Editor’s note: I had the distinct pleasure of meeting with the PCoE coordinator, Kai Goebel, thanks to the Speed2Design program by Littelfuse (I urge you to enter the contest and experience an incredible journey behind the scenes at NASA with some of this country’s brightest and innovative minds). For those of you who say we should not be spending money on space-related research---take another look as you read on and think about what the following can do for safety and reliability in the commercial and industrial sectors regarding battery, IGBT and other critical areas where failure of a component is not an option.

Prognostics: An engineering discipline focused on predicting the time at which a system or a component will no longer perform its intended function.

At the core of prognostic technology development is, as NASA puts it, “The investigation of physics-of-failure at the component level. Modeling damage initiation and propagation at this level is a key element in describing component health. Just as important is the investment of resources into algorithm development to provide the estimates for remaining component life and for uncertainty management.”
Practical examples of Prognostics research

Application Examples
- Electro-Mechanical Actuators
- Electrochemical Storage
- Electronics
- Valves, Pumps
- Composite Materials
- Solid Rocket Motors
- Rover
- UAV
- Distributed Health Management

Green Application Examples
- Wind Mills
- Biomass
- Building Health Management
- Microgrid Health
Two areas in Kai Goebel’s lab intrigued my power management engineering mind: Battery and IGBT prognostics work.

**Battery prognostics**

My interest here is fueled by the Boeing 787 battery “failures” and electric vehicle battery “failures”, both using the Lithium Ion technology. I’m a firm believer that any technology, if designed properly, is safe—and that includes Lithium Ion cells as well as Nuclear Power.

Batteries in the International Space Station (ISS), the Chevy Volt or the Boeing 787 all need to know and understand battery exhaustion which can cause system performance degradation or even a catastrophic failure. NASA also performed the prognostic analysis for the Mars Rover batteries—you can’t change batteries easily up there.

Goebel’s team has taken on the responsibility to examine this phenomenon with the following goals:

- Investigating prognostic algorithms
- Provide a framework for a variety of applications
- Improve the state-of-the-art battery health management
- Demonstrate these capabilities on hardware
- Integrate prognostics with decisioning framework

This video shows an example application of an electric unmanned aerial vehicle (eUAV), a green development possibility in aviation, being tested, monitored and evaluated for optimum operation travel time and distance with a safe landing that can be predicted under many varying conditions.

**Video courtesy of NASA**

Here is the way NASA PCoE goes about the algorithm development process:

The key to useful prognostics is not just to determine the remaining life estimate, but to assess the confidence of the uncertainty estimate expressed through a Probability Density Function (pdf). The pdf allows the computation of confidence bounds.

In 2006, a catastrophic battery failure occurred in NASA’s Mars Global Surveyor. Investigations revealed that the Surveyor was given a command to go into a safe mode. That positioned the battery radiator toward the sun which inevitably raised the batteries temperature and they lost their charge capacity.

Prognostics and Health Management (PHM) dynamic models have been built for lithium ion batteries in hybrid electric and plug-in hybrid EVs. The models, take into their estimations, nonlinear equilibrium potentials, rate and temperature dependencies, thermal effects, and transient power response. Highly sophisticated reasoning schemes have been applied to feature vectors whose job is to estimate state-of-charge (SOC), state-of-health (SOH), and state-of-life (SOL). The problem was that end-of-life was still difficult to predict from SOC and SOH estimates because environmental and load conditions will differ from the training set.

Using advanced regression, classification, and state estimation algorithms help solve this problem.
and aid in the data collection scheme for battery health management. The dramatic improvement between different prediction techniques was found to be in their ability to learn complex non-linear degradation behavior from the training data and discard external noise sources.

**The particle filter approach**

The *particle filter (PF) approach*, as compared to other regression methods, was found to give results in remaining useful life (RUL) distributions which have better precision (narrower pdfs) by several $\sigma$s, if approximated as Gaussian. The main drawback in this method is that it requires a more complex implementation and computational overhead than the other methods---an acceptable tradeoff. See reference [1] for Goebel’s 2008 paper on this.

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**Goebel discussed the Science of predicting RUL during my trip**

The prognostics architecture is shown in Fig. 1. In discrete time $k$, the system is provided with inputs $u_k$ and provides measured outputs $y_k$. The damage estimation module uses this information, along with the system model, to compute an estimate $p(x_k, \theta_k | y_{0:k})$, represented as a probability distribution. The prediction module uses the joint state-parameter distribution and the system model, along with hypothesized future inputs, to compute EOL and RUL as probability distributions $p(EOL_{kp} | y_{0:kp})$ and $p(RUL_{kp} | y_{0:kp})$ at given prediction times $k_p$.

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*Prognostics architecture (Image courtesy reference [2])*
RUL is derived by extrapolating out capacity estimates (of the 100 particles or points of sampled values used in this application) into the future (See Figure 2) until the predicted capacity hits a certain pre-determined end-of-life threshold. The weight vector of the PF algorithm is used to calculate the RUL distribution.

The Prognostics lab has a very good environmental chamber (Image courtesy of NASA Ames)

Kai Goebel told me that the University of Maryland is also doing some very good recent prognostics work that is useful in NASAs algorithm (See reference [3]) They showed an integrated approach to predict RUL of lithium ion batteries by using model-based and data-driven methods. They developed an empirical model to emulate the battery degradation trend. To update the model, they made real-time measurements. An online model update set of data was proposed in a PF-based framework to deal with prognostics uncertainties that come from many sources in the prediction like battery unit-to-unit variations. Essentially, the PF uses the self-adapted aging model to predict the RUL of the battery in the form of a pdf. They used filtered data in a moving window, employing the Levenberg-Marquardt optimization method, to adjust the model’s parameters in real-time based on nonlinear
least-squares optimization.

In the experimental results in reference [3], Type A battery has a rated capacity of 0.9Ah; type B battery has a rated capacity of 1.1Ah. The battery capacity was estimated via Coulomb counting method.

Prognostics results of A1 at the 22th cycle using the proposed prognostics algorithm. The update degradation model fits the historical aging curve well (the real data between the 1st and the 22th cycle) The Random Walk Particle Filtering (RWPF) method did not fit the historical aging curve as well as the proposed method in reference [3] (Image courtesy of reference [3]).
Prognostics results of A2 at the 100th cycle using the proposed prognostics algorithm. The update degradation model fits the historical aging curve well (the real data between the 1st and the 100th cycle). The Random Walk Particle Filtering (RWPF) method did not fit the historical aging curve as well as the proposed method in reference [3] (Image courtesy of reference [3]).

Time lapse of prognostic results

Goebel demonstrated a time lapse of the prognostic results in action in the following photos I took in the lab:
Lithium ion cells in thermal blocks

Lithium ion cells were placed in thermal blocks to uniformly control cell temperature and control temperature transients (Image courtesy of reference [1])
Prognostic test bed at NASA Ames Research Center (ARC) to investigate different prognostic methodologies (Image courtesy of reference [1])
The power semiconductor element: Insulated Gate Bipolar Transistor (IGBT) analysis

NASA Ames also showed me their latest project that investigates aging characteristics of power semiconductor components. Algorithms are also developed as we speak for remaining life estimation here as well as what we saw in batteries.

The semiconductor industry naturally does common and mature reliability work with these ICs, but NASA’s work focuses on condition-based health management. So, this is the determination of any presence of abnormal conditions and also estimation of remaining life depending upon anticipated future usage.

I saw the latest IGBT test equipment for IGBTs during my visit to the Prognostics lab
This effort is critical in improving the safety of operations and will significantly contribute to improved mission success rates with the added bonus of reducing the cost of unscheduled maintenance. (How might this help the commercial and industrial semiconductor industry and those who use them in their designs?)

IGBT test platforms are being built to run tests at NASA Ames (Image courtesy of NASA Ames)

Normally thermal and electrical stresses are the common aging methodologies. Thermal cycling and ongoing temperature overstress are the most common thermal stress methods. Thermal cycling, with its rapid changes in temperature differentials, is the companion test to accelerate aging in electronics.
The system implementation is divided up into stages to manage the project complexity. It consists of a set of commercial instruments attached to a custom-built hardware system controlled by a software framework developed in LabVIEW. (Image courtesy of NASA Ames)

Preliminary thermal overstress tests were done on IR IGBTs #IRG4BC30KD during the system development. The IGBT was attached to the transistor test board without a heatsink.

**Test conditions**

- The IGBT collector-emitter junction was connected in series with a load power supply plus a 0.2Ω load resistor.
- A 50Ω current measurement resistor was connected between the gate driver and the IGBT gate.
- A thermocouple was attached to the IGBT case to measure temperature.
- The gate signal was a PWM signal with 10V amplitude and a frequency of 10 kHz that had a 40% duty cycle, like a small SMPS would have.
- A hysteresis temperature controller with set points of 329oC and 330oC was connected to the system and switched the gate voltage for its control mechanism.
- The load power supply voltage was then increased from 0 to 4V over several minutes until the heatsink temperature rose to 330oC and the temperature controller began cycling.
- An additional temperature controller, with set point at 340oC, was programmed to turn off the load power supply and end the test when thermal runaway and latching failure would occur.

The IGBTs failed early in the first few minutes or survived 1 to 4 hours before loss of gate control and thermal runaway.

A scatter plot of package temperature vs. switching transient peak voltage for a single IGBT under degradation. (Courtesy of NASA Ames)

This experiment is ongoing and the scientists are observing a degradation trend with transient peaks in similar temperature ranges decreasing over 10% during the experiment. The root cause is in question. An indicator of semiconductor degradation under severe conditions is observed and could be intrinsic degradation. But a more likely cause is thermal impedance degradation of the package causing increases in internal temperatures. Tests will continue to investigate this failure precursor’s cause. Stay tuned.
References

1 Prognostics in battery health management, Kai Goebel, Bhaskar Saha, Abhinav Saxena, Jose R. Celaya, and Jon P. Christophersen, 2008

2 Model-based Prognostics with Concurrent Damage Progression Processes, Matthew J. Daigle, Member, IEEE, and Kai Goebel, Member, IEEE

3 Prognostics of Lithium-Ion Batteries Using Model-Based and Data-Driven Methods, Chaochao Chen and Michael Pecht, Center for Advanced Life Cycle Engineering (CALCE) University of Maryland, College Park, USA

Good book by Wiley "Intelligent Fault Diagnosis and Prognosis for Engineering Systems"

More EDN articles on this topic:

- Boeing 787 battery/charging system solutions—Good design or not?
- Boeing 787 and Lithium Ion battery failure
- Proper Lithium-Ion battery charging and safety
- The Dreamliner saga: When your solution is more than just a software patch
- Dreamlining Boeing and batteries
- Teardown: High-voltage Li-ion battery stack management - the drive for safe power