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AN ADVANCED BATTERY MANAGEMENT SYSTEM FOR LITHIUM ION BATTERIES

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ABSTRACT

This paper describes the development of a Battery Management System (BMS) State of Charge/Health (SOC/SOH) algorithm that was developed and proven for three different lithium ion based cell chemistries (nanophosphate, lithium manganese oxide, lithium iron phosphate). In addition, a universal BMS architecture based on this algorithm was developed that can support other chemistries, capacities, and formats. Algorithm performance was compared to actual data in the laboratory environment and also to data from a lithium iron phosphate hybrid electric vehicle pack that was integrated with an XM1124 hybrid electric HMMWV operating in a vehicle environment under realistic conditions. The system demonstrated accuracy within 5% in a software upgradeable, low cost package.

INTRODUCTION

Lithium-based batteries promise excellent performance, although they require careful management to avoid personnel injury and equipment damage. Consequently, there is extreme interest in developing an accurate Battery Management System (BMS) to take advantage of the positive attributes of lithium-based chemistries without sacrificing flexibility and safety. However, the lack of adequate BMS standardization and inaccurate state estimation algorithms have hampered the widespread adoption of lithium chemistries in spite of their advantages.

In this paper we describe our BMS and present results that show that we can provide State of Charge (SOC) estimation accuracy to better than 5%; that we can utilize existing life cycle data from battery manufacturers to estimate State of Health (SOH) and State of Life (SOL); and that we have a universal architecture that is adaptable to other chemistries, capacities, and formats. The primary application that we describe is for Silent Watch, but the BMS is also adaptable for other Hybrid Electric Vehicle (HEV) applications.

SYSTEM DESCRIPTION

Figure 1 illustrates our concept for a BMS that provides health monitoring for a typical 24 VDC Silent Watch pack [1]. In most lithium-based battery pack applications, the pack is comprised of a number of series- and parallel-connected cells to achieve the required voltage, current, and energy/power capacity. As one example, a typical Silent Watch configuration could consist of eight submodules of six parallel-connected, prismatic, 3.3 V, 20 Ah cells (8S6P). In total, there are 48 cells in this configuration, the nominal pack voltage is 26.4 V, and the capacity is 120 Ah. The parallel-connected cells are referred to as "super-cells" and require relatively little oversight compared to the series-connected cells, which pose the most challenges because of the need for cell balancing. The BMS monitors the voltage and temperature of each super-cell, and the series current of the overall pack via individual super-cell sense modules. Although the Silent Watch battery pack described above uses eight series-connected super-cells, this Universal BMS architecture is expandable to any number of super-cells,

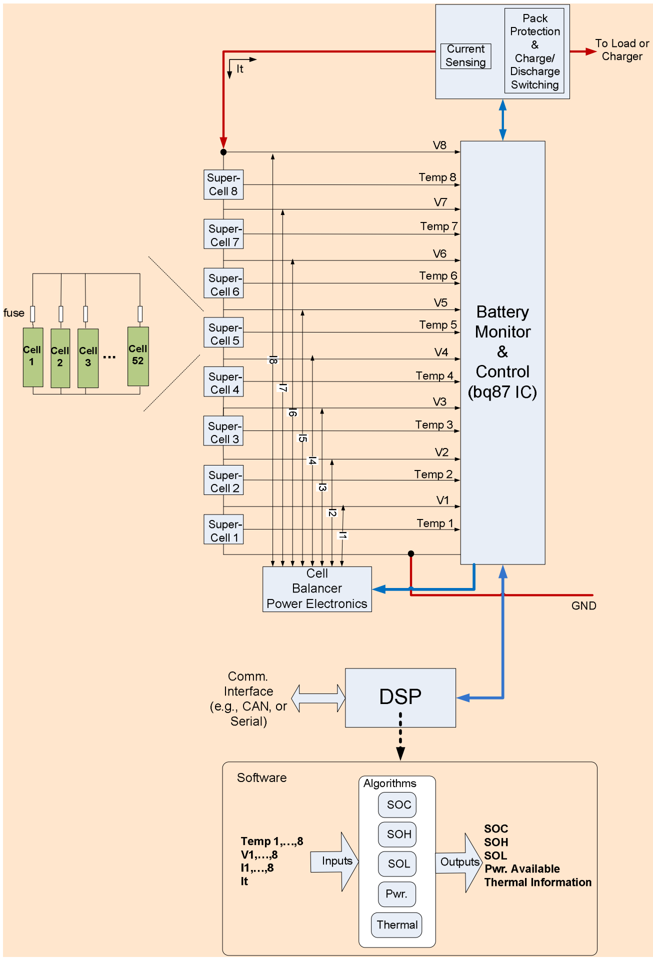

Figure 1: BMS architecture for a 24 VDC lithium-ion Silent Watch battery pack.

extending support from Silent Watch to that of HEV power packs, for example. The master Central Processing Unit (CPU) provides control and reporting functions and manages charge cycle and balancing for each individual super-cell, thereby ensuring safety and highly competitive performance. The CPU also uses SOC/SOL/SOH, power availability, and thermal monitoring algorithms to optimize and report on cell performance. Finally, reporting to the vehicle communications interface or a higher level controller is provided via a bi-directional communication bus.

Silent Watch Requirements

This BMS aims to benefit a new breed of lithium-based battery packs currently being developed. Reference [2] shows one example. The energy for Silent Watch applications is currently provided by two series-connected lead acid batteries, such as the ArmaSafe 6T, 12 VDC, 120 Ah battery. Silent Watch energy needs range from an average power requirement of 1.5 kW for 2 to 6 hours to a short-term peak power requirement of almost 5 kW [1]. There are two most obvious ways to achieve this goal using standard format lithium-ion cells that we know are of interest for Silent Watch applications. These include the 26650 cylindrical cells and the Prismatic cell. Figure 2 shows the configuration of 8 submodules of 52 parallel-connected A123 26650, 3.3 V, 2.3 Ah cells (8S52P). In total, there are 416 cells, the nominal pack voltage is 26.4 V, and the capacity is 120 Ah. Figure 3 shows the configuration of 8 submodules of 6 parallel-connected A123 prismatic, 3.3 V, 20 Ah cells (8S6P). In total, there are 48 cells, the nominal pack voltage is 26.4 V, and the capacity is 120 Ah. Some important additional considerations in a battery pack design are the cost, power density, energy density, and volume of the packaging, which depend on the specific requirements of the application.

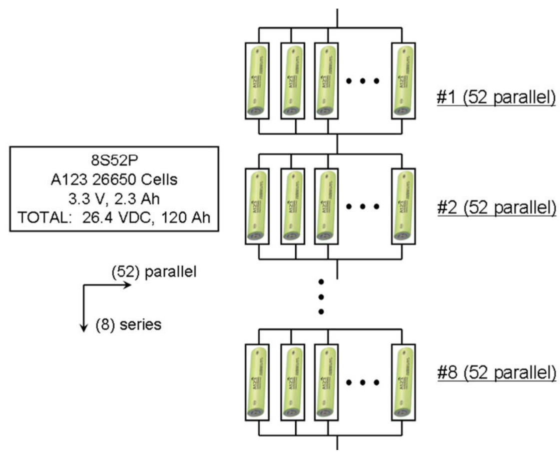

Figure 2: 24 VDC lithium-ion pack based on 26650 type cylindrical cells (8S52P).

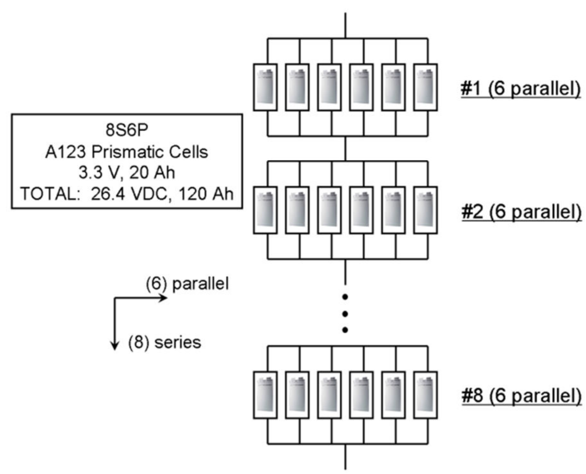

Figure 3: 24 VDC lithium-ion pack based on prismatic lithium cells (8S6P).

In both cases, an effective method for configuring a BMS is to provide voltage, temperature, SOC, SOL, and SOH estimation; and cell balancing at the submodule level. This method ensures a minimal number of sensing points and hardware size, while still achieving the main goal of providing accurate pack monitoring. However, cell level electrical protection and temperature monitoring may still be needed at some level to guarantee maximum safety.

Algorithm Details

There are four primary elements to the BMS: (1) accurate status reporting (SOC, SOH, SOL, power availability, and temperature); (2) cell charge control; (3) cell discharge control; and (4) cell balancing. Creare's Universal BMS will support multiple lithium-based as well as other battery chemistries by using model-based techniques to estimate SOC, SOH, and SOL. Our model-based algorithms are data driven so that the code structure of the BMS and the core of the algorithms are independent of cell chemistry. While the numeric parameters of the models used by the algorithms will depend explicitly on the chemistry via table-based model data storage, these parameters can be updated easily via software upgrades/downloads. This approach makes it very simple to adapt a BMS to new chemistries that may not have been previously considered. Therefore, we need to be able to create accurate, analytical models of the battery cells that will be used by the BMS.

In the Enhanced Self Correcting (ESC) model, our battery cell is based on a simplified electrical circuit analog, where the characteristic equation for the loaded terminal voltage $y(t)$ is [3- 5]:

$$y(t) = \mathrm{OCV}(z(t)) - i(t)R + f_1(t) + f_2(t) + h(t). \qquad (1)$$

An equivalent-circuit schematic diagram for this equation is shown below in Figure 4. It is comprised of what we refer to as static (R and OCV) and dynamic (f_1, f_2, and h) model components, which are separately found through static and dynamic modeling tests. The static modeling tests are the OCV tests as a function of SOC and temperature, and the dynamic tests are comprised of dynamic power profiles. We obtained characterization data (open-circuit-voltage and other circuit parameters) for the LGC E1 [6], ATL LFPP [7], and A123 Systems 26650 cells [8] by modeling of the static and dynamic relationships for all three different cells.

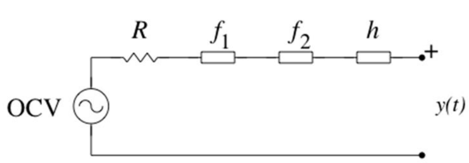

Figure 4: Circuit equivalent model of the ESC cell model.

Test Results

To evaluate our BMS algorithms for the Silent Watch application, we adopt the profile of power versus time shown in Figure 5 [2]. This profile repeats every 2,200 seconds, with air conditioning demands of 3.4 kW at 25% duty cycle; communications equipment requiring 0.6 kW at 6% duty cycle; and other navigation, movement tracking system, driver vision enhancement, displays, etc., requiring 0.6 kW continuous. Present Silent Watch battery packs use 24 V, 120 Ah lead-acid batteries. To approximate this capability using the cells explored in this project, battery packs are configured as:

- LGC LMO E1 cell: 7S13P, 125 Ah, 27 V.
- ATL LFP power cell: 8S6P, 144 Ah, 26 V.
- A123 26650 LFP cell: 8S53P, 122 Ah, 26 V.

In actual laboratory testing, we subjected the three cell types to the Silent Watch power profile at 25°C to evaluate the estimation algorithm accuracy. The cells used for these tests were of the same manufacture as those used to create the cell model, but were physically different cells, thus having slightly different capacities, resistances, and so forth. More specifically, the Silent Watch tests on the physical cells started with fully charged cells. Following charging, each cell was slowly discharged to 0% SOC based on cell terminal voltage. Voltage, current, and net ampere hours discharged were recorded every second, and the net ampere hours discharged was used to construct a "true" SOC versus time trace for the purpose of evaluating the SOC estimation algorithms. For all three cell types, the time-domain terminal voltage and current are shown in Figure 6, and the SOC estimation during the test is shown in Figure 7. The RMS SOC error using cell tests is shown in Table 1. These results show that SOC estimates accurate within 5% are possible using these methods.

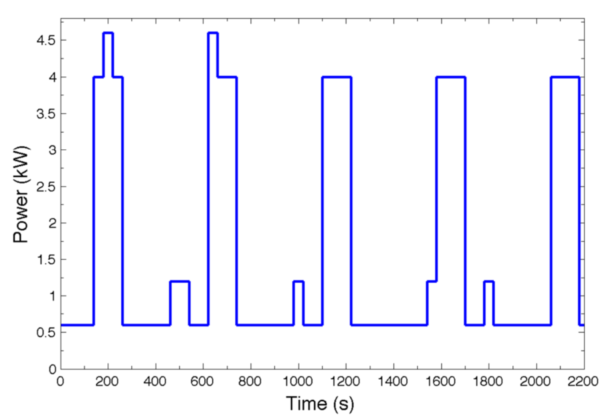

Figure 5: Silent Watch power profile.

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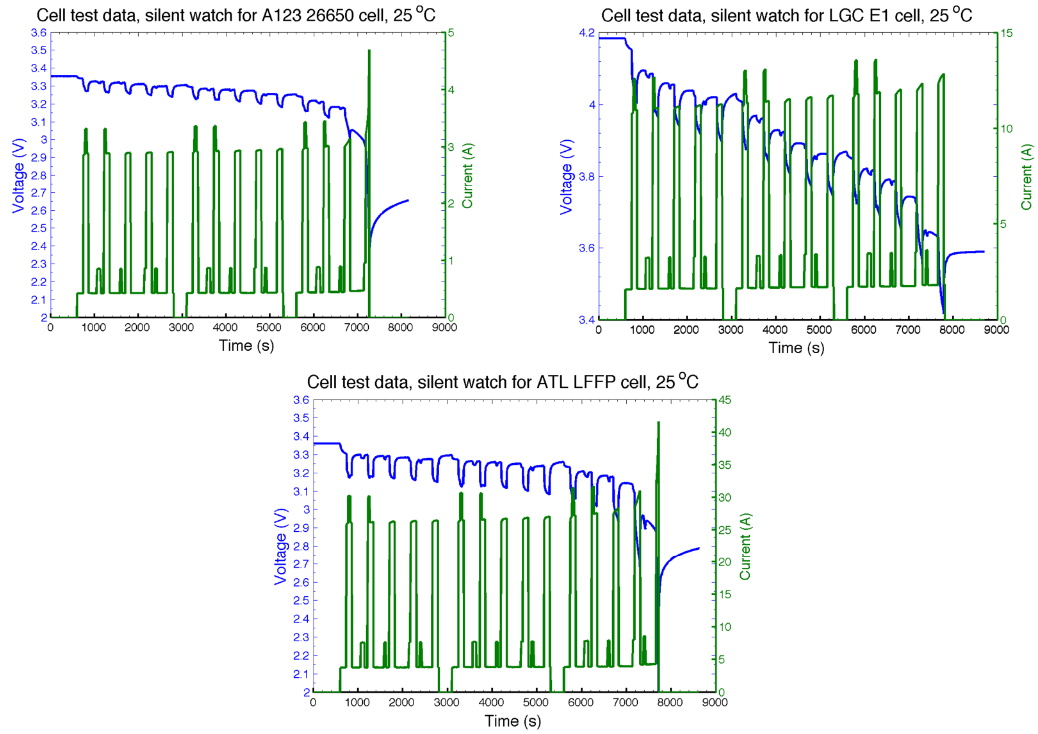

Figure 6: Data collected from three cells for Silent Watch profile repeated three times.

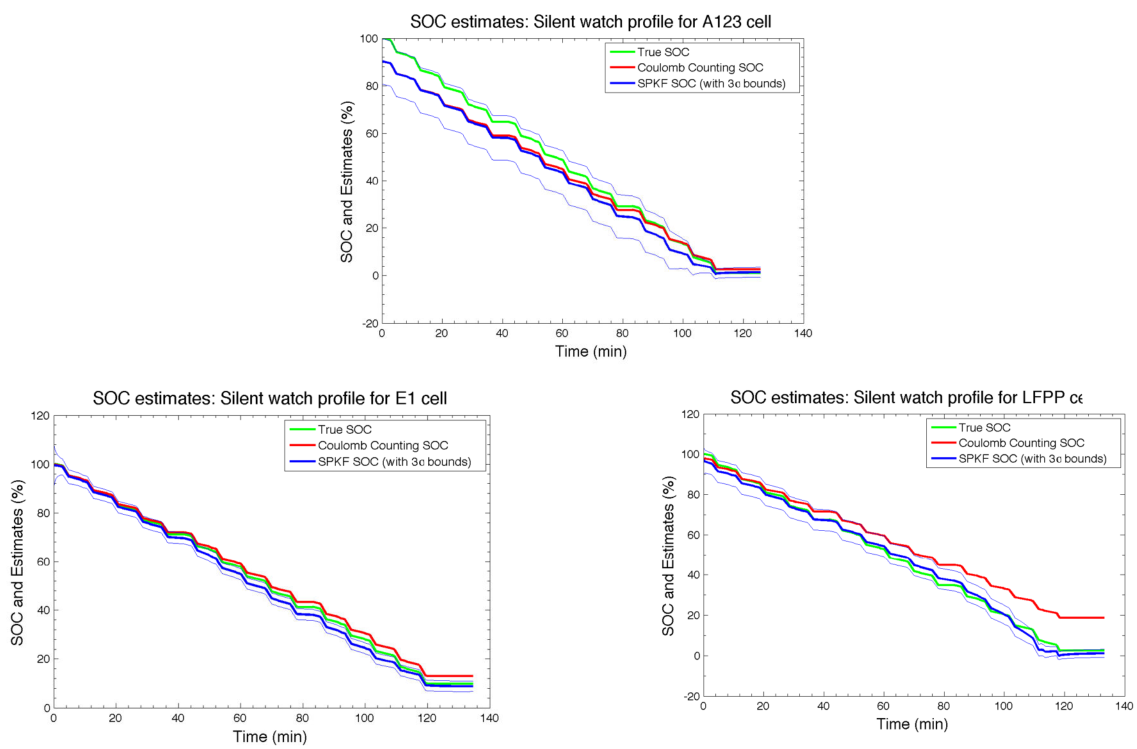

Figure 7: SOC estimation results for cell test data, Silent Watch profile.

Table 1: RMS SOC estimation errors for Silent Watch profile, real data.

A123 26650 cell	2.9%
LGC E1 cell	2.2%
ATL LFP power cell	2.2%

Figure 7 also shows SOC estimates based on Coulomb counting as a baseline. This reference is valuable to show how the Sigma Point Kalman Filter (SPKF) algorithms adapt to adjust to cell characteristics that are unexpected. Both the SPKF and the Coulomb counting methods initialize their SOC estimates using the first voltage measurement, assuming it is a stable open-circuit-voltage value. From that point, the Coulomb counting method accumulates net ampere-hours depleted from the cell, and calculates SOC as (initial SOC) – (net ampere-hours depleted)/(nominal cell capacity). Coulomb counting cannot recover from errors in initial SOC, measurement errors in net ampere-hours depleted, or in assumed nominal cell capacity. However, the SPKF methods can. The SPKF algorithm automatically balances information from the current sensor and the voltage sensor. However, when the sensed voltage contains very little information, it must rely on the current sensor for most of its estimation updates. Near very high SOC and very low SOC, the sensed voltage contains more information, and the SPKF uses this information to adapt its estimate more aggressively and converge to the correct value.

SOC Estimation Using Operational Data

In addition to evaluation for the Silent Watch application, we also evaluated performance for an advanced HEV lithium-ion pack produced by A123 Systems for the XM1124 HMMWV [9, 10, 11]. The battery pack was configured as 27 series-connected modules, each module being a group of 4S6P A123 LFP 26650 cells. The overall rating of the pack was 350V and 13.8Ah. The pack was first bench tested under various conditions, then integrated into an XM1124 Series Hybrid HMMWV where it underwent a group of vehicle performance tests.

The first data set (Figure 8) is a laboratory-controlled simulated drive cycle (bench test) and the second (Figure 9) is a road test driving up Mount Sano in Huntsville, AL (vehicle test). In the bench test, SOC estimates are compared between two developmental SOC estimators provided with the pack (Pack SOC, Volt SOC), a simple coulomb counter, and the SPKF SOC estimator developed during this program. In the vehicle test, a temperature-compensated coulomb counter from the vehicle SOC estimator (ICBM SOC) is also compared to the others. The SPKF SOC estimates were created using the identical code base as was used to evaluate the Silent Watch data sets in the second progress report. All models and tuning parameters were the same.

For the laboratory test shown plotted in Figure 8, we initialized a coulomb counter and the SPKF to the same initial SOC estimate. All estimates, except for the voltage-based "Volt SOC" estimate, agree quite well. The "Pack SOC" and SPKF SOC estimate closely agree and track together within a few percent. Upon closer review, it is observed that the Coulomb Counter also tracks virtually identically with the SPKF SOC. The SOC estimates shown in the vehicle test of Figure 9 also show that the SPKF estimate tracks the Coulomb counter well, whereas the others deviate by 20 to 40% from that value.

State of Health Estimation

The definitions of SOH and SOL include a discrete indication of whether the cell is healthy or not (SOH), and a continual estimation of remaining useful life as the battery ages (SOL). Both will be determined by estimating the real-time values of certain key parameters (e.g., capacity fade and internal resistance) in the ESC model, and comparing them to life cycle data provided by the cell manufacturer. The approach will use system identification techniques (which can be implemented with Kalman Filters as well) to estimate key parameters of the cell as it ages. These parameter values are updated as the cell ages, and therefore serve as battery cell health indicators. We focus on capacity fade and internal resistance to determine SOL and SOH.

SOL estimation is based on historical cycle-life data of the particular cell being used. We have obtained preliminary cycle life data of the 18650 1100 mAh, and 26650 2200 mAh Lithium Iron Phosphate (LiFePO4) cells from Tenergy Battery Corp. (Manufacturer items #30028 and #30030, respectively). The following equations can be used to obtain the capacity left as a function of cycle number assuming the application will use these cells with a discharge rate of 1°C.

$$Capacity\ left_{18650} = -0.00055432\,x^2 - 0.14698\,x + 1123.1 \quad (2)$$

$$Capacity\ left_{26650} = -0.0026587\,x^2 - 0.03513\,x + 2172.9 \quad (3)$$

where x is the number of cycles already exercised (which need to be counted). Note that data were obtained for the first 300 cycles, and the equations above are extrapolating beyond the 300 cycles of data obtained. Note also that the estimated capacity fade computed in this way can be compared to that produced by the model-based approach, and used as a computational sanity check benchmark for the adaptive model, to remain within physically meaningful bounds.

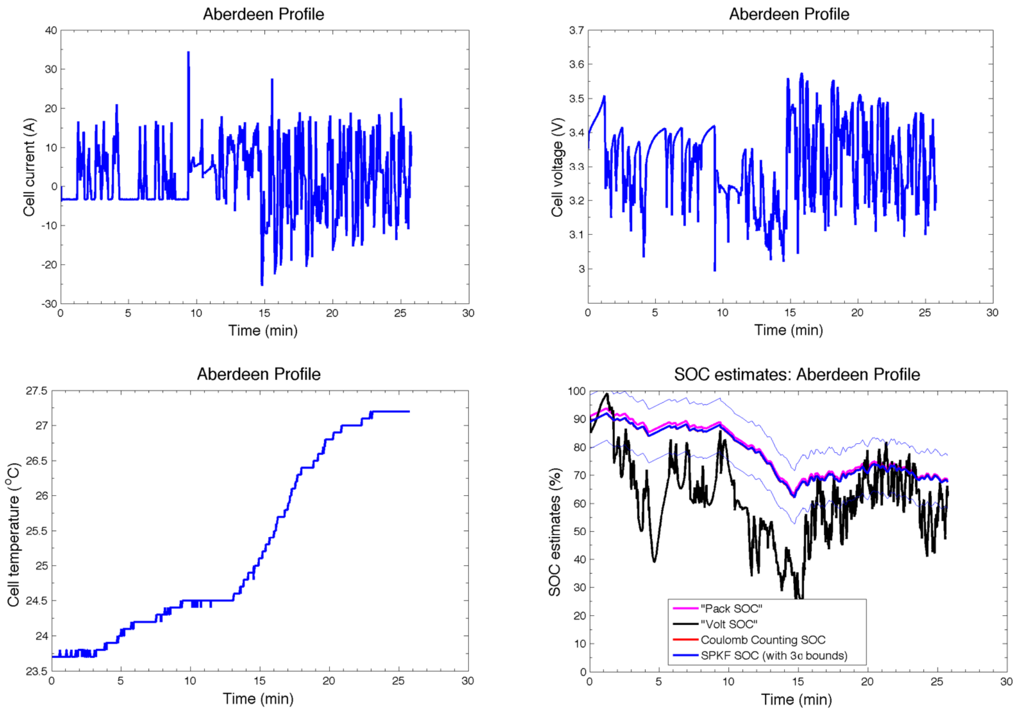

Figure 8: Bench test: laboratory controlled simulated drive cycle.

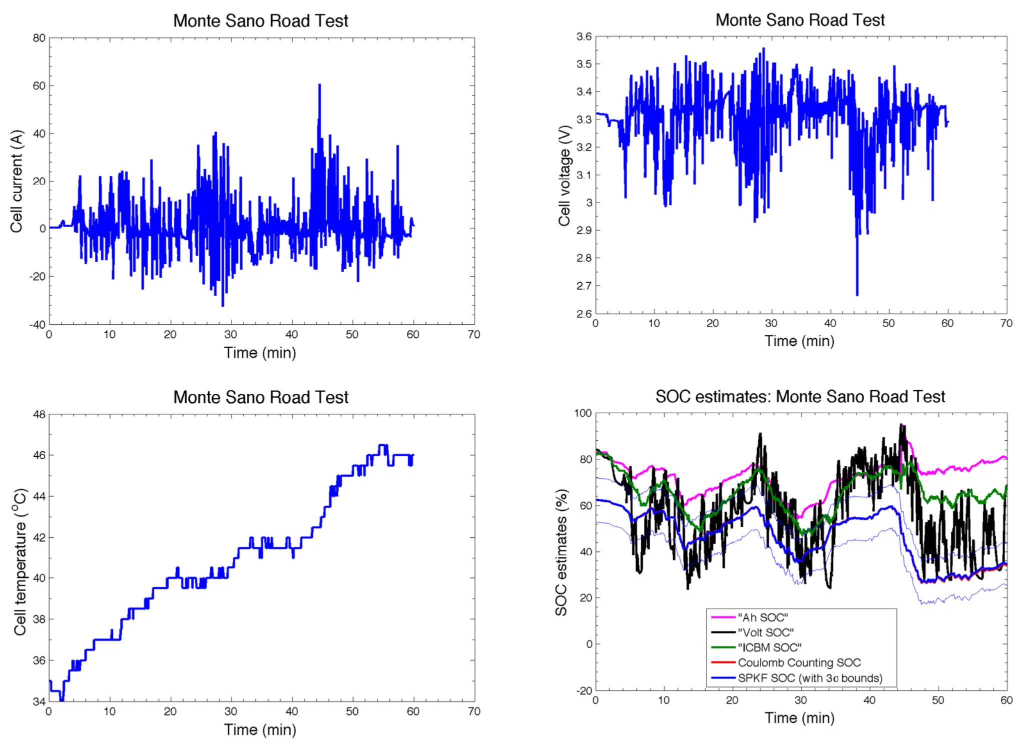

Figure 9: Vehicle test: road test up Mount Sano in Huntsville, AL.

Figure 10 shows how the data might be used to estimate SOL of a 18650 cell. The plot shows the analytical life cycle curve (blue) superimposed on actual cycle life data (red). The capacity of the new cell is 1125 mA-hr, and the capacity fades to 80% of this value (industry accepted measure of end of life) at roughly 500 charge cycles. As the cell ages and the capacity fades, the number of estimated remaining charge cycles is continually updated. The plot shows that the present capacity is roughly 1030 mA-hr, and this implies that there are roughly 200 charge cycles remaining.

UPCOMING PLANS

Our overall objective is to develop a BMS that forms a universal architecture that supports a wide range of battery chemistries, capacities, and manufacturer products.

During this work we demonstrated the feasibility of our standard BMS concept, and in subsequent work our intent is to complete development of a series of prototypes and demonstrate performance in a typical Silent Watch application.

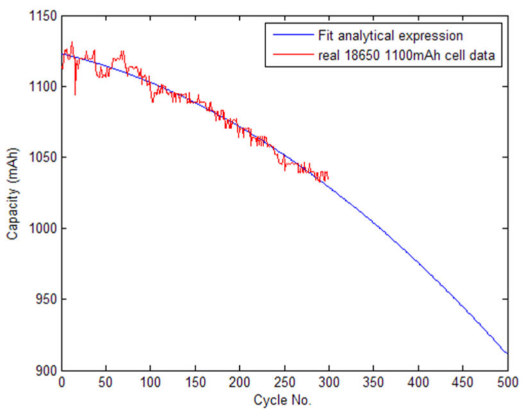

Figure 10: Comparison of equation 3 result with real 18650 Tenergy cell cycle life data.

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