

Practical PHM for Medium to Large Aerospace Grade Li-Ion Battery Systems

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ABSTRACT

In this paper we will discuss some practical aspects of health management for a rechargeable Li-ion battery system for aerospace applications. Industry working groups have developed guidance for the flight certification of this type of battery system, and we will show how this guidance is used in the design. We will also discuss safety features embedded in the battery system related to industry guidance; including cell energy balancing, internal temperature monitoring and emergency fuses. The keys to battery prognostics and health management (PHM) are analytic State of Charge (SoC) and State of Health (SoH) algorithms implemented in these battery systems. We show how these are developed and how we have tested them before deployment. These battery systems also collect data that is made available to the aircraft processing systems, e.g., Aircraft Health Management System, On-board Maintenance System, etc.. This allows for near real-time confirmation of proper operation of these battery systems as well as adherence to MSG-3 maintenance standards. We close with a brief discussion of the practical limitations in our implementation and a discussion of our ongoing and future development in this area.

1. INTRODUCTION

Lightweight, high capacity, rechargeable batteries, primarily based on compounds of lithium, are becoming widely available due in part to increased demand for electric vehicle energy storage. The cost of individual battery cells continues to drop, making these battery systems more

affordable for consumer products, where they are replacing mature technologies such as NiCd (Nickel Cadmium) and NiMH (Nickel Metal Hydride) (Economist (2008), Electropaedia).

This trend has impacted the aerospace industry as well, where lithium based batteries are starting to replace mature technologies for aircraft energy storage.

Aerospace batteries are required to deliver power reliably, have a reasonably long life, have a consistent output over their lifetime, and be certifiably safe. In addition, with a high premium on weight, in order to replace the older technology, they should be lightweight when compared to the traditional technologies.

While lithium based products still require more electronics than the NiCd and SLA (sealed lead acid) products, lithium chemistries are of considerably greater energy density than traditional technologies. Further, costs are trending downward. For example, a 2012 report in the McKinsey Quarterly (Hensley et al. 2012) shows that the price, around \$500/kWh then, could fall to \$200/kWh by 2020 and to about \$160/kWh by 2025. Though the numbers are approximations which do not deal with variations in lithium based chemistries, etc., they do illustrate the potential for lithium based energy storage as an advantageous alternative.

Lithium chemistries, being of considerably greater energy density than the traditional technologies, are also more volatile. This volatility has resulted in the need for development of battery management and safety monitoring subsystems for lithium-based battery systems. Despite many well publicized thermal issues with Li-ion batteries in recent times (see e.g., Chang et al., 2010, George, 2010, FAA, 2011, and NTSB, 2014), these systems are certifiably safe and reliable.

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Our battery systems have integrated battery PHM in the form of cell energy balancing, SoH as a measure for remaining useful life estimation, internal fault detection, and system status monitoring. These subsystems are supported by the integration of data collection, processing, storage and reporting; thus integrating high density energy storage and battery management into a single embedded package.

By additionally integrating the ability to send monitored data to the aircraft data systems, which can then be off-boarded for immediate processing, these battery systems enable redundant and sophisticated processing for both remaining useful life predictions as well as near real-time stress level assessments.

2. BATTERY SYSTEMS DESIGNED TO ENHANCE SAFETY

When any technology is developed or modified for use in a civil aviation application, a critical step in the deployment process is system certification. This is the process by which regulatory authorities are assured of the safety of the system with respect to itself and the environment. The civil aviation authorities work to ensure the safety of all concerned by levying the need to demonstrate that all risks have been reduced to an acceptable level prior to certifying the system for flight. Some of the standards, guidelines, and recommended practices published by organizations such as SAE and RTCA that are applicable to the certification of aviation batteries and battery systems are:

- ARP4754: Guidelines for Development of Civil Aircraft and Systems
- ARP4761: Guidelines and Methods for Conducting the Safety Assessment Process on Civil Airborne Systems and Equipment
- DO-160: Environmental Conditions and Test Procedures for Airborne Equipment
- DO-178: Software Considerations in Airborne Systems and Equipment Certification
- DO-227: Minimum Operational Performance Standards for Lithium Batteries
- DO-254: Design Assurance Guidance for Airborne Electronic Hardware
- DO-311: Minimum Operational Performance Standards for Rechargeable Lithium Battery Systems; see also FAA memorandum recommending the use of DO-311 (FAA, 2010)
- DO-347: Certification Test Guidance for Small and Medium Sized Rechargeable Lithium Batteries and Battery Systems

The number and types of tests required to certify a system for flight is determined by the impact on flight safety as determined by the safety analysis of that system, which, as may be inferred by the number of industry specifications listed above, may be considerable. There are generally five

design assurance levels (DAL) of safety assessment in the collective guidance. With the introduction of lithium based chemistries for aviation applications in recent years, regulatory “Special Conditions” are being levied on a case-by-case basis to supplement the number and types of tests required to certify traditional chemistries.

The additional monitoring and controlled levied by the “Special Conditions” drive the need for more electronic circuit based protection sub-systems. There is also need for high reliability/redundancy of the protection circuitry in order to satisfy the means of compliance associated with rechargeable lithium batteries.

There are some applications wherein an indication of battery status prior to dispatch is required for the flight crew. The status message for such an application may be a “Clear to Dispatch” indication, and may be annunciated to the crew on the flight deck, with the minimum criteria for the indication being SoH and/or SoC above required levels.

A common practice for measuring battery capacity is based on the voltage of a battery or the charge current of the battery, with the capacity of the battery being checked periodically via off-wing testing. These capacity tests are performed by removing the battery from the aircraft, fully charging it in a specialty shop, then determining the capacity stored by measuring the energy extracted through a complete discharge. This gives the new capacity of the battery (reflecting its SoH). The battery is then returned to the aircraft or serviced, if needed. This labor intensive method is meant to give confidence that the capacity (SoH) of the battery is not less than the required minimum level; allowing for an assurance of safety until the next battery off-wing test takes place.

With SoH data supported via “off-wing” tests, the crew reviews the SoC estimated data in real-time (i.e. via battery voltage) prior to flight. This provides the crew a go/no-go determination method.

2.1. Advancement in Battery PHM

The focus of battery PHM has been its application to automobiles (electrical vehicles (EV) and hybrid electrical vehicles (HEV)) but the techniques are similar when applied to civil aviation applications. The need for increased system certification and qualification testing brings additional constraints which need to be thoroughly dealt with before the product can be deployed. See the proceedings of the recent workshop (PHM Society, 2011) for an overview of the current state of the art in PHM research.

Typically, large rechargeable battery stacks consist of smaller cells that are connected in series and parallel to get the requisite voltage range and current capacity. Most of our Li-ion batteries contain eight modules in series that generate the requisite voltage, and the number of cells within each module connected in parallel as needed to supply the

necessary current. Consequently, the desired output for a given application can be adjusted in a modular fashion by adding or removing individual module packs and cells to meet the application requirements.

Charging and discharging the module cell stacks is a critical function because over-charging or over-discharging may prematurely degrade the cells within them. When all cells in a module are not identical, as is almost surely the case in practice, there is a danger of overcharging or excessively discharging any given cell if mechanisms are not emplaced to prevent it. The management of these functions is essential to maximize the life of the battery cells. This is fairly well known but see, e.g. the Battery University on the web for a lay exposition of this fact (batteryuniversity.com).

Our battery management system has a dedicated Battery Management Unit (BMU); circuitry to implement fault detection, safety assessment, fault diagnostics, SoH, SoC and communications via industry standard ARINC 429 to the central Aircraft Health Management System (AHMS).

The BMU combined with the battery chargers, allow the battery modules to be charged independently so as to prevent charging at higher than allowed voltages as may occur if one were charging modules in series. Further, the modules are discharged in a balanced fashion; meaning that the system is continuously working to balance the voltage in each module to better utilize the energy in the modules and to prevent any single module from prematurely terminating a discharge.

The independent charging system ensures that the cells are charged at the cell voltage level, the very act of which eliminates the need for independent balancing techniques during charge. Moreover, during the discharge cycle, cell energy is redistributed to ensure more energy can be removed from the system before low voltage cut-off.

Cell temperature has a critical role in the management of lithium based battery systems. We have incorporated a multi-stage power-down process by which the BMU ensures the control of the operation temperature of the battery system. There are multiple monitoring points for the temperature, including at the battery cell level and the internal ambient temperature of the entire battery system. Additional safety mechanisms in the battery system include physical fuses for over current protection.

3. SOC AND SOH FUNCTIONS

The topic of battery management is of considerable interest presently. As a result, there are numerous discussions in the literature covering a wide array of methods for SoC and SoH calculations. SoC, usually in a percentage, is a measure of the charge stored in a battery relative to its maximum charge storage capacity. Some aircraft batteries are essential for continuous safe flight and landing. In such case, the FAA Special Conditions require an indication of the SoC

for the flight crew. The dispatch ready requirement for the SoC may vary per application however a common value chosen is when the SoC is greater than 90%. When this condition is met, the dispatch criteria are declared to be satisfied.

SoH, expressed as a percentage, is a measure of actual capacity with respect to the declared battery capacity. We express the SoH as the ratio of the estimated battery capacity (in Ah) to the battery capacity when new, i.e., $SoH = \frac{SoH_t}{SoH_{new}}$. In this sense, the SoH can be additionally used as an advance indication of the future usefulness of a battery.

Our lithium batteries provide a signal to the flight crew indicating that the battery can perform the required mission in the form of a “Clear to Dispatch” signal. For battery systems whose mission involves starting aircraft engines, there may be an additional ‘Clear to Start’ indicator. Both of these indicators may be generalized as an indication that the battery has sufficient available capacity, given the present environmental conditions and age, needed to perform a task. We began this work with these criteria in mind and with an economically beneficial intention of eliminating the need for removing the battery for SoH testing.

3.1. Estimation of SoC and SoH

There are several practical constraints to consider for an embedded SoC estimator; not the least is the need to include present environmental conditions in the state model (not a trivial matter as these state parameters are, themselves, dynamic and must be estimated) as well as available computational throughput. There are numerous methods for measuring SoC and SoH in current literature. For example, Di Domenico et al. (2010) use a model of the transport phenomenon in their approach and Lin et al. (2013) use thermal conduction models in theirs. The approach that we initially settled on was to employ the Unscented Kalman filter (UKF). A good description of the UKF is available in Kim et al. (2009) or Terajanu (2011). We used the UKF to develop an estimator used to build the SoC algorithm.

During validation and under certain conditions, the results were promising but not consistent. The testing clearly exposed the sensitivity of the filter, which relies on a system state, or battery model. Even slight variations in the battery model caused divergence in the filter such that, in the end, the results required further refinement prior to being directly implemented as targeted.

The sensitivity of the system parameters led us to conclude that an adaptive model, necessary to accurately reflect the physical changes in the battery due to aging, was not likely to prove sufficient for our needs at this time. Such an adaptive model is impractical given our computational constraints and the need for a much larger set of data to fully characterize the different environmental effects. This is

not to say that the UKF is a bad observer for this problem in general. Other researchers have been very successful in its application. See for example, Daigle et al. (2012), and we may reconsider it at a future time. Our current program constraints drove us to look further.

3.2. State of charge (SoC)

While refinements with the UKF carried forward, in a parallel fashion, we set about exploring alternate methods for tracking the SoC. An alternate method for calculating the SoC relies on coulomb counting (CC). This method maintains an accurate audit of charge moving in and out of the system over time. The basic requirements for this method are to have accurate measuring of the magnitude and direction of the current flow. There are a variety of physical effects to overcome, hardware related and chemically based obstacles, which make even such a seemingly simple approach quite involved. There are non-linear effects stemming from environmental conditions, battery life, power losses, and measurement accuracy due to hardware limitations, which need to be considered. The ability to provide this estimate within the required accuracy depends critically on sensor accuracy and knowing the SoH of the battery. As SoC tracking via CC requires knowing how much total charge can be held by the battery, the two cannot be separated. The type of application facing the SoC algorithm is a strong determining factor in the suitability of the CC method, along with the accuracy requirements on the SoH and current sensor. Tracking the SoC of an automobile's battery is very different when compared to tracking the SoC of an airborne vehicle. This is due in part to the different charge and discharge scenarios experienced in those two examples. If relatively frequent full charge cycles are experienced, as in the case of civil aviation, calibration of the SoC estimate can take place with the completion of each charge cycle. This mitigates drift due to current sensing inaccuracies.

Voltage-based SoC estimation is another method for tracking SoC, and used in lead-acid batteries. However, because in Li-ion cells, the voltage decreases non-linearly with the SoC, this method requires precise measurement of the system voltage, accurate predefined knowledge of the voltage decay profile under a myriad of conditions and accurate knowledge of ambient conditions as well as knowledge of operational history to be effective in estimating SoC for these chemistries. These requirements make voltage-based SoC less appealing than the CC method, which, as noted, relies most heavily on the current sensor and SoH accuracy. The exact voltage discharge curve, depends on the specific chemistry of the Li-Ion cell used. In our case, lithium iron phosphate (LiFePO_4) is used. Unfortunately (at least for the purpose of voltage based SoC tracking), this chemistry has a very large section of the voltage curve that is nearly constant during discharge. In fact, approximately 80% of the charge might be stored

within 130 mV of the voltage profile, making it very difficult to use the relationship between the voltage and the state of charge in this region.

Other methodologies have been proposed in the literature, including physics and empirical model-based techniques. Like any analytical model, a physics-based model trades off complexity for accuracy. There are various approaches taken in the literature; such as Di Domenico et al. (2010), that incorporates a model of the transport mechanism of Li ions in the electrolyte to estimate charge. See also Malinowski (2011).

One can also identify critical parameters for an empirical model, conduct experiments and use the experimental data to identify correlations. Figure 1, taken from Electropaedia, shows the result of a series of experiments that has established usable capacity as a function of discharge rate and temperature. This data can be turned into lookup tables or more sophisticated regression models to form the basis of an empirical SoC model. This has shown success both in the laboratory and in practical applications, though it also illustrates the need for a very large set of data solely to characterize one aspect of the SoC.

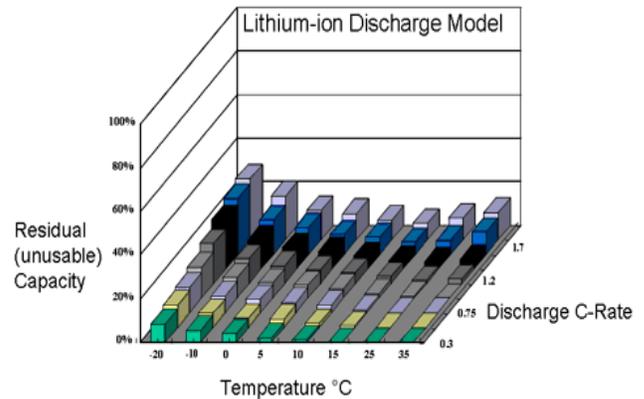


Figure 1: Experimental data to support a model

For our battery system, the design goal was to implement a SoC (and SoH) algorithm for aerospace applications that gives an estimate within a given error band when compared to the actual SoC and to do so in real-time. The end goal is to eliminate the need for periodic removal of the battery system from the host aircraft for SoH testing.

3.2.1. The implemented algorithm

Our early empirically based SoC algorithms were not successful in reaching our targets. Validation testing exposed weaknesses in correlating the slower time constants of the model with the rapid dynamic responses resulting from changing load conditions. As a result, a new approach was formulated which combined a voltage based method and the CC tracking method. The SoC is determined by using a weighing factor to change the amount of reliance on

SoC calculated based on CC vs. the open circuit voltage (OCV) vs. SoC data on the cells (this data is collected during assembly and stored on the battery). The weighting scheme will be described further below.

A charge cycle is completed when the upper cut off voltage is reached in constant current mode followed by a constant voltage charge. Most often in civil aviation, the battery will complete a charge cycle on a regular frequency. By definition when fully charged the actual SoC is at 100%. We calibrate the SoC estimate by setting it to 100% whenever the unit completes a charge. This is done during the testing phase.

The OCV charge/discharge curve for lithium iron phosphate has a large, nearly constant voltage region, e.g., a 15% SoC range may be represented by an approximately 3 mV voltage change. Voltage readings in nearly constant regions are not sufficiently reliable due to the necessary accuracy of the measurement in such a region. For this reason, our algorithm incorporates a disparity weighting technique for the final SoC estimate. When not charging or discharging, the SOC_{OCV} is combined with the most recent SOC_{CC} by weighting the contribution from each method as a function of the OCV.

The weighting curve is given through incremental or differential capacity analysis as a scaling factor.

$$Q_{diff} = \frac{1}{Q} \frac{d(Ah)}{dV}, \quad (1)$$

Where Q_{diff} is the differential capacity, Q is the total capacity in coulombs, and $d(Ah)/dV$ is the derivative of the amount of charge added or removed with respect to the cell voltage change.

The method relies on the fact that in regions where a large amount of charge ($d(Ah)$) is stored with a very small change in voltage (dV), the SOC_{CC} is likely to be more accurate than the SOC_V , and is thus amplified.

With this real-time algorithm in place several tests were run in our actual battery system, at a variety of currents and temperatures. The test set included “ping-pong” testing; where we ran charge and discharge cycles for a variety of fixed time periods to quantify the effect of drift in the SoC estimate over time, drift being a known weakness of the CC method. In the long run, the drift is overcome by the battery charge cycle. When the battery charges to full capacity during normal operation, the SoC is known to be 100%. When reset to the known value, the drift resulting from the CC accumulation measurement error is eliminated and the cycle restarts. The results, which meet our expectation, are discussed in the results section.

3.3. State of Health (SoH)

As in the case of SoC, there are several methods for measuring SoH. Model-based, as well as empirical, methods

are popular for determining SoH Williard et al. (2011) give a brief survey of some of these techniques. Hu et al. (2011) develop a multi-scale model for determining SoC and SoH based on an Extended Kalman Filtering technique. He et al. (2011) demonstrated an empirical model based on simple regression equations and optimal updating techniques. Le et al. (2011) show some very promising results using empirical techniques for the determination of SoH. A comprehensive presentation from Salman, et al. (2011) discusses what GM Research has been doing in all BPHM fields. Similarly, Klein (2011) gives a good overall perspective of BPHM.

Typically, aviation batteries have an end of life defined as when the measured capacity is at 80% of the declared capacity. Capacity for this definition is determined at a rate of discharge that would result in the rated capacity of a new battery (1C) at room temperature. In most existing batteries, the capacity can only be measured in the lab. This requires the battery to be removed prior to testing and replaced which testing is completed. The goal of a SoH calculation is to determine the battery degradation without removing the battery from the installation.

To mitigate uncertainty we intentionally load stress the battery to compare the impedance of the cells at the present time against the impedance of those same cells when they were new.

The basis for our SoH estimation is a multi-stage load test built into the battery. When the assembly of a battery unit is complete, an initial impedance test is conducted. This initial impedance is saved in the BMU and used as the baseline for the SoH calculations for the life of the battery unit.

SoH tests are initiated automatically by the BMU at regular time intervals or at an end-of-charge event. The accuracy of the SoH results is increased when the battery SoC is at a known level; therefore the SoH test is run after every completed battery charge.

The BMU initializes the module level impedance calculation by loading modules at a discharge rate designed to completely deplete the battery within 1 hour, or a 1C discharge rate. The individual module voltages and currents are logged. The BMU then initializes a high rate discharge for all modules. Again the module voltages and currents are logged. The voltage and current deltas are calculated and compared to determine the modules impedances.

Cell impedance can be influenced greatly by temperature therefore the cell impedances must be scaled by a temperature scaling factor so the measured impedance can be correlated to the initial impedance measurement. This temperature factor polynomial was experimentally derived and is of the form:

$$T_f = \frac{(a+T*(b+T*c))}{(1.0+T*(d+T*(e+T*f)))} \quad (2)$$

Where T_f is the temperature scaling factor, T is the measured temperature and a , b , c , d , e and f are experimentally determined coefficients.

A ratio of the temperature scaled module impedances to the initial module impedances, Z_{dc_ratio} , is calculated and used as an input into another polynomial that was also experimentally derived.

The SoH polynomial is shown in (3).

$$SoH = \frac{(g+Z_{dc_ratio}*h)}{(1.0+Z_{dc_ratio}*(i+Z_{dc_ratio}*j))} \quad (3)$$

Where Z_{dc_ratio} is the ratio of temperature scaled impedance to initial impedance and g , h , i and j are experimentally determined coefficients.

Combined with boundary conditions and weighted data such as temperature historical measurements, the results have correlated well to the actual SoH of the battery modules.

4. RESULTS

Before discussing the results, the legends in the following figures will be described. The BMU has an on board embedded system which logs and reports the SoC, as measured by the Securaplane system, over time. This corresponds to the “BMU Reported SoC” seen in the graph legends. A precision external data logging system was connected to the BMU to measure the voltage across and current into a given module. These voltages and currents were used to calculate the “Measured SoC” seen in the graph legends. The % error from the graph legends corresponds to the absolute value of the percent error between the “BMU Reported SoC” and “Measured SoC” as seen in equation 4.

$$\% \text{ Error} = \left| \frac{\text{"BMU Reported SoC"} - \text{"Measured SoC"}}{\text{"BMU Reported SoC"}} \right| \quad (4)$$

The two figures (Figure 2: Module A - SoC and Percent Error and Figure 3: Module B - SoC and Percent Error) show how our SoC algorithm tracks the measured SoC for two individual modules, A and B. The algorithm is generalized for all modules and as such the percent error does vary between modules; this accounts for the error discrepancy between module A and module B when comparing Figures 2 and 3.

Also of note is the jump in the BMU reported SoC data at the end of the data sets. This is the aforementioned algorithm calibration when the end-of-charge is detected. The error between the final SoC value and 100% arises when a 0% SoC is assumed when the module is not actually at a 0% SoC value. This calibration can be seen in the Figure 2 and 3 for both modules A and B.

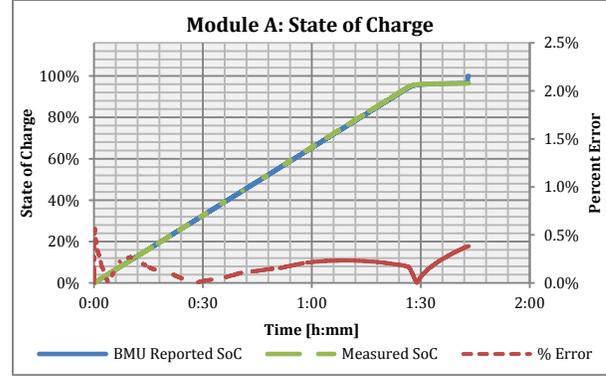


Figure 2: Module A - SoC and Percent Error

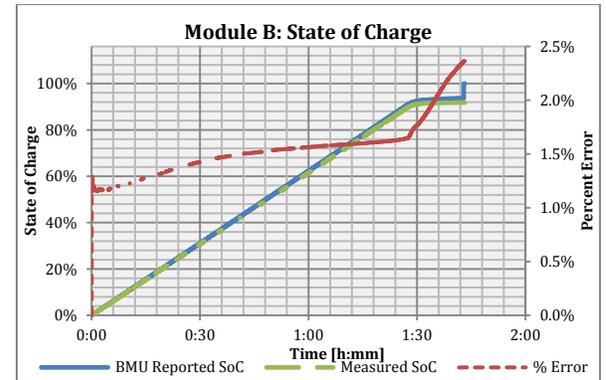


Figure 3: Module B - SoC and Percent Error

Also included in the figures is the absolute value of the percent error for modules A and B. For both modules this error is under 2% for the majority of the charge cycle. The rise in percent error near the end of the graphs occurs as all modules transition to the constant voltage portion of the charging cycle and the charge current decreases. Due to the dynamic range of current required to be measured, our BMU inaccurately measures very low current values. This is the source of the error during the constant voltage charge mode.

The “ping-pong” test results for module A are shown in Figure 4: Module A - “Ping Pong” Test Results. This figure shows the robustness of the algorithm over time with varying levels of current charge or draw. A divergence between the measured SoC and the BMU reported SoC can most easily be observed at 1:15, 2:15 and 3:15 on the figure. The BMU is required to measure a large current range; ones of amps to hundreds of amps. The divergence in Figure 4 is due to the BMU’s inaccuracy measuring currents on the lower end of the measurement spectrum. To verify the accuracy of the algorithm an additional dataset was created and plotted which compensates for the incorrect current readings of the BMU.

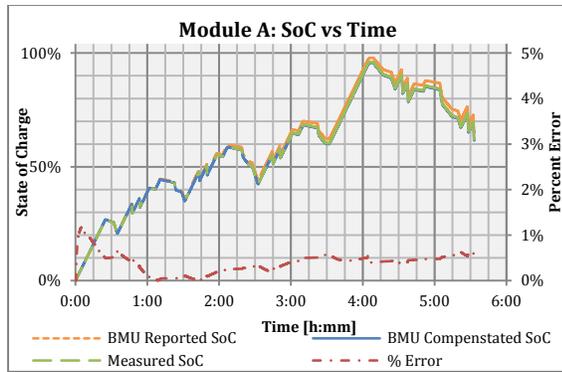


Figure 4: Module A - "Ping Pong" Test Results

SoH testing on substantially depleted battery modules has not yet been completed. However initial test results shown in Figure 5: Module B SoH show relatively stable readings that establish a downward trend. The SoH progressing lower as the battery is aged is congruent with the expectation. Earlier results (prior to test number 26) show inaccuracies in the temperature scaling coefficients that are shown to be resolved from test 26 onwards. These initial results are promising; however more exhaustive testing is required to validate our SoH algorithm.

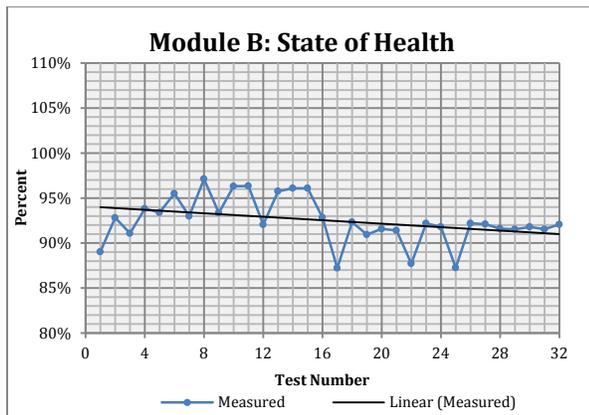


Figure 5: Module B SoH

5. FUTURE WORK

The practical implementation of high accuracy SoC and SoH algorithms in embedded real-time battery systems has proven quite challenging. Such implementations require both measurement accuracy and robustness to environmental effects. The most significant challenge has proven to be developing accurate scaling factor calculations for consistent SoH results and having all necessary parameters accurately measured by the BMU for precise SoC results. Improvement to the algorithm's accuracy and robustness can be attained through further refinement of

these parameters and increased hardware sensitivity and characterization.

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BIOGRAPHIES

Dr. Mike Boost Mike Boost is the Vice President, Technology at Securaplane, a Meggitt company, and holds a Ph.D. in Electrical Engineering from Concordia University in Montreal, Canada. Mike has over 20 years of experience working on power generation and conversion, 12 years within aviation. Through his career, Mike has researched

and developed disruptive technologies focusing primarily on: Power conversion equipment including multi-chemistry battery chargers, cyclo-converters, and engine start inverters; and Energy storage devices including rechargeable lithium engine start batteries. Mike's lithium experience began in 2006 with R&D for a rechargeable lithium system. Currently, Mike is overseeing numerous lithium projects which include engine start and emergency lithium batteries.

Kyle Hamblin obtained his B.S. in Electrical Engineering from the University of Akron, Akron, Ohio, USA. From 2008 to 2010 he worked on wireless power transfer and charging systems for NiMH and lithium battery technologies in the consumer electronics industry. In 2011 he transferred to Meggitt Aircraft Braking Systems and ultimately to Meggitt USA in 2012. His research interests include power management, wireless power transfer, embedded systems, health management of Li-ion battery systems as well as robotics.

John Jackson was born in Columbus, Georgia. He received the BS CmpE degree (with highest honors) from the Georgia Institute of Technology, Atlanta, Georgia, USA, and the ME EE degree from the University of Arizona, Tucson, Arizona, USA, in 2003 and 2007, respectively. From 2004 to 2005, he worked for the University of Arizona, as a Graduate Teaching Assistant for an introductory circuit analysis course. From 2005 to 2006, he worked for Securaplane, a Meggitt company., as an Electrical Engineering Intern in the Sustaining Engineering Group. In 2007, he was promoted to a full-time Electrical Engineer and has since worked on several projects that utilize Li-ion battery technology. His research interests include analog behavioral modeling of Li-ion batteries for SPICE simulation, battery management system design, and low-power circuit design techniques for battery applications.

Dr. Yair Korenblit obtained a B.S. in Materials Science and Engineering with a minor in Electrical Engineering from the University of Florida, Gainesville, Florida, USA. He also obtained an M.S. in Materials Science and Engineering and a Ph.D. in Polymer, Textile and Fiber Engineering, both from the Georgia Institute of Technology, Atlanta, Georgia, USA. He has been working with Meggitt, USA Inc. since 2012 on topics ranging from lithium-ion state of charge and health to project management and materials engineering issues. He has previously worked on carbon materials for energy storage applications for approximately five years at the Ulsan National Institute of Science and Technology (Ulsan, Korean) and the Georgia Institute of Technology and was involved in shorter term projects involving various research topics ranging from structural to medical materials. He has won multiple oral and poster presentation and fellowship awards while working on energy storage research at the Georgia Institute of Technology. He is a member of the IMechE.

Dr. Ravi Rajamani joined Meggitt in 2011 as an Engineering Director, after spending nearly 11 years with United Technologies Corporation, first at the Research Center, and then with its Pratt & Whitney division. Before this he was with the General Electric Company for 10 years, most closely associated with its Research Center and the Power Generation business, but working with all other businesses as well. While his interests have changed over the years, his primary focus has been the area of controls and diagnostics of gas turbines for aerospace and industrial applications. He has published four book chapters, numerous papers in refereed journals and conference proceedings, has been invited to speak at conferences and institutions around the world, and has 24 patents to his name. He is active within SAE's Engine Health Management (E-32) and Integrated Vehicle Health Management (HM-1) committees, currently serving as the chair of HM-1. He is also active in the PHM Society and is serving as the general chair of the 2014 European PHM conference in Nantes.

Thom Stevens has been in advanced research and development in the aerospace and defense industries since 1999. He holds a Bachelor of Science Degree in Electrical Engineering and a Bachelor of Science Degree in Computer Science and Engineering, both from Northern Arizona University. After entering industry in 1999, he earned a Master of Science Degree in Electrical and Computer Engineering from the University of Arizona in 2006, where he developed a novel method for anticipating change in dynamic systems. Thom is currently pursuing an interdisciplinary Ph.D. in Statistics and Cognitive Science. Thom's research interests include adaptive systems and predictive methods.

Joe Stewart received his Master of Science in Electrical Engineering from the Washington University, St. Louis, MO. in 1992 and Bachelor of Science in Electrical Engineering from the University of Colorado, Boulder CO. in 1988. Most of his career has been developing application and embedded systems software for various avionic platforms. His current research interest is in advanced signal processing algorithms for computing the State of Charge for Lithium Ion batteries for the Aviation industry.