short parking durations are considered
611 not suitable for charging.

612
Some characteristics of the enhanced driving cycle are com-
613 pared with those of the standard cycle UDSS, and the results
614 are presented in Fig. 9. The comparison indicates that more
615 aggressive characteristics are associated with the real-world 616

617 cycle, whereas, on average, the two cycles may be considered
618 interchangeable.

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

626 The data files of the duty cycles and the collected raw data
627 are available to the public on the World Wide Web through a
628 unique Digital Object Identifier number [36]. Forty-four mil-
629 lion speed–time data points, stamped with date and time, and
630 collected over the course of one year are made available. The
631 latitude and longitude of the position of the vehicles recorded
632 on a secondly basis are masked by mapping the starting point of
633 every trip to (0,0) to respect the confidentiality agreement with
634 the participants in the data-collection phase. However, personal
635 information about the participants is used to label the parking
636 locations as home or work. Labeled parking locations, as well
637 as the duration of parking events needed for further analyses
638 with different charging scenarios in the case of plug-in electric
639 vehicles, are included in the data files. The parking events that
640 are less than 30 min in duration are labeled short stops. Parking
641 events happening along the street are not potentially suitable
642 for charging. The locations of the parking events longer than
643 30 min in duration are marked home, work, shop, and street. The
644 effectiveness of the methodology presented in this study, even
645 with far fewer data points (about 1 million data points, which
646 is equal to about 2% of the data points used in this study),
647 for simulation-based optimization of a PHEV was shown in [29].

648

VI. CONCLUSION

649 A new approach to the development of a duty cycle that ad-
650 dresses the requirements associated with the design of electric
651 vehicles—e.g., HEV, PHEV, BEV, and extended-range vehi-
652 cles, has been proposed and implemented on a 24-h timescale.
653 It provides a complete data set for optimization of battery
654 size for on-road vehicles in a typical North American urban
655 setting. For example, power and energy demand in the daily
656 operation of a sedan is directly related to the rate of acceleration
657 and deceleration and time spent in different traffic modes;
658 charging scenarios depend on parking times and duration. The
659 driving behavior of a fleet of 76 participants in a one-year
660 voluntary data-collection program in the city of Winnipeg is
661 analyzed to develop a driving cycle and is composed of two
662 24-h duty cycles for weekdays and weekends. This cycle pro-
663 vides information about the time and duration of driving in
664 different traffic categories, as well as information on parking
665 times when the vehicle is not in use. Further vehicle simu-
666 lation tools can use the daily duty cycles developed to op-
667 timally design propulsion systems, drive-train configurations,
668 and storage components for PEV technologies under real-world
669 driving conditions. Furthermore, this information can be used
670 to analyze the impact of daytime charging by a fleet of plug-
671 in electric vehicles on the electric utility grid that may create a
672 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 673
that can be used to optimally address energy drivers simultane- 674
ously facing transportation by displacing fossil fuels with new 675
renewable energy generations with the direct consequences of 676
increasing the renewable energy ratio of various jurisdictions. 677

To achieve this goal, 25 parameters characterizing a driving 678
cycle for further PEV simulations are recognized, and two 679
candidate daily cycles having the closest match to the average 680
of the parameters are selected. The candidate cycles are then 681
incrementally enhanced by replacing their microtrips with those 682
extracted from the same traffic group, minimizing a figure of 683
merit defined based on the characterizing parameters. Finally, 684
the processed parking data are included to complete two 24-h 685
duty cycles. The final result is therefore reflecting more accu- 686
rately a realistic driving pattern than driving cycles resulting 687
from methodologies that patch snippets of driving data from 688
different drivers or occasions to make a driving cycle. Although 689
the data collected represent driving behavior in the city of 690
Winnipeg, MB, Canada, the methodology presented here can 691
be extended to any other urban area of interest. 692

There exist a few directions to continue the research on or 693
using the collected data. Other methods for development of a 694
driving cycle may include a stochastic approach for selecting 695
and patching snippets of speed–time traces using a probability 696
matrix [14], [21], which might be enhanced to incorporate 697
power and energy requirements of the vehicle. Future work 698
may also concentrate on one specific driving pattern, for in- 699
stance, a commuter, to develop a dedicated driving cycle best 700
mirroring that particular driving pattern. The driving cycle may 701
also be used for a wide range of applications, such as energy 702
assessment of the vehicles in daily use in urban transportation, 703
analysis of charging scenarios in PHEVs and PEVs, vehicle-to- 704
grid analysis, and statistical assessment of driving cycle vari- 705
ability on hybrid drive-train design. Finding other applications, 706
particularly from a social driving behavior perspective, can also 707
be viewed as an important extension of the work. 708

ACKNOWLEDGMENT

709

The authors would like to thank Prof. D. Blair and R. Smith 710
from the Department of Geography, University of Winnipeg, for 711
providing the collected travel data. Ongoing discussions with 712
Emerging Energy Systems at Manitoba Hydro, in particular 713
with T. Molinski, are acknowledged. Special thanks to Presen- 714
tech Inc. for integrating the parking study with their proprietary 715
firmware. 716

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nonlinear optimization, and power-electronic appli- 872
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AUTHOR QUERIES

AUTHOR PLEASE ANSWER ALL QUERIES

AQ1 = Please provide publication update in Ref. [29].

Notes:

Note that reference [4] and [6] are the same. Therefore, reference [6] was deleted from the list. Citations were renumbered accordingly. Please check.

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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. 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 PHEVs to lower the battery size and cost includes providing additional daily charging opportunities during periods when the 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

Manuscript received April 13, 2010; revised June 21, 2010; accepted July 16, 2010. This work was supported by the AUTO21 Network of Centers of Excellence under Project DF302-DBS. The review of this paper was coordinated by Dr. A. Khaligh.

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Digital Object Identifier 10.1109/TVT.2010.2061243

84 velocities [14]. It is therefore concluded that such cycles cannot
85 completely emulate the real-world daily power demand of a
86 vehicle. More importantly, they do not provide information
87 on parking times as opportunities for charging in the case of
88 emerging plug-in vehicles. In addition, it is important to base
89 duty cycles on larger data sets to reduce statistical errors.

90 An extensive literature survey conducted revealed no refer-
91 ence to the development of a daily driving cycle, taking into
92 account power and energy demands as major requirements for
93 representing the real-world data. Most studies have focused on
94 developing urban driving cycles using snippets extracted from
95 recorded speed–time traces to estimate vehicular emissions and
96 fuel consumption in different cosmopolitan areas [15], [19].
97 The objective of these studies is to represent the driving infor-
98 mation in a collected data set using a single driving cycle. Some
99 other studies discuss the effectiveness of the methodologies
100 used in developing driving cycles to represent the inherent char-
101 acteristics of driving behavior in the collected data [20], [21].

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

121 The study presented in this paper addresses the gap in the
122 literature by developing a statistical methodology and con-
123 structing the needed duty cycles based on a database of over
124 44 million Global Positioning System (GPS) data points
125 recorded over the course of one year in Winnipeg, MB, Canada.
126 Depending on the context, the terms “driving cycle” and
127 “duty cycle” may convey different meanings. In this paper,
128 a “driving cycle” refers to a history of daily driving periods
129 represented by a speed-versus-time curve. A “duty cycle” refers
130 to a profile of daily usage of power by the vehicle, which is
131 typically represented by a 24-h history of driving and parking
132 events. Note that, in the case of an HEV, only a driving cycle
133 is sufficient to calculate vehicle’s power demand, whereas in
134 the case of a plug-in vehicle, parking times also become vital
135 as they may be used for charging from the electric grid, and
136 therefore, they should be included in the daily profile. Parking
137 times are also important to utilities servicing jurisdictions with
138 large vehicular loads, as they can be used to predict and control
139 the load on the grid.

140 The objective of the present study is to first develop a
141 new driving cycle most closely mirroring the characteristics of

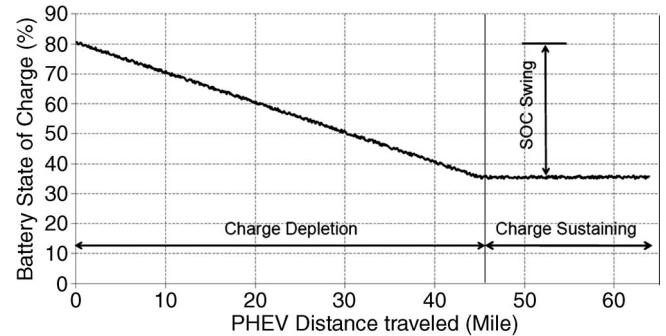


Fig. 1. Typical variation in the SOC of a PHEV battery.

urban driving, including real-world energy and power demands. 142
Once this is achieved, this study aims to incorporate a pattern 143
representing most probable downtimes of the vehicles to charge 144
during their daily usage profile. A comprehensive daily duty 145
cycle is a crucial component for optimal design of plug-in 146
vehicular drive-trains. This study improves the conventional 147
methods of driving cycle generation [26], [28]. The present 148
study also establishes a set of performance measures required to 149
assess a driving cycle suited for electric/plug-in hybrid vehicles. 150
The methodology used in the precedent study for simulation 151
of a plug-in vehicle is enhanced by including 25 parameters 152
to characterize different velocity brackets in a driving cycle 153
[29]. The uniqueness of this study is proposing a methodol- 154
ogy that addresses the particular requirements associated with 155
the design of plug-in vehicles in construction of a 24-h duty 156
cycle. 157

Following the introduction, in Section II, duty cycle re- 158
quirements to be fulfilled for enhanced simulation and opti- 159
mization of plug-in vehicles are discussed. Data collection, 160
driving cycle generation, and characterization are described 161
in Section III. Parking data analysis for weekdays and week- 162
ends is presented in Section IV. The resulting 24-h duty 163
cycles are given in Section V, and driving characteristics 164
are critically compared with those of the standard cycle for 165
urban driving, i.e., the UDSS. Conclusions are presented 166
in Section VI. 167

II. DUTY CYCLE REQUIREMENTS FOR PLUG-IN VEHICLES 168

The total distance that a plug-in vehicle can electrically 169
drive is an important measure for the vehicle’s performance 170
assessment. For instance, PHEVs are usually classified ac- 171
cording to their all-electric range (AER), which is defined as 172
the total miles electrically driven after a full recharge before 173
the engine turns on for the first time [30]. A fully recharged 174
PHEV operates in charge-depleting mode until the battery is 175
depleted to a target state-of-charge (SOC), at which point, the 176
vehicle switches to charge-sustaining mode, using the internal 177
combustion engine to maintain the target SOC [3]. Fig. 1 shows 178
the typical variation in the SOC of the battery in the operating 179
modes of a PHEV. 180

Obviously, the instantaneous power demand resulting from 181
the driving style of the driver is critical in the definition of the 182
AER. The standard cycle UDSS is usually used to measure 183

TABLE I
CHARACTERIZING PARAMETERS AND THEIR VALUES

Parameter	Database average		Final duty cycles	
	weekday	weekend	Weekday	weekend
1 Average speed of the entire driving cycle in km/h	31.4	35.3	32.6	35.0
2 Average running speed in km/h	39.8	43.9	40.3	43.4
3 Total daily distance traveled in km	32.2	33.9	31.6	35.2
4 Average acceleration of all acceleration phases in m/s ²	0.6	0.6	0.55	0.59
5 Average deceleration of all deceleration phases in m/s ²	-0.6	-0.6	-0.59	-0.6
6 Average number of change in acceleration rate (+/-) in one driving period	6.5	7.2	7.83	7.9
7 Average daily power demand in kW	7.9	8.3	8.92	9.3
8 Maximum power demand in kW	59.3	72.2	49.45	60.0
9 Total daily energy demand in Mj	17.3	17.7	16.41	18.2
10 Average daily breaking power in kW	-5.3	-5.4	-5.47	-6.0
11 Root mean square of acceleration in m/s ²	0.8	0.8	0.66	0.69
12 Average length of a driving period in km	0.9	1.2	0.75	1.03
13 Time percentage of Idling (zero velocity) in %	21.8	20.7	19.1	19.31
14 Time percentage of acceleration: acceleration > 0.1 m/s ² in %	31.4	31.3	36.5	35.1
15 Time percentage of Cruising (acceleration [-0.1, 0.1] m/s ² , speed > 5 m/s) in %	14.9	16.7	9.8	10.5
16 Time percentage of deceleration: acceleration < -0.1 m/s ² in %	31.2	30.9	34.4	34.9
17 Time percentage of creeping (acceleration [-0.1, 0.1] m/s ² , speed < 5 m/s) in %	0.6	0.5	0.32	0.14
18 Time percentage of driving at very low speed bracket [0 20] km/h in %	94.5	90.6	85.3	90.5
19 Average speed in very low speed bracket [0 20] km/h	6.6	10.3	7.3	6.5
20 Time percentage of driving at low speed bracket [20 50] km/h in %	58.9	59.6	62.0	61.0
21 Average speed in low speed bracket [20 50] km/h	18.9	20.8	19.2	28.1
22 Time percentage of driving at moderate speed bracket [50 80] km/h in %	36.7	36.9	37.4	36.4
23 Average speed in moderate speed bracket [50 80] km/h	32.9	30.2	34.9	29.0
24 Time percentage of driving at high speed bracket [80 100] km/h in %	9.9	10.0	8.9	10.6
25 Average speed in high speed bracket [80 100] km/h	16.3	15.0	16.9	15.1

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
 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) de-
 veloping 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 parame-
 ters 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 cat-
 egorizing 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 represen-
 tative speed-time trace is selected among a large number of

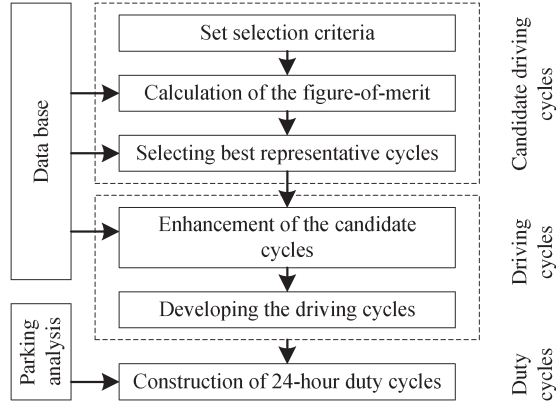


Fig. 2. Methodology of developing a 24-h duty cycle.

240 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 import-
 244 ance [17].

245 In this paper, emphasis is placed on the energy and power-
 246 demand aspects of a cycle to address the concerns in plug-
 247 in vehicle design and optimization, as mentioned previously.
 248 Therefore, the second methodology is used in this study to
 249 develop a cycle realistically mirroring the characteristics of
 250 urban driving. This study adopts an adequately long-term ap-
 251 proach to data collection from a fleet of instrumented vehicles
 252 to reduce the risk of unreal driving behavior resulting from
 253 any influence of the onboard instruments that may potentially
 254 bias drivers’ driving behavior. Over a one-year timescale, the
 255 vehicle owners presumably drive on their ordinary travel routes,
 256 whereas onboard instruments automatically timestamp the ve-
 257 hicle’s location and speed on a secondly basis.

258 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 full-
 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.

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

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

A. Selecting the Candidate Driving Cycles

302 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 braking 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.

309 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:
 313

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

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

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

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

TABLE II
VALUES OF PARAMETERS USED IN POWER AND ENERGY CALCULATION

Parameter	ρ	A_f	C_D	V_W	m	θ
Value	1.2 kg/m ³	2.5 m ²	0.3	0 m/s	1550 kg	0

334 rolling friction F_F , 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

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

$$F_F = (1 + v/100) \cdot mg \cdot \cos \theta / 100 \quad (5)$$

$$F_G = mg \sin \theta \quad (6)$$

337 ρ 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,
339 m is the mass of the vehicle, g is the gravitational constant
340 (9.8 m/s²), and θ 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 participant vehicles 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 breaking 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

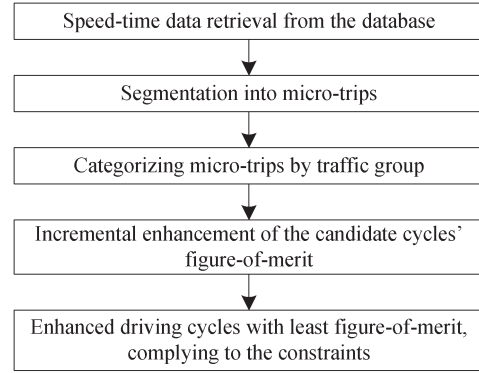


Fig. 3. Methodology of enhancing the candidate cycles.

TABLE III
MICROTRIP CLUSTERING CRITERIA

Traffic category	Average speed	Acceleration
Congested	Low: [0 5] km/h	Mild: [-0.1,0.1] m/s ²
Urban	Moderate: [5,40] km/h	Harsh: [-3.0,3.0] m/s ²
Highway	High: [40 100] km/h	Moderate: [-1.0,1.0] m/s ²

groups characterized by average speed and acceleration, as
372 given in Table III. Here, each microtrip of the candidate cycle is
373 iteratively exchanged with microtrips of the same traffic group
374 until the best figure of merit σ is obtained. 375

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

Speed-acceleration frequency distribution (SAFD) plots pro-
391 vide the needed information about the time proportions of
392 individual driving modes [34]. The use of microtrips of the
393 same traffic group serves to maintain the matching of the SAFD
394 of the two candidate cycles to that of the SAFD of all recorded
395 cycles. 396

An alternative approach to developing a driving cycle is to
397 use random selection methods to select the appropriate number
398 of classified microtrips required to construct a representative
399 cycle matching well with the average characterizing parame-
400 ters with the lowest figure of merit. Random combination of
401 microtrips has been used by other researchers as a means to
402 construct representative driving cycles [35]. Another approach
403 to improve the current methodology would be to give a weight-
404 ing factor to the terms in the definition of the figure of merit [see
405 (1)] to adjust sensitivity of the final result to bias characterizing
406 parameters in accordance with their importance in the final
407

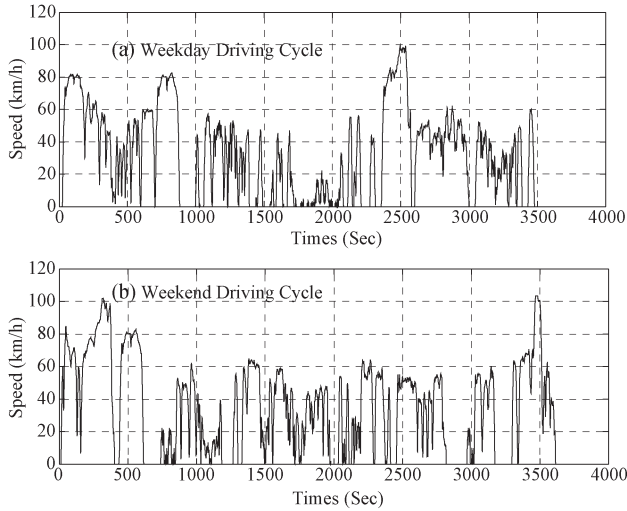


Fig. 4. Enhanced candidate driving cycles. (Top) Weekday. (Bottom) Weekend.

408 duty cycle. In this paper, all weighting factors are considered
 409 equal to 1. Evidently, energy needed and power demand for
 410 traveling the same distance in different traffic modes are not
 411 equal. It is also well understood that the aggressiveness of the
 412 driver in accelerating and decelerating the vehicle increases
 413 power consumption. However, it should be noted that replacing
 414 microtrips of the candidate cycle with microtrips of the same
 415 traffic mode, but potentially from different driving styles, is
 416 not misleading from an energy perspective. This is due to the
 417 fact that all parameters defining aggressiveness, energy level,
 418 and power consumption are already included in the 25 char-
 419 acterizing parameters used in this study, and the replacements
 420 increasing the figure of merit to larger values are not con-
 421 sidered. Implementing alternative enhancement methodologies
 422 mentioned earlier and their performance assessment are left for
 423 further work. Fig. 4 shows the enhanced weekday and weekend
 424 candidate driving cycles. The metric units are used throughout
 425 the study.

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

430 Durations of the weekday and weekend cycles are 3484 and
 431 3616 s, respectively. The maximum velocity is higher in the
 432 weekend cycle, i.e., 114 km/h, whereas in the weekday cycle,
 433 the maximum velocity is 89.6 km/h. The enhancement process
 434 does not necessarily finish by yielding a figure of merit equal to
 435 zero, but a considerable improvement can be expected as, in this
 436 study, the initial values were improved by approximately 40%.
 437 The figure of merit for the enhanced weekday and weekend
 438 driving cycles are 0.15 and 0.2, respectively. Fig. 5 shows
 439 the SAFD plot for weekday and weekend enhanced candidate
 440 driving cycles.

441 The two patterns are different in nature. Stop-and-go events
 442 characterized by larger acceleration or deceleration rates at low
 443 speeds are more probable in the weekday pattern. However,
 444 high-speed events are more probable in the weekend pattern.
 445 The driving pattern on the weekend is slightly more aggressive

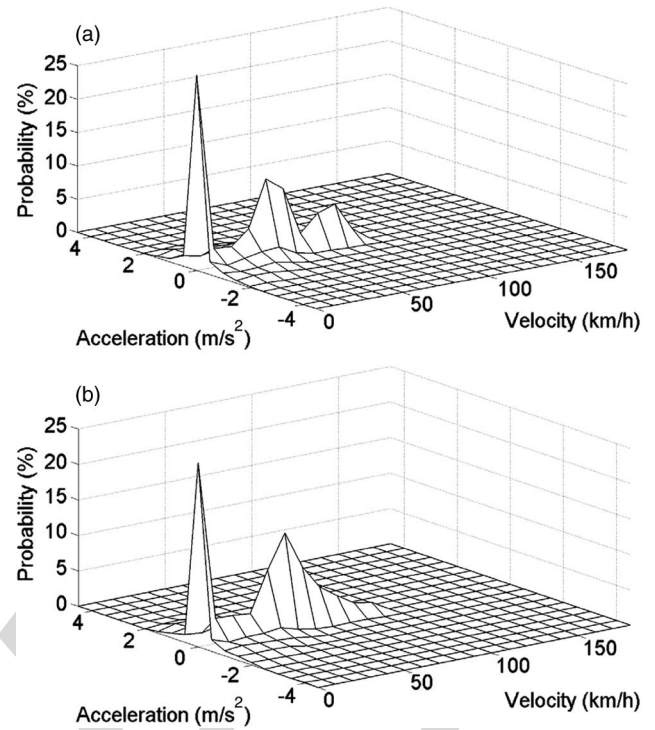


Fig. 5. SAFD plots for the enhanced candidate driving cycles. (a) Weekday. (b) Weekend.

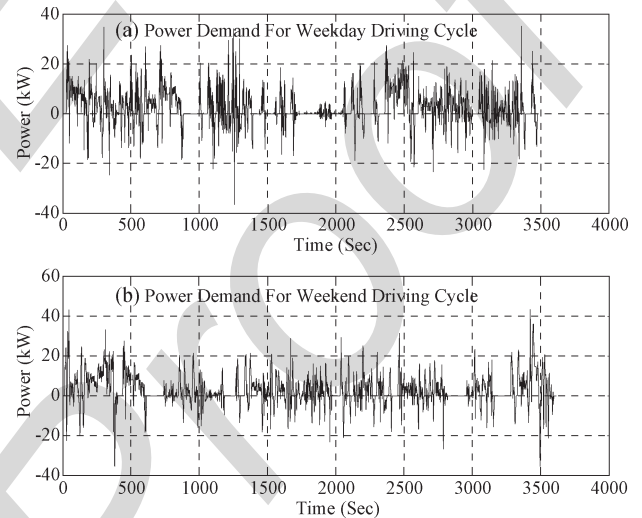


Fig. 6. Power-time traces for the enhanced candidate driving cycles. (a) Weekday. (b) Weekend.

446 due to higher acceleration and deceleration rates, which results
 447 in higher power demand for weekend driving patterns.

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

458

IV. PARKING ANALYSIS

459 Vehicle parking at home, the workplace, commercial lo-
 460 cations, and on the street constitutes a critically important
 461 element of a modern duty cycle that can address a multitude
 462 of drive-train topologies, storage technologies, and controllers.
 463 Developing models to analyze the parking behavior in an urban
 464 area for city planning may require detailed information on the
 465 parameters affecting parking behavior during the day, such as
 466 travel demands, district-based knowledge on cost of parking,
 467 nature of activities in the area of interest, and supply and
 468 demand on an hourly basis. However, from the charging per-
 469 spective only, relatively long parking times provide potential
 470 charging times to increase the SOC of an onboard energy
 471 storage device. A typical duration for a full charge under normal
 472 charging conditions (110 V and 15 A) for current competitive
 473 battery technologies used in electric vehicles, namely, lithium
 474 ion and nickel metal hydride, is approximately 6 h; the mini-
 475 mum duration for partial charging is presently not known with
 476 a high confidence level. Therefore, it is expected that most
 477 plug-in electric vehicles will be charged mainly overnight. If
 478 a relatively long parking time (e.g., more than 3 h) during the
 479 day is considered as a realistic scenario for a reasonable share
 480 of the urban fleet, it is possible to downsize the battery storage
 481 capacity and reduce the capital cost of a plug-in vehicle or,
 482 in the case of a PHEV with a fixed size of battery storage,
 483 drive more miles on electricity to improve cost effectiveness.
 484 In addition, fast charging schemes using level 2 (120 V and
 485 30 A) and direct dc chargers will facilitate full charging in
 486 shorter charging durations, i.e., as low as 20 min, depending
 487 on the battery technology and dc charging infrastructure.

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

504 An extensive literature survey reveals that a few studies
 505 have focused on the potential charging aspect of parking times
 506 as a part of daily activities of vehicles; none seem to have
 507 incorporated this into a duty cycle. This aspect is of critical
 508 importance to address energy drivers in transportation and
 509 allow the displacement of fossil fuels with new renewable
 510 energy generation. The analysis conducted by the Argonne
 511 National Laboratory (ANL) shows that, in the United States,
 512 66% of the vehicles driven to work are parked more than
 513 3 h before noon, potentially allowing a second charge before
 514 the electric utility peak demand begins [37]. It was also ob-
 515 served that vehicles were parked for a short time for shop-

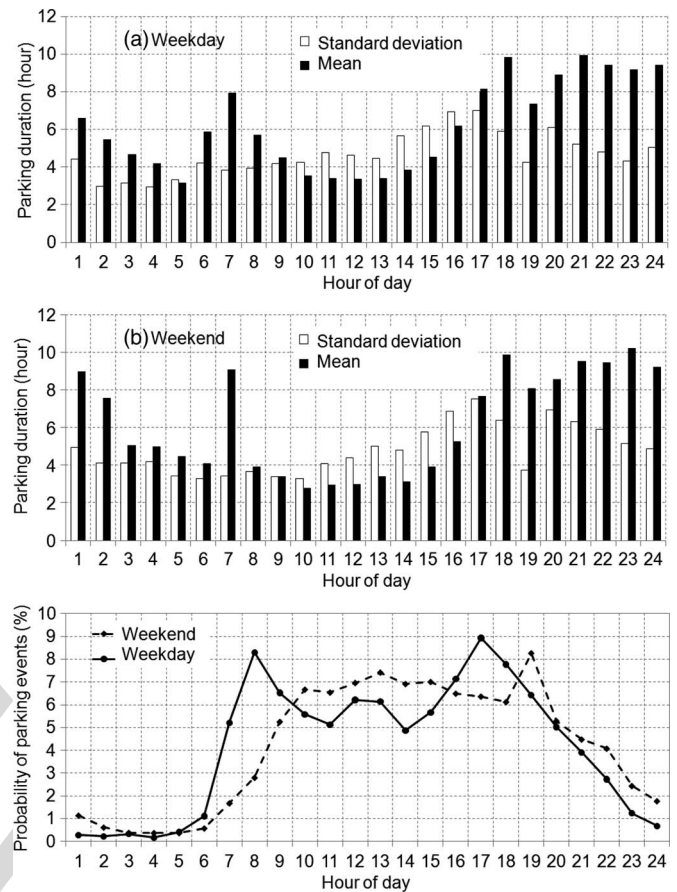


Fig. 7. Mean and standard deviation of parking duration by hour of day. (a) Weekdays. (b) Weekends. (c) Probability of parking events by hour of day for both weekdays and weekends.

ping purposes, and parking was often during peak electric 516 demand [36]. 517

In this paper, GPS-based data loggers provide information 518 on location, type of parking, and duration of parking events. 519 The type of parking can be determined from the driver's 520 behavior, where it is relatively simple to determine where 521 the person lives and works; commercial parking locations 522 are found by digitizing commercial parking lots in Winnipeg. 523 Street parking is deduced from a car staying on the street. Note 524 that studies dedicated to record the instantaneous speed of the 525 vehicle for certification purposes, such as that leading to the 526 FTP72 standard cycle and its enhanced cycles, do not provide 527 information on parking times. Here, probable parking times 528 and average duration for each parking event, as well as the 529 standard deviation of the data points, are included to adequately 530 reflect a daily driving and parking profile for electric vehicle 531 design of drive-train topologies. 532

Parking times of less than half an hour are arbitrarily clas- 533 sified in our study as short; the distribution of such parking 534 events shows that, in early mornings and afternoons, this type 535 of parking is the most likely. It is important to note that stop 536 times of less than 2 min, happening at stop signs or traffic 537 lights, are excluded from short parking. The results of short 538 parking times are not presented here as it is assumed that, in 539 the real world, these occasional parking events are not favored 540 by drivers for charging. However, a cumulative parking time 541

542 representing short parking times per day will be included in the
543 final duty cycles. The results of studying parking periods that
544 exceed 30 min are shown in Fig. 7.

545 Fig. 7(a) and (b) shows mean values and standard deviations
546 of parking durations by hour of day for weekdays and week-
547 ends, respectively.

548 Two distinct patterns in daily parking behavior can be recog-
549 nized, namely, a mean value less than or equal to the standard
550 deviation and a mean value larger than the standard deviation.
551 Long parking duration with a mean value larger than the stan-
552 dard deviation happens between 8 P.M. and 6 A.M., showing
553 that the majority of drivers tend to park their vehicles for a long
554 time. However, when the standard deviation is greater than the
555 mean value of parking duration, the data show an increase in
556 daily trips, happening between 10 A.M. and 4 P.M., and the
557 average of the mean values is about 4 h. Peaks in probability
558 of parking events in terms of hour of day, as shown in Fig. 7(c),
559 reflect the difference in nature of activities between weekdays
560 and weekends. While there is only one peak in the weekend
561 curve happening at 7 P.M., there are three peaks occurring at
562 7 A.M., 12 P.M., and 5 P.M. during weekdays.

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

583 V. ASSEMBLY OF THE DRIVING CYCLES

584 Analysis was performed on the raw GPS data in conjunction
585 with the digitized maps of the roads and commercial parking
586 locations to characterize the driving and parking behavior of
587 the vehicles under the one-year span of the survey in the
588 city of Winnipeg. Using the method shown in Fig. 2, two
589 24-h vehicle usage profiles representing a daily duty cycle
590 were developed for both weekdays and weekends. The parking
591 patterns obtained from the analysis of parking times, as well as
592 cumulative short parking events, are included in the daily duty
593 cycles for weekdays and weekends. In creating this, the average
594 distance traveled in driving events is considered to separate
595 the final driving cycle into parts, and then, parking events are
596 inserted in between in the most probable way. The resulting
597 cycles are shown in Fig. 8 and are meant to represent the

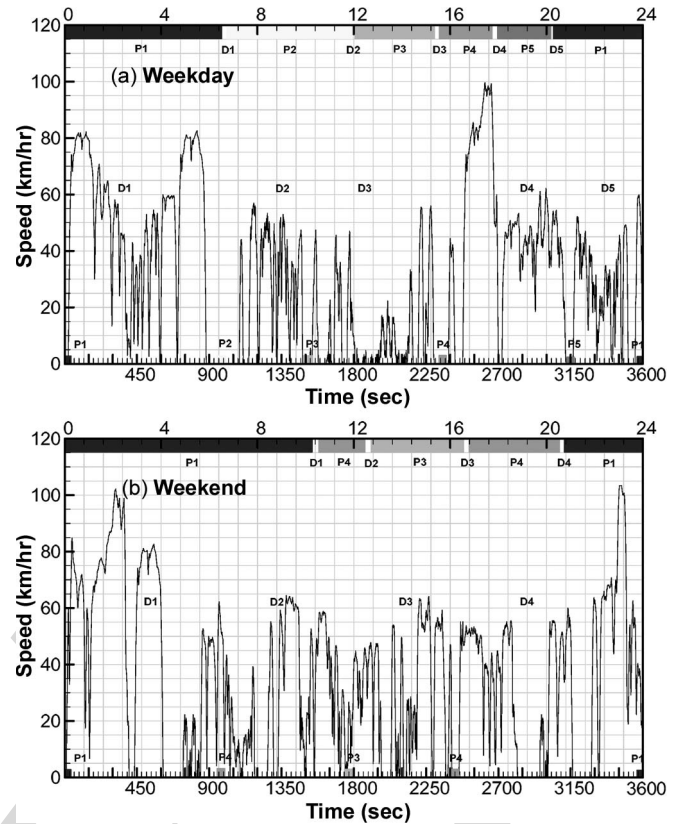


Fig. 8. Resulting 24-h duty cycles. (a) Weekdays. (b) Weekends.

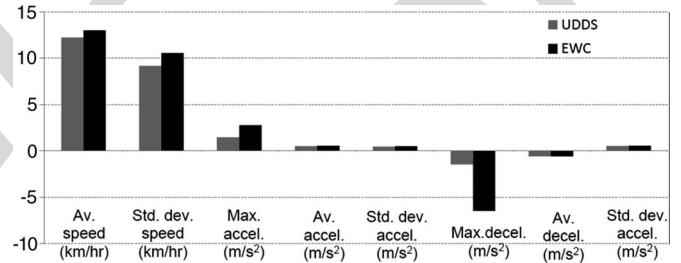


Fig. 9. Comparison between the standard cycle UDSS and the enhanced weekday cycle (EWC).

44 million data points into a condensed duty cycle for studies
598 pertaining to plug-in hybrids, including optimization of power
599 trains [29]. In Fig. 8, D stands for driving, P stands for parking
600 periods, P1 stands for home, P2 stands for work, P3 stands
601 for commercial, P4 stands for short stops, and P5 stands for
602 street parking. The driving cycles are on a 1-h basis, and the
603 duty cycles, with long parking times included, are on a 24-h
604 basis and are both combined into the same figure. The parking
605 durations on a 24-h scale designated by color codes are also
606 shown on a 1-h driving scale for the sake of clarity. The parking
607 events that potentially can be used for charging are P1, P2, or P3
608 when the vehicle is most probably parked in a parking spot with
609 access to level-1 or level-2 charging. The parking events that
610 happen on the street or short parking durations are considered
611 not suitable for charging. 612

Some characteristics of the enhanced driving cycle are com-
613 pared with those of the standard cycle UDSS, and the results
614 are presented in Fig. 9. The comparison indicates that more
615 aggressive characteristics are associated with the real-world 616

617 cycle, whereas, on average, the two cycles may be considered
618 interchangeable.

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

626 The data files of the duty cycles and the collected raw data
627 are available to the public on the World Wide Web through a
628 unique Digital Object Identifier number [36]. Forty-four mil-
629 lion speed–time data points, stamped with date and time, and
630 collected over the course of one year are made available. The
631 latitude and longitude of the position of the vehicles recorded
632 on a secondly basis are masked by mapping the starting point of
633 every trip to (0,0) to respect the confidentiality agreement with
634 the participants in the data-collection phase. However, personal
635 information about the participants is used to label the parking
636 locations as home or work. Labeled parking locations, as well
637 as the duration of parking events needed for further analyses
638 with different charging scenarios in the case of plug-in electric
639 vehicles, are included in the data files. The parking events that
640 are less than 30 min in duration are labeled short stops. Parking
641 events happening along the street are not potentially suitable
642 for charging. The locations of the parking events longer than
643 30 min in duration are marked home, work, shop, and street. The
644 effectiveness of the methodology presented in this study, even
645 with far fewer data points (about 1 million data points, which
646 is equal to about 2% of the data points used in this study),
647 for simulation-based optimization of a PHEV was shown in [29].

648

VI. CONCLUSION

649 A new approach to the development of a duty cycle that ad-
650 dresses the requirements associated with the design of electric
651 vehicles—e.g., HEV, PHEV, BEV, and extended-range vehi-
652 cles, has been proposed and implemented on a 24-h timescale.
653 It provides a complete data set for optimization of battery
654 size for on-road vehicles in a typical North American urban
655 setting. For example, power and energy demand in the daily
656 operation of a sedan is directly related to the rate of acceleration
657 and deceleration and time spent in different traffic modes;
658 charging scenarios depend on parking times and duration. The
659 driving behavior of a fleet of 76 participants in a one-year
660 voluntary data-collection program in the city of Winnipeg is
661 analyzed to develop a driving cycle and is composed of two
662 24-h duty cycles for weekdays and weekends. This cycle pro-
663 vides information about the time and duration of driving in
664 different traffic categories, as well as information on parking
665 times when the vehicle is not in use. Further vehicle simu-
666 lation tools can use the daily duty cycles developed to op-
667 timally design propulsion systems, drive-train configurations,
668 and storage components for PEV technologies under real-world
669 driving conditions. Furthermore, this information can be used
670 to analyze the impact of daytime charging by a fleet of plug-
671 in electric vehicles on the electric utility grid that may create a
672 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
673 that can be used to optimally address energy drivers simultane-
674 ously facing transportation by displacing fossil fuels with new
675 renewable energy generations with the direct consequences of
676 increasing the renewable energy ratio of various jurisdictions. 677

To achieve this goal, 25 parameters characterizing a driving
678 cycle for further PEV simulations are recognized, and two
679 candidate daily cycles having the closest match to the average
680 of the parameters are selected. The candidate cycles are then
681 incrementally enhanced by replacing their microtrips with those
682 extracted from the same traffic group, minimizing a figure of
683 merit defined based on the characterizing parameters. Finally,
684 the processed parking data are included to complete two 24-h
685 duty cycles. The final result is therefore reflecting more accu-
686 rately a realistic driving pattern than driving cycles resulting
687 from methodologies that patch snippets of driving data from
688 different drivers or occasions to make a driving cycle. Although
689 the data collected represent driving behavior in the city of
690 Winnipeg, MB, Canada, the methodology presented here can
691 be extended to any other urban area of interest. 692

There exist a few directions to continue the research on or
693 using the collected data. Other methods for development of a
694 driving cycle may include a stochastic approach for selecting
695 and patching snippets of speed–time traces using a probability
696 matrix [14], [21], which might be enhanced to incorporate
697 power and energy requirements of the vehicle. Future work
698 may also concentrate on one specific driving pattern, for in-
699 stance, a commuter, to develop a dedicated driving cycle best
700 mirroring that particular driving pattern. The driving cycle may
701 also be used for a wide range of applications, such as energy
702 assessment of the vehicles in daily use in urban transportation,
703 analysis of charging scenarios in PHEVs and PEVs, vehicle-to-
704 grid analysis, and statistical assessment of driving cycle vari-
705 ability on hybrid drive-train design. Finding other applications,
706 particularly from a social driving behavior perspective, can also
707 be viewed as an important extension of the work. 708

ACKNOWLEDGMENT

709

The authors would like to thank Prof. D. Blair and R. Smith
710 from the Department of Geography, University of Winnipeg, for
711 providing the collected travel data. Ongoing discussions with
712 Emerging Energy Systems at Manitoba Hydro, in particular
713 with T. Molinski, are acknowledged. Special thanks to Presen-
714 tech Inc. for integrating the parking study with their proprietary
715 firmware. 716

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nonlinear optimization, and power-electronic appli- 872
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AUTHOR QUERIES

AUTHOR PLEASE ANSWER ALL QUERIES

AQ1 = Please provide publication update in Ref. [29].

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