Available online at www.sciencedirect.com
ScienceDirect
Journal of Power Sources 174 (2007) 366–372
JOURNAL OF POWER SOURCES
www.elsevier.com/locate/jpowsour

A roadmap to understand battery performance in electric and hybrid vehicle operation

Matthieu Dubarry, Vojtech Svoboda, Ruey Hwu, Bor Yann Liaw *

Hawaii Natural Energy Institute, University of Hawaii at Manoa, 1680 East West Road, POST 109, Honolulu, HI 96822, USA

Available online 3 July 2007

Abstract

This work attempts to bridge laboratory and real-life battery testing data with a comprehensive analysis to provide a coherent approach for a realistic model to simulate battery performance, including life prediction. From electric vehicle field-testing results, we explain how to handle real-life data through driving cycle analysis to establish a scheme of "building blocks" that can be validated by test results obtained in the laboratory. We also show that a simple battery model can be built upon laboratory test data and validated by real-life duty cycles, therefore deriving a more realistic understanding and prediction of battery performance.

Keywords: Battery performance model simulation; Electric and hybrid vehicles; Life prediction; Duty cycle; Field testing; Driving cycle analysis

1. Introduction

To date, assessment and understanding of battery performance primarily rely on testing in the laboratories. Very limited effort has been put into field testing with detailed data collection and analysis. The reason that the field-testing approach was not favored is because that such testing is costly, labor-intensive, and virtually no control. On the other hand, the difficulties in conducting field testing and analysis hamper the development of suitable methodologies to gain experiences in real life for a practical understanding of battery performance. Thus, it is no surprise that experiences from field tests to date are mostly limited to statistical in nature [1–4], presenting limited value for use in technical improvements of battery design or operation.

In pursuing better understanding of battery performance in real life, we often come across three major challenges:

1. Availability of adequate test protocols and analytic tools to understand the data collected in the laboratory for life prediction.
2. Availability of viable battery modeling and simulation tools to extend our laboratory experiences to real-life duty cycles; therefore, we can predict battery performance and life in more complex and less controlled settings.
3. Capability to develop suitable protocols and analysis techniques to allow us collect and analyze data collected in the real-life operating conditions to derive battery's performance characteristics in relation to its usage.

In this work, we propose a roadmap delineating how to address these challenges and to enhance more realistic understanding of battery performance in real life. Some of the critical steps involved are listed as follows:

1. Collect relevant data in the field operation.
2. Formulate a systematic approach to analyze duty cycles according to their operating conditions and usage.
3. Analyze performance characteristics of the batteries.
4. Derive correlation between duty cycles and performance characteristics.
5. Develop a predictive model and simulation capability to allow prediction of battery performance and life based on duty cycles in real-life operation.

Before we describe the details of how to pursue this approach, it is quite important to point out the difficulty in formulating a systematic approach to analyze driving or duty cycles. First, it is important to realize that no well-documented methodology to conduct driving cycle analysis has been accepted to date. The current approach to study driving cycle is conceptualized on characterizing the driving conditions for a specific type of road (facility type) and situation (level of service), such as in

* Corresponding author. Tel.: +1 808 956 2339; fax: +1 808 956 2336.
E-mail address: bliaw@hawaii.edu (B.Y. Liaw).

0378-7753/$ – see front matter © 2007 Elsevier B.V. All rights reserved.
doi:10.1016/j.jpowsour.2007.06.237

a city, highway, or urban environment to derive the classification of driving patterns for use in the industry and government, for example, for urban or emission studies. This conventional approach is however very difficult to use in driving cycle analysis. For instance, on a jammed highway with bumper-to-bumper traffic, the driving would be more like on a downtown street than on highway. To overcome this difficulty, we took a different approach using a fuzzy logic pattern recognition (FL-PR) technique, which is based on a typical perception of a "reasonable assembly" (as expressed with a fuzzy membership function) of a driving pattern that corresponds to a driving on a specific road type. Using this linguistic, qualitative expression method to classify each small section of a driving cycle enables us to classify driving patterns based on driving conditions, instead of road type and level of service. This approach makes the driving cycle analysis possible on a consistent, systematic manner. This is also applicable for duty cycle analysis.

In 2001–2003, we have evaluated a fleet of 15 Hyundai Santa Fe electric sport utility vehicles (e-SUV). We use the data collected on board in field-testing as a model system to illustrate this approach via the analyses of driving and duty cycles to reveal the performance characteristics of the vehicle and battery. We show how real-life data were collected and analyzed, performance profiles characterized, and useful correlations derived for construction of a predictive model of battery performance, potentially suitable for prediction of battery service life. Fig. 1 presents an overview of the steps involved in the development of a battery life predictive tool that can incorporate real-life data and analysis. We show that it is beneficial to have field and laboratory testing in parallel. This two-prone approach is based upon a "building block" concept that connects the laboratory and real-life data. In this concept, we analyze driving cycle and duty cycle by breaking them down to smaller blocks of well defined characteristics. These "building blocks," which we call "driving pulses" and "power pulses," respectively, for driving cycle and duty cycle, allow us to construct arbitrary driving cycles and duty cycles that can be used in laboratory testing and computer simulation. Through the analysis of the correspondence between driving pulses and power pulses, we can sort out the relationship of vehicle driving cycle versus battery duty cycle. Therefore, the stress imposed on the battery from the duty cycle can be correlated with the vehicle usage based on the driving cycle. This is a very important aspect of the building block concept that makes the connection between performance and operating conditions.

Regarding model construction and validation, it is important to derive a set of "universal" building blocks for driving and duty cycle to facilitate simulation. A large population of building blocks can be generated from field testing and systematic analyses. A small set of representative building blocks is then selected for validation using laboratory testing. This process serves as the bridging instrument between laboratory and real-life conditions. The laboratory testing allows us to develop and validate a set of "universal" building blocks with performance characteristics characterized for vehicle and battery operation. These well-defined building blocks can be used as modules in the construction of "well-behaved" driving and duty cycle for modeling and simulation. One useful aspect of these well-behaved driving or duty cycles is to employ them as "standard" test protocols for laboratory evaluation and benchmarking. For instance, we can use this process to characterize the associated stress factors on battery performance in cycle life testing and use them for life prediction. Another valuable aspect is to use these modules to synthesize arbitrary driving or duty cycles for performance prediction.

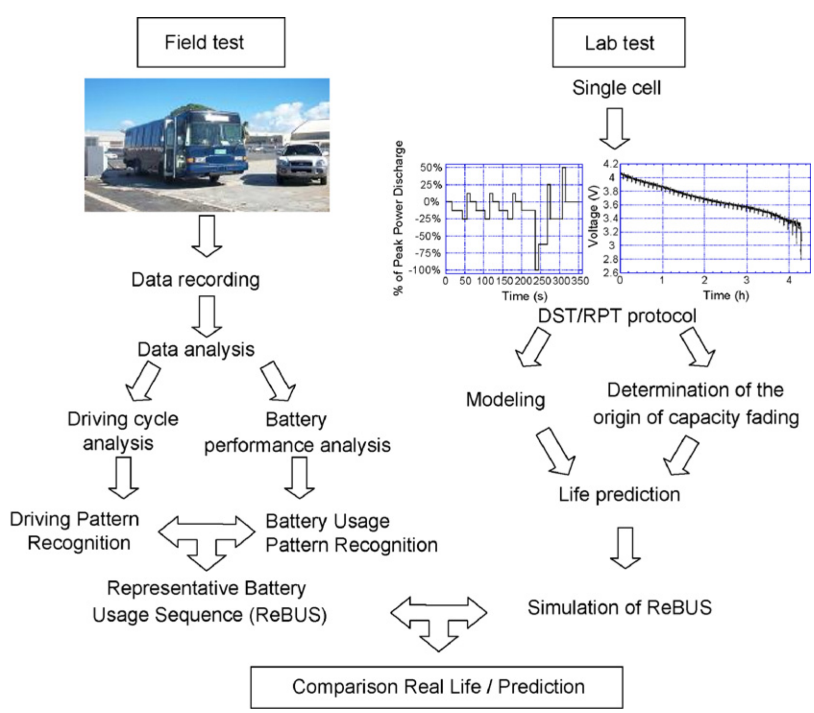

Fig. 1. Schematic of life prediction approach from field and laboratory testing.

Fig. 2. Hyundai Motor Company's Santa Fe e-SUV and the onboard data logger used for data acquisition.

2. Data collection

2.1. Field testing

Fifteen Santa Fe e-SUVs, each equipped with an Enova 60 kW Panther drivetrain, were built by Hyundai Motor Company (HMC) in South Korea. They were delivered to Honolulu, Hawaii, in July 2001 for a 2-year evaluation and road-worthy testing administrated by the Hawaii Electric Vehicle Demonstration Project (HEVDP) office. These 15 vehicles were dispatched to the Hickam Air Force Base (HAFB), City and County of Honolulu (C&C), Hawaiian Electric Company (HECO), and HEVDP office for field testing and operation. The vehicles on HAFB were primarily used for security and errands. Driving on HAFB has to observe speed limits strictly. Vehicles at C&C and HECO were used for commute and daily business services. Those at HEVDP were used for errands and some commutes occasionally. The driving profiles therefore represent a variety of usage.

Each vehicle is equipped with an on-board data logger (see Fig. 2), which communicates with the power control unit (PCU) and battery management unit (BMU) on the vehicle to log data in a second-by-second interval. Periodically, typically every 2 weeks, the data stored on the logger were transferred to a laptop computer and then processed to the database in the laboratory for further analysis. Both trip and charging data were collected, including detailed data from the drivetrain and battery modules. The data collected include more than 255,000 km and 25,000 trips. The data were used to analyze driving and duty cycles with the unique FL-PR approach developed in this laboratory [5–7].

2.2. Laboratory testing

For cycle life test of batteries in the laboratory, we typically use the Dynamic Stress Test (DST) cycle as a test protocol, which is designed to test electric vehicle battery performance under an emulated urban driving cycle condition [8]. A DST schedule consists of a series of regenerative braking and discharge regimens for a total of 360 s (Fig. 3a). A DST cycle comprises the discharge of the battery using the DST schedule repeatedly until it is 80% or fully discharged (Fig. 3b). The battery is then fully recharged using the algorithm provided by the manufacturer. Upon a number of DST cycles was applied (typically 50), the battery is then subjected to a reference performance test (RPT) designed to characterize the battery performance and its degradation through cycle life. The RPT consists of four core tests: three designed to determine the cell capacity under constant current, constant power, and DST discharge regimes; and one related to the SOC-dependent peak power capability.

3. Data analysis

3.1. Driving and duty cycle analyses

We used a systematic approach [5–9] to conduct driving and duty cycle analysis from the second-by-second trip data. In this approach, we used FL-PR techniques [5–7] to derive detailed breakdown of driving patterns and pulsed power patterns (PPP) in the driving and duty cycles, respectively, so the driving schedule for each trip can be summarized as a function of vehicle operating time, mileage or power usage. The breakdown of the driving schedule is based on the summary of the sequential "driv-

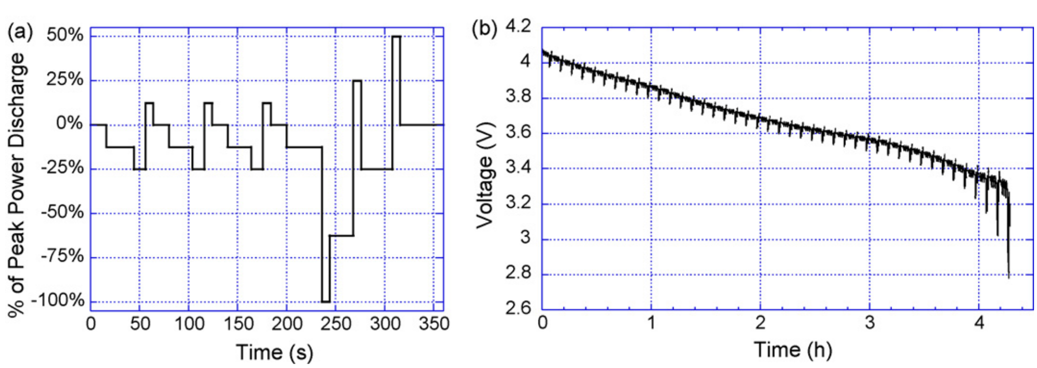

Fig. 3. (a) Details of a DST schedule and (b) example of a discharge regime using the DST protocol in the cycle tests.

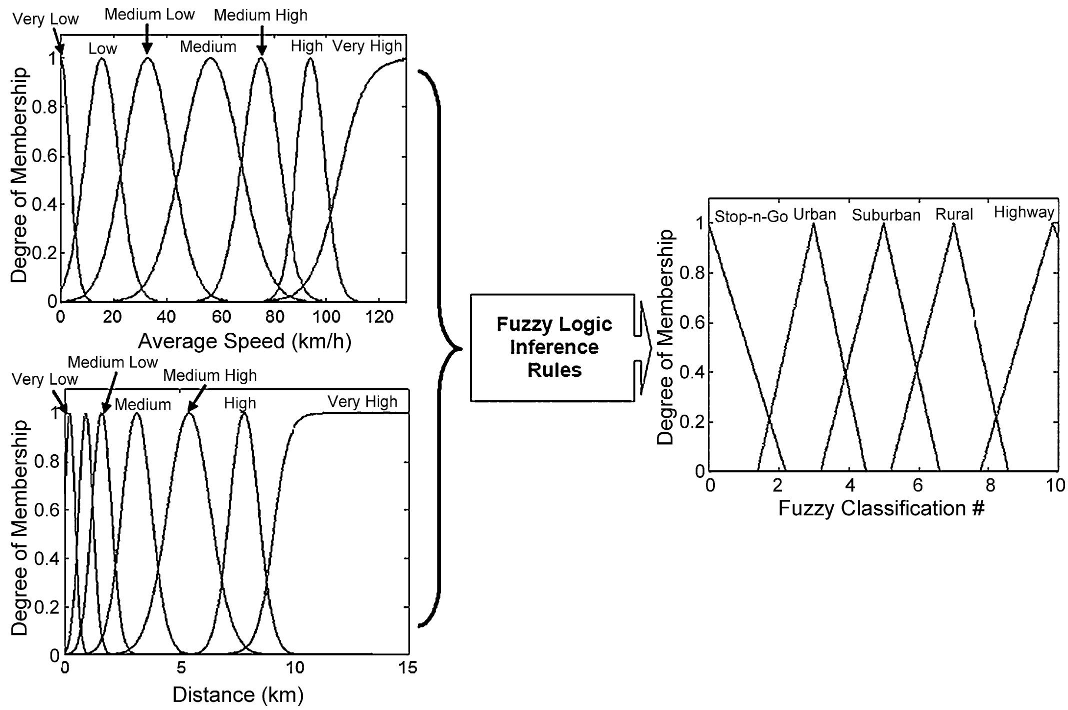

Fig. 4. The fuzzy logic pattern recognition (FL-PR) technique used to classify driving pattern for driving cycle.

ing pulses," which are defined as active driving periods between two subsequent stops. Similarly, a duty cycle can be broken down to a time-series of "power pulses" and each power pulse is depicted by two adjacent points in time when power consumption is at the same level as the baseline (as consumed by auxiliary power unit). A power pulse is characterized by a set of conjugate parameters such as average power and energy consumed, which can be used to define PPP using a FL-PR technique and classification. The PPP can also be classified by peak power and its frequency of occurrence in the schedule. A duty cycle is then expressed by a time-series of power pulses with a composition of PPP's.

FL-PR interpretation provides a convenient method to classify and assign an output value (e.g., defining a driving pattern) to each individual driving pulse between two stops based on fuzzy membership functions and rules [5–7]. The advantage of this FL-PR approach is the ability to systematically breakdown the trip into sections of sequential driving pulses that permit us to recognize a unique driving pattern associated with each driving pulse.

In the analysis of driving pattern, we found that average speed and distance driven of an active driving period between the two sequential stops could be used for driving pattern recognition. By calculating these two parameters for all the driving pulses recorded in the database, a dispersion plot can be used to reveal the distribution of average speed and driving distance for all the driving pulses in the database. From such a dispersion plot, we create a set of fuzzy rules to recognize the driving pattern associated with each driving pulse. As a result, an output fuzzy number representing the driving pattern, from stop-and-go to highway, can be assigned to each driving pulse in the database.

Fig. 4 presents the FL-PR inference system that was used to classify each set of average speed and distance of a driving pulse to a corresponding driving pattern. It should be noted that, although the five driving patterns in Fig. 4 are used commonly to indicate the type of road a driving schedule is conducted, there is no consensus on how to characterize them in a consistent manner to produce a quantitative, meaningful characteristic. In contrast, our classification depicted in FL-PR technique is offering an interesting solution and comprehensive approach toward this direction. We however focus on driving type classification, which is not necessarily associated with the road type.

Applying this FL-PR technique to driving cycles, we show that in Fig. 5 we can yield a breakdown of driving types in a trip, where every driving pulse has been associated with a specific driving pattern. For the first 200 s of this trip, the driving pulses are short in duration and low in speed, which is consistent with the stop-and-go type identified by the fuzzy rules. For the next 400 s, the pulses are longer and the average speed is higher but still quite moderate, which corresponds to a suburban driving type. The highway part of this trip consists of two long driving

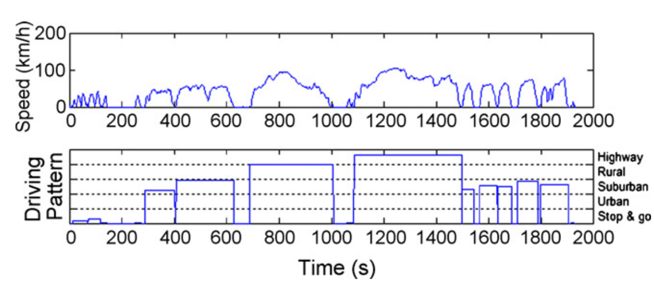

Fig. 5. Driving cycle of a trip (speed vs. time curve, top) and the associated driving pattern summary depicted by the fuzzy rules (bottom).

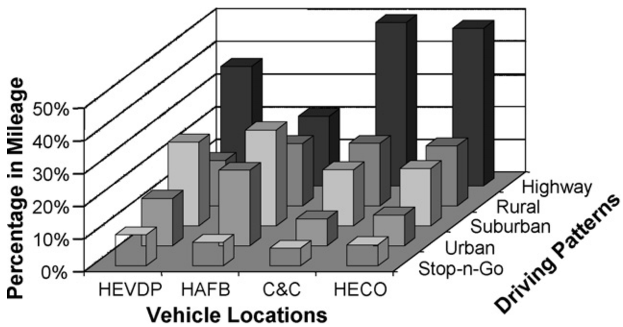

Fig. 6. Distribution of driving patterns by operating locations.

pulses with high average speed. The last part of the trip is made of shorter high speed pulses which are consistent with a suburban driving on 2×2 lanes with intermittent traffic stops.

This driving pattern analysis can be applied to all the trips in the database to yield a consistent interpretation of the driving cycle with well-defined driving pattern summary in series. Once the entire database was properly indexed, we then began to investigate vehicle utilization patterns, for example, at four different locations. Some detailed analysis has been reported elsewhere [9].

Fig. 6 shows the summary of vehicle driving pattern distribution among the four locations. Despite the difficulty in mining a large number of very dispersive driving cycles operated by the operators, a consistent, detailed analysis like this can reveal the variety of operation and utilization patterns of the fleet and the resulting variations in energy utilization efficiencies.

The next step in the approach is to determine PPP for duty cycles. The PPP's are supposed to have strong implications of battery usage, particularly in terms of stress imposed on the battery during operation, for the assessment of degradation. To analyze power pulses, we employed two conjugate parameters: in this case, the peak power of each power pulse and the number of pulses per unit duration (such as minutes) to characterize PPP. These two parameters are supposed to be critical to battery performance and degradation. Therefore, the intensity of the peak power and frequency of occurrence may define the primary stress factor to battery performance and degradation.

The utility of PPP was explored as follows: first, we identified the peak power and occurrence frequency for all power pulses. The distribution of the peak power with the percentage of its appearance is summarized in Fig. 7. The figure shows some interesting disparity in driving habits (in conjunction with

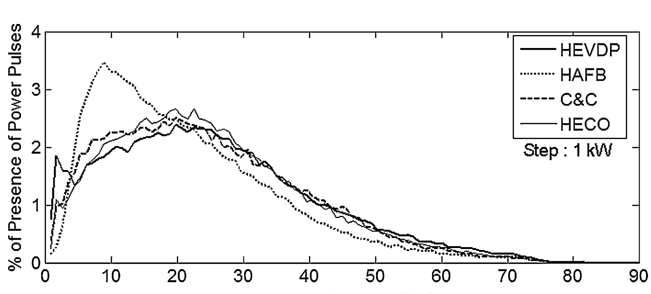

Fig. 7. Peak power distribution by vehicle locations.

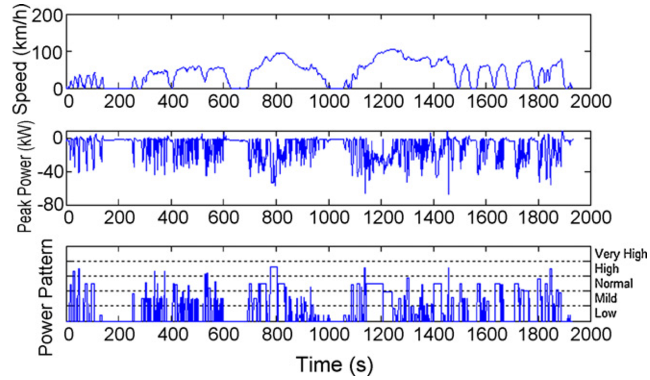

Fig. 8. Driving cycle (top), duty cycle (middle), and the associated PPP curve (bottom) determined by a fuzzy logic matrix (not shown).

the driving patterns shown in Fig. 6) among different locations; especially for HAFB, where speed limit on the base has significant impact on the driving pattern and PPP. Detailed discussion on this analysis will be published elsewhere [10].

Fig. 8 presents the PPP analysis performed on the same trip shown in Fig. 5. Interestingly, although PPP and driving pattern were synchronized, the information revealed by the PPP is far more spontaneous, complicated, and with more details than by driving pattern. It is worth noting that PPP includes regenerative braking, which is a characteristic that is not traceable in driving pattern. However, it imposes a unique impact on battery performance. The spontaneous details revealed by PPP offer an opportunity for us to analyze the impact of PPP on battery performance. There are other subtle differences between PPP and driving pattern in the driving and duty cycle analyses; for example, from 940 to 1000 s, the slow deceleration of the vehicle corresponds to a period where almost no power was drawn. This could reflect a situation in a downhill drive where the vehicle was running at a considerably high speed, while the consumption of energy is very small.

More importantly, through the characterization of driving pattern and PPP, we make a connection between driving/duty cycles and battery stress factors, which will allow us to conduct battery modeling and simulation in the presence of operating conditions in real life, which may exhibit situations different from laboratory test protocols. Therefore, field-testing could provide a broader range and more complex conditions than laboratory tests and allow us to assess battery performance in a more complicated setting.

The above postulation motivates us to analyze the relationship between PPP and driving pattern more in depth. Fig. 9 exhibits the distribution of peak power per pulse as a function of driving pattern, as originated from the fuzzy classification number. Also displayed is the mean peak power versus driving pattern as shown by the white line. In general, the mean peak power increases linearly with driving pattern, from stop-and-go to highway driving type (where fuzzy classification number >1). There is a different correspondence for stop-and-go if fuzzy classification number <1. More profoundly, the peak power distribution along with the driving pattern exhibits a rather wide bandwidth of dispersion; in some cases, over the entire power

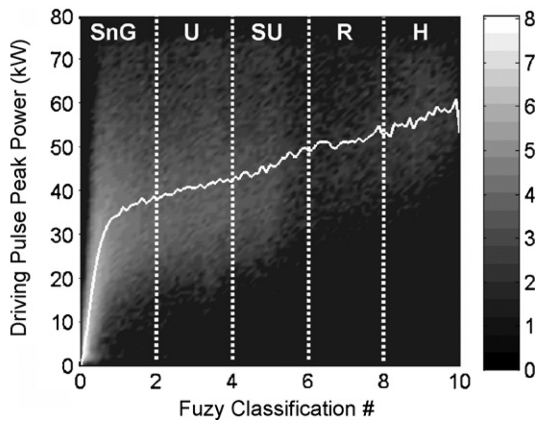

Fig. 9. Dispersion curve of peak power vs. driving pattern. The white line is the mean peak power vs. driving pattern curve that can be used to construct a synthetic duty cycle from a driving cycle, either in real-life or from a hypothetic condition.

range of the motor. This observation implies that the driver had a very wide spread of interactions with driving conditions. One index we can use to describe this phenomenon is the disparity of a peak power pulse from the mean value for a specific driving pattern, which may reveal the extra stress exerting on the battery. The magnitude of this disparity can be measured as a stress factor. For example, a peak power pulse of 55 kW can be an aggressive driving in an urban area, but quite normal on a highway. Therefore, the peak power itself might not be a good measure of the stress to the battery, but the disparity to the mean could.

The ultimate goal of the PPP and driving pattern analyses is to establish a battery usage pattern (BUP), in which the stress factor exerted on the battery can be used to assess degradation of the battery pack. We thus developed a third set of fuzzy rules which use PPP and driving pattern as inputs to derive a vehicle usage pattern (VUP), as shown in Fig. 10. This VUP allows us to determine if a driving pulse can be characterized as degree of aggressiveness in driving by taking into account of both the power draw and the driving condition.

One of the benefits of this VUP analysis is the creation of a representative battery usage schedule (ReBUS) for a specific driving cycle. A simple example is the synthesis of a driving cycle based on a unique combination of driving patterns and the associated mean peak power as presented in Fig. 9. This synthetic driving cycle can represent any specific region or a series

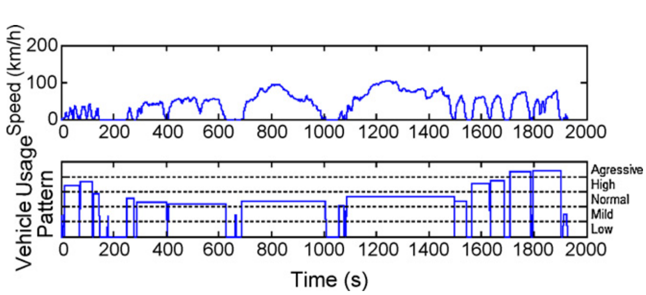

Fig. 10. Vehicle usage pattern (VUP) based on driving pattern and PPP via a fuzzy rule interpretation.

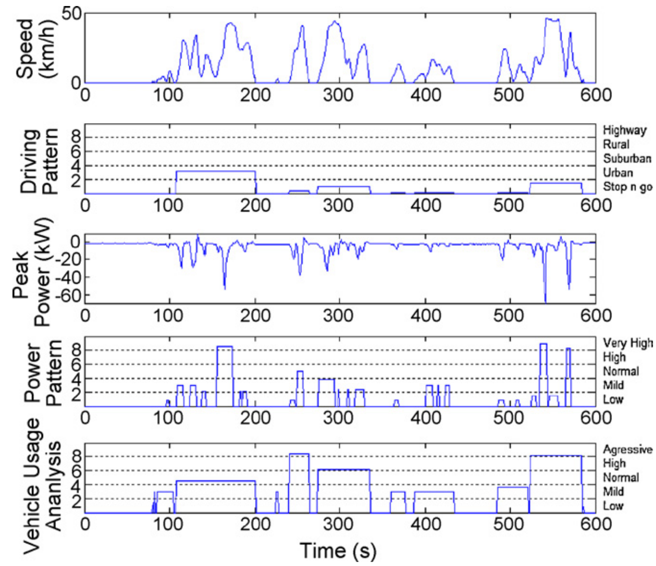

Fig. 11. Example of a series of aggressive city driving.

of hypothetical driving conditions for a specific use. The corresponding duty cycle will become a useful ReBUS for battery testing on a laboratory test stand, mimicking real-life operation, similar to a dynamometer testing of a vehicle using a standard driving schedule such as the federal urban driving schedule (FUDS).

Fig. 11 illustrates an exemplified summary of the analyses discussed so far in this work. It displays a series of 600 s aggressive city driving. The driving pulses are very short and the maximum speed does not exceed 50 km h^{-1}, representing a trip composition only with stop-and-go and urban driving. In this trip there are three acceleration periods that exhibit very high peak power pulses, thus an aggressive driving after all.

The driving pattern and PPP analyses give us an entry to the correlation of vehicle and battery usage. The detailed usage patterns for the vehicle and battery pack will allow us assess the impacts from the operating conditions on the battery performance. The quantification of these usage patterns also allow us synthesize arbitrary driving cycles for the vehicle and the associated duty cycles for the battery, which in turns can allow us conduct more realistic testing and evaluation. This approach can help vehicle and battery design via high fidelity simulations. In the following section, we shall explain how to perform battery modeling and simulation for life prediction.

3.2. Battery simulation and life prediction

An equivalent circuit battery model (Fig. 12) can be a useful, yet simple and realistic, tool for predicting battery performance or even life [11]. The parameterization of the model can be as simple as those based on the Ohmic and Faradic behavior as determined by electrochemical impedance measurements to yield a set of reliable parameters, including rate dependence [12], for battery simulation. It is worth noting that since these parameters can be easily determined from laboratory testing, the equivalent circuit model is convenient to be used and validated.

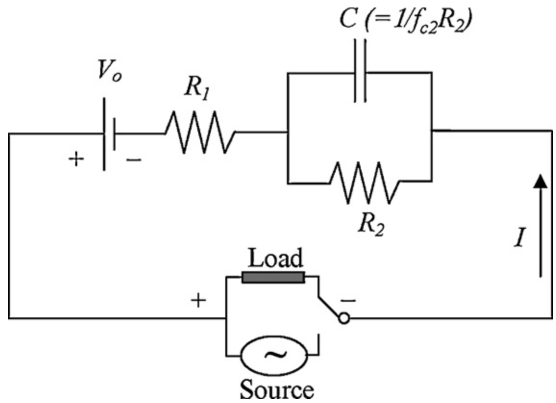

Fig. 12. An equivalent circuit model for battery simulation.

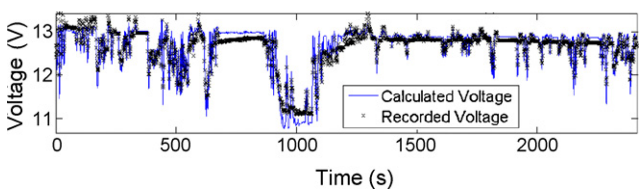

Fig. 13. Comparison of simulated and field-tested cell voltage profile.

Once the change of the parameters, primarily the resistance, with life is characterized through accelerated life testing, the battery life can thus be predicted for a duty cycle.

3.3. Model validation

Once a satisfactory laboratory model is obtained, it is possible to predict battery life based on duty cycle characteristics, including standard test schedules. There are at least two schemes of validation we can pursue. One is to use laboratory test results based on standardized procedures [8]. For instance, we can use those tested by the DST/RPT protocols (Fig. 3) to validate the model prediction. Another important one is to simulate battery performance based on data collected in the field, even at different stages of battery life [12]. Fig. 13 presents a simulated voltage excursion of a battery (solid line) versus the field-recorded data (×) for a trip that resembles the ReBUS derived from the database. A comparison between simulated and trip data shows that, even with some discrepancies, the simulation works quite well for a real trip. The fidelity of the simulation will warrant a better prediction of battery life.

4. Conclusion

We have illustrated that combining laboratory and field tests we can gain much more insights of the battery performance through careful data collection, analysis and interpretation, modeling and simulation, and finally, cross validation. Driving and duty cycle analysis, with fuzzy-logic pattern recognition techniques, allows us to build driving pulse and power pulse based “building blocks” to make the connection between field and laboratory tests. With this approach, we can establish a better understanding of battery performance under real-life usage. Via high fidelity modeling, we can then predict the battery life more accurately.

It is important to mention that the purpose of our driving and duty cycle analyses is to derive a collective set of building blocks that have been validated as a modular unit for synthesis of driving and duty cycles. This is the basis for constructing ReBUS for any hypothetical driving cycle that can be used for any regional or general-purpose applications to evaluate vehicle or battery performance. Once a hypothetical driving cycle can be defined for any application, we can synthesize a duty cycle as a ReBUS for testing on either a battery test station or a dynamometer with a drivetrain. Battery service life under this ReBUS can be evaluated in the laboratory to mimic real-life situations.

Acknowledgements

This work is performed under a contract (HEVDP Contract # 46049, Supplement 5) with the Hawaii Center for Advanced Transportation Technologies (HCATT) under the support (Federal Other Transaction Agreement No. DTRS56-99-T-0017) from the U.S. Air Force Advanced Power Technology Office (APTO) at the Robins Air Force Base in Georgia. We would like to thank Hyundai Motor Company, Enova Systems, HAFB, C&C, and HECO for their assistance in providing infrastructure to collecting the vehicle test data.

References

[1] C.J.T. van de Weijer, PhD Dissertation, Technical University of Graz, Austria, October 1997.
[2] I.J. Riemersma, P. Hendriksen, N.L.J. Gense, R.T.M. Smokers, Methodology for the Development of Representative Driving Cycles, http://www.automotive.tno.nl/VM/EST/publicaties/Paper%20Cycle%20Development.pdf.
[3] K.J. Kelly, A. Rajagopalan, Benchmarking of OEM Hybrid Electric Vehicles at NREL, US DOE/National Renewable Energy Laboratory, Technical Report # NREL/TP-540-31086, August 2001.
[4] H.C. Frey, J. Zheng, Environ. Sci. Technol. 36 (2002) 5184.
[5] B.Y. Liaw, K.P. Bethune, C.S. Kim, Time-series field trip data analysis using adaptive recognition approach. Analysis on driving patterns and vehicle usage for electric vehicles, in: Proceedings of the 19th Electric Vehicle Symposium (EVS-19), Busan, South Korea, October 19–23, 2002, p. 348.
[6] B.Y. Liaw, B. Dailliez, A. Teeters, K.-Y. Youn, C.-S. Kim, Vehicle usage analysis for Hyundai Santa Fe Fleet in Hawaii, in: Proceedings of the 20th Electric Vehicle Symposium (EVS-20), Long Beach, CA, November 15–19, 2003.
[7] B.Y. Liaw, J. Asian Electric Vehicles 2 (2004) 551.
[8] USABC Electric Vehicle Battery Test Procedures Manual, US Department of Energy/INEEL, Revision 2, January 1996.
[9] M. Dubarry, M. Bonnet, B. Dailliez, A. Teeters, B.Y. Liaw, J. Asian Electric Vehicles 3 (2005) 657.
[10] B.Y. Liaw, M. Dubarry, J. Power Sources 174 (2007) 76.
[11] B.Y. Liaw, R.G. Jungst, G. Nagasubramanian, H.L. Case, D.H. Doughty, J. Power Sources 140 (2005) 157.
[12] M. Dubarry, B.Y. Liaw, J. Power Sources 174 (2007) 856.