

Vehicle Evaluation, Battery Modeling, and Fleet-testing Experiences in Hawaii: A Roadmap to Understanding Evaluation Data and Simulation

Matthieu Dubarry¹, Nicolas Vuillaume², Bor Yann Liaw³, and Thomas Quinn⁴

¹ Hawaii Natural Energy Institute, SOEST, University of Hawaii

² Hawaii Natural Energy Institute, SOEST, University of Hawaii

³ Hawaii Natural Energy Institute, SOEST, University of Hawaii, bliaw@hawaii.edu

⁴ Hawaii Center for Advanced Transportation Technologies, tquinn@htdc.com

Abstract

Hawaii is an attractive proving ground for electric and hybrid vehicles (EHV) evaluation. Envisioning and embracing the needs for environmental-friendly advanced transportation technology developments, the Hawaii Center for Advanced Transportation Technologies (HCATT) and the Electrochemical Power Systems Laboratory (EPSL) at the Hawaii Natural Energy Institute (HNEI) of the University of Hawaii, are working together to promote and facilitate EHV development in Hawaii. This paper reports some of the recent activities in EHV evaluation, battery modeling, and fleet testing in the HCATT program. The fleet of EHV in this program includes battery-powered EV (BEV) and battery-fuel cell hybrid electric vehicles (HEV). We will present vehicle test results, battery modeling and simulation tool developments, and data analysis approaches that we developed and used in the program.

Keywords

electric and hybrid vehicles, battery, fuel cell, modeling and simulation

1. INTRODUCTION

Hawaii is an attractive proving ground to conduct electric or hybrid vehicle (EHV) testing and analysis. The climate is always mild with ambient temperature remains almost constant yearly round. The variety of terrains and road conditions around Honolulu provides a wide range of driving conditions, from busy downtown to steep mountain curvy roads, in-between highway and suburban, all within short driving ranges. Even the mild climate often induces significant weather variations, due to wind, precipitation, and terrain influences.

In the past decade, HCATT and EPSL have engaged in a variety of BEV and plug-in hybrids (PHEV) evaluations. Substantial amount of data and experiences have been collected over this period. Three prominent eras have been staged. The first one included a fleet of more than 40 S-10 pickup trucks and Geo Prizm sedans, all battery-powered, integrated by US Electricar (Torrance, CA) during 1995-2000, with a number of unique custom made vehicles (including hybrid transit buses) and rapid charging infrastructure. In the second era, a close collaboration with Hyundai Motor Co. (Seoul, Korea) enabled 15 Santa Fe SUVs powered by Panasonic Ni-MH battery packs tested in Honolulu. In the current era, collaboration with the Air Force Advanced Power Technology Office (APTO) has led to the establishment

of an Air Force demonstration site for ground vehicles and logistic infrastructure at the Hickam Air Force Base in Honolulu, focusing on various hybrid powertrain evaluations, including hydrogen-based infrastructure and supporting logistics. One of significant undertakings in this effort is data collection and analysis of the field test data recorded during the field evaluations.

To date fleet data analysis and interpretation, including driving cycle analysis, remain very challenging. Despite continuous progress made in the past few years, no consistent approach have been accepted by the research community at large to allow a systematic and detailed characterization of the driving pattern except those based on standard driving schedules running on dynamometers or well-documented tracks [Ericsson, 2000, 2001; An et al., 1993, 1997, 1998; Barth et al., 1999, 2002; Tong et al., 1999; Butler et al., 1999; Rahman et al., 1999; Young et al.; 2000; Dembski et al., 2002; Ergeneman et al., 1997; Kent et al., 1978; Simanaitis et al., 1977; Andre et al., 2004; Tsai et al., 2005]. Experiences from field-testing are mostly limited to statistical analyses [Weijer et al., 1997; Riemersma et al., Kelly et al., 2001; Frey et al., 2002], offering limited value for use in technical improvements of battery design or operation.

In the past few years, we have developed an alternative approach based on fuzzy logic pattern recognition [Liaw et al., 2002, 2003, 2004, 2007; Dubarry et al., 2005; 2007]. This simple and comprehensive approach provides a better understanding of driving cycle analysis. Recently the same technique has been used to analyze

the power usage of the vehicle operation with respect to driving pattern, taking into account road conditions and driving habits [Dubarry *et al.*, 2007; Liaw *et al.*, 2007]. Besides being able to characterize driving cycles, we also devoted efforts to address other key issues such as life prediction of the power sources using reliable computer simulation models. Such models have to consider both material specificities (chemistry, origin of degradation, etc.) and environmental conditions (pack configuration, temperature, duty profile, etc.). Based on our knowledge of battery performance and its degradation mechanism [Dubarry *et al.*, 2006, 2007; Barker *et al.*, 1995, 1996; Aurbach *et al.*, 1999; Buqa *et al.*, 2005], we were able to develop some predictive tools to simulate battery behavior in a single cell or in a pack [Liaw *et al.*, 2004]. By adding these new tools to our prior capability in driving cycle analysis, we now have a suite of software applications dedicated to fleet data acquisition, display, analysis, and simulation with the ability to handle a large set of real-life data.

2. DATA COLLECTION

The most successful collection of real-life test data was obtained from the fleet of 15 Santa Fe e-SUVs (Figure 1, top) prototyped by Hyundai Motor Company (HMC) in South Korea. Each vehicle was powered by a Panasonic nickel metal hydride (Ni-MH) battery pack and an Enova 60 kW Panther drivetrain. An on-board data logger was used in each vehicle for data collection on a time-series basis. More details about the data collection and driving cycle analyses are available in our

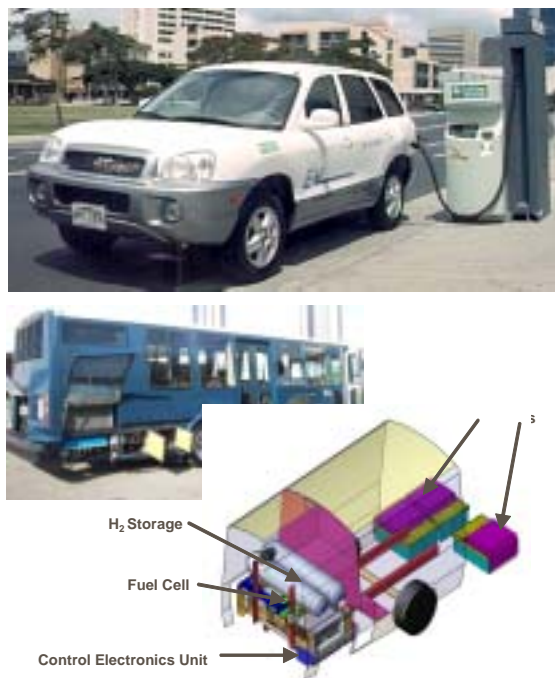


Fig. 1 (Top) Hyundai Santa Fe BEV and (Bottom) Plug-in hybrid electric bus tested at HAFB by HCAT.

previous reports [Liaw *et al.*, 2002, 2003, 2004, 2007; Dubarry *et al.*, 2005; 2007]. The data collected includes more than 255,000 km and 25,000 trips in the database for the e-SUVs during a two-year test period.

More recently, a plug-in battery - fuel cell hybrid bus (Figure 1, bottom) with a 20 kW Hydrogenics PEM fuel cell auxiliary power system for power-assist and a 140 Ah Hawker VRLA battery pack for propulsion has been in operation at Hickam Air Force Base (HAFB), Honolulu, Hawaii. This plug-in hybrid bus is also equipped with an on-board data logger, 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, the data stored on the logger were transferred to a computer and then processed to the database in the laboratory for further analysis. Both trip and charging data, including detailed data from the drivetrain, battery modules and fuel cell power control unit, were collected for the bus operation.

3. FLEET DATA ARCHIVAL AND ANALYSIS

3.1 Data management

Data transferred from on-board loggers to the database can be retrieved by a MATLAB® graphical user interface (GUI) that allows the display of second-by-second data in a variety of parameters for a given trip (e.g., pack voltage, current, power, vehicle speed, temperatures at different locations, etc.), allowing a quick screening and selection of trips for analysis (Figure 2).

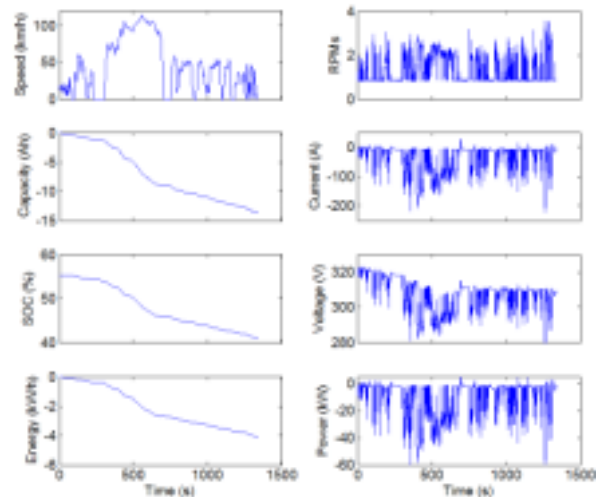


Fig. 2 An example of available data from the Santa Fe EV database, exhibited as driving and duty cycle.

3.2 Driving cycle analysis

Average speed and distance are two variables often used to describe a driving cycle. They are representative of the driving cycles mainly because if the speed is almost

monotonic, driving over a long distance at a high speed indicates that the driving is most likely on a highway. Likewise, traveling at a low speed over a short distance with frequent stops represents a city driving with congested traffic. The problem is a trip is rarely monotonic, and most of the time a trip comprises many different driving conditions irregularly. Therefore, no single scheme can easily reflect this sporadic nature of driving cycles. It is difficult to describe a driving cycle in a consistent and quantitative manner. Many attempts by numerous laboratories have been made to address this problem in various approaches. The difficulty remains in seeking a coherent representation of driving cycles. Our recent work [Liaw et al., 2002, 2003, 2004, 2007; Dubarry et al., 2007] proposed the use of a fuzzy-logic pattern recognition (FL-PR) technique to characterize driving events in a systematic manner. The FL-PR approach offers a bifurcation to merge descriptive and numerical nature of driving events into a common platform for analysis. We also proposed the concept of “driving pulses” as building blocks to compose driving cycle with a series of driving events. A “driving pulse” is an active driving period between two sequential stops within a trip (Figure 3). With proper classification of driving event for each driving pulse, we thus compose the trip into a sequential composition of driving events, called

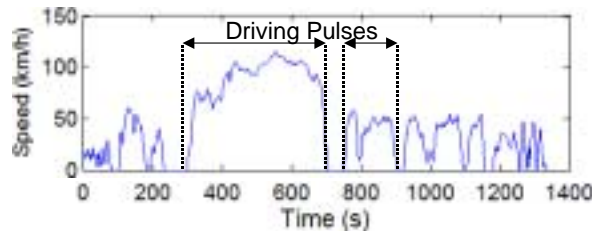


Fig. 3 Schematic representation of a trip (or driving cycle, as represented by a speed vs. time curve) broken down into a series of isolated “driving pulses”.

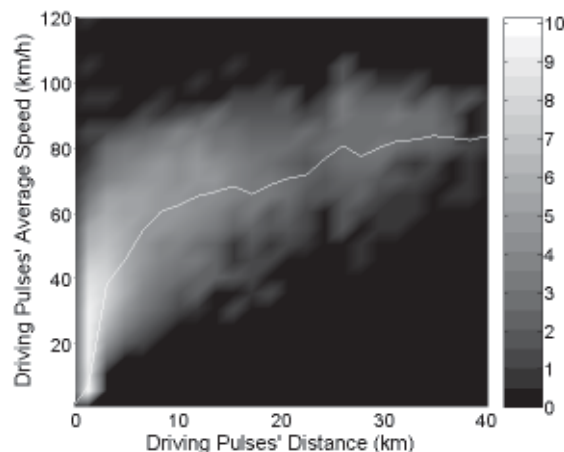


Fig. 4 Distribution of average speed vs. distance in the matrix representing all driving pulses in the database.

“driving cycle profile.” To classify driving events, we further proposed to use a matrix of average speed and distance for each driving pulse in a fuzzy set with degree of membership association to define a driving event (Figure 4). The curve in white represents the mean value profile in the matrix for all driving pulses from more than 25,000 trips in the database. The shade of gray represents the distribution (density) of data points (driving pulses) in the matrix, as shown by the scale bar on the right.

Five common driving event classifications are used in the fuzzy classification: “stop-n-go” for heavy traffic downtown driving, “urban” and “suburban” for metropolitan area driving, “rural” and “highway” for intercity driving. This FL-PR technique is then set to classify each driving pulse a specific driving event classification. Figure 5 presents an example of a randomly selected trip with the result of the FL-PR classification. From the speed vs. time curve (top) it is difficult to give any consistently meaningful description to the progression of the trip; but with driving cycle analysis (bottom), it is more comprehensive to depict the driving history, in which the trip started in a downtown area and then the vehicle went through the highway to another urban area. We can immediately enjoy the benefits of this FL-PR driving cycle analysis, which allows better comprehension of a trip. Furthermore, through normalization (in percentage of distribution of each driving event classification in a trip as a function of time or distance), we can begin to compare trips in a systematic manner. This comparison can be performed with statistical analysis of each trip [Liaw et al., 2007; Dubarry et al., 2005] with sufficient temporal and spatial resolutions. This approach to driving cycle analysis has been discussed in more details in our recent publications [Liaw et al., 2002, 2003; Dubarry et al., 2007; Liaw et al., 2007, 2004; Dubarry et al., 2005].

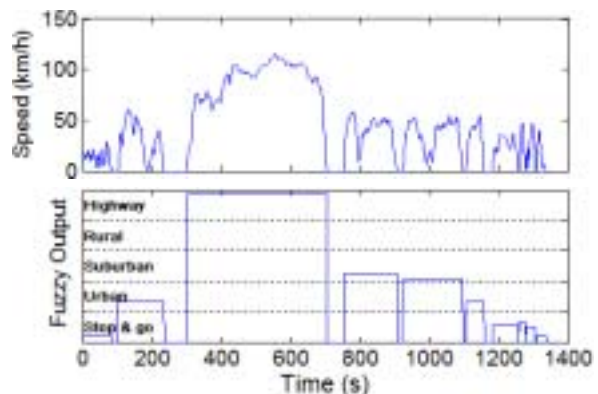


Fig. 5 An example of driving cycle analysis using the FL-PR technique.

3.3 Duty cycle analysis

A similar FL-PR technique can be applied to the analysis of duty cycle of a trip. An analysis on the power usage during a trip provides useful information regarding the duty cycle that the batteries (and powertrain) endured. The power pulses exhibit high degree of spontaneous fluctuations in the duty cycle, far more complicated than the driving cycle (see Figure 6). Thus, the use of driving pulses cannot fully satisfy the requirement for duty cycle representation. We thus proposed a different “power pulse” scheme, which employs a duty event in a higher frequency profile (than that used by the driving pulses, due to the nature of the power spectra), as the building block for duty cycle analysis. It is worth noting that the vehicle speed spectra usually exhibit lower frequency patterns than the power spectra. Duty cycles are often more dynamic and spontaneous (Figure 6) with a higher pulse frequency than the driving cycles [Liaw *et al.*, 2007]. A power pulse is defined by the duration of an active power variation (positive for regenerative braking and negative for driving) above or below a baseline background power draw [Liaw *et al.*, 2007] (Figure 7).

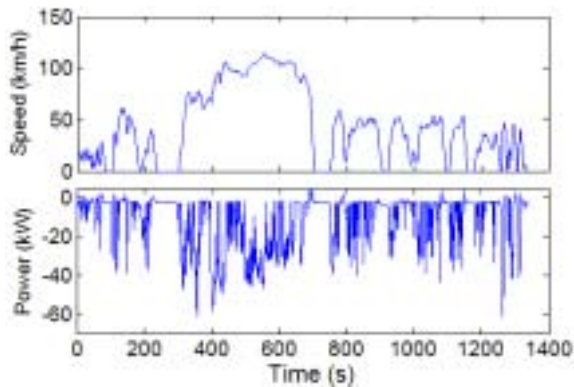


Fig. 6 Speed vs. time curve for driving cycle and the corresponding power vs. time curve for duty cycle.

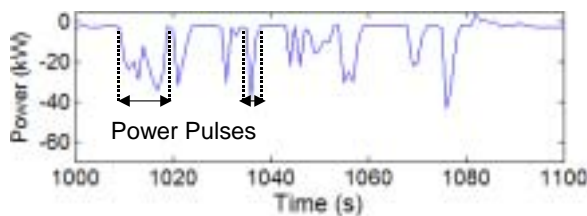


Fig. 7 Schematic to illustrate power pulses.

A power pulse’s peak power value and its frequency (of occurrence in $1/\text{duration}$) can be used, as a conjugated metric, to describe a power spectrum, which depicts the power usage of the vehicle. It is also worth mentioning that this conjugated metric is associated with battery degradation: the peak power level represents the inten-

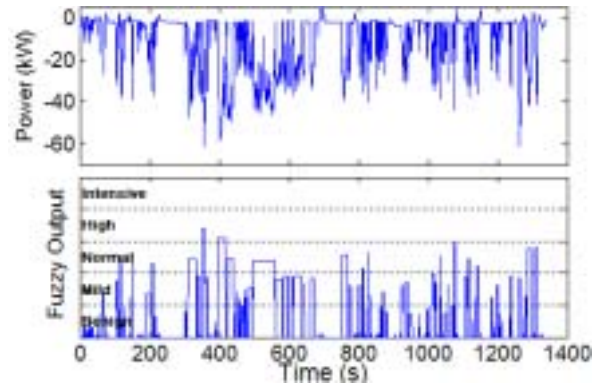


Fig. 8 An example of duty cycle analysis using the FL-PR technique.

sity of discharge and charge, and the frequency depicts how often this fluctuation occurs. Both variables can amplify battery degradation, depending on the ability of the battery in handling peak power pulses. This power pulse analysis and the membership functions used in the power event classification for duty cycle analysis have been discussed in [Liaw *et al.*, 2007]. The membership functions used in the peak power and pulse frequency metric allow us define power usage in a range of classification from “benign” to “intensive”, as illustrated by an example in Figure 8 for duty cycle analysis.

3.4 Driving pattern classification

Although driving and duty cycle analyses allow us classify driving and duty events, respectively, we however did not address the interrelation between the two profiles. The duty profile is directly related to the stress applied to the power source system. However, what we would like to know is how the driving profile affects the powertrain performance. To put this aspect into a better perspective, we can use the grading of a road as an example. The grade can raise a significant disparity in driving and duty events from a “nominal condition.” Climbing a steep hill versus cruising on a flat terrain will lead to a distinct disparity in speed and power consumption over the same distance. Thus, the inclination may drastically change the correspondence between power consumption and speed; a high-speed event does not necessarily correspond to high power usage. This might be difficult to decipher in the driving cycle analysis, but it should be easy to tell when the duty cycle analysis is considered simultaneously. One can use a “driving pattern,” which is supposed to include this factor, in describing a driving event. The driving pattern should have taken into account both road condition and driving habit. The driving pattern can be derived from a combination of the two analyses with a new set of FL-PR rules. Such a driving pattern classification may provide a comprehensive assessment of vehicle usage with respect to

powertrain performance.

3.5 Battery test schedules

To date, to evaluate vehicle performance, it is common to use standardized driving schedules for testing [An et al., 1993, 2000, 2001; Barth, 1999, 2002; Tong, 1999; Butler, 1999; Dembski et al., 2002; Ergeneman et al., 1997; Kent et al., 1978; Simanaitis et al., 1977; Andre et al., 2004; Tsai et al., 2005; Weijer et al., 1997; Riemersma et al.]. Likewise, to assess battery performance, we also typically use standard protocols, such as those recommended by the U.S. Advanced Battery Consortium (USABC) or the Society of Automotive Engineers (SAE) to test batteries. For example, the USABC recommends a “dynamic stress test” (DST) schedule for a variable power test in the laboratory. This schedule is supposed to mimic an aggressive urban driving [Electric Vehicle Battery Test Procedures Manual, 1996]. The schedule consists of a 360-second series of regenerative braking and discharge regimens (Figure 9b). We can repeatedly apply such a schedule in an accelerated cycle life test of a battery until the battery discharges to a certain depth of discharge. The Federal Urban Driving Schedule (FUDS) is another common schedule used for variable power testing. These schedules are often similar to those used by internal combustion engines [www.dieselnet.com/standards/cycles/].

A deficiency in using these standard test schedules is that the test results often bear little relevance to a much broader range of real-life situations. It would be of tremendous merits to apply our understanding of battery performance in the laboratory testing to real life. One possible way is to validate laboratory test scenarios with real life data.

To explore such a possibility, we began with the analysis of battery data from field-testing and compared them with those obtained from standard test schedules. For

instance, we can compare the test result of DST cycle to that extracted from an aggressive rural driving profile selected from our database. Via this comparison, we could verify the feasibility and validity of our approach. Figure 9 shows a comparison of (a) a selected aggressive rural driving profile from the database and (b) that of the DST cycle. Although the power pulses are shorter in this specific profile, the peak power distribution is similar. The availability of such a profile, for instance, allows us to collect and compose a set of analogous, real-life samples to validate our classification method, which can further validate driving patterns.

4. BATTERY TEST DATA COLLECTION AND ANALYSIS

Laboratory battery testing is designed to assess battery performance with a defined protocol. Accelerated cycle life test is typically designed to determine battery's life expectancy in a duty cycle. In the case of EV or HEV applications, it is desirable to test the battery with protocols that are close to real-life use. As such, as recommended by USABC [Electric Vehicle Battery Test Procedures Manual, 1996], battery cycle life testing usually involves two regimes, an accelerated aging test regimen and a reference performance test (RPT) regime designed to characterize the battery performance and its degradation through duty cycle aging. The accelerated aging test can be performed using the DST cycle (or any duty cycle extracted from the database) to determine the ability of the cell to handle power pulses mimicking real driving situations, or it can be performed by cycling the battery at a high constant current.

The RPT consists of three core tests. Two of them involve the determination of cell capacity under constant current (CC) and constant power (CP), while the third one reveals the SOC-dependent peak power capability (PPC), in which the test regime consists of applying 30-sec high current (9C) discharge step after a low current (C/10) discharge to displace the cell with 10% of the rated capacity between each two steps.

4.1 Utilities of reference performance tests

The RPT's assess the performance characteristics of the cell and their evolution upon duty cycle aging. The CC tests are used to establish the rate capability of the cell and its capacity retention ability (CRA). The evolution of CRA is characterized by the degree of capacity loss, whereas the rate capability is usually specified by the Peukert constant k calculated from the Peukert equation $Q = I^k \times t$ where Q is the rate capacity, I the current and t the discharge duration. The closer the k is to unity, the better the rate capability. Figure 10a presents the Peukert curves for a commercial $\text{LiNi}_{0.8}\text{Co}_{0.15}\text{Al}_{0.05}\text{O}_2$ (LNCAO)

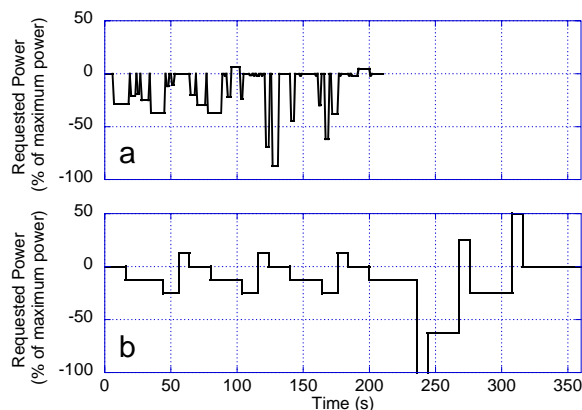


Fig. 9 Comparison of (a) a real-life aggressive rural driving profile (ARDP) and (b) the DST schedule recommended by the USABC.

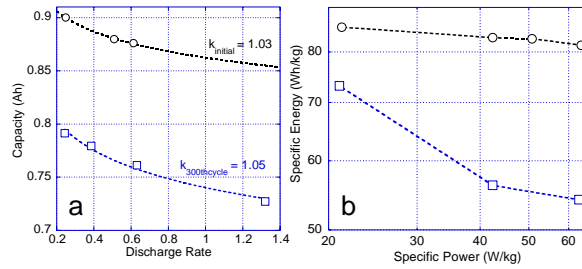


Fig. 10 Peukert and Ragone curves of a commercial LNCAO cell at initial state (o) and after 300 cycles (*). cell at its initial state (o) and after 300 cycles (*) respectively. From this plot it is clear that the battery lost about 10% of its capacity after 300 cycles. It also shows that the cell lost rate capability as k increased from 1.03 to 1.05. More complete analysis of this LNCAO cell has been reported elsewhere [Dubarry et al., 2006, 2007]. The CP tests are designed to establish the Ragone curves, which assess the trade-off of specific energy and specific power. Figure 10b shows the Ragone curves for the LNCAO cell at its initial state (o) and after 300 cycles (*). At the initial state the battery can deliver almost the same amount of energy over a wide range of power. Such ability degraded noticeably upon duty cycle aging. Figure 11 presents the PPC of the LNCAO cell [Dubarry et al., 2007] under duty cycle aging. Although the PPC remained acceptable in the first 200 cycles, substantial degradation was observed after that. Routine RPT's give over-all spectra of the state of the battery with information on its abilities to handle rate, power, and peak power pulses. The test results, however, did not provide any diagnostic information of the degradation.

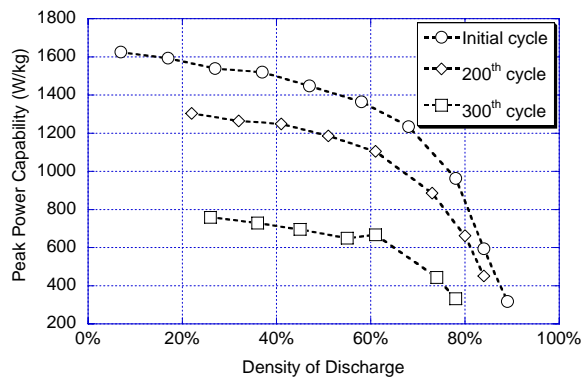


Fig. 11 Peak power capability of a commercial LNCAO cell.

4.2 Incremental capacity and potentiometric analyses

In order to understand the origins of the capacity loss, we employed electrochemical techniques to investigate the charge and discharge behavior of the cell under duty cycle aging. Among several available electrochemical techniques, two of them appear effective and useful since

they do not require additional testing, are non destructive and can be easily applied based on test results already yielded from the cycle aging and RPT's.

One of them is incremental capacity analysis (ICA) [Dubarry et al., 2006, 2007; Barker et al., 1995, 1996, 1996] which can be used to interpret kinetic evolution of electrochemical processes. The incremental capacity (IC) curve displays the capacity change per voltage interval. Each IC peak on the curve indicates a specific reaction in the cell. By deciphering the changes in the shape and intensity of the peak, we can investigate the shift in the underlying reaction kinetics, which allows a chronicle mechanistic understanding of the degradation. Figure 12 illustrates an example in the study of the graphite anode behavior. In this presentation, each electrochemical process exhibits a specific signature representing the type of reaction and the associated kinetics. While Li ions intercalates in a graphite electrode, one can observe the characteristics of staging phenomena. Each staging process is supposed to exhibit a potential plateau [Aurbach et al., 1999; Buqa et al., 2005] in the course of intercalation with the associated IC peak on the left-hand side of the plot. The IC curve exhibits a better sensitivity to the variation in kinetics than the potential excursion curve, especially in the 0.15-0.2 V region. Following the evolution of the IC peaks upon cycling, we can interpret and derive possible degradation mechanisms [Dubarry et al., 2006, 2007].

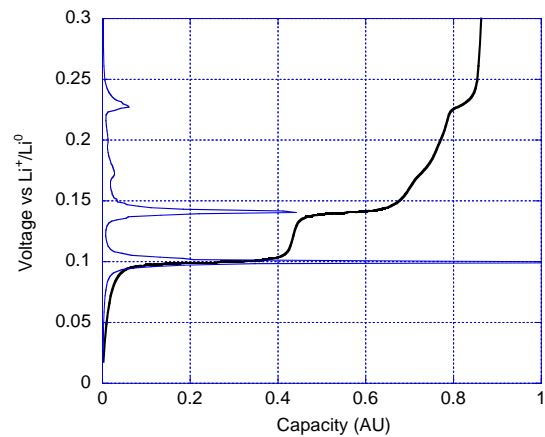


Fig. 12 C/50 discharge curve of a Li/graphite cell and the associated IC peaks (left side).

By measuring the open circuit voltage (OCV) of the cell we can use this potentiometric technique to study the static behavior (close to thermodynamic equilibrium) of the electrochemical processes in the cell. For instance, it can determine the state of charge (SOC) of the cell [Dubarry et al., 2006, 2007 (2)]. By letting a battery rest after reaching the end of charge or discharge voltage, we can correlate the SOC in correspondence to the ter-

mination condition. Continuous monitoring the change of SOC upon termination in the cycle aging, we can follow the evolution of SOC and capacity loss upon cycling. This observation allows us to trace the degree of underdischarge and undercharge as means to assess their contribution to CRA. Combining this method with the ICA, we can map degradation in terms of different origins [Dubarry et al., 2006, 2007 (3)].

5. BATTERY MODELING AND SIMULATION

Even with these useful techniques that help us derive such an understanding of how capacity lost, to reduce such knowledge into practical applications remain challenging. One of the obstacles is the lack of suitable modeling tools to allow such a knowledge transformation. For instance, a prediction of life expectancy of a battery cell remains difficult. To date, battery life prediction can be achieved only via laboratory testing with proper aging protocols [Broussely et al., 2001; Spotnitz et al., 2002; Ramadass et al., 2004, Dubarry et al., 2007; Liaw et al., 2004, 2005]. To permit accurate life prediction, a large set of test conditions is usually required, which is very time consuming and labor intensive. Due to time constrain, it is almost impossible to test batteries for such a large set of conditions. To enable timely life prediction of a cell under any given conditions, we believe that high fidelity battery modeling and simulation is an effective approach to allow such a knowledge transfer and life prediction. We have thus developed a unique empirical approach to model battery behavior using an equivalent circuit model [Dubarry et al., 2007; Liaw et al., 2004, 2005] with resistance mapping technique [Dubarry et al., 2007]. Figure 13 presents the equivalent circuit model that we used. The function of the equivalent circuit model is to mimic battery behavior with a circuitry of simple electrical components. Each component in the circuit has a physical meaning in reflection of the nature of the battery. V_o represents the open circuit voltage of the cell as a function of the SOC, reflecting the thermodynamic property of the chemistry. R_1 represents the ohmic resistance introduced by the cell fabrication. The R_2C block represents the electrochemical kinetics associated with the electrochemical reac-

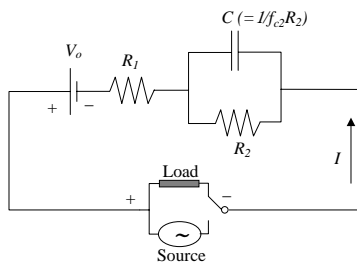


Fig. 13 Equivalent circuit model used for battery modeling and simulation.

tions. R_1 and R_2C can be estimated by electrochemical impedance spectroscopy (EIS) and V_o by very low rate polarization.

The most difficult part in the parameterization for the model is to evaluate the resistance R_2 , which is usually dependent on SOC, rate, temperature, and the age of the cell. Our approach is to use a four dimensional (4D) matrix to calculate the resistance for any given SOC, C rate, temperature, and age. For each C rate, temperature, or age, the R_2 values vs. SOC are extracted from relevant experimental data. This 4D matrix comprises a unique algorithm, which allows interpolation and extrapolation of the R_2 values over a wide range of conditions. This 4D matrix can be visualized as a suit of 3D maps. For example, R_2 values can be viewed as a function of C rate and SOC, as shown in Figure 14, which presents the 3D C rate - SOC resistance map at room temperature and for the initial state of a commercial LiCoO₂ cell. With this map, the performance characteristics of this commercial cell can be simulated for different rates in the duty cycles at room temperature. Capturing accurate performance characteristics is an important step toward the simulation of battery modules and packs that are often configured for practical applications in mobile and storage devices and systems.

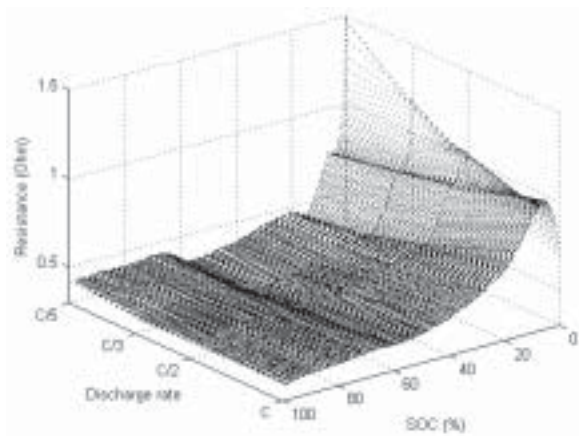


Fig. 14 An example of the initial state C rate - SOC resistance map at room temperature for a commercial LiCoO₂ cell.

6. BATTERY PACK SIMULATION

The essence to describe the behavior of a battery pack in an EV or HEV begins with the accurate simulation of a single cell battery. To simulate the behavior of a battery pack requires much more considerations extrinsic to the nature of the cell chemistry. First of all, a pack is wired network of cells in a specific configuration. Any variations in cell chemistry, material processing, and electrode fabrication will introduce a distribution of cell

characteristics intrinsic to “imbalance” of the cells in the pack. Compounding with external operation conditions, such an intrinsic imbalance will be elevated to intensified variations in individual cell behavior. This complicated imbalance issue troubles the pack management greatly in practical applications, particularly in EHV where packs are usually more complex than those used in portable devices such as cellular phones, laptop computers, and other audio and video players.

Battery testing and modeling probably can catch these imbalance issues adequately, although current efforts in dealing with these problems remain ineffective. In our thesis, we believe a high fidelity model and simulation starts at the quantification of the intrinsic imbalance of the cells. With proper quantification of this intrinsic imbalance distribution, we should be able to implement suitable measures in the pack model to emulate the pack behavior with the intrinsic variations in cells with the specific configuration.

Only if the intrinsic imbalance were properly addressed, the external fluctuations in the operating conditions and their impacts on the cell behavior can be emulated and understood properly. These external factors introduced in the pack operation can have profound impacts on cell imbalance. For instance, a temperature gradient in the pack or a distribution of the initial capacity of the cells in the pack can be present almost in every practical instance of applications. Quantifying compound imbalance from the intrinsic distributions plus the influences from the external factors is a tangible way to understand the pack performance. In order to deal with these specific issues and to predict pack life expectancy, we started to develop models with quantified cell intrinsic imbalance variations. The equivalent circuit model is a good starting point, which provides cell models as modular blocks in a “wired” configuration by electrically connecting single cells in a specific topology. With suitable software environment and integration, we can then control either cells or small subscale battery modules in the simulation to understand the pack performance characteristics. Results of the comparison of the model and real life data from our vehicle fleet will be published elsewhere in the future.

7. CONCLUSION

Analyzing results from a fleet of EV or HEV is very crucial but challenging. The use of fuzzy logic driving pattern recognition technique can help the interpretation of the field test data collected from such a fleet. This approach appears intuitive, comprehensive, practical, and useful in the driving cycle analysis of real-life trip data. This methodology also allows analyzing and comparing trips consistently in a systematic manner. It

also helps in side-by-side evaluations of vehicle usage and powertrain performance, including analysis of battery pack and fuel cell stack (although such analysis was not discussed in this paper).

A better understanding of the power source systems still requires laboratory evaluations. We demonstrated that, with simple protocols, a carefully crafted test procedure can give useful information about life expectancy and battery performance characteristics. Nevertheless, such test procedure will not be able to give any diagnostics of the capacity loss in the exercise of duty cycle tests. We proposed to use the incremental capacity analysis and relaxation potential (potentiometric) measurements to allow deciphering the loss mechanisms. We found that these two techniques are powerful and easy-to-handle tools to determine the thermodynamic SOC limits during duty cycle aging and identify the origin of the capacity loss in the process. This approach can help us develop a better understanding of the degradation behavior of the batteries and packs and can help us prevent premature failure in the field.

Using computer modeling and simulation is a tangible manner to transfer the knowledge from the laboratory to the field. We explained that it is necessary to make an accurate prediction of the life expectancy of the cell as the basis of controlling the battery pack performance. There are many factors that can impact the battery pack performance, including the intrinsic distributions of cell characteristics that constitute the initial cell imbalance in the pack. Further complication from the variations in operating conditions can only worsen the imbalance issues. An effective way to address these imbalance issues started from an accurate characterization of the cell variations. With correct model approach, we can thus begin to understand the variations in the pack performance under different operating conditions.

Acknowledgements

We would like to thank the US Air Force Advanced Power Technology Office (APTO) at the Robins Air Force Base in Georgia to support this work. Gratitude also went to our collaborators who have been actively contributing to the project in a profound manner over the years in vehicle integration and testing, including Enova Systems (Torrance, CA and Honolulu, HI) and battery manufacturers involved in the program.

References

- André, M., The ARTEMIS European driving cycles for measuring car pollutant emissions, *Science of the Total Environment*, Vol. 334-335, 73-84, 2004.
- An, F., and M. Barth, Critical issues in quantifying hybrid electric vehicle emissions and fuel consumption,

- Society of Automotive Engineers (SAE) technical paper 981902*, 1998.
- An, F., and M. Ross, A model of fuel economy and driving patterns, *Society of Automotive Engineers (SAE) technical paper 930328*, 1993.
- An, F., F. Stodolsky, and D. Santini, Hybrid options for light-duty vehicles, *Society of Automotive Engineers (SAE) technical paper 1999-01-2929*, 1999.
- An, F., M. Barth, and G. Scora, Impacts of diverse driving cycles on electric and hybrid electric vehicle performance, *Society of Automotive Engineers (SAE) technical paper 972646*, 1997.
- Aurbach, D., B. Markovitsky, I. Weissman, E. Levi, and Y. Ein-Eli, On the correlation between surface chemistry and performance of graphite negative electrodes for Li ion batteries, *Electrochimica Acta*, Vol. 45, 67-86, 1999.
- Barker, J., M. Y. Saidi, and R. Koksang, Differential capacity as a spectroscopic probe for the investigation of alkali metal insertion reactions, *Electrochimica Acta*, Vol. 41, 2639-2646, 1996.
- Barker, J., R. Koksang, and M. Y. Saidi, An electrochemical investigation into the lithium insertion properties of Li_xNiO_2 (0 d" x d" 1), *Solid State Ionics*, Vol. 89, 25-35, 1996.
- Barker, J., Three Electrode Electrochemical voltage spectroscopy (TEVS): evaluation of a model lithium ion system, *Electrochimica Acta*, Vol. 40, 1603-1608, 1995.
- Barth, M., and M. Todd, Simulation model performance analysis of a multiple station shared vehicle system, *Transportation Research C*, Vol. 7, 237-259, 1999.
- Barth, M., T. Younglove, C. Malcolm, and G. Scora, *Mobile source emissions new generation model: Using a hybrid database prediction technique*, Report to the US Environmental Protection Agency, 2002.
- Broussely, M., S. Herreyre, P. Biensan, P. Kaszlejna, K. Nechev, and R. J. Staniewicz, Aging mechanism in Li ion cells and calendar life predictions, *Journal of Power Sources*, Vol. 97-98, 13-21, 2001.
- Buqa, H., D. Goers, M. Holzapfel, M. Spahr, and P. Novak, High rate capability of graphite negative electrodes for lithium-ion batteries, *Journal of the Electrochemical Society*, Vol. 152, A474-A481, 2005.
- Butler, K. L., M. Ehsani, and P. Kamath, A Matlab-based modeling and simulation package for electric and hybrid electric vehicle design, *IEEE Trans. on Vehicular Tech.*, Vol. 48, No. 6, 1770-1778, 1999.
- Dembski, N., Y. Guezennec, and A. Soliman, Analysis and experimental refinement of real-world driving cycles, *Society of Automotive Engineers (SAE) technical paper 2002-01-0069*, 2002.
- Dubarry, M., and B. Y. Liaw, Development of a universal modeling tool for rechargeable lithium batteries, *Journal of Power Sources*, Vol. 174, 856-860, 2007.
- Dubarry, M., M. Bonnet, B. Dailliez, A. Teeters, and B. Y. Liaw, Analysis of electric vehicle usage of a Hyundai Santa Fe fleet in Hawaii, *Journal of Asian Electric Vehicles*, Vol. 3, No. 1, 657-663, 2005.
- Dubarry, M., V. Svoboda, R. Hwu, and B. Y. Liaw, A roadmap to understand battery performance in electric and hybrid vehicle operation, *Journal of Power Sources*, Vol. 174, 366-372, 2007.
- Dubarry, M., V. Svoboda, R. Hwu, and B. Y. Liaw, Capacity and power fading mechanism identification from a commercial cell evaluation, *Journal of Power Sources*, Vol. 165, 566-572, 2007.
- Dubarry, M., V. Svoboda, R. Hwu, and B. Y. Liaw, Capacity loss in rechargeable lithium cells during cycle life testing: The importance of determining state-of-charge, *Journal of Power Sources*, Vol. 174, 1121-1125, 2007.
- Dubarry, M., V. Svoboda, R. Hwu, and B. Y. Liaw, Incremental capacity analysis and close-to-equilibrium OCV measurements to quantify capacity fade in commercial rechargeable lithium batteries, *Electrochemical Solid State Letters*, Vol. 9, No. 10, A454-457, 2006.
- Electric Vehicle Battery Test Procedures Manual*, Revision 2, USABC/US DOE/INEL, January 1996.
- Ergeneman, M., C. Sorousbay, and A. Goktan, Development of a driving cycle from road traffic measurements for the prediction of pollutant emissions and fuel consumption, *International Journal of Vehicle Design*, Vol. 18, 391-399, 1997.
- Ericsson, E., Independent driving pattern factors and their influence on fuel-use and exhaust emission factors, *Transportation Research D*, Vol. 6, 325-345, 2001.
- Ericsson, E., Variability in urban driving patterns, *Transportation Research D*, Vol. 5, 337-354, 2000.
- Frey, H. C., and J. Zheng, Probabilistic analysis of driving cycle-based highway vehicle emission factors, *Environ. Sci. Technol.*, Vol. 36, 5184-5191, 2002.
- Kelly, K. J., and A. Rajagopalan, *Benchmarking of OEM hybrid electric vehicles at NREL*, US DOE/National Renewable Energy Laboratory, Technical Report # NREL/TP-540-31086, August, 2001.
- Kent, J. H., G. H. Allen, and G. Rule, A driving cycle for Sydney, *Transportation Research*, Vol. 12, 147-152, 1978.
- Liaw, B. Y., and M. Dubarry, From driving cycle analysis to understanding battery performance in real-life electric hybrid vehicle operation, *Journal of Power Sources*, Vol. 174, 76-88, 2007.
- Liaw, B. Y., B. Dailliez, A. Teeters, K.-Y. Youn, and C.-S.

- Kim, Vehicle usage analysis for Hyundai Santa Fe fleet in Hawaii, *Proceedings of the 20th Electric Vehicle Symposium (EVS-20)*, Long Beach, CA, November 15-19, 2003.
- Liaw, B. Y., Fuzzy logic based driving pattern recognition for driving cycle analysis, *Journal of Asian Electric Vehicles*, Vol. 2, No. 1, 551-556, 2004.
- Liaw, B. Y., G. Nagasubramanian, R. G. Jungst, and D. H. Doughty, Modeling of lithium ion cells - a simple equivalent-circuit model approach, *Solid State Ionics*, Vol. 175, 835-839, 2004.
- Liaw, B. Y., K. P. Bethune, and C. S. Kim, Time-series field trip data analysis using adaptive recognition approach. Analysis on driving patterns and vehicle usage for electric vehicles, *Proceedings of the 19th Electric Vehicle Symposium (EVS-19)*, Busan, South Korea, October 19-23, 348-359, 2002.
- Liaw, B. Y., R. G. Jungst, G. Nagasubramanian, H. L. Case, and D. H. Doughty, Modeling capacity fade in lithium-ion cells, *Journal of Power Sources*, Vol. 140, 157-161, 2005.
- Rahman, Z., K. Butler, and M. Ehsani, A study of design issues on electrically peaking hybrid electric vehicle for diverse urban driving patterns, *Society of Automotive Engineers (SAE) technical paper 1999-01-1151*, 1999.
- Ramadass, P., B. Haran, P. M. Gomadam, R. White, and B. N. Popov, Development of first principles capacity fade model for Li-ion cells, *Journal of the Electrochemical Society*, Vol. 151, No. 2, A196-A203, 2004.
- Riemersma, I. J., P. Hendriksen, N. L. J. Gense, and R. T. M. Smokers, Methodology for the development of representative driving cycles, <http://www.automotive.tno.nl/VM/EST/publicaties/Paper%20Cycle%20Development.pdf>, 2007.
- Simanaitis, D. J., Emission test cycles around the world, *Automotive Engineering*, Vol. 85, 34-43, 1977.
- Spotnitz, R., Simulation of capacity fade in lithium-ion batteries, *Journal of Power Sources*, Vol. 113, 72-80, 2003.
- Tong, H. Y., W. T. Hung, and C. S. Cheung, Development of a driving cycle for Hong Kong, *Atmospheric Environment*, Vol. 33, 2323-2335, 1999.
- Tsai, J.-H., H.-L. Chiang, Y.-C. Hsu, B.-J. Peng, and R.-F. Hung, Development of a local real world driving cycle for motorcycles for emission factor measurements, *Atmospheric Environment*, Vol. 39, 6631-6641, 2005.
- van de Weijer, C. J. T., *Heavy-duty emission factors – development of representative driving cycles and prediction of emissions in real-life*, PhD dissertation, Technical University of Graz, Austria, 1997.
- Young, C., M. R. Smith, T. Younglove, and M. J. Barth, Analysis of weekday/weekend driving differences in an in-use vehicle fleet, *Proc. the 10th CRC On-Road Vehicle Emissions Workshop*, San Diego, CA, 2000.

(Received November 5, 2007; accepted December 8, 2007)