Selecting the Best Battery System Suitable for Electrical Energy Storage

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In a recent report commended by the Electricity Advisory Committee (EAC) to the U.S. Department of Energy (DOE), battery energy storage system (BESS) remains a plausible solution for future smart grid design [1]. The most common BESS technology in use today is lead-acid batteries, fueled by the rapid growth in the sectors of telecommunications and Internet data centers. There are other alternatives for BESS, including Li-ion, Na-S, Zn-Br, vanadium-redox and polysulfide-bromide redox flow batteries. Although Na-S and Zn-Br are being used for evaluation at the present time, the overall performance and life cycle costs for all potential BESS remain to be assessed and characterized in field evaluations and demonstrations.

With more renewable electricity generation by solar and wind sources, even with power electronic conditioning, the sporadic nature of the generation profiles from these resources creates unconventional erratic pulsing ripples in the grid, as well as in the charging behavior to the BESS; therefore, BESS cannot be treated as a simple DC source and sink anymore. The manufacturer specification and performance report are often based on well controlled constant current or constant power experiments, far from the real usage of the batteries. Figure 1 presents an example of a BESS operating under the energy generation patterns associated with a solar panel and/or a wind turbine and the duty cycle of a typical office. To sustain battery operation to ten years or more, battery life and performance need to be better predicted in a manner far more complicated than those projected by test results obtained from conventional laboratory testing with rigid test protocols. Therefore, accurate model prediction and simulation is a necessity in managing BESS in renewable generation and smart grid.

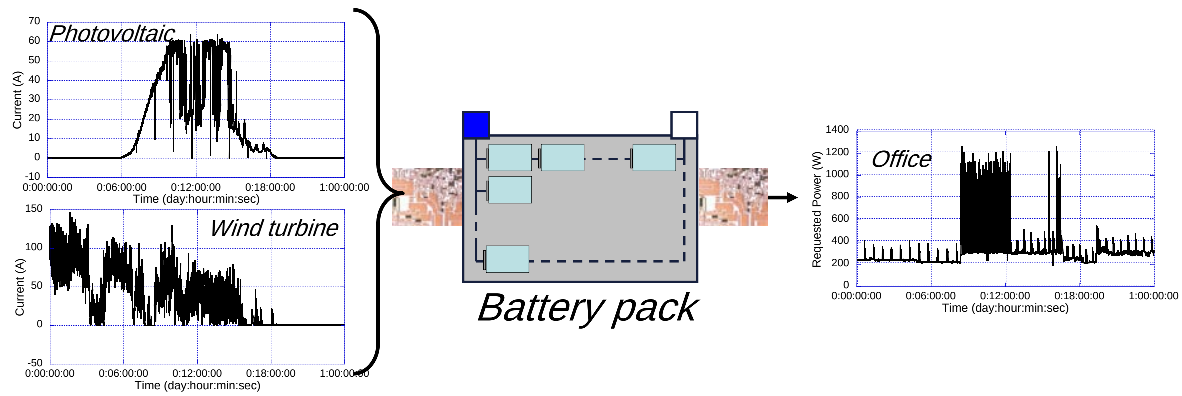

Figure 1: Example of real generation and duty cycles to be applied to battery packs.

We have recently made significant progresses in the battery modeling and simulation with excellent fidelity and accuracy in predicting battery behavior from cells to packs [2,3]. The model is based on a simple semi-empirical equivalent circuit model (ECM) in a Randle circuit like diagram, replicating the complicated cell behavior under dynamic operating conditions as suggested in Figure 1. In the model, an Ohmic resistance R_1, a Faradaic resistance R_2, and a capacitance C depicts the cell's reaction to any perturbation by the external load. Their values can be determined by impedance spectroscopy or other experimental methods. It is worth mentioning that the Ohmic resistance R_1 comprises contact resistance, electrolyte resistance, and electrodes' intrinsic electronic resistance. The Faradaic resistance R_2 represents the variations in the electrochemical behavior in the cell, which include reaction kinetics at the electrode-electrolyte interfaces and mass transport in the electrodes. Due to the non-linear nature of the Faradaic resistance, R_2 is a strong function of the current perturbation, SOC, cell age, and temperature; as well as some other factors that depend on the application and operating condition. There is no simple mathematical model that can explain this behavior; thus, this resistance usually has to be extracted from extensive laboratory testing under a specially designed protocol. Figure 2 presents the schematic of the model for a $LiCoO_2$ based Li-ion cell. On the left, the open circuit voltage vs. SOC is shown to represent the cell thermodynamic property. On the right, the R_2 variations as a function of C rate and SOC are shown, depicting the kinetic property of the cell.

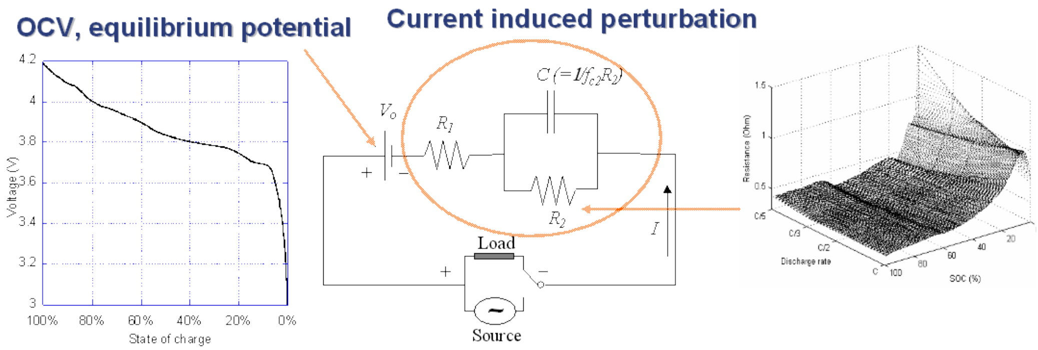

Figure 2: A generic ECM used for a $LiCoO_2$-based Li ion battery.

This framework offers several advantages. It is easier to code the model using common control software application platforms such as those offered by MATLAB or generic C codes. The model requires less computational resources than other techniques such as those using first principle models. Computation resources are often a limiting factor in on-board, real-time applications. The ECM can be adaptive to various battery chemistries and operated in a variety of operating environments, including real-time usage on a chip. For a specific chemistry, the user needs to acquire the OCV vs. SOC curve and the resistance map to enable the model to simulate the corresponding cell behavior. Figure 3 presents the resistance map and the simulated discharge curves for a commercial lead acid battery module. The fidelity of the model is vested largely in the accuracy of the measurements and the resolution of the test equipment. It should be emphasized that the model should have the fidelity to model the cell behavior and its performance variations that come from the manufacturing processes in order to be useful in handling battery management and control, which we shall elaborate later in the discussion.

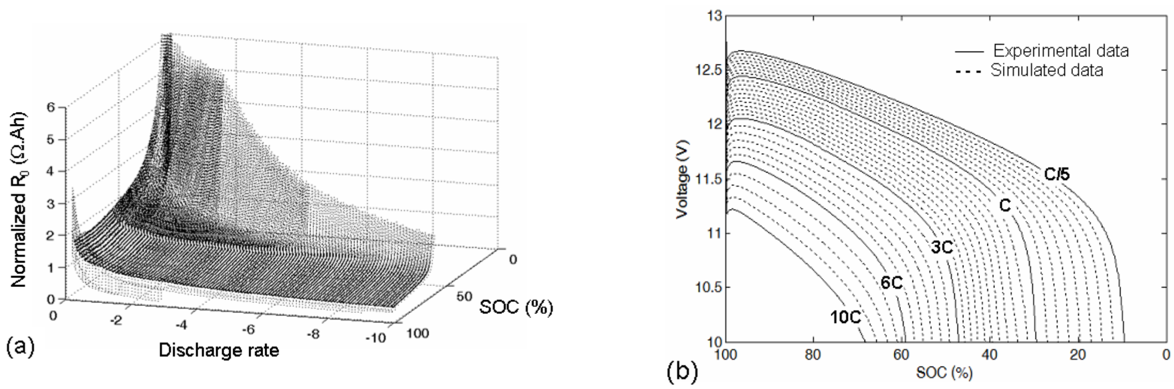

Figure 3: Resistance map and simulated discharge curves for a lead acid battery.

For BESS, due to the large number of cells used in the bank, we need to progress the modeling capability from the cell level to a pack or system configuration. A major difficulty, that is hampering an accurate pack simulation, is cell-to-cell variations intrinsic to a batch of batteries. In a large assembly of cells, the cell variations will play a key issue from the onset as a source of imbalance among the cells in the pack.

The imbalance among cells in a pack can be caused by several factors, either extrinsic or intrinsic to the cell properties. Extrinsic attributes may include current variations in parallel strings or voltage variations in series, which lead to unevenness in the extent of cell reaction. Extrinsic attributes could be due to variations in contact resistance among the cells or temperature gradients created by improper thermal management in the pack. Possible intrinsic attributes may include variations in cell quality that result in variations in the amount of active material, composition, and physical property among the cells. As a result of the tolerance margin built into the processing steps, the intrinsic attributes are inherent to a manufacturing process. Such inhomogeneity in the cell fabrication will introduce dissimilarity in the cells' property and resulting performance variations. It is therefore important to analyze and quantify these variations and understand their origins.

By using electrochemical data obtained from the conditioning cycles of a batch of 100 cells made by a manufacturer we have developed an *in-situ* analysis technique to derive three critical and independent attributes that lead to cell variations [4]. These attributes are: the amount of active material, the polarization resistance, and some localized kinetic effects. The amount of active material dictates how much capacity is available at low rates (or the maximum available capacity). The variations in the active material loading can be determined from very low rate (e.g., C/25) charging and discharging behavior of the cells and the corresponding relaxed cell voltages at the end of charge (EOC) and end of discharge (EOD). The polarization resistance mainly dictates the voltage of the cell during polarization. Variations in the polarization resistance among the cells will create various magnitudes of polarization in overpotential among them, which in turn may introduce various degrees of undercharge and/or underdischarge thus lead to capacity disparity. The variations in the extent of undercharge or underdischarge can be determined by incremental capacity analysis. The last attribute is a catch-all term which comprises mostly localized kinetic effects that determine the rate capability, the cell's ability to handle current, which dictates what fraction of the capacity can be delivered. A convenient way to express the rate capability is represented by the Peukert's coefficient of the cell. Our methodology in this *in situ* analysis can decipher these attributes and variations and incorporate them into each individual single cell model to give highly accurate cell characteristics in the pack model prediction. In Figure 4, two cells from the batch were simulated based on the single cell model described on Figure 2 with individualized cell parameters. Without taking into account the cell variations, the simulation using a generic set of parameters determined from a sample cell testing will be off, depending on the degree of disparity in the dissimilarity between an individual cell and the sample cell. When the individualized cell parameters are used, the simulation can be in almost perfect agreement. As expected, at a low rate, the amount of active material plays a key role in determining the available capacity (left). At higher rates, the role of the reaction kinetics is more important (right).

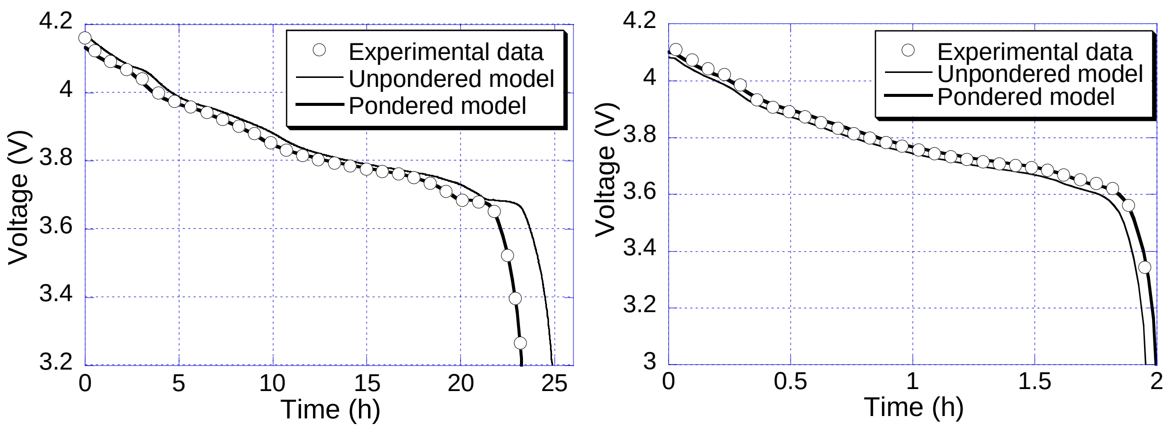

Figure 4: Simulation of a cell with different amount of active material (left) and kinetic properties (right) from those of a sample cell.

The next step in enabling the model prediction in practical applications is to predict the degradation behavior of a BESS, which is duty cycle dependent. The dependence on duty cycle makes a practical battery life prediction literally impossible. A possible solution is to derive usage patterns and corresponding duty cycles from field testing [5]. Once such usage patterns and duty cycles were available, the battery can then be tested with such representative duty cycles to estimate the cycle life. The approach comprises fuzzy-logic pattern recognition (FL-PR) techniques, which can be used to perform driving event and duty cycle analyses. This approach has been successfully applied to electric vehicle performance analysis via the creation of a compositional driving event profile called "driving cycle profile" to represent a trip. The same approach was used to analyze battery performance via the construction of "active duty profile" to express battery usage under various driving conditions. Figure 5 presents an example of this technique. On the left is the FL-PR map that depicts the associations of duty events with intensity of power profile and frequency to classify the duty event in terms of power usage from benign to intensive operation. This duty event classification can be used to specify impacts of power events on battery operation and life. On the right-hand side plot of Figure 5 is an example of employing this classification technique to a randomly selected vehicle trip in which the duty cycle and the corresponding power events are analyzed to reveal their overall usage patterns and the level of stress factors to the batteries in the pack.

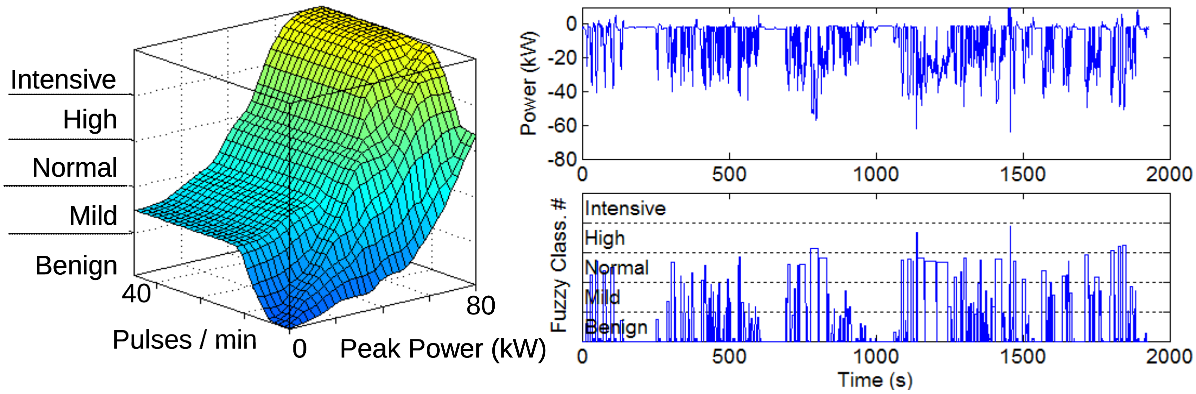

Figure 5: Duty cycle analysis from a FL-PR interferometer (left) on the power vs. time curve (right).

The combination of the event and duty cycle analysis enables us to understand both vehicle drivetrain and battery performance in synergetic details and in a systematic manner. The analysis can be used to derive a representative usage pattern and duty schedule that represents the typical usage of the vehicle in a location. This technique can also reveal the characteristics of a specific trip in comparison with the overall event distribution in the database. The representative usage schedule can be used in both testing and modeling of battery behavior and life. Figure 6 shows the overall power event distribution in a database that consists of more than 100,000 km of driving data from trips performed in the field testing. We can also select a specific trip that has a similar power event distribution (bottom figure) and use this trip as a representative usage schedule (typical driving and duty cycle) for laboratory testing.

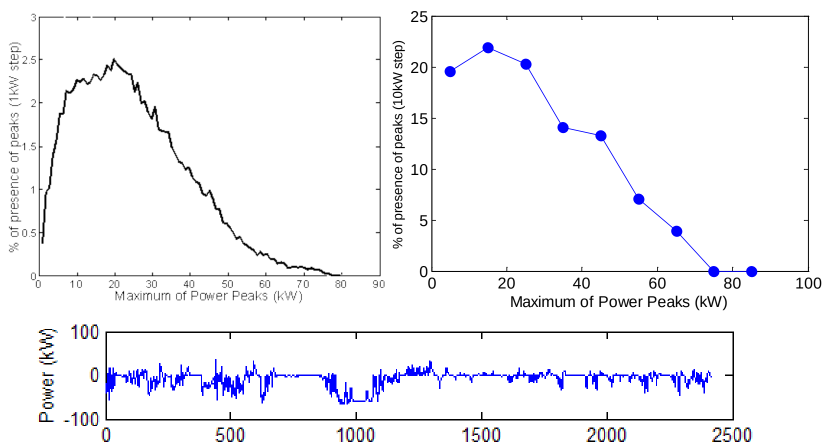

Figure 6: (left) A nominal power usage distribution profile determined from a collection of trip data in a database that comprises more than 100,000 km of driving distance in a Honolulu electric vehicle fleet, (right) a representative power usage distribution profile summarized from the left plot, and (bottom) a trip that exhibits the representative power usage schedule.

A further step in understanding battery degradation is to quantify the degree of degradation in the battery according to its degradation mechanism. To create a proper degradation pathway in the battery, we use a specific protocol to perform aging experiments. An analysis technique was developed to determine the impact of various duty cycles (or duty event patterns) on battery service life. An effective method of analyzing attributes to battery degradation has been developed by us [4,5] in order to classify the degree of contribution from various stress factors (or degradation modes) to the capacity fading. A key step in the analysis of degradation (and its mechanisms) is to refer the aging phenomena to a reliable reference, such as the thermodynamic SOC, to allow such quantifications for each stress factor and its underlying mechanisms that contribute to the aging degradation. The determination of SOC can be achieved by allowing the cell to rest after any charge or discharge events and then compare the relaxed cell voltage to an OCV vs. SOC curve. This OCV vs. SOC curve can be obtained from either a GITT experiment or a technique that utilizes a pseudo-equilibrium profile that takes the average of the discharge and charge curves obtained at very low rates (such as those below C/25 in which the polarization is essentially minimized to meet the criteria of pseudo-equilibrium).

Another essential capability is to quantify the evolution of degradation under different degradation mechanisms in the cell. An effective tool is the incremental capacity analysis where the –dQ/dV versus cell voltage profiles were analyzed in time steps through the degradation pathway. A detailed time resolution in the degradation with the underlying mechanisms can be achieved and quantified. Accompanied with the monitoring of the evolution of the internal resistance change in the cell, we are able to identify several degradation modes in Li-ion battery chemistry including loss of active material, undercharge and underdischarge. Combining these techniques, we were able to map the degradation mechanisms in the cell (Figure 7) by displaying and quantifying the different contributions from each mechanism; including loss of active material, loss of lithium inventory, irreversible change of chemistry, as well as resistance- or kinetically induced undercharge and underdischarge.

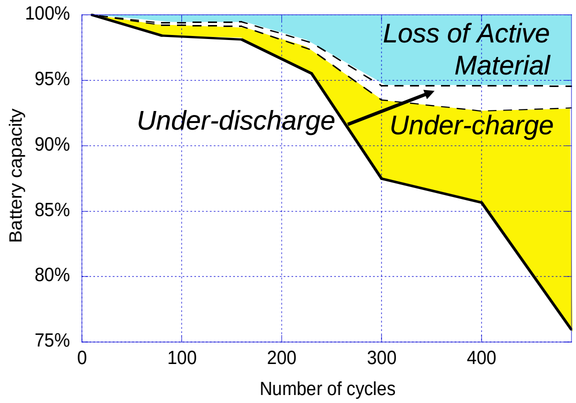

Figure 7: Example of a degradation map for a $Li_xNi_{0.85}Co_{0.1}Al_{0.05}O_2$ commercial cell.

With this approach we can associate "stress factors" to any duty cycle regime, classify the intensity of a stress factor, and quantify its impact on the battery's "state of health" as an input to the battery life prediction. For instance, a very aggressive duty event regime may have an index of 3 in a stress factor, indicating that one such regime may have an equivalency of 3 "nominal" duty cycles in the cycle life (in terms of cycle number) in reference to a cycle life test in the laboratory. Figure 8 illustrates an example of relating the resistance map that is associated with the evolution of the age of the cell (in terms of cycle number in cycle life) under a specific duty cycle schedule (left) and the prediction of the elapsed age on the same cell based on the estimation from an *in-situ* technique like incremental capacity analysis (right) [6]. It should be noted that the experiment is consisted of two sets of data: one is resulted from the aging accelerated using a complex pulsed schedule and the other revealing capacity fading determined at every 50 aging cycles via the performance reference tests. The map on the left of Figure 8 was constructed from the performance reference tests, whereas the elapsed life estimation (on the right) was interpreted from the pulsed aging data, emulating real life duty cycles.

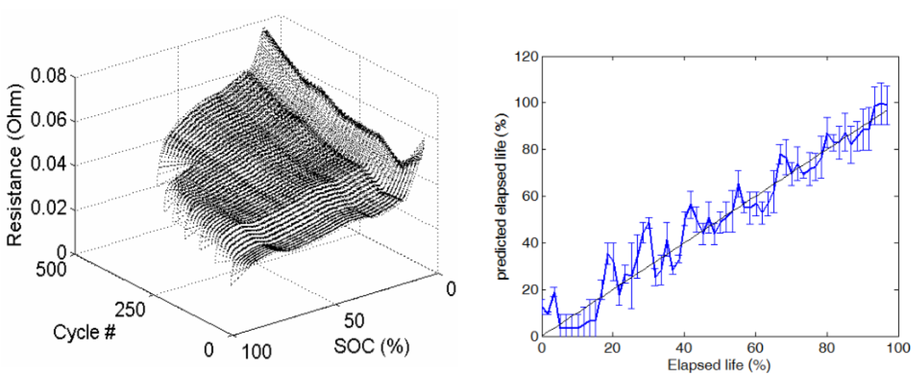

Figure 8: (Left) Resistance evolution as a function of cycle number and SOC and (right) the estimation of elapsed life of a cell via an *in-situ* analytic technique such as the incremental capacity analysis.

In summary, through this long and complicated practice, we show that using these approaches developed in our laboratory, an accurate model can be developed for selecting a suitable BESS for applications in energy storage and/or smart grid. In addition, this method also provides accurate SOC and state of health information that can be used in battery management, in which via a proper monitoring system of cell performance in a battery pack we can perform real time diagnosis and prognosis to prevent dramatic premature failures of the BESS.

References:

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