August 30, 2018

Applying Failure Prognostics to Reduce the Duration of Automotive Electronics Reliability Testing

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GYRS 2018 GUANGBIN YANG RELIABILITY SYMPOSIUM

Objectives and Outline

Objective: Introduce a new application for prognostics and generate interest in this application in the reliability engineering community. Why? Because it presents interesting and challenging problems and the automotive industry will greatly benefit from it.

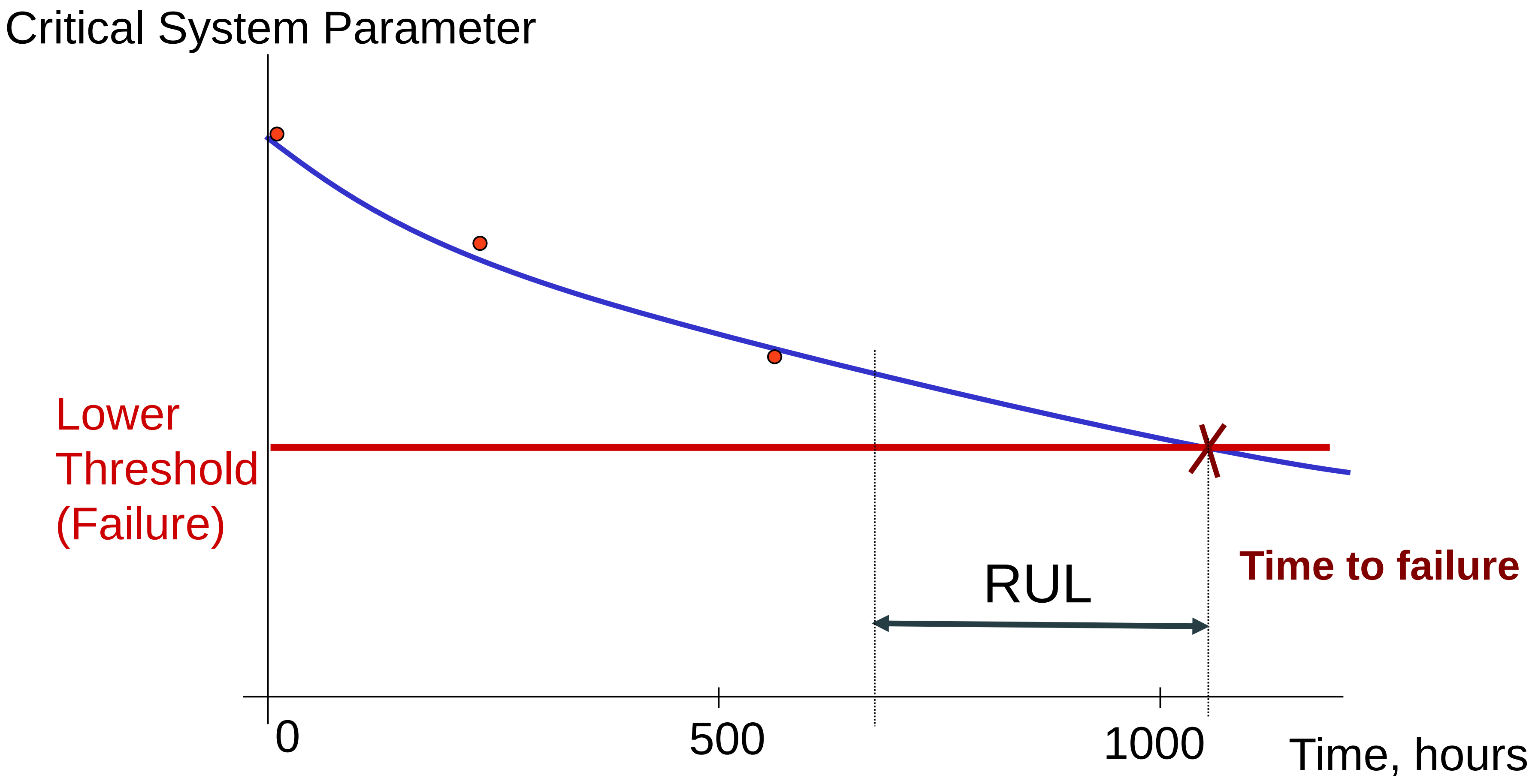
Outline

- Prognostics Basics
- Automotive Electronics Reliability Testing
- Application of prognostics in order to achieve significant cost/time savings
- Case study: Automotive Electronics Module
- Conclusions and future work

What is Prognostics?

- **Prognostics** is an engineering discipline focused on **predicting** the time at which a system or a component will no longer perform its intended function (fail).
- The predicted time then becomes the **remaining useful life** (RUL), which is an important concept in decision making.
- Prognostics predicts the future performance of a component by assessing the extent of deviation or **degradation** of a system from its expected normal operating conditions.
- The science of prognostics is based on the analysis of **failure modes**, **detection of early signs of wear** and aging, and fault conditions.

Prognostics Simplified



RUL = Remaining Useful Life

Prognostics Basics and Applications

Main types of prognostics:

Data-driven (pattern recognition, machine learning techniques, neural nets, stochastic models, etc.)

Model-based prognostics utilizes physical models of the system for the estimation of RUL (fatigue, crack growth, electro-migration, etc.) SAE-J3168 - Reliability Physics Analysis of Electronic Equipment (in the works)

$$TTF = Ae^{\frac{E_A}{k \cdot T}}$$

Hybrid approaches (fusion) attempt to leverage the strength from both data-driven as well as model-based approaches

Industries: Multiple applications in the aerospace, defense, automotive, railway, and other industries.

Example of an Automotive Electronics Validation Test Flow

5-Point Functional/Parametric Check

Leg 1	Leg 2	Leg 3	Leg 4	Leg 5
Mechanical Fatigue:	**Thermal Fatigue:**	**Enclosure Tests**	**Corrosion Tests**	**Electrical Tests:**
High Temperature Durability	Thermal Shock	Dust	Salt Mist	Reverse Polarity
Mechanical Shock	Powered Temperature Cycling	Water	Salt Spray	EMC
Potholes	Humidity Testing	Seal		Parasitic Currents
Door slam	Post-thermal fatigue vibration			Electrical Overload
Vibration + Thermal Cycling				Isolation Resistance

5-Point Functional/Parametric Check

Realities of Accelerated Reliability Testing in the Automotive Electronics

- Reliability demonstration test should represent 15 years vehicle life in the field.

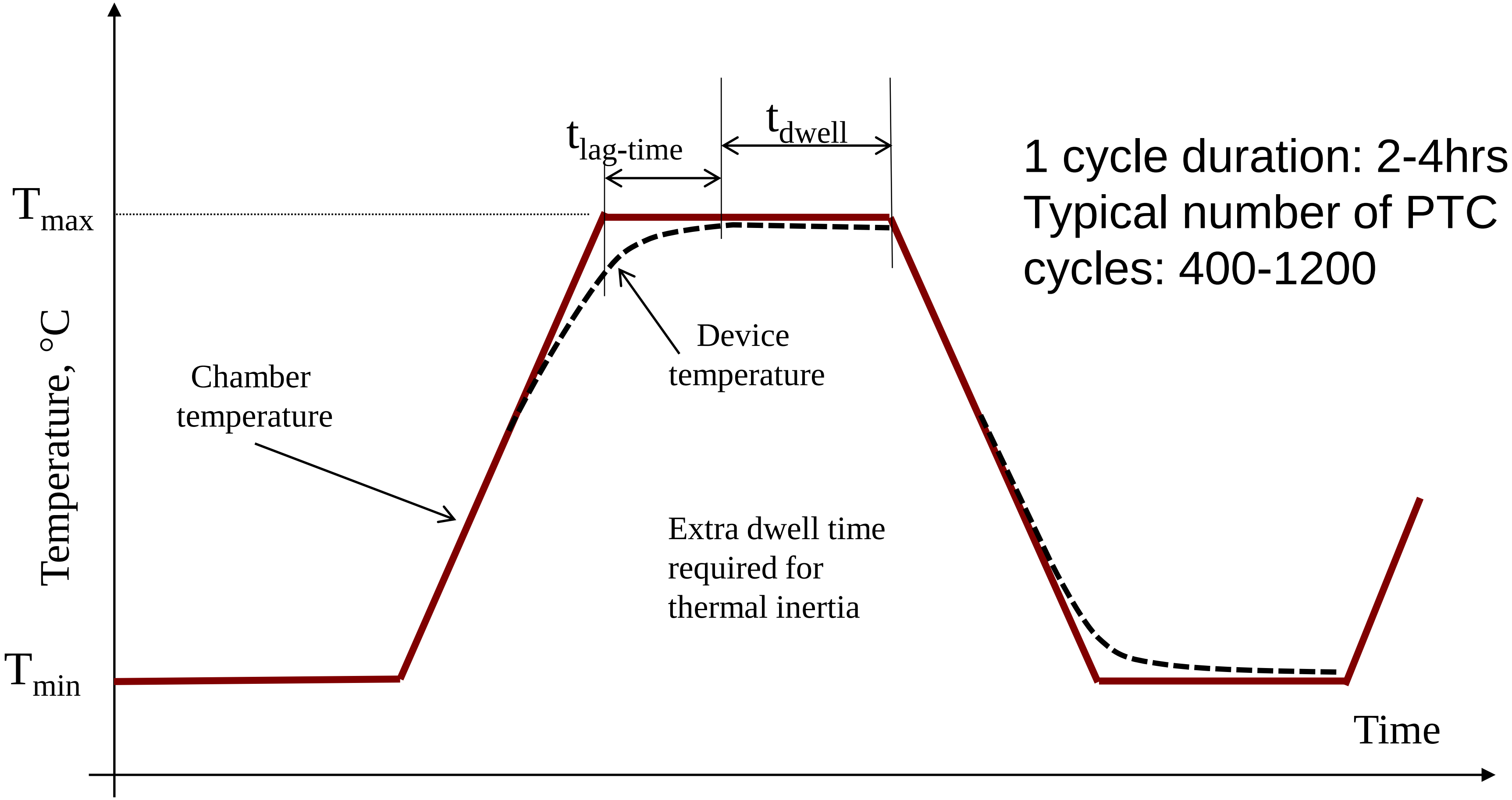
- Coffin-Manson acceleration model for the low cycle metal fatigue (thermal cycling) linking shear strain range $\Delta\gamma$ and the expected life

Time to Failure = $A(\Delta\gamma)^{-m}$ This model has its limitations and we are still at 2-4 month of temperature cycling testing. Longer for power electronics.

- Newer products are operating near their limits and it is often difficult to accelerate testing due to technology limitations (e.g. displays). Electronics with cooling also limits the ability to accelerate reliability testing

- Some of these tests, e.g. Power Temperature Cycling testing (PTC) are monitored tests, hence we don't need to add much cost to utilize prognostics.

Power Temperature Cycling (PTC) Test



1 cycle duration: 2-4hrs
Typical number of PTC cycles: 400-1200

Acceleration Factor:
Coffin-Manson model

$$AF = \left(\frac{\Delta T_{Test}}{\Delta T_{Field}} \right)^m$$

m = 2-4 fatigue, ***m*** = 7-9 fracture
m = 2.5 tin-lead solder
m = 2.65 lead-free solder

ΔT = Temperature excursion during the cycling.

Typical test duration: 2-4 months, longer for PwE

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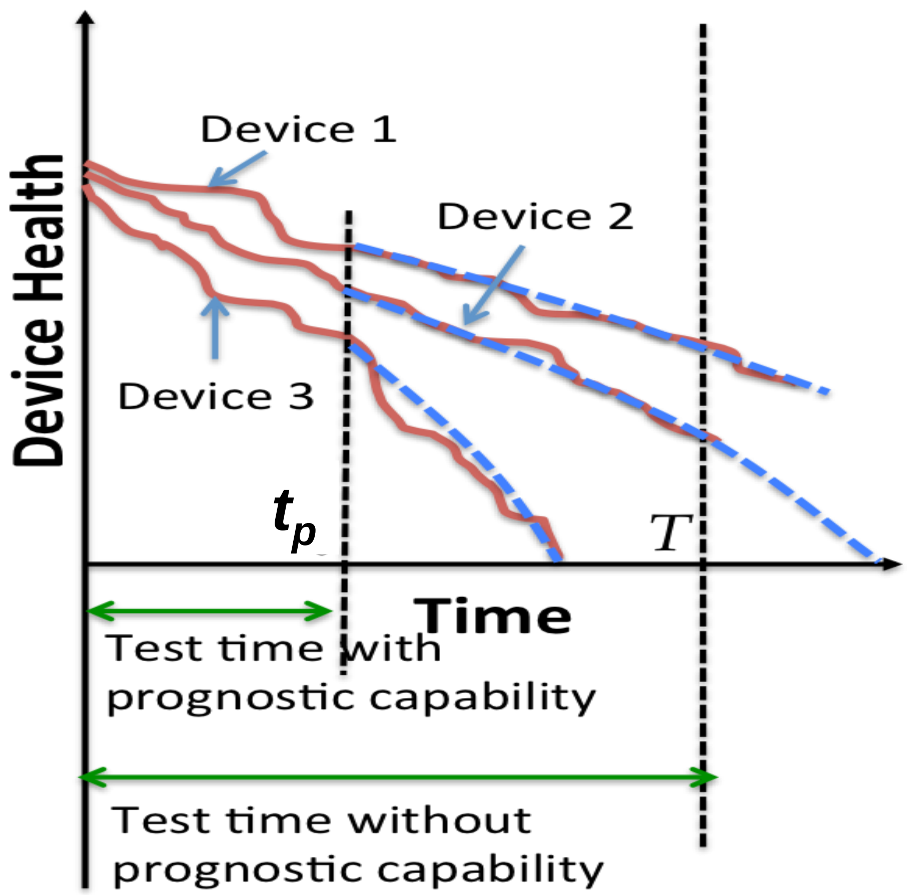
Test Time Reduction Concept



Once a failure prediction method is established using the data obtained through accelerated stress tests, the duration of subsequent tests can then be shortened to a time at which reliable failure time estimates can be obtained.

Instead of running tests to failure or to a bogey (equivalent of one mission life), one could run a test until t_p and use the prognostic algorithm to estimate the time to failure or to assess whether the product would have survived until the actual pass target time T. In these cases there will be a time saving of $T - t_p$

Case Study:

Automotive Electronics Module: Test Setup and Monitoring

High Voltage DC Power Supply Rack

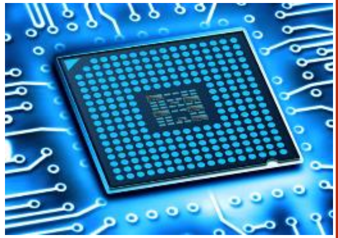
AC Loads (drive motors)

DC-DC Out Load

Test Units

Automotive Electronics Module

371 monitored parameters

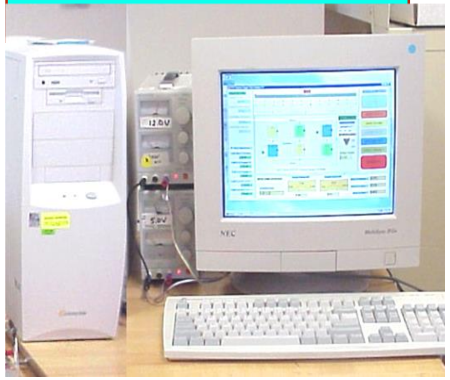


Load & Signal Boards

Monitoring System

Power Supply

System Interface tool (data collection and communication)



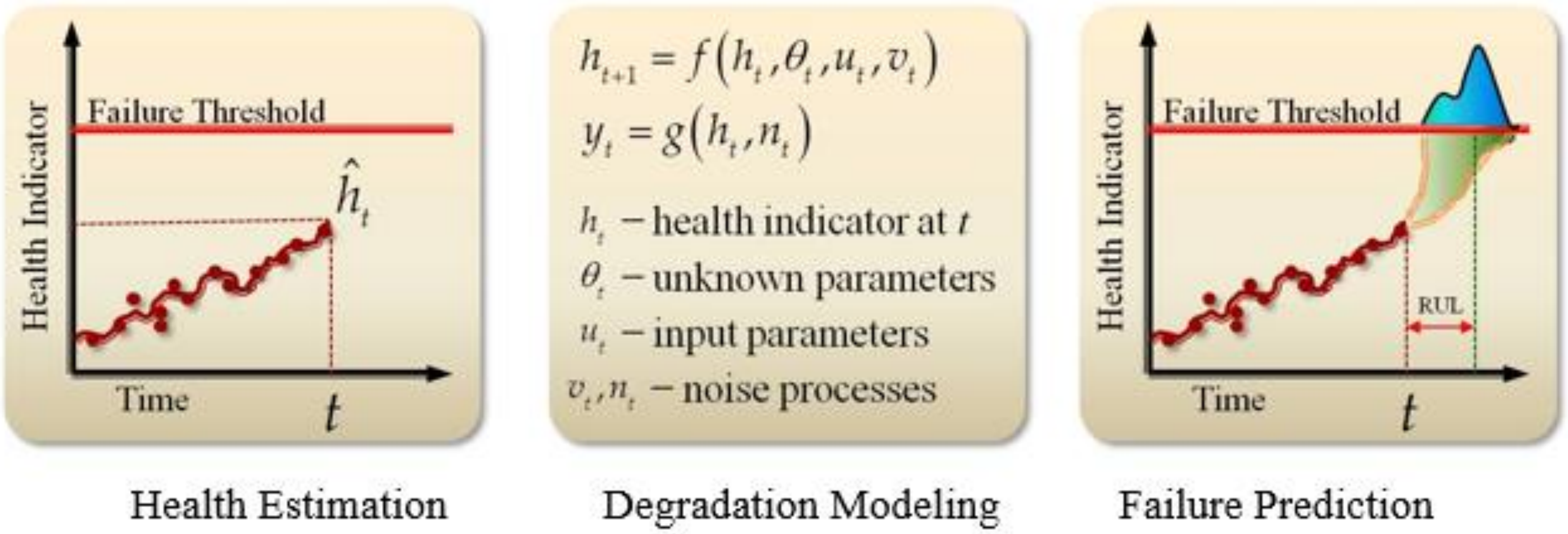
6 electronic modules were tested PTC
800 cycles
2 out of 6 failed
Times to failure
Other units – RUL confirmation
Monitoring: 371 parameters are recorded in a real time (mostly currents and voltages, analog signal counts, 1-0)

Monitoring Data Sample

Time	Parameter 1	Parameter 2	Parameter 3	Parameter 4	Parameter 5	Parameter 6	…
17:46:53	0.02	16.02	4.99	0.12	24.78	24.78	58.77
17:47:28	0.03	18.06	5	0.11	24.73	24.75	58.85
17:48:05	13.85	19.72	5	0.12	24.75	24.84	58.77
17:48:46	0.02	21.61	4.99	0.11	24.73	24.84	58.77
17:49:19	0.02	23.63	5	0.12	24.81	24.75	58.7
17:49:56	13.87	25.35	4.99	0.12	24.78	24.73	58.85
17:50:34	0.02	26.97	4.99	0.11	24.81	24.84	58.85
17:51:11	0.02	29.08	4.99	0.11	24.84	24.87	58.85
17:51:46	13.86	30.62	4.99	0.11	24.78	24.75	58.77

- The number of the monitored parameters is defined by the product team and specified in the product documentation.
- Number of parameters to monitor depends on the complexity of the product and is usually in hundreds and in some cases can reach 1000.
- Monitoring frequency depends on the capacity of the monitoring rack, technical requirements, and other factors.

Steps involved in prognostics approach:



<u>1. Health Estimation</u>: product's degradation in health is quantified and expressed as a health indicator (HI). The HI could be an estimate of the accumulated damage or a drift in *in-situ* monitored parameter reflecting degradation in the product.

<u>2. Degradation Modeling</u>: a PoF or data driven model is developed to estimate the progression of degradation in system/component health based on the current health and operating conditions.

<u>3. Failure Prediction</u>: the time of failure is estimated by integrating the degradation model with knowledge about future operating conditions using an appropriate regression technique.

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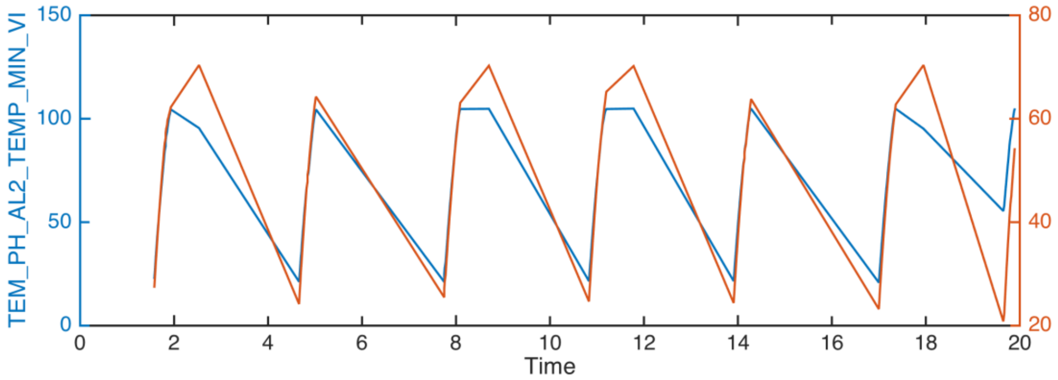
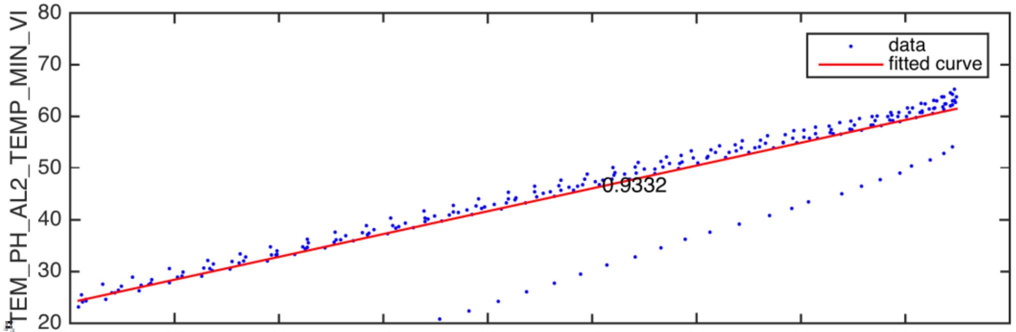
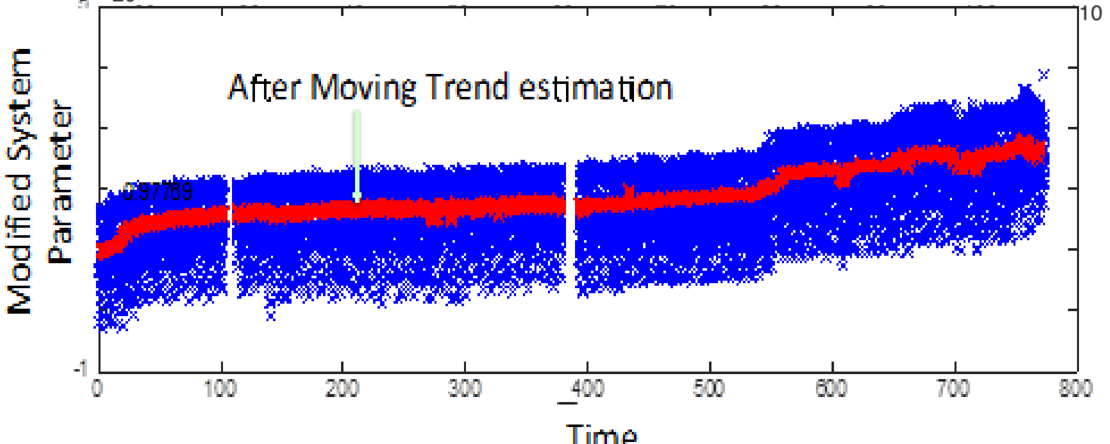
Parameters Correlated With the Cycled Temperature

A number of monitored parameters were correlated with the chamber temperature and hence were showing cyclical trends. This required mathematical transformation.

At the same time other parameters were not correlated with the temperature and could be analyzed as is.







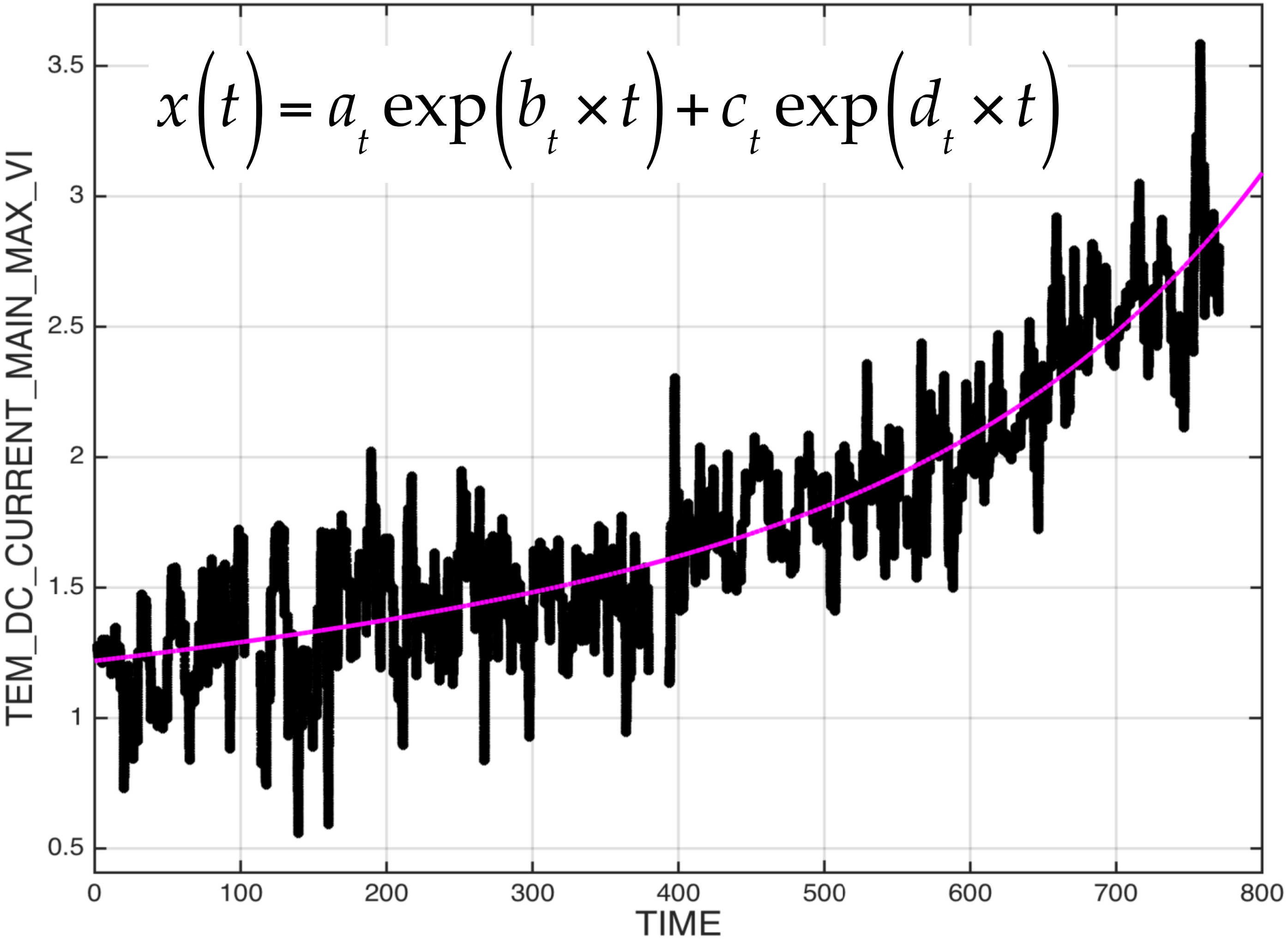
The difference between the actual measurement and estimated system parameter is used as the normalized parameter value $\boldsymbol{I_{norm,t}}$ at time $\boldsymbol{t}$ as shown here:

$$\hat{I}\left(T^{ch}\right) = p_1 T^{ch} + p_0$$

$$I_{norm,t} = I_{meas,t} - \hat{I}\left(T_t^{ch}\right)$$

Degradation Model – Data Driven Double Exponent

$$x(t) = a_t \exp(b_t \times t) + c_t \exp(d_t \times t)$$

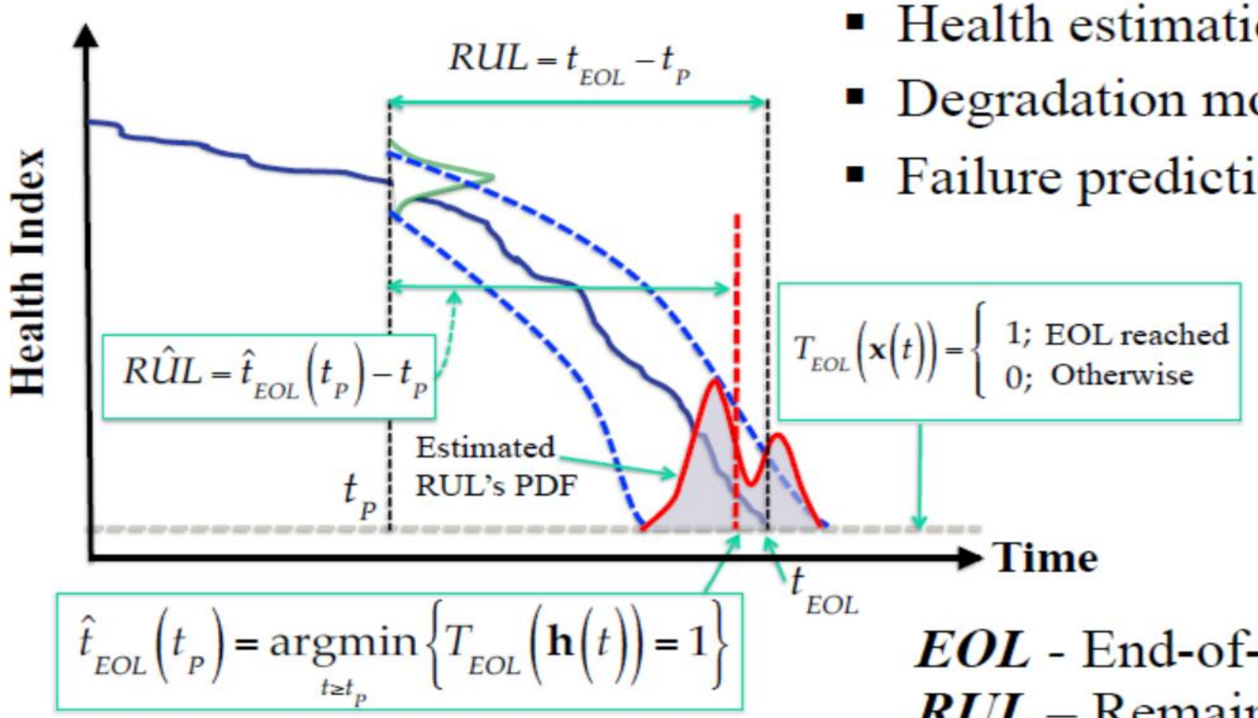


$x\ (t)$ = the preprocessed and trend estimated system parameter of interest at time t

Degradation model capturing a degradation trend in the system parameters of interest

$$\theta_t = \begin{bmatrix} a_t \\ b_t \\ c_t \\ d_t \end{bmatrix}$$

Prognostics and RUL Estimation



- Health estimation method
- Degradation model and
- Failure prediction method.

EOL - End-of-Life
RUL – Remaining Useful Life

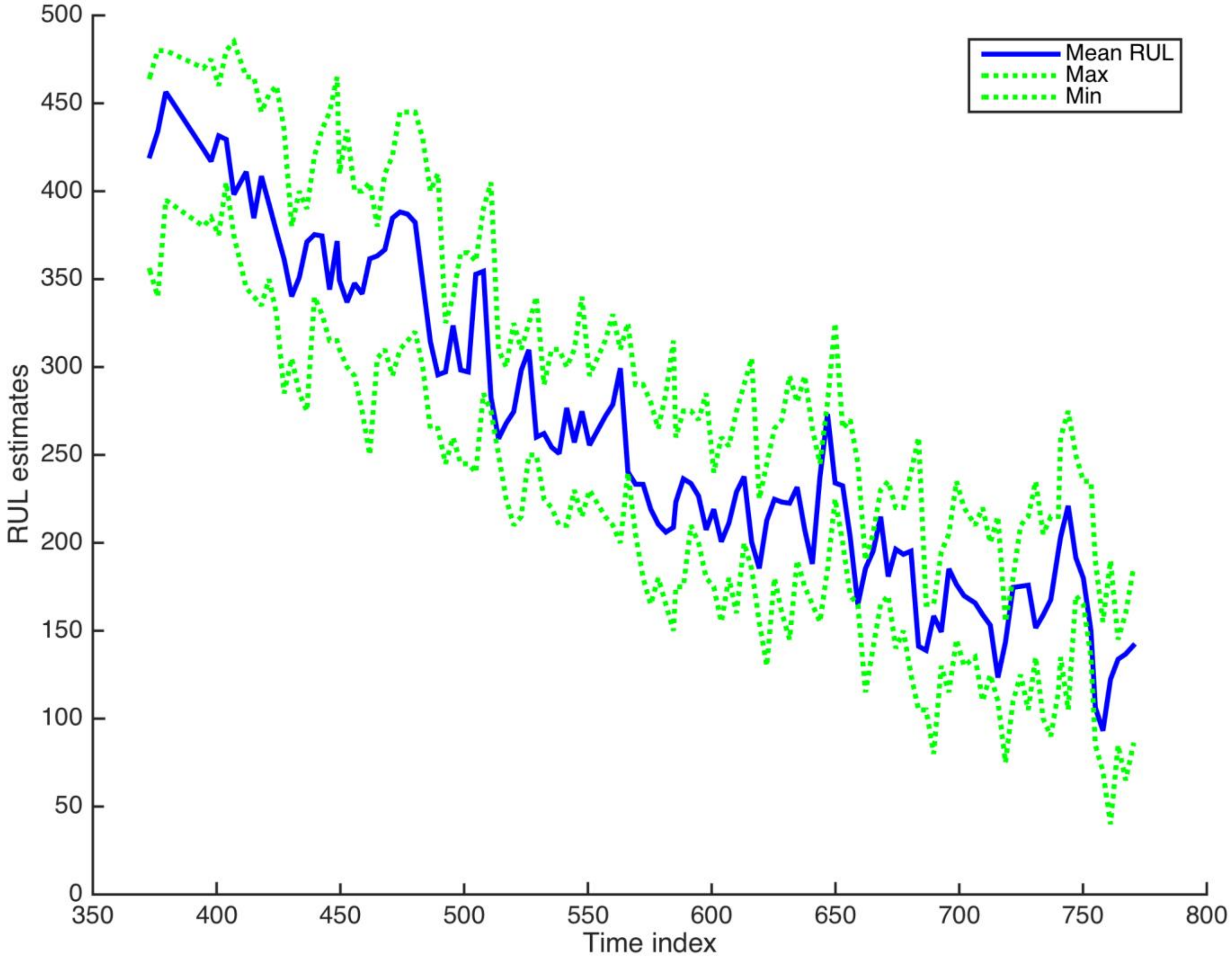
The conditional probability $\boxed{p\big(RUL(t_P)|\boldsymbol{y}(t_0\!:t_P)\big)}$ **is estimated in two steps. First step is the damage estimation step, where both state and parameter vectors are estimated i.e.** $p\big(x(t),\boldsymbol{\theta}(t)|\boldsymbol{y}(t_0\!:t)\big)$**.**

Particle filter is used to calculate vector $\theta_t = [a_t \quad b_t \quad c_t \quad d_t]^T$

And the second step is to estimate the RUL itself

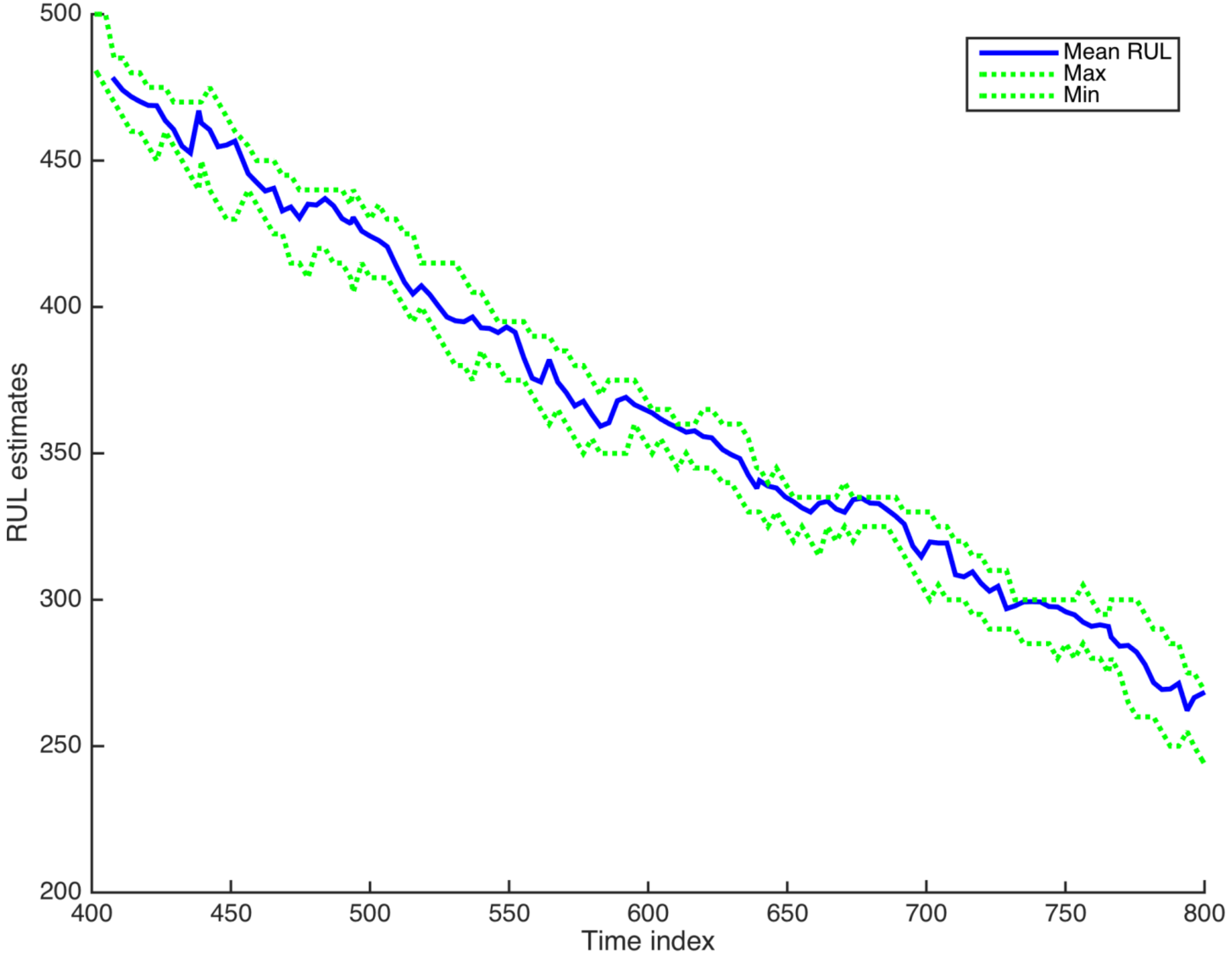
UNIT 1 RUL Prediction

$$p\big(RUL(t_P)|\boldsymbol{y}(t_0\!:t_P)\big)$$



Time of prediction (X-axis) vs. RUL prediction (Y-axis). The green lines represent 90% confidence bounds. The graph suggests that even after 750 hours of testing, the model and algorithm predict the RUL >100 hours i.e., the Unit 1 will survive for another 100 hours before reaching the failure threshold.

UNIT 2 RUL Prediction



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Results and Further Applications

- **Two of the ‘good’ units were tested to failure and failed within 10% of the predicted time to failure.**

- **Realistic expectations of the prognostics: not all of our tests will soon be shorted in half, since we understand that prognostics is based on the product specific knowledge and that knowledge will need to be accumulated for the new products. However it can be very helpful in repeat iterations of DV and PV (Validation Testing)**

Challenges of the Application of Prognostics to Validation Testing

- Design and monitoring parameters vary from product line to product line and sometimes significantly (e.g. navigation vs. occupant sensing vs. active safety)
- Some failure mechanisms may be of a binary nature
- Selecting the right parameters as health indicators (or combinations thereof) can be challenging, plus there is typically a lot of noise in the system
- Future efforts will need to be directed at studying how particular failure modes and failure mechanisms affect the parameters of the automotive electronics during monitoring. New technology, autonomous vehicles, etc.
- We haven’t fully solved this problem, only portion of it (a special case). More involvement of the PHM and the automotive community will be needed

Conclusions and Future Work

- The proposed application of prognostics has a potential to shorten the design life cycle by significantly reducing the duration of the ‘long tests’, such as temperature cycling and high temperature endurance and therefore saving thousands of dollars in development cost plus intangible benefits

- The methodology outlined offers a comprehensive approach to understanding the overall product reliability and presents a viable alternative to a ‘traditional’ validation testing purely based on acceleration models. It is also applicable to the cases where acceleration is difficult or impossible due to the products already operating close to their operating limits.

- Future efforts will need to be directed at studying how particular failure modes and failure mechanisms affect the parameters of the automotive electronics during monitoring.