A New Application for Failure Prognostics – Reduction of Automotive Electronics Reliability Test Duration

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ABSTRACT

This paper presents a novel application of failure prognosis to shorten the time of reliability testing. Typically, prognostic outcome is used to make real time health management decisions such as modify mission plan, change system operation parameters to reduce stress and increase remaining useful life, and more. In this work we demonstrate the use of prognostics to reduce the duration of lengthy and expensive tests, such as power temperature cycling and high temperature endurance in the automotive electronics validation process.

1. INTRODUCTION

Accelerated stress testing is an integral part of the automotive electronics reliability assessment process. Its goal is to replicate the stress conditions that will accumulate the same damage as is expected during the product's mission life (in the automotive industry it is 15 or more years in predominantly harsh environment) but in a shorter time. In the automotive and several others industries this process is referred as Product Validation, which typically consists of two stages, *design validation* (DV) and *process validation* (PV). DV is quantitative and qualitative verification that is usually performed on prototype or pilot parts to ensure that the component design meets the requirements for environmental stress, durability, and reliability.

PV pursues the same goals, assessing the effects of production manufacturing and is conducted on production or production intent parts. Readers interested in automotive validation process are referred to General Motors standard GMW3172 (2004) and Kleyner and Nebeling (2016). Furthermore, during the qualitative stages of DV and PV the product is expected to demonstrate certain reliability that is predefined based on customer engineering requirements. This goal is achieved by either testing the product to failure or conducting a success-based testing. In the case of test to failure, the life data (times to failure) are analyzed and a statistical distribution (often two or three parameter Weibull) fit to the data allowing an estimation of the reliability and confidence level for the mission life of the product. In the case of test to success, the product is subjected to a test representing one mission life (test to a bogey) where all the test units are expected to pass the test without failure. The reliability and confidence level are then calculated based on the sample size using the binomial distribution, for more details see (see O'Connor and Kleyner (2012)).

A typical product reliability test flow consists of several environmental stresses that include temperature cycling, vibration, mechanical shock, high temperature operation, high humidity exposure, exposure to dust, low pressure operation (induced by high elevation) and more (see GMW3172 (2004)). Some of these tests duration can be in the order of months. For example, a temperature cycling test designed to adequately represent the automotive field life of 10-15 years can span 2-5 months and high temperature endurance test (HTE) can also take months to accumulate the damage that is the same as the damage expected in product's service life.

The situation with long temperature cycling tests is even worse for power electronics, such as inverters, converters, rectifiers, battery chargers and others used in hybrid and electric vehicles, since those devices typically have higher weights and sizes compared to the 'conventional' automotive electronics. Figure 1 shows a general power-temperature cycling (PTC) diagram with the required temperature dwell time t_{dwell} at the top and the lag time $t_{lag-time}$ required for the device temperature to reach the ambient temperature. The higher the thermal mass of the system the longer the $t_{lag-time}$, which further increases the test duration, sometimes adding extra months to the overall validation schedule.

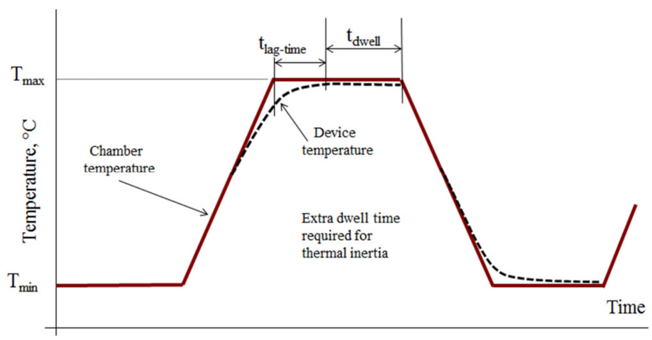


Figure 1: Temperature cycling profile indicating the difference in chamber to device/system temperature.

Systems such as battery chargers and the electronic devices that are connected to them are expected to be in powered state much longer than the 'conventional' automotive electronics due to overnight charging. This results in significant increase in the duration of the temperature operation tests which puts strain on the product validation process with mounting cost and time reduction pressure. An additional issue with testing power electronic products, such as inverters and converters is the use of liquid cooling for high power ICs, which makes the test acceleration very difficult due to high sensitivity of those ICs to the ambient and junction temperatures. In some of the applications, the maximum operating temperatures are approaching maximum allowable temperatures for the operation of silicon circuits, making test acceleration more difficult and sometimes impossible. Thus, the only way to accumulate the same amount of damage anticipated in the field is by increasing the accelerated stress testing duration.

An additional complicating factor is a frequent need to re-run some of the reliability tests, in the cases when product fails the first round of tests or when last minute product design changes are introduced after the validation process is complete. Even though program management plans only on one round of DV and PV, this best-case scenario seldom happens thereby prompting additional iterations of validation testing (e.g. DV2, DV3, etc.) Product knowledge accumulated at the first iteration is rarely utilized to make the following test iterations shorter. Here is where degradation analysis and prognostics offer additional opportunities of reducing the test duration by utilizing the knowledge accumulated during the previous phases of product testing. The application of prognostics to product validation (or qualification) has been discussed in the past (Pecht and Gu (2009), Challa, Rundle, and Pecht (2013), Pecht, George, Vasan, and Chauhan (2014)). However, the crux of these articles is to utilize the knowledge first accumulated at Failure Modes, Mechanisms and Effect Analysis (FMMEA) stage to define the accelerated testing duration and further utilizing in-situ test data and/or physics of failure (PoF) models to capture early degradation and intermittent faults. In this paper, a case study involving a power electronic controller and data driven prognostics approach is demonstrated to show the capabilities of prognostics-based product qualification.

2. PROGNOSTICS-BASED TEST DURATION REDUCTION

The above-mentioned challenges with automotive electronics validation testing are forcing us to search for alternative solutions and prognostics presents one of the possible alternatives to a long, expensive, and repetitive testing. Application of prognostics to automotive electronics validation was discussed in general terms by Braden and Harvey (2014), who also suggested the use of data monitoring. Traditionally, the monitoring expectations were focused on failure identification by observing the system parameters and triggering an alarm when any of the monitored parameters cross their upper or lower limits as defined by an engineering specification document. However, in prognostics-based approach those parameters would need to be viewed in terms of characteristics of the state of health and used to detect a degradation pattern.

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. For illustration purpose (see Figure 2a), let us assume a product that fails at time T and a suitable prognostic algorithm exists that can predict the product's time to failure with uncertainty bounds $\pm c$ at time t_0. Now instead of running tests until the product fails, one could run a test until t_0 and use the prognostic algorithm to estimate the time to failure.

Not all tests are run till product failure. Even in success based testing, test time can be shortened to a time $\boldsymbol{t_0}$ and one could use prognostic algorithm to check whether the product would have survived until the actual pass target time $\boldsymbol{T}$. This concept is illustrated in Figure 2. In both cases, a and b, there will be a time saving of $\boldsymbol{T - t_0}$.

In this paper we will demonstrate how prognostics can be used to reduce the duration of the longest and most expensive tests, such as PTC and HTE providing an opportunity for a significant test reduction. Clearly, it would be a tremendous cost, time and resource saving if any of the 'long test' times can be shortened. The total cost savings would vary from program to program depending on the complexity of the system, duration of the test, monitoring and test equipment, engineering support, and other factors. The tangible savings can be in tens of thousands of dollars per validation-round (DV1, DV2, DV3, etc.) The cost would involve test and monitoring equipment usage, floor space, engineering and technician time. Intangible savings would include shortening of the development program time, meeting the customer deadlines, reducing the waste time in the cases of repeat validation, customer goodwill, and being first to market.

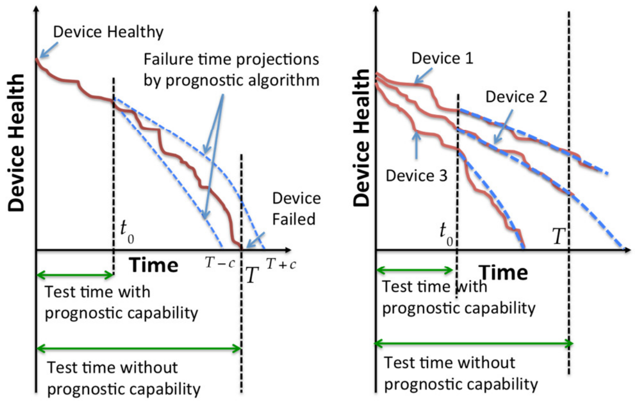


Figure 2: An illustration demonstrating the reduction of test time by incorporating prognostic capability for tests (a) requiring and (b) not requiring "test-to-failure."

3. APPLICATIONS TO AUTOMOTIVE TESTING

The prognostics problem involves the prediction of a system end-of-life (EOL) from which the remaining useful life (RUL) is estimated. Figure 4 diagram shows a general framework for product prognostics and diagnostics and illustrates the process flow utilized in this case study. Figure 5 shows the typical steps involved in prognostics approach such as (1) health estimation, (2) prognostic modeling, and (3) failure prediction steps (see).

In the health estimation step, 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. In many prognostic applications, a system or a component parameter that generally exhibits parametric deviation with system degradation is used as a health metric. For some systems, such a pre-cursor parameter(s) reflecting product's health might not exist. In such cases, parameters contributing to system degradation will be identified and ranked (i.e. parameter selection), and fused to build an HI metric. This will be the case for the proposed study, where *in-situ* monitored parameters are investigated to construct a system health indicator.

In the degradation-modeling step, a PoF or a data driven model is developed to estimate the progression of degradation in system/component health based on the current health and operating conditions. In the failure prediction step, the time to failure is estimated by integrating the degradation model with the knowledge about future operating conditions using an appropriate regression technique.

The data used for this prognostic study is system dependent and contains information pertaining to 'time in test', system-monitoring parameters, temperature measurements, and fault flags. The key for health metric identification is the positive correlation with 'time in test'. Some of the challenges encountered while developing prognostics method for automotive electronic systems are:

- Large number of parameters is typically being monitored (in hundreds)
- System parameters that specifically monitor the functionality of the electronic unit, do not always reflect the degradation of the system
- Degradation process in electronic systems is usually not as apparent as in mechanical systems and sometimes exhibit a 'binary' attribute in terms of the monitored parameters.

3.1. Case Study 1: Power Electronic Controller (PEC)

The system considered for this case study is a Power Electronic Controller (PEC) module, which is a high voltage electronic module operating in the range of 270-360V, containing 5 printed wiring assemblies with more than 1400 components that are part of a traction inverter (50kW output and 250A), starter inverter (20kW and 80A) and DC-DC converter (2800W).

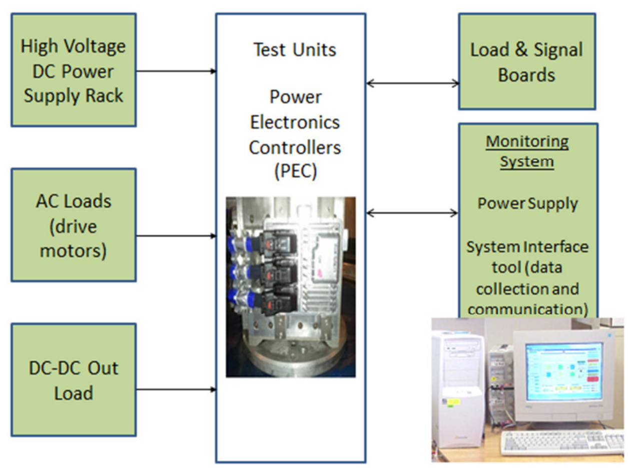


Figure 3: PEC Monitoring system

The data acquisition system, which is part of the accelerated stress testing setup Figure 3, monitors 371 parameters. Some of these parameters represent the operational (e.g. input/output currents and voltages) and test conditions of the unit (e.g. chiller flow rate, battery voltage etc.), the system performance in real time, and some parameters are fault flags for diagnostic purpose. Some of the system performance parameters had predefined limits that are often established based on experience and product specifications rather than on a PoF approach.

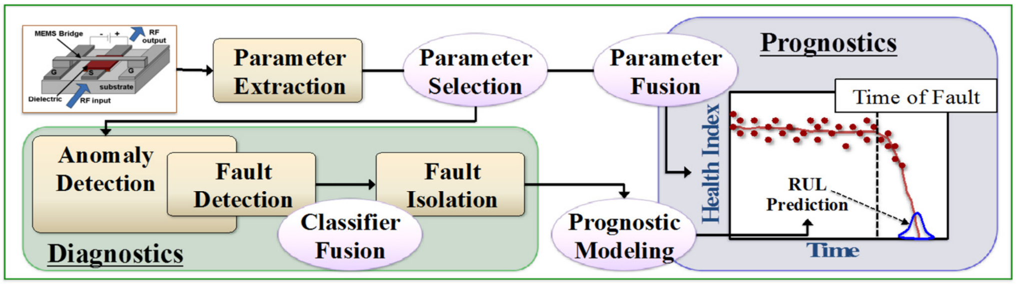
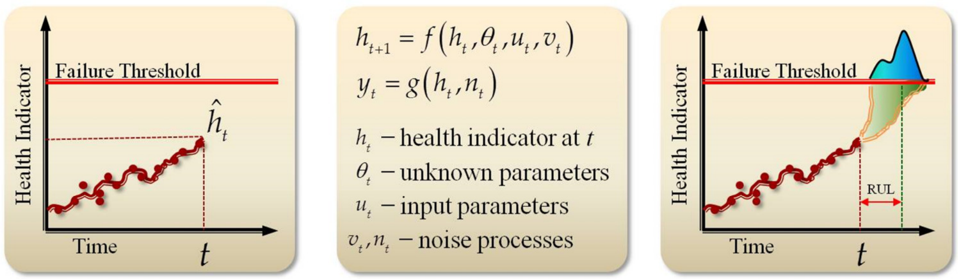


Figure 4: Framework for product diagnostics and prognostics.



Health Estimation Degradation Modeling Failure Prediction

Figure 5: Typical steps involved in prognostics approach.

3.2. Health Estimation

The first step in the prognostic development process is to develop an HI. Typically, one or more of the monitored system parameters are used as an HI vector. To verify the presence of such parameters, a GUI was first created in MATLAB to initially investigate the trend exhibited by individual parameters with respect to system degradation. None of the system-performance parameters were found to exhibit monotonic trend, which would be a highly desirable characteristic for a health metric to facilitate prognostics. However, several system parameters were found to correlate, either negatively or positively with temperature cycling conditions as shown in Figure 6. Hence, for each unit under study, the first 20 hours for each parameter was Pearson correlated i.e., $\frac{cov(I,T^{ch})}{\sigma_I \sigma_{T^{ch}}}$ with the temperature cycling conditions; where I and T^{ch} denote the system parameter and chamber temperature respectively. The parameters that exhibited high correlation with temperature were then subjected to normalization with respect to chamber temperature.

Normalization with respect to chamber temperature T^{ch} was achieved by first, identifying the linear relationship of a system parameter I, with chamber temperature as shown in Eq. (1). Second, for a given chamber temperature T_t^{ch} at time t the system parameter value $\hat{I}(T^{ch})$ is estimated using the linear relationship established in Eq. (1), where p_0 and p_1 represent the first order polynomial coefficients. Finally, the difference between the actual measurement and estimated system parameter is used as the normalized parameter value $I_{norm,t}$ at time t as shown in Eq. (2).

$$\hat{I}(T^{ch}) = p_1 T^{ch} + p_0 \quad (1)$$

$$I_{norm,t} = I_{meas,t} - \hat{I}(T_t^{ch}). \quad (2)$$

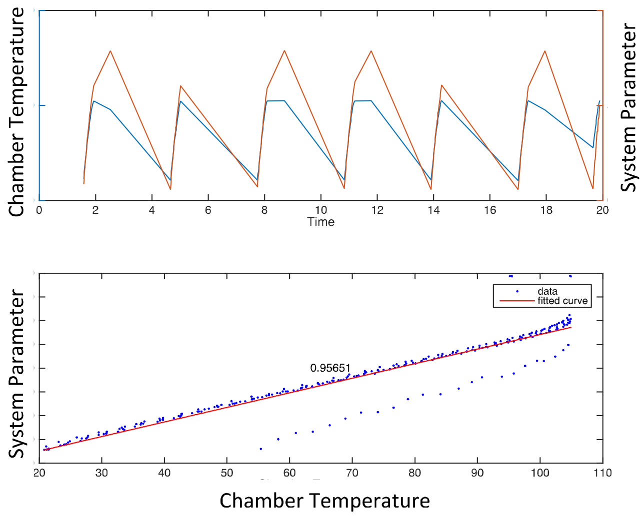


Figure 6: Example of a system parameter that is positively correlated with chamber temperature.

Some of the system parameters that were correlated with chamber temperature exhibited monotonic trends on the macro-level, but were noisy. Thus, moving average technique was used to smoothen a noisy data set. The principle behind this technique was adopted to smoothen the fluctuations in actual data set due to temperature cycling conditions and non-linear monotonic trend estimation was used to classify trend-able parameters. The moving average was performed by convolving the normalized system parameters with a weight vector of length $per + 1$,

$$wt = [(2per)^{-1} \quad (per)^{-1} \quad \cdots \quad (2per)^{-1}]_{(per+1)x1} \tag{3}$$

where per denotes the data length of one temperature cycle. Trend estimation was performed next by evaluating the Spearman correlation of the resulting system parameter with time in test. Spearman correlation was chosen for trend estimation, so that even parameters that do not change linearly with time, but change in a monotonic fashion can be identified. Spearman correlation follows the Pearson correlation with the only difference that the rank of the input data is used instead of the raw data itself. For PEC system, two parameters out of the 371 monitored parameters were found to exhibit monotonic trend after preprocessing for trend estimation.

Figure 7 shows one such system parameter before (blue) and after (red) moving average smoothening. These two parameters were used as the health state vectors for the PEC system.

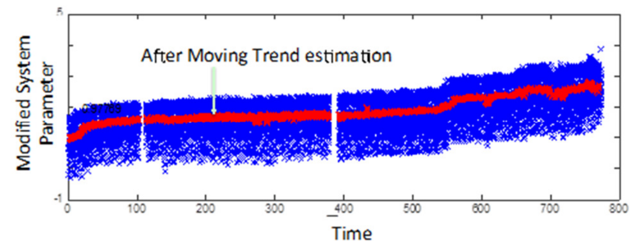


Figure 7: Example of a system parameter that is processed and trend estimation

3.3. Degradation Modeling

Once the health indicators were constructed from monitored parameters, the next step (step 2 in Figure 4) in prognostics method development is to establish a degradation model to capture a degradation trend in system parameters. Since no PoF knowledge is available at the time of this study, we resort to a data driven model using a curve fit. The best curve fit was found to be a sum of double exponential process. This is because, the degradation trend of the two health vectors exhibits a slow variation phase, followed by a rapid degradation phase. This type of behavior has been encountered in multiple applications e.g. diminishing battery capacity or resistor degradation, where a sum of double exponential process was found to provide accurate RUL estimates. Hence, we use a sum of double exponential process to capture degradation trend in preprocessed and trend estimated system parameters, as shown in Eq. (4):

$$x_t = a_t exp(b_t \times t) + c_t exp(d_t \times t) \tag{4}$$

where x_t denotes the preprocessed and trend estimated system parameter of interest at time t, and we will designate $\theta_t = [a_t \quad b_t \quad c_t \quad d_t]^T$ as the unknown parameter vector that is estimated along with the state. The initial values for x and θ are estimated from the first set of DV tests.

3.4. Prognostics

The final step in prognostic method development is the RUL estimation step, where the goal is to predict the time when the health state vector will evolve beyond a certain desired region of acceptable performance. This region represents the condition where the system performance no longer guarantees reliable system operation and is expressed through a set of requirements $\{r_i\}_{i=1}^{n_r}$. For example, n_r could represent the length of the health vector, indicating a failure threshold for each identified monotonically trending system parameter and, $r_i: \mathbb{R} \rightarrow \mathbb{B}$ denotes a function that maps a subspace in the actual health state space to the Boolean domain, $\mathbb{B} \triangleq \{0,1\}$. These individual requirements can be combined into a single threshold function for a system $T_{RUL}: \mathbb{R}^{n_x} \rightarrow \mathbb{B}$ that is defined as follows

$$T_{RUL}(x(t)) = \begin{cases} 1, & 0 \in \{r_i\}_{i=1}^{n_r} \\ 0, & otherwise \end{cases} \quad (5)$$

where $T_{RUL} = 1$ denotes that at least one of the system's subsystem or sub-assembly has violated a set requirement. Now, EOL and RUL are defined as

$$EOL(t_P) \triangleq inf\{t \in \mathbb{R}: (t \geq t_P) \wedge (T_{RUL}(x(t)) = 1)\} \quad (6)$$

$$RUL(t_P) = EOL(t_P) - t_P \quad (7)$$

where EOL represent the shortest time from the time of prediction at which the system has failed. In practice, uncertainty in modeling, measurement, and choice of initial state for $\boldsymbol{x}(t_0)$ leads to uncertainty in the estimation of $(\boldsymbol{x}(t), \boldsymbol{\theta}(t))$. Thus, it is reasonable to model EOL and RUL as probability distributions, instead of point estimates. Hence, the goal of prognostics is to calculate the conditional probability, $p(RUL(t_P)|\boldsymbol{y}(t_0\!:t_P))$, at time t_P (see Figure 8). The variables with a cap and without a cap denote estimates and the actual values, respectively.

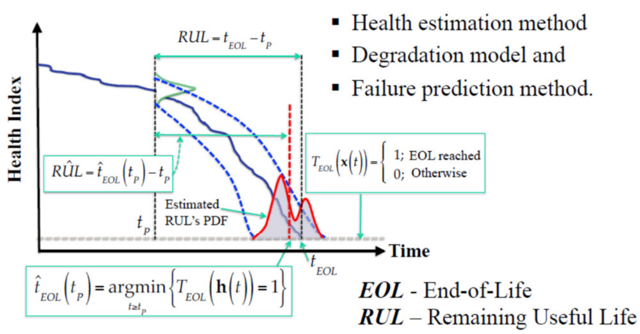


Figure 8: Prognostics uncertainty model.

The conditional probability $p(RUL(t_P)|\boldsymbol{y}(t_0\!:t_P))$ is estimated in two steps. First step is the damage estimation step, where both state and parameter vectors are estimated i.e., $p(x(t), \boldsymbol{\theta}(t)|\boldsymbol{y}(t_0\!:t))$ is computed. Many stochastic filtering algorithms such as unscented Kalman filter or Particle filter can be used to jointly estimate state-parameter vectors with nonlinear system models. Particle filter is widely used in the prognostic community for its capability to estimate the state of a nonlinear system with non-Gaussian noise without having to apply a constraint on the state and parameter vector's *pdf*. For the same reason, a particle filter is used in this study.

In particle filters, the state-parameter *pdf* is represented using a set of discrete weighted samples, typically referred to as particles

$$\{(x_t^i, \boldsymbol{\theta}_t^i), w_t^i\}_{i=1}^{M} \quad (8)$$

where M denotes the number of particles, and for each particle i, x_t^i denotes the health state estimate, $\boldsymbol{\theta}_t^i$ represents the parametric deviations estimate, and w_t^i denotes the weight at time t. At each time instant, the particle filter uses the past estimates of state and parameter along with real time measurements to estimate the current state. To realize this multi-step computation, first the parameter vector $\boldsymbol{\theta_t}$ is estimated from the previous time instant parameter estimates using some process that is independent of the state x_t. The typical solution is to use a random walk process, i.e., $\boldsymbol{\theta_t} = \boldsymbol{\theta_{t-\Delta t}} + \boldsymbol{\xi_{t-\Delta t}}$, where $\boldsymbol{\xi}$ is sampled from a distribution such as zero-mean Gaussian. Once the parameter vector is updated, the system health is estimated based on Eq. (4) after which the associated weights are computed using the principle of importance resampling. At the end of an iteration the estimated state and parameter vector, particles are studied for degeneracy and resampled if necessary. During resampling, the particles with least weights are eliminated thereby allowing us to concentrate on the particles with larger weights.

The second step in model-based prognostics involves the RUL prediction, where the goal is to compute $p(RUL(t_P)|\boldsymbol{y}(t_0\!:t_P))$ at time t_P using the joint state-parameter estimate $(x(t_P), \boldsymbol{\theta}(t_P)|\boldsymbol{y}(t_0\!:t_P))$. The idea to solve the RUL prediction problem is to simply let the state and parameter vector – particles to evolve without Bayesian updating, until the threshold function evaluates to $T_{EOL}(x_t^i) = 1$ for each particle. The predicted time $t\!: t \geq t_P$ at which $T_{EOL}(x_t^i) = 1$ provides the EOL, from which RUL is estimated using Eq. (7).

The failure prediction results for two PEC system is shown in Figure 9 and Figure 10. The plots in Figure 9 and Figure 10 have the time of prediction in *x*-axis and the RUL at that predicted time on the *y*-axis. The green (outer) lines represent the uncertainty bounds in the RUL estimates. The graph in Figure 9 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. Similar interpretation can be made for the graph in Figure 10. Both PEC systems did not reach functional failure. Hence, by assuming the end prediction is accurate, we can see that reliable RUL estimates can be generated as early as 400 hours into PTC testing. With design target close to 900 hrs, an accurate predictions as early as 400 hours indicates that prognostics methodology can be used to predict EOL as soon as 50% of the damage is accumulated (assuming Miner's rule for damage accumulation), where damage is estimated using, $D = \frac{t_P}{EOL}$. This means, there is a significant test time saving opportunity.

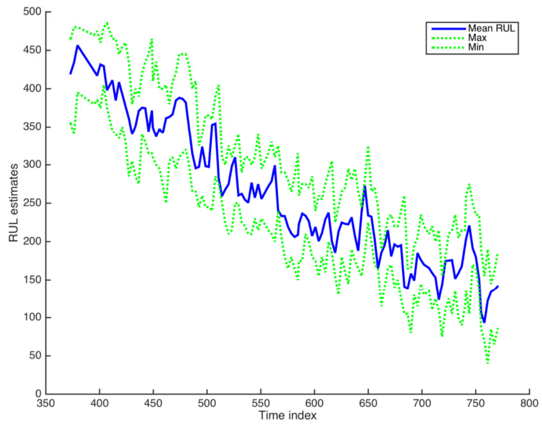


Figure 9: RUL prediction result for PEC - Unit 1.

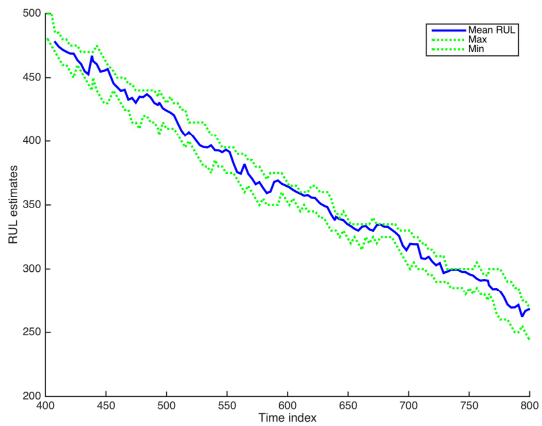


Figure 10: RUL prediction result for PEC - Unit 2.

3.5. Case Study 2: Engine Controller Unit (ECU)

A prognostic approach, similar to the one implemented in the previous case study was employed to conventional engine controller units (ECUs). However, unlike the PEC system, the ECU accelerated test data contained only 5 parameters (chamber temperature, input voltage, output frequency, output voltage, and duty cycle). It was identified that the system output voltage was linearly related to the chamber temperature, and the corresponding voltage intercept with respect to the chamber temperature was changing with degradation in system health. This attribute was utilized to construct an HI and a simple linear degradation model

$$x_t = x_{t-\Delta t} + (\alpha_t \times \Delta t) \tag{9}$$

was applied along with a particle filter to estimated EOL and predict the system RUL. Here, α is the unknown parameter similar to θ in Eq. (4). The RUL prediction result for one ECU unit is shown in Figure 10. This system failed on the 20th day of the PTC test. Accurate RUL prediction results were generated as early as 12 days into the PTC test. Thus, significant number of days can be saved in repeated testing cycles by using failure prognostics methodology.

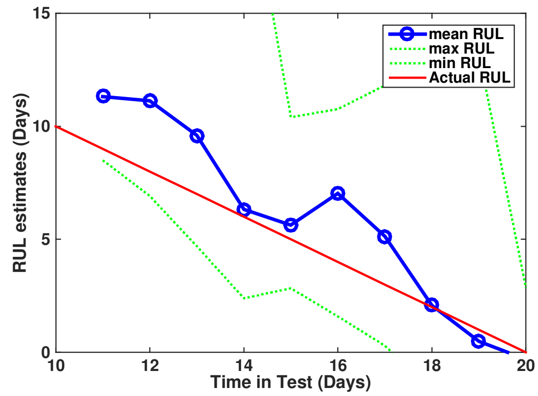


Figure 10: RUL prediction result for ECU.

4. CONCLUSION AND FUTURE WORK

In this paper we demonstrates how prognostics can be used to reduce the duration of the longest and most expensive product validation tests with a case study of an automotive PTC testing. Implementation of a real time prognostic engine into existing monitoring systems presents several benefits:

1. Prognostic based validations are expected to significantly reduce life demonstration test time, resulting in significantly reduced execution costs, since it will no longer be needed to run a test to a bogey (equivalent of one mission life) or to run a test to failure, which takes even longer than a success-based testing.

2. The proposed application of prognostics has 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.

3. The methodology outlined offers a comprehensive approach to understanding overall product reliability and presents a viable alternative to validation testing where test acceleration is difficult or impossible due to the products already operating close to their operating limits.

4. Application of prognostics to validation testing also presents a lot of challenges. 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. Data fusion offers potentially the best performance results especially since it is a holistic approach

A wider debate is required within the automotive reliability and test community on the acceptance of such methodologies and more importantly how it may be standardized so that test results are repeatable globally within an organization and between different organizations. This arises from the fact that the decision to terminate testing early rests on a prognosis, the accuracy of which is dependent upon the product monitoring data quality and proprietary expert knowledge databases.

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NOMENCLATURE AND ACRONYMS

θ	unknown parameter vector in degradation model
x_t	system health at time t
ξ	process noise for random walk
t	time
T^{ch}	chamber temperature
DV	Design Validation
EOL	End of Life
GUI	Graphical User Interface
HI	Health Indicator
HTE	High Temperature Endurance
pdf	Probability Density Function
PEC	Power Electronics Controller
PoF	Physics of Failure
PTC	Power Temperature Cycling
PV	Process Validation
RUL	Remaining Useful Life

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BIOGRAPHIES

Andre Kleyner has 30 years of engineering, research, consulting, and managerial experience specializing in reliability of electronic and mechanical systems designed to operate in severe environments.

He received the doctorate in Mechanical Engineering from University of Maryland, and Master of Business Administration from Ball State University. Dr. Kleyner is Global Reliability Engineering Leader with Delphi Electronics & Safety and an adjunct professor at Purdue University. He is an ASQ Fellow, a CRE, CQE, and Six Sigma Black Belt. He also holds several US and foreign patents and authored multiple professional publications including three books on the topics of reliability, statistics, warranty management, and lifecycle cost analysis. Andre Kleyner is also the editor of the Wiley book Series in Quality and Reliability Engineering published by John Wiley & Sons.

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