

Characterizing One-day Missions of PHEVs Based on Representative Synthetic Driving Cycles

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ABSTRACT

This paper investigates series plug-in hybrid electric vehicle (PHEV) behavior during one-day with synthesized representative one-day missions. The amounts of electric energy and fuel consumption are predicted to assess the PHEV impact on the grid with respect to the driving distance and different charging scenarios: (1) charging overnight, (2) charging whenever possible. The representative cycles are synthesized using the extracted information from the real-world driving data in Southeast Michigan gathered through the Field Operational Tests (FOT) conducted by the University of Michigan Transportation Research Institute (UMTRI). The real-world driving data include 4,409 trips covering 830 independent days and temporal distributions of departure and arrival times. The sample size is large enough to represent real-world driving. The driving cycle synthesis approach proposed by Lee, and Filipi [2],[3] based on a stochastic process and subsequent validation procedure is used to create real-world driving cycles. To cover the entire range of real-world driving distance, ten synthetic cycles are created ranging from 4.78 miles to 40.71 miles following the real-world driving distance distribution. The PHEV behavior over one-day is characterized through a simulation based approach. The PHEV simulation is executed using Matlab simulink based Powertrain System Analysis Toolkit (PSAT) developed by Argonne National Laboratory (ANL) and in-house Matlab codes. The amounts of the electricity and fuel consumptions over one-day are predicted under different driving distances and different charging scenarios. The

prediction of the PHEV behavior can be directly linked to the loads on the local distribution network.

INTRODUCTION

Accurate prediction of electricity demand of a plug-in hybrid electric vehicle (PHEV) over one day is important for the studies of the PHEV impact on the grid. The market penetration of the PHEVs is expected to be continuously growing in the near future due to the increasing emphasis on fuel savings and the reduction of green house gas emissions. Stringent CAFE fuel economy limit requires 35.5 mpg by 2016 in US and the CO₂ limit in Europe by 2012 is 130 g-CO₂/km. These strict regulations accelerate the research on alternative propulsion technologies including hybrid electric vehicle (HEV), electric vehicles (EV), and PHEV. Series PHEVs, or extended range electric vehicle (EREV), have unique benefits of utilizing electricity generated from the electric power plant sector in part and providing comparable driving ranges to the conventional vehicles [1]. Thus, zero-emission driving is achieved within all electric range (AER), and longer driving beyond the AER is possible. However, the flexibility in utilizing different types of energy sources also increases the system complexity, thus, requiring sophisticated vehicle level design-optimization and control to achieve the maximum fuel economy and the targeted AER. The AER is highly dependent on real-world driving patterns, and the driving patterns are changing with respect to the driving distances [2]. Therefore, preparation of representative driving

cycles depending on driving distance is critical for analyze the PHEV impact on the grid.

The electric energy consumption per mile is directly related to the driving aggressiveness in the real-world driving. Several studies considered real-world cycles for PHEV design [1],[4],[5] and PHEV 24-hour mission analysis by Lee and Filipi [6]. However, measured naturalistic driving cycles show variability driving patterns, and the predicted net specific battery energies with the measured cycles within the AER show wide distribution with the same driving distances [6]. Thus, selecting one or a few measured cycles to represent real-world driving patterns is difficult, and developing a representative cycle would be very advantageous.

Certification driving cycles have been developed to evaluate vehicle emissions, e.g. UDDS (Urban Dynamometer Driving Schedule) and HWFET (Highway Fuel Economy Test) cycles [7],[8]. They were also used for determining fuel economy. However, they cannot capture the dependence of the driving patterns on the driving distance in case of PHEV analysis, since certification tests have to be repeated a number of times in order to evaluate the charge depleting range. Recent analysis of the real-world driving in USA shows that UDDS and HWFET are much less aggressive than naturalistic driving patterns, thus leading to significant under-prediction of peak power and specific energy per mile [1],[4],[5]. Combinations of different cycles [4] and scaling of the UDDS [8] were used in PHEV analysis to overcome parts of this deficiency. However, starting with cycles developed several decades ago for emission certification limits the degree of reality in analysing vehicle power and energy issues.

Novel ways to representing real-world driving patterns with a single trip with respect to driving distance are necessary to investigate the PHEV impact on the grid with a small number of simulations. The driving cycle procedure proposed by Lee and Filipi [2],[3] is used to prepare representative real-world driving cycles with its verified representativeness through the assessment of the statistical criteria in the synthesis procedure [3]. The proposed approach uses only driving data, i.e. it does not include vehicle related information or subjective parameters while synthesizing schedules (ex. vehicle velocity vs. time). Thus, the resulting synthetic cycles are general and independent of vehicle types and vehicle control strategy. The synthesis procedure used the extracted driving cycle information (velocity and acceleration) from the naturalistic driving data. The data were measured during Filed Operational Tests (FOT) in Southeast Michigan by the University of Michigan Transportation Research Institute (UMTRI) [9]. In this study, total of 830 days 4409 individual trips are randomly selected from the FOT data including wide varieties of driving patterns from short distance to long distance trips. Hence, they can be sufficient to represent the real-world driving patterns in the Southeast Michigan.

This paper presents the approach with the consideration of representative naturalistic driving patterns to predict the electric energy consumption, the battery state of charge (SOC) when a PHEV arrives at a given location, and hence the energy demand for charging imposed on the distribution network. Ten synthetic cycles following the one-day driving distance distribution are constructed, then, one-day schedules are prepared by locating the synthesized cycles on the 24-hour time axis. Two different charging scenarios, (1) "charging overnight", and (2) "charging whenever possible", are investigated to predict the effect of different charging pattern on the battery SOC and the charging electricity amount from the grid. Then, the PHEV simulation is executed using the Matlab Simulink based Powertrain System Analysis Toolkit (PSAT) due to its proven prediction accuracy of each PHEV component [7],[8]. The predicted time histories of component responses provide valuable information for the component sizing of the PHEV system to achieve the desired performance and the AER. Vehicle behavior under daily driving and charging time will determine emissions and environmental impact.

The present paper is organized as follows. First, the real-world driving data and their statistics were shown. Then, the overall procedure of the naturalistic driving schedule synthesis is presented. Synthetic driving cycles are constructed and the trends of important statistical variables are analysed with respect to the driving distance. Next, the PHEV behaviour during one-day missions (24-hour missions) is investigated and compared to the simulation results with the certification cycles. Finally, electricity demands from the grid with different charging scenarios are predicted with the driving distant dependent naturalistic driving patterns, and findings are summarized in the conclusions.

SYNTHESIS OF NATURALISTIC DRIVING CYCLES

The driving cycle synthesis approach based on a stochastic process and subsequent validation procedure using statistically significant criteria proposed by Lee and Filipi [2], [3] is used construct a set of representative real-world driving cycles. The hypothesis of the approach is that cycles representative of real-world driving patterns can be constructed using the information extracted from naturalistic driving data. The data should include wide range of driving distances and various driving patterns, such as urban roads, freeway, and mixed. In the cycle synthesis process, real-world driving information is extracted in a form of transfer probability matrices (TPMs). Cycles are then synthesized based on Markov chain to deal with the random characteristics of driving cycles. Finally, the synthesized cycles are assessed by reviewing the statistically significant variables to verify the representativeness. When all variables satisfy the criteria, the synthesized cycle is selected as a representative real-world cycle. To represent the entire

driving range, ten synthetic cycles are prepared evenly distributed over the observed driving distance range.

REAL-WORLD DRIVING DATA

The real-world driving data in Southeast Michigan are provided from the University of Michigan Transportation Research Institute (UMTRI) by the Field Operational Test (FOT) [9]. UMTRI outfitted 11 midsize sedans with data acquisition devices for monitoring up to 200 variables, and the data include the information of departure times, arriving times, and vehicle speed profiles versus time with 0.1 second samplings. In this work, total 830 days 4409 trips of the selected day driving data are used to extract driving information for driving cycle synthesis. The sample size is rich enough to represent real-world driving in the US Midwestern region with a high level of confidence. From the time participants turned on the key to the time they turned off the key, all data including their instantaneous time and speed were recorded and logged as a separate trip. The driving distance range of each trip is wide from less than one mile up to 66.9 miles. The driving data also show wide spectrum of driving patterns, such as local-way driving, freeway driving, and mixed driving.

The aggressiveness of the real-world driving cycles is widely distributed even at the same driving distances. The predicted distributions of the net battery energy consumption under AER by Lee and Filipi [6] in Fig. 1 show the variety of real-world driving patterns. They indicate that a single measured trip cannot capture the averaged (or representative) naturalistic driving patterns. Therefore, the construction of one of a few representative cycles depending on the driving distance is necessary for the PHEV simulation. Another notification is that the specific battery energies of the naturalistic driving cycles are mostly located in between the HWFET and US06 cases, and 7% of the naturalistic cycles exceed the US06. When PHEV is analyzed using repetitions of federal driving schedules over a long distance, the resulting battery duty schedules and total energy consumption will obviously be very different from the predictions under real-world conditions. Clearly, naturalistic driving patterns are critical for the accurate assessments of PHEV behavior.

The departure time distribution and arrival time distribution are shown in Fig. 2. Daily driving consists of several individual trips with temporal distribution and several rest periods. The departure time is the starting time of outgoing trips from home, and the arrival time is the ending time of the last trip to home. Since the driving data were measured consecutively, we assume that longest rest times separate each day. After reviewing the resting patterns of the entire data-set, the threshold time to separate days is set to 5 AM. Figure 2 (a) shows the highest peak around 7~8 AM. The mean value of the departure times is 10:31(expressed as "Hour: Minute") and the standard deviation (std) is 3:16. The

arrival time distribution shows two separated peaks, one around 17:30 and the other around 20:30. This observation is plausible in a sense that people tend to come back home without visiting any other places or tend to visit some places after arriving at home such as markets, gas stations, and restaurants. The mean value of the arrival times is 19:10 and the std is 3:37.

Daily driving distance distribution is shown in Figure 3. The daily driving distance is the summation of each trip distance within one day. The daily driving distance range in the data is from 1.51 miles to 137.2 miles, and the wide driving distance range implies the richness of driving patterns. The distance is divided into ten subsections to represent specific driving patterns associated with the driving distances. Driving information for the cycle synthesis is extracted from each

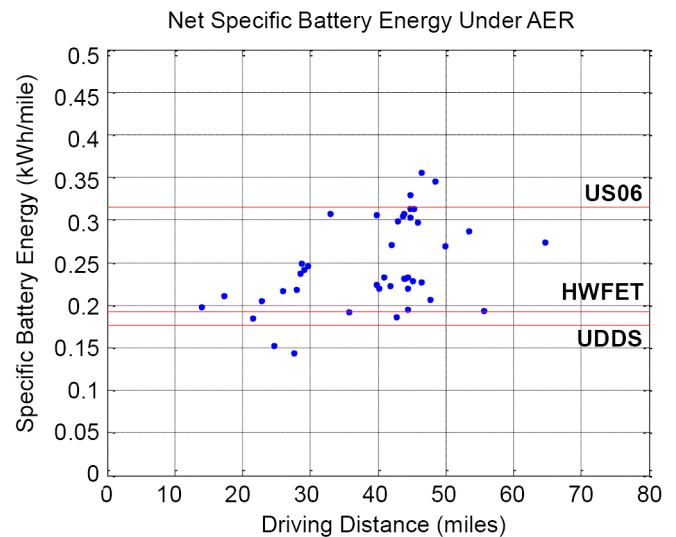
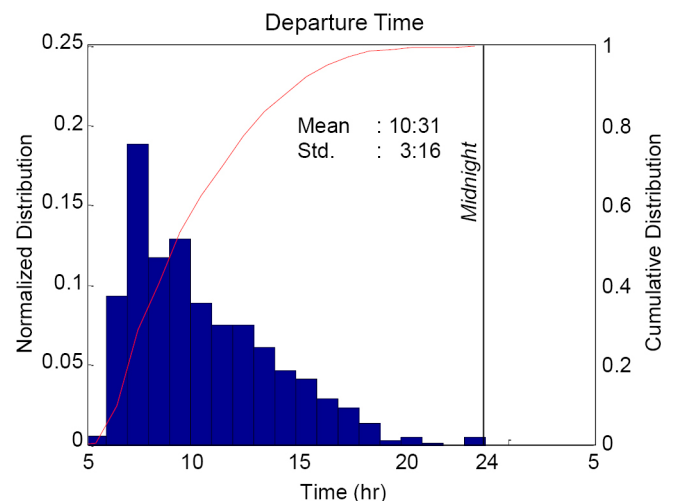


Figure 1. Net specific battery energy distribution of the target series PHEV under AER and velocity profiles of certification driving cycles [6]



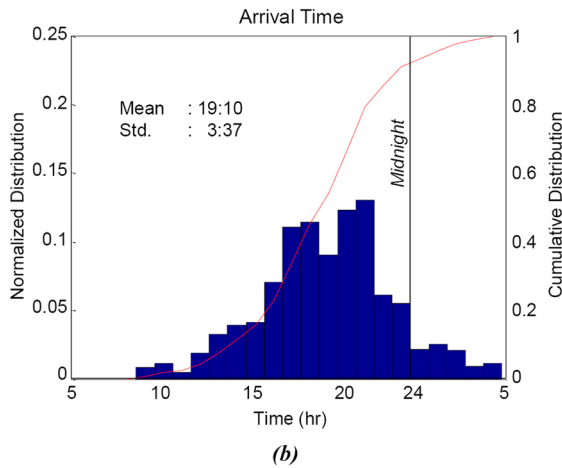


Figure 2. Statistical distribution of daily driving schedules: (a) departure times; (b) arrival times

divided section and used to synthesize cycles within the divided distance range. The mean distance is 34.98 miles and the std of the distances is 19.56 miles. The driving distance located at 70% of the cumulative distribution is 40 miles, and the distribution is skewed a bit to the right compared to the NHTS data at short-to-medium distance trips [10]. The FOT data are based on real measurements in the Southeast Michigan, yet the NHTS data are based on the surveys of drivers overall the United States. This study relies on the measured data and considers them representative of driving in the urban/suburban Midwest region, and driving characteristics are directly analyzed from them.

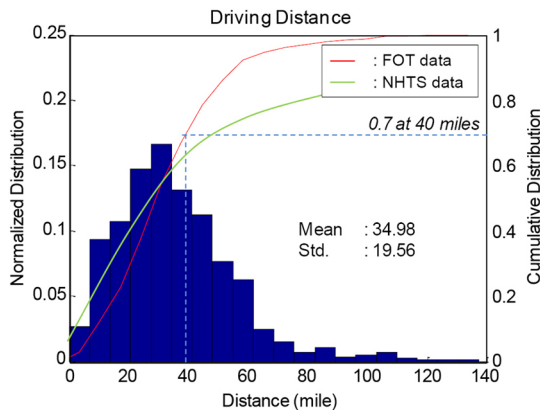


Figure 3. Daily driving distance distribution

DRIVING CYCLE SYNTHESIS PROCEDURE

A stochastic process combined with subsequent assessment procedure for the representativeness using statistically significant variables is used to prepare a driving cycle set for PHEV behavior characterization. The overall procedure

presented in [2] is illustrated in Fig. 4. Initially, real-world driving cycles for the extraction of real-world driving information are selected within the concerning driving distance range. Markov chain uses the extracted information to synthesize the cycles. A discrete-time Markov chain is a sequence of random variables $X_1, X_2, X_3, \dots$ with the Markov property are expressed as

$$\begin{aligned} P(X_{n+1} = x_{n+1} \mid X_1 = x_1, X_2 = x_2, \dots, X_n = x_n) \\ = P(X_{n+1} = x_{n+1} \mid X_n = x_n) \end{aligned} \quad (1)$$

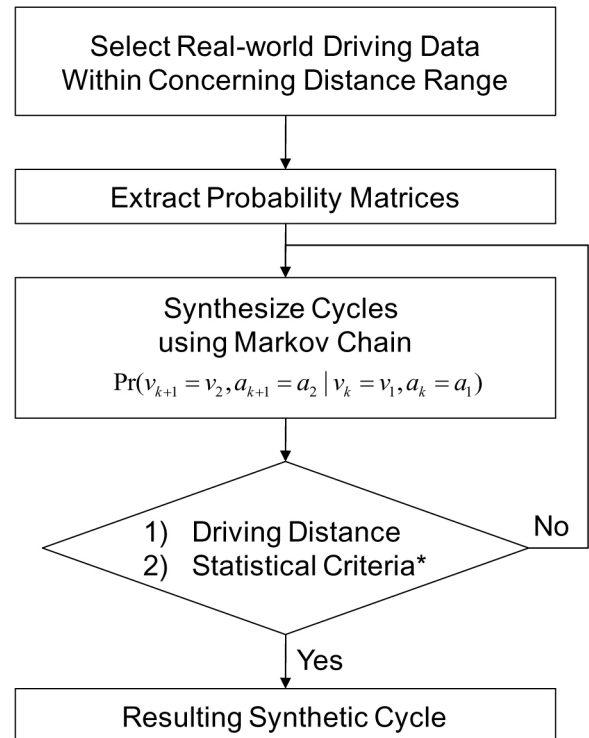


Figure 4. Naturalistic driving cycle synthesis procedure using Markov chain and statistical criteria

The set of possible values that the random variables X_n can take is called the state space of the chain. The conditional probabilities $p_{ij} := P(X_{n+1} = j \mid X_n = i)$ are called transition probabilities. The probability used in the synthesis procedure is time-independent (or time-homogeneous). The sum of all probabilities leaving a state must satisfy

$$\sum_j p_{ij} = \sum_j P(X_{n+1} = j \mid X_n = i) = 1. \quad (2)$$

To satisfy the Markov property in eqn. (1) that represents future states depend only on the present states, an adequate number of states should be chosen. The required states could be selected by investigating the simplified vehicle dynamics equation. The vehicle dynamic equation is expressed as

$$F_{net} = F_{prop} - F_{RR} - F_{WR} - F_{GR} = m_e a_{veh} = m_e \dot{v}_{veh}, \quad (3)$$

where F_{net} is the net force applied to the vehicle, F_{prop} is the propulsion force from the powertrain, F_{RR} is the rolling resistance force, F_{WR} is the wind resistance force, F_{GR} is the grade resistance force and all external forces applied to the vehicle, m_e is the equivalent vehicle mass, v_{veh} is the vehicle velocity, and a_{veh} is the vehicle acceleration. From the eqn. (3), the vehicle dynamics is expressed by velocity and acceleration, and they are chosen as the states for the Markov chain. The TPM is then generated in the form of a two dimensional matrix with velocity and acceleration at current time t_k . The velocity and acceleration are discretized with the number of M and N , respectively. The conditional probability is expressed as

$$P_{i,j,k+1|p,q,k} = P(v_{k+1} = v_i, a_{k+1} = a_j | v_k = v_p, a_k = a_q), \quad (4)$$

where i and $p=1,2,\dots,M$ and j and $q=1,2,\dots,N$, and the overall TPM structure is shown in Fig. 5.

The representativeness of the synthesized cycles is certified by satisfying statistical criteria. The statistical criteria are obtained through a generalized linear regression analysis of the response variable (specific power at the wheels), and the procedure is described as follows: Initially, a number explanatory variables (initially, 27 variables are selected and the shown in [2]). Regression analysis is then executed to find the least significant variable and the fitting quality. The least significant variable is dropped based on t -test results while the resulting regression equation can represent the response variable well. The regression equation is assessed using the normal probability plots of the residuals and the histogram of the residuals. If the normal probability plot is not a straight line or the histogram of the residual is skewed after dropping the least significant variable, the last dropped variable is necessary to describe the response, thus, must be recovered. The final regression equations include all statistically significant variables to predict the response variable, and the significant explanatory variables are used to assess the representativeness of synthesized driving cycles. The variables are:

1. Standard deviation of velocity (mph),
2. Mean positive acceleration (m/s^2),
3. Standard deviation of acceleration (m/s^2),
4. Percentage of driving time under positive acc. (%),
5. Percentage of driving time under negative acc. (%),

6. Mean positive velocity (mph),
7. Percentage of idle time (%),
8. Number of stops/mile (1/mile).

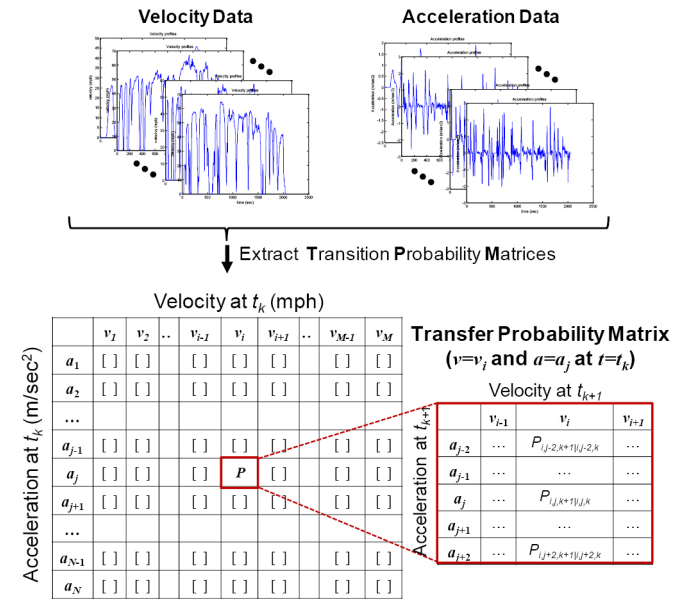


Figure 5. Illustration of the procedure to extract transition probability matrix (TPM) from real-world driving data

SYNTHETIC CYCLES

In this paper, the driving distance is divided into ten different bins as shown in Fig. 6 to predict the amount of the charging electric energies of one PHEV per day with respect to the day driving distances. The representative driving distances in each bin are selected as the distances with the median cumulative distribution in that bin. The probability distribution of the driving distance is regressed with the form of a chi-square distribution (χ^2 -distribution):

$$P(x_n) = \frac{x_n^{(v-2)/2} e^{-x_n/2}}{2^{v/2} \Gamma(v/2)}, \quad (5)$$

where $\Gamma(\cdot)$ is the Gamma function defined as $\Gamma(z) = \int_0^\infty t^{z-1} e^{-t} dt$, x_n is the normalized driving distances defined as x/Al , and x is the departure time, Al is the reference discretized step of the driving distance corresponding to the histogram in Fig. 3, and v is determined to minimize the root mean square (rms) error of the response variable using the sequential quadratic programming (SQP). A different structure of the distribution function can be used, but the proposed function shows a good fit to the raw data distribution. The probability distribution must satisfy