Adaptive Remaining Useful Life Estimator™ (ARULE™)

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ABSTRACT

An important aspect of an Integrated Electronics Prognostics System is to process Prognostic Health Management (PHM) data collected from a system platform to produce Remaining Useful Life (RUL) estimations, which are then input into a condition-based maintenance system. In this paper we present generic Fault-to-Failure Progression (FFP) models and adaptive methods to produce RUL Estimations. The models and an adaptive-reasoning processor have been designed and implemented as a MATLAB-based program that can be ported to JAVA and C. The program, called Adaptive RUL Estimator™ (ARULE™), is designed for use for a system component or assembly subject to fatigue damage. 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 to let an application specify a model and invoke ARULE: ARULE adapts a model to the data and then uses the adapted model to produce RUL estimates with increasing accuracy. Presented are examples from Lithium-ion battery health data, power supply filter capacitor ripple voltage data and Ball Grid Array (BGA) solder joint fault data.[1]

1. INTRODUCTION

A common prognosis method is to apply the environment and use conditions to one or more reliability-based or acceleration models, such as a Coffin-Manson model, to produce a Remaining Useful Life estimate (NIST/SEMATECH, 2009). Reliability models are probability/statistics based, but their usefulness and applicability is dependent on well-defined acceleration tests and coefficient fitting to produce estimates. They are exemplified by "bathtub" curves" as shown in Figure 1.

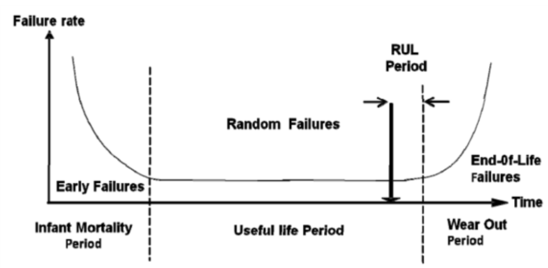

Figure 1. Bathtub curve.

We present a method, Adaptive Remaining Useful Life Estimator[2], which accepts Fault-to-Failure Progression (FFP) signature data (Goodman, 2007), adapts an FFP model to the data and then uses the adapted model to produce RUL estimates.

2. ARULE APPROACH

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

2 Patent pending.

2.1 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.

2.2 Degradation Fault Profile Signature

Design and testing has begun to have ARULE recognize and use 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 paper, the difference being that FFP signatures generally increase in magnitude while DFP signatures generally decrease in magnitude..

2.3 Healing (Annealing)

Real components and systems exhibit healing in the sense that as stresses are reduced, the level of damage tends to lessen as, for example, lattice damage in solid state devices anneal. ARULE recognizes and accounts for evidence of healing in the data.

2.3 Open Architecture

ARULE uses an open-architecture Application Programming Interface (API) to do the following: (1) let a model be defined or used; (2) to accept input data, (3) to produce output RUL estimates and (4) to return an adapted model (see Figure 2).

```
[RC RS MODEL] = AMGR(MODE,MNAME,MLOC,NF) ;    %
get model to initialize
```

Figure 2: API to get an ARULE model

2.4 Correlate Measurements: Invasive to Non-invasive

Non-invasive data measurements should be used to create an ARULE model. One way to do that is to find an ideal, but invasive set of data, such as that shown in Figure 3, and then correlate the ideal data to some non-invasive data such as that shown in Figure 4. Figure 3 is the plot of leakage current for aged filter capacitors installed in a switched mode power supply (SMPS): Figure 4 shows a plot of non-invasive ripple voltage measurement and the FFP model (mauve-colored plot) with the inflection points highlighted.

The sensor used to take the measurements of ripple voltage was a diagnostic sensor in that the measurements of interest exceeded a defined “as good as new” value of less than 1.5 mV.

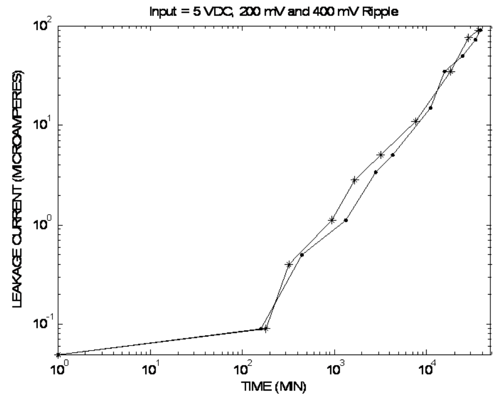

Figure 3. Invasive leakage current data.

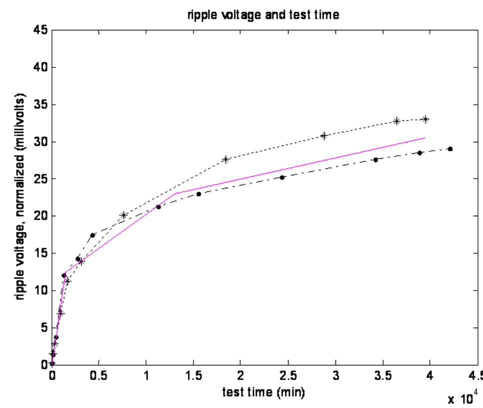

Figure 4. Non-Invasive Ripple Voltage.

2.5 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.

2.6 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.

2.7 FFP and DFP Examples

Some FFP examples are the following: leakage current, ripple voltage, fault counts and increase in frequency. Some DFP examples are the following:

battery charge, loss of transmission power, fuel capacity and decrease in frequency.

3. ARULE EXAMPLES USING REAL DATA

In this section, we present some battery health examples of using ARULE to produce RUL estimates.

3.1 Battery Health

In 2008, a NASA team (Goebel, 2008) headed by Dr. Kai Goebel examined Prognostic Health Management (PHM) issues using battery health management of Gen 2 cells, an 18650-size lithium-ion cell as test case. Dr. Goebel observed that prognostics attempts to estimate remaining component life when an abnormal condition has been detected. He further observed that the key to useful prognostics is not only an accurate remaining life estimate, but also an assessment of the confidence in the estimate.

The methodology was very similar to that outlined in the previous section: NASA identified a FFP signature as being the electrolyte resistance plus the charge transfer resistance (R_E + R_{CT}) and a DFP signature as being the battery charge; NASA defined a 30% fade in capacity as a failed battery state; and NASA verified there was a linear correspondence between capacity, C/1, and the (R_E + R_{CT}) impedance.

3.2 Impedance and Uncertainty Distribution

A 70-week test was performed during which (R_E + R_{CT}) impedance measurements were taken. A second-degree polynomial was used at prediction points to extrapolate out to the damage threshold, and confidence bounds were projected onto the damage threshold to show the uncertainty distribution. Figure 5 shows the resulting plot.

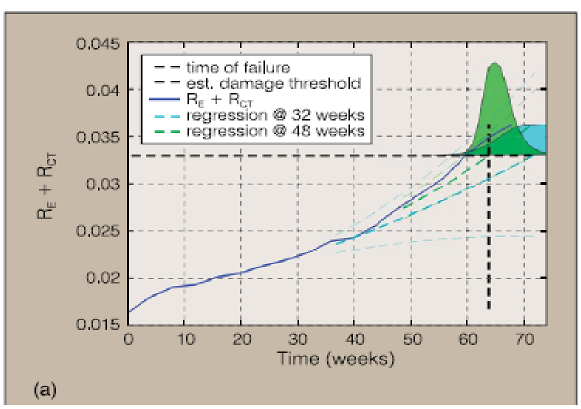

Figure 5: Impedance and uncertainty distribution

3.3 Capacity and Uncertainty Distribution

Similar techniques were used to produce the capacity and uncertainty distribution shown in Figure 6.

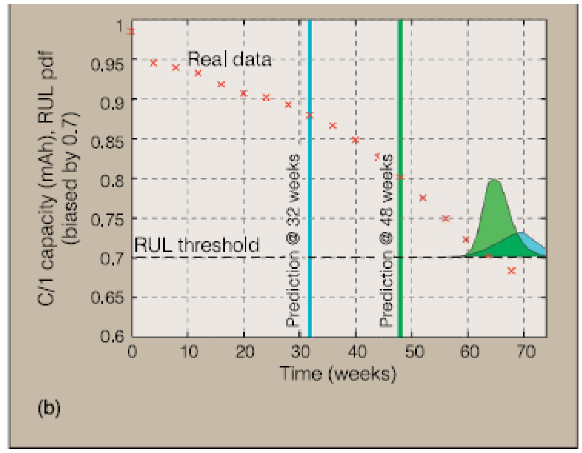

Figure 6: Capacity and Uncertainty Distribution

3.4 Summary Evaluation of the NASA Results

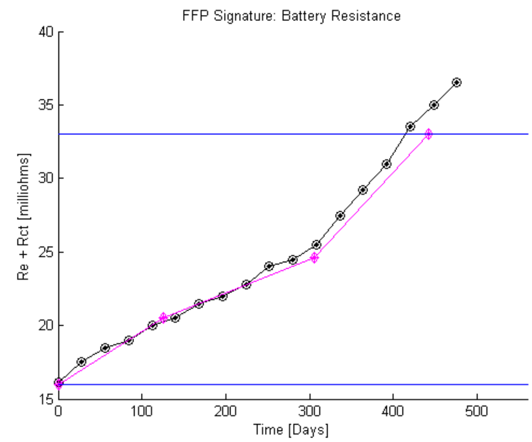

Figure 7) that had a 441-day (63 weeks) predicted failure date.

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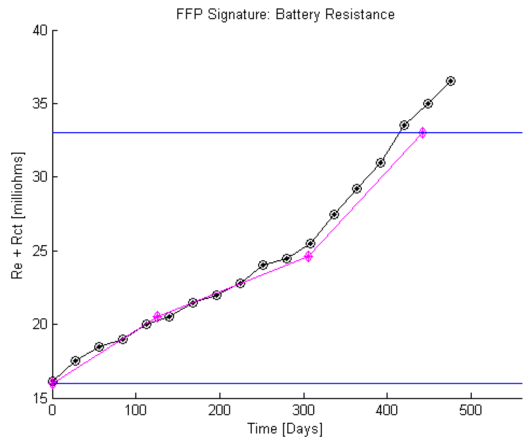

Figure 7. Battery impedance (black) and ARULE model (red).

The data was then given point-by-point to ARULE, and the returned RUL estimates were saved and plotted versus time (see Figure 8); and the accuracy of each returned RUL estimate was plotted (see Figure 9).

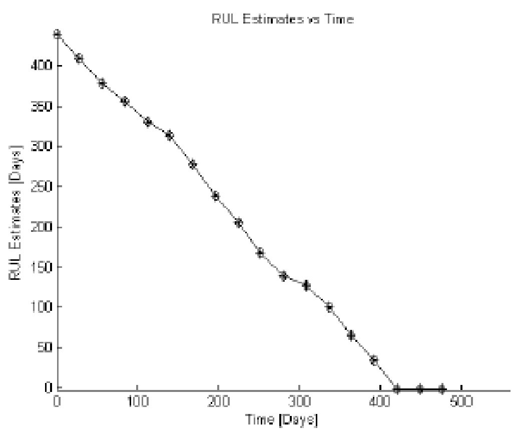

Figure 8. RUL estimates, resistance data.

Referring to Figure 9, it is seen that the RUL estimates from ARULE converge and the 32-week is less than 5%: the penultimate RUL estimate had an error of 1.5%, and the estimate prior to that had an error of 2.3%. These estimates are extremely accurate given a 4-week sampling period.

Especially note the convergence from a 441-day predicted failure of the model to the actual defined failure of 420 days.

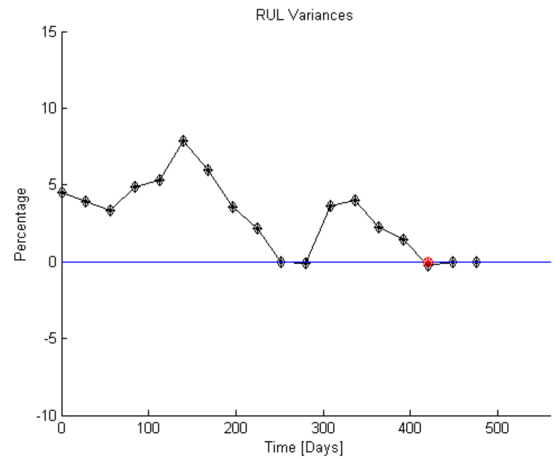

Figure 9. Accuracy of the RUL estimates from ARULE.

3.6 EXTRAPOLATED DATA and ARULE

We then used the same ARULE model to process the extrapolated NASA data. As seen **Figure 10**, the result is the model predicts the same failure day (441 days), but the data indicates a failure at day 504.

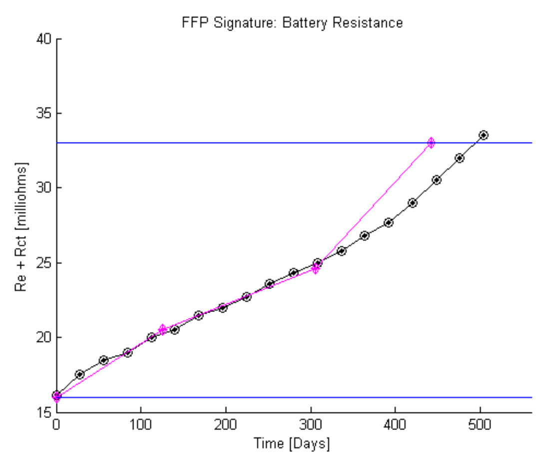

Figure 10. Extrapolated NASA data, same ARULE model.

The ARULE estimates are shown in **Figure 11**. Notice that ARULE adjusted the RUL estimate after day 329 to take into account for a higher rate of change in the extrapolated data compared to the model.

Most importantly, note that after the ARULE adjustment ending at 358, ARULE converged on an accurate failing date of 504 days.

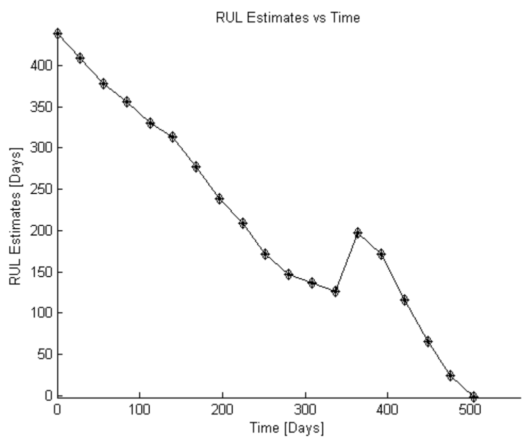

Figure 11. RUL Estimates.

Figure 12 shows the accuracy of the RUL estimates for the extrapolated data. Again, the ARULE accuracy is largely dependent on the period of time between data points. For the battery health data, because the period was 28 days, on the ARULE estimates will have, on average, an accuracy of +/- 14 days.

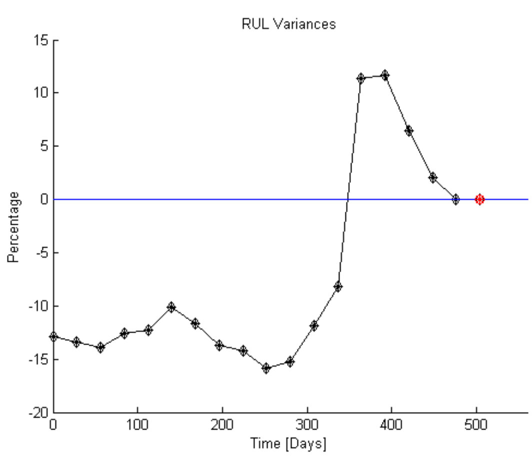

Figure 12: RUL accuracy for the extrapolated data.

4. ARULE OPERATIONAL CHARACTERISTICS

ARULE has been evaluated using ripple voltage measurements and counts of solder ball intermittent faults and has been evaluated as being equally valid. The primary reason is because the ARULE engine has been designed and development to be independent of the type of data it is processing, and it is independent of the units of measure of the data.

ARULE is a fast processor because it does not have to process or reprocess large amounts of data: (1) the model is the required memory for accurate RUL estimating and (2) the model is adapted to the data as each data point is processed.

ARULE is cognizant that the data can exhibit both degradation and healing; that the rate of accumulated damage as exhibited by the data can increase, remain the same, or decrease.

5. SUMMARY and CONCLUSION

ARULE is a fast, accurate Remaining Useful Life estimator for Condition Based Maintenance (CBM) applications and is currently evaluated as being at Technology Readiness Level (TRL) of 5. ARULE uses efficient memory and calculation methods: It takes less than 200 microseconds to produce an estimate. It is anticipated that the processing speed will be improved when ARULE is ported to a non-MATLAB platform.

ARULE is tuned to produce early projected end of life estimates.

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Sonia Vohnout *earned her MS in Systems Engineering from the University of Arizona in Tucson. With a diverse background and experience, Sonia manages Ridgetop's commercialization efforts from its many government-funded projects. Sonia joined Ridgetop after successfully building an electronic subassembly business in Mexico, working as a Systems Engineer at IBM and handling overseas installations of software with Modular Mining Systems (now part of Komatsu). During her 20 year career in the various industries, she has held executive management and senior technical positions. Sonia has also co-founded several companies. Sonia is a board member of the Society for Machinery Failure Prevention Technology (MFPT) (www.mfpt.org), an interdisciplinary technical organization strongly oriented toward practical applications. Sonia is also the founder of the Prognostic and Health Management (PHM) Professionals LinkedIn Group (www.linkedin.com), a fast-growing group whose objectives are to: Discuss PHM related topics, network with others in the PHM community, and increase awareness of PHM.*