Ridgetop Group Develops Fast and Accurate Prognostic Algorithm to Reduce Costs of Aviation Electronics Maintenance

Adaptive Remaining Useful Life Estimator™ ARULE™

The aviation industry has long been plagued by the need to keep numerous spare line replaceable units (LRUs) on hand because the state of the art for "predicting" component failures and performing preventive maintenance has been based on general statistical methods. The most common method, based on mean time between failures (MTBF), is costly because it schedules pre-emptive replacement of LRUs based on the average of a broad range of time-to-failure (TTF) records rather than on the actual condition of assemblies and components. As a result, LRUs that might still be good are replaced arbitrarily, and assemblies that have had intermittent failures with no known cause are replaced rather than repaired on the flight line.

Condition-Based Maintenance Breakthrough

Electronic prognostics leader Ridgetop Group has developed ARULE™, Adaptive Remaining Useful Life Estimator™ (patent pending), the first prognostic algorithm that provides a fast, accurate remaining useful life (RUL) estimate for use in integrated electronic prognostic systems in condition-based maintenance (CBM) applications.

ARULE employs memory and calculation methods that are so efficient that an accurate RUL estimate can be produced on a system component or assembly in less than 200 microseconds. This breakthrough high speed is particularly important in a system that has thousands of different pieces of equipment for which accurate health information needs to be obtained in a very short period of time, such as a net-centric CBM system for multiple squadrons and groups in a wing.

How ARULE Works With ePHM Data

An integrated electronic prognostic and health management (ePHM) system processes data collected from sensors to produce RUL estimates, which are then put into a CBM system. ARULE is currently designed for use in a system component or assembly subject to fatigue damage. ARULE processes data (real-time or otherwise) that represent either a fault-to-failure progression (FFP) or a degradation fault profile (DFP) signature. An FFP or DFP signature represents a physical state, such as temperature, noise, voltage, or current, that exhibits a measurable change related to the effects of damage. Some FFP examples are leakage current, ripple voltage, fault counts, and increase in frequency. Some DFP examples are battery charge, loss of transmission power, fuel capacity, and decrease in frequency. When ARULE accepts FFP signature data[1], it adapts an FFP model to the data, then uses the adapted model to produce RUL estimates. The models and an adaptive-reasoning processor have been designed and implemented in both the MATLAB® and Java™ programming languages.

Generic fault-to-failure models can be used as is, or modified, or one or more new models can be defined. Data sets can be linked to a model-processor pair. ARULE has an application programming interface (API) to let an application specify a model and invoke ARULE. ARULE then adapts a model to the data, and uses the adapted model to produce RUL estimates with increasing accuracy. ARULE has been tested with lithium-ion battery health data, as described in this article, power supply filter capacitor ripple voltage data, and data from ball grid array (BGA) solder joint faults in printed circuit boards.

ARULE Approach

The ARULE approach requires a diagnostic sensor to obtain data that is above a predefined "good-as-new" floor and below a "failed" ceiling.

[1] D. Goodman, J. Hofmeister and J. Judkins, Electronic Prognostics for Switched-Mode Power Supplies, Microelectronics Reliability, Vol. 47, Issue 12, December 2007, pp. 1902-1906.

Fault-to-Failure Progression Signature

The progression of data from a floor to a ceiling is defined as a fault-to-failure progression (FFP) signature. The FFP profile can be modeled to have beginning and end times, and floor and ceiling magnitudes. As data is presented to ARULE, the model is adjusted to account for changes in data position, velocity, and acceleration. After the model is adjusted for a received data point, it is used to produce an RUL estimate.

Degradation Fault Profile Signature

ARULE recognizes and uses a degradation fault profile (DFP) signature, such as that represented by decreasing power output of a system. ARULE handles DFP signature data in a similar manner to the FFP examples presented in this article, the difference being that FFP signatures generally increase in magnitude while DFP signatures generally decrease in magnitude.

Open Architecture

ARULE uses an open architecture application programming interface (API) to do the following: (1) let a model be defined or used; (2) accept input data and output RUL estimates and an adapted model (see Figure 1).

GET-INITIALIZE MODEL

```
%***************************************************************************
%   get ARULE model
%***************************************************************************
MODE    = 0 ;    % 0 = init, 1 = process data points
[RC RS MODEL ] = AMGR(MODE,MNAME,MLOC) ;   %  get model to initialize

if RC == 0
    MODE = 1;                      % process data
    INMOD = struct(MODEL) ;        % get the model structure
else
    display('MODEL NOT FOUND')
    display(MNAME)
    error('TBA')
end
```

INPUT: MODEL & DATA   OUTPUT: MODEL & RUL

```
%***********************************************************************
%   place a data point into the data space
%***********************************************************************
   [RC RS MODEL RUL] = AMGR(MODE,MNAME,MLOC,INMOD,DATA) ;

   INMOD = MODEL ;          % get updated model for next data pt
```

Figure 1: API to get an ARULE model

Exponential Functions and Fatigue Damage

Fatigue damage phenomena can be modeled using single exponential functions, double (or higher) exponential functions, or as compound exponential functions.

Straight-line Representations of Models

Appropriate logs of exponential functions result in one or more straight lines, which in turn can be used to approximate real data. Some examples are Bode plots, square-law diode equation, and electron/hole mobility. Manipulating the straight-line representations of models is the equivalent of manipulating the models.

ARULE Examples Using Real Data

NASA Battery Health Study

In 2008, a NASA team[2] headed by Kai Goebel, Ph.D., examined PHM issues using battery health management of Gen 2 cells, with an 18650-size lithium-ion cell as a test case. NASA identified an FFP signature as being the electrolyte resistance plus the charge transfer resistance (RE + RCT) and a DFP signature as being the battery charge; NASA defined a 30% fade in capacity as a failed battery state; and verified there was a linear correspondence between capacity, C/1, and the (RE + RCT) impedance.

ARULE Modeling of Battery Health Data

Ridgetop used the NASA impedance data to create an ARULE FFP model (pink plot shown in Figure 2) that had a 441-day (63-week) predicted failure date.

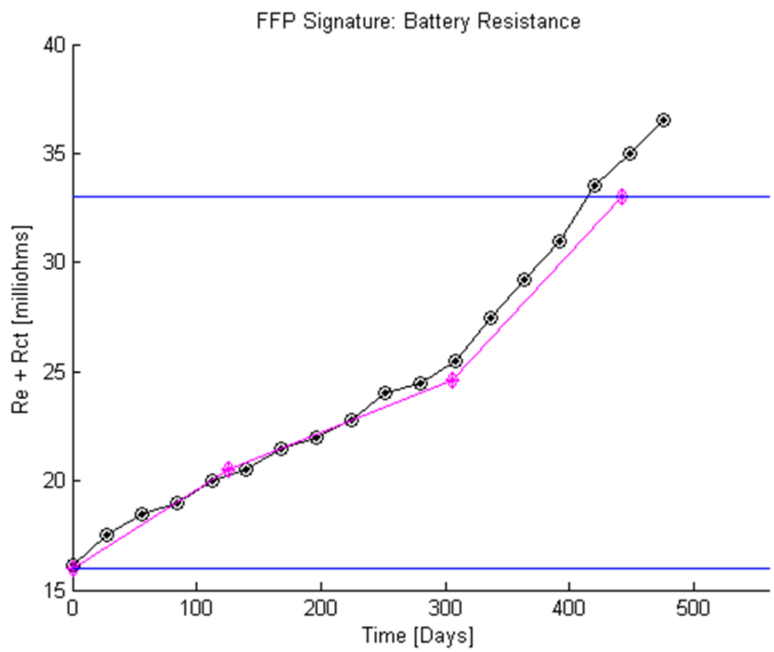

Figure 2: NASA impedance data (circled dots) was used to create ARULE model (diamonds)

The data was processed point-by-point by ARULE, and the returned RUL estimates were saved and plotted versus time (Figure 3). The accuracy of each returned RUL estimate was calculated and plotted, as shown in Figure 4.

[2] K. Goebel, B. Saha, A. Saxena, J.R. Celaya and J. Christophersen, Prognostics in Battery Health Management, IEEE Instrumentation & Measurement Magazine, August, 2008, pp. 33-40.

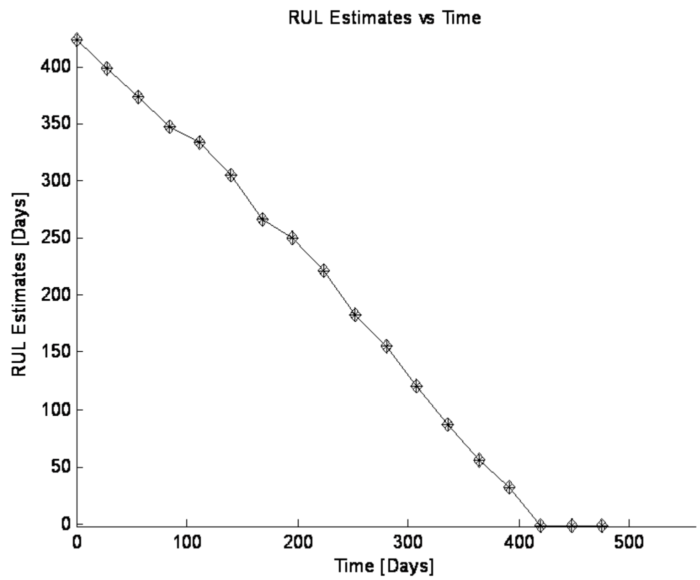

Figure 3: RUL estimates produced by ARULE for the battery resistance data

Figure 4 shows that the RUL estimates from ARULE converge, and the error in the RUL predictions made after about 180 days is less than 5% (20 days or less), which is very accurate given a 28-day measurement period. In Figure 3 note the convergence from a 441-day predicted failure of the original model to the actual failure on the 420th day.

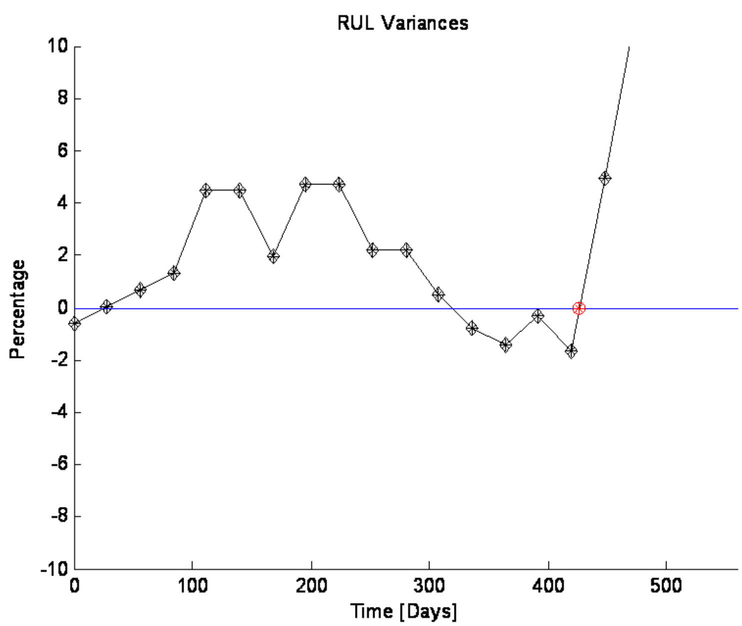

Figure 4: Accuracy of ARULE estimates; each black dot is the percent error between predicted time and actual failure time; actual failure time is shown by red dot at 420 days

Ridgetop then used the same ARULE model to process extrapolated NASA data that diverges from the model as shown in Figure 5: the non-adapted model predicts failure day in 441 days, but the data reaches the failure threshold much slower: 504 days. The extrapolated data diverges from the model at about 336 and as shown in Figure 6, ARULE detected the divergence and adjusted model accordingly on day 364 and predicted failure on day 504.

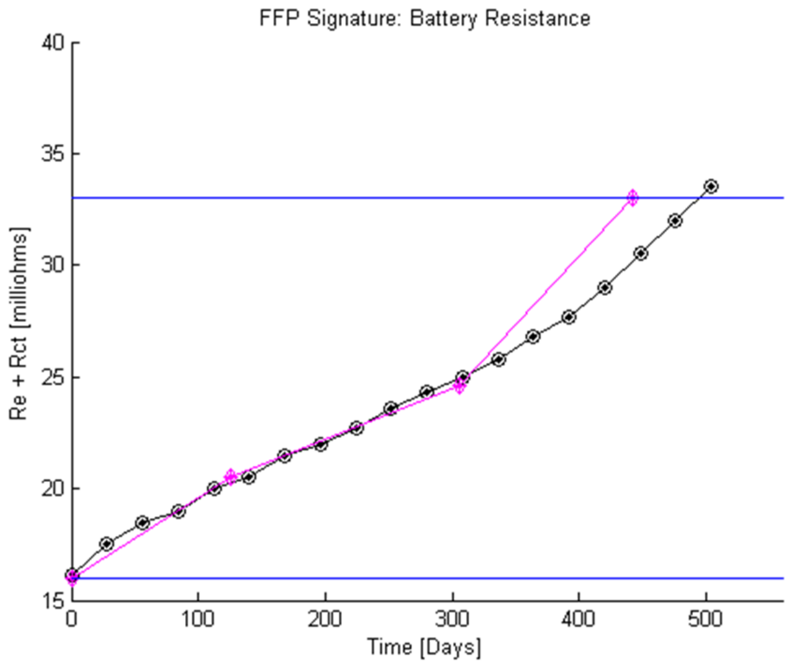

Figure 5: Extrapolated NASA data using the same ARULE model

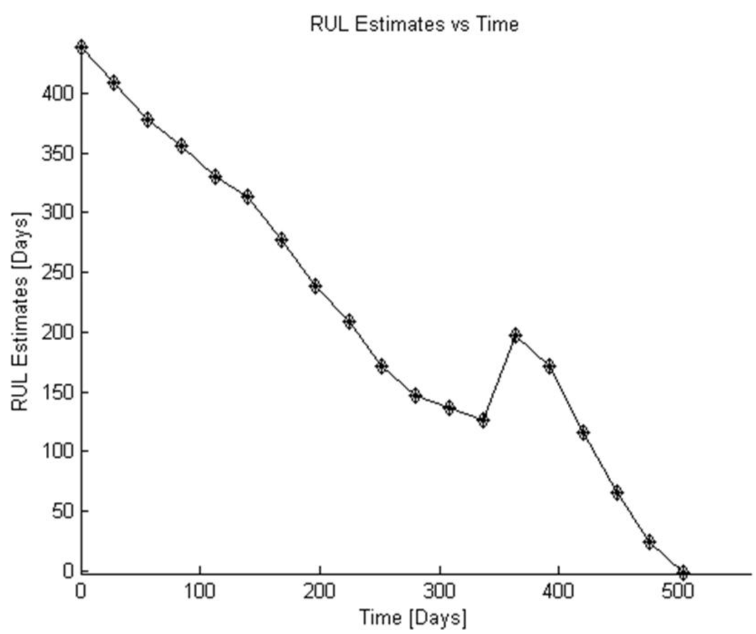

Figure 6: RUL estimates, showing the model correction automatically occurring at day 3290

ARULE Operational Characteristics

ARULE accuracy has been successfully proven using ripple voltage measurements, opto-isolator gain, counts of solder ball intermittent faults, and battery resistance. valuations indicate both as equally valid. The primary reason for this level of versatility is the ARULE engine has been designed and developed to work independently of the type of data and the units of measure it is processing.

- ARULE is accurate because the model is adapted to the data as each data point is processed.
- ARULE is a fast because of the compactness of the model, which incorporates past history and the predicted future.
- ARULE is cognizant that the data can exhibit both degradation and healing, and that the rate of accumulated damage as exhibited by the data can increase, remain the same, or decrease.
- ARULE is designed to favor early rather than late projected end-of-life estimates.

Conclusion

The use of effective electronic prognostics and health management (ePHM) methods in condition-based maintenance (CBM) systems is a priority in the industry, but as yet ePHM has seen little on-board implementation. Prognostics such as ARULE in CBM will enable “just-in-time” maintenance, which lowers costs because it enables the operator to purchase replacements only when individual assemblies or components are known to be nearing the end of life, eliminating the need to maintain a large inventory. Prognostics also increases safety and saves money by avoiding failures and unscheduled down time that can affect critical missions.

ARULE is a fast, accurate remaining useful life estimator for CBM applications and is currently evaluated as being at Technology Readiness Level (TRL) of 6. Current development plans call for ARULE to be at TRL 7 by the second quarter of 2010 after field testing by two major government prime contractors.