A Model-based Prognostics Methodology for Electrolytic Capacitors Based on Electrical Overstress Accelerated Aging

José R. Celaya[1], Chetan Kulkarni[2], Gautam Biswas[3], Sankalita Saha[4], Kai Goebel[5]

[1] *SGT Inc. NASA Ames Research Center, Moffett Field, CA, 94035, USA*
jose.r.celaya@nasa.gov

[2,3] *Vanderbilt University, Nashville, TN, 37235, USA*
chetan.kulkarni@vanderbilt.edu
biswas@eecsmail.vuse.vanderbilt.edu

[4] *MCT. NASA Ames Research Center, Moffett Field, CA, 94035, USA*
sankalita.saha@nasa.gov

[5] *NASA Ames Research Center, Moffett Field, CA, 94035, USA*
kai.goebel@nasa.gov

ABSTRACT

A remaining useful life prediction methodology for electrolytic capacitors is presented. This methodology is based on the Kalman filter framework and an empirical degradation model. Electrolytic capacitors are used in several applications ranging from power supplies on critical avionics equipment to power drivers for electro-mechanical actuators. These devices are known for their comparatively low reliability and given their criticality in electronics subsystems they are a good candidate for component level prognostics and health management. Prognostics provides a way to assess remaining useful life of a capacitor based on its current state of health and its anticipated future usage and operational conditions. We present here also, experimental results of an accelerated aging test under electrical stresses. The data obtained in this test form the basis for a remaining life prediction algorithm where a model of the degradation process is suggested. This preliminary remaining life prediction algorithm serves as a demonstration of how prognostics methodologies could be used for electrolytic capacitors. In addition, the use degradation progression data from accelerated aging, provides an avenue for validation of applications of the Kalman filter based prognostics methods typically used for remaining useful life predictions in other applications.

1. Introduction

This paper proposes the use of a model based prognostics approach for electrolytic capacitors. Electrolytic capacitors have become critical components in electronics systems in aeronautics and other domains. This type of capacitors is known for its low reliability and frequent breakdown in critical systems like power supplies of avionics equipment and electrical drivers of electro-mechanical actuators of control surfaces. The field of prognostics for electronics components is concerned with the prediction of remaining useful life (RUL) of components and systems. In particular, it focuses on condition-based health assessment by estimating the current state of health. Furthermore, it leverages the knowledge of the device physics and degradation physics to predict remaining useful life as a function of current state of health and anticipated operational and environmental conditions.

1.1 Motivation

The development of prognostics methodologies for the electronics field has become more important as more electrical systems are being used to replace traditional systems in several applications in fields like aeronautics, maritime, and automotive. The development of prognostics methods for electronics presents several challenges due to great variety of components used in a system, a continuous development of new electronics technologies, and a general lack of understanding of how electronics fail. Traditional reliability techniques in electronics tend to focus on understanding the time to failure for a batch of components of the same type. Just until recently, there has been a push to understand, in more depth, how a fault progresses as a function of usage, namely, loading and environmental conditions. Furthermore, just until recently, it was believed that there were no precursor of failure indications for electronics systems. That is now understood to be incorrect, since electronics systems, similar to mechanical systems, undergo a measurable wear process from which one can derive features that can be used to provide early warnings to failure. These failures can be detected before they happen and one can potentially predict the remaining useful life as a function of future usage and environmental conditions.

Avionics systems in on-board autonomous aircraft perform critical functions greatly escalating the ramification of an in-flight malfunction (Bhatti & Ochieng, 2007; Kulkarni et al., 2009). These systems combine physical processes, computational hardware and software; and present unique challenges for fault diagnosis. A systematic analysis of these conditions is very important for analysis of aircraft safety and also to avoid catastrophic failures during flight.

Power supplies are critical components of modern avionics systems. Degradations and faults of the DC-DC converter unit propagate to the GPS (global positioning system) and navigation subsystems affecting the overall operation. Capacitors and MOSFETs (metal oxide field effect transistor) are the two major components, which cause degradations and failures in DC-DC converters (Kulkarni, Biswas, Bharadwaj, & Kim, 2010). Some of the more prevalent fault effects, such as a ripple voltage surge at the power supply output can cause glitches in the GPS position and velocity output, and this in turn, if not corrected can propagate and distort the navigation solution.

Capacitors are used as filtering elements on power electronics systems. Electrical power drivers for motors require capacitors to filter the rail voltage for the H-bridges that provide bidirectional current flow to the windings of electrical motors. These capacitors help to ensure that the heavy dynamic loads generated by the motors do not perturb the upstream power distribution system. Electrical motors are an essential element in electro-mechanical actuators systems that are being used to replace hydro-mechanical actuation in control surfaces of future generation aircrafts.

1.2 Methodology

The process followed in the proposed prognostics methodology is presented in the block-diagram in Figure 1. This prognostics methodology is based on results from an accelerated life test on real electrolytic capacitors. This test applies electrical overstress to commercial-off-the-shelf capacitors in order to observe and record the degradation process and identify performance conditions in the neighborhood of the failure criteria in a considerably reduced time frame.

Electro-impedance spectroscopy is used periodically during the test to characterize the frequency response of the capacitor. These measurements along a reduced order model based on passive electrical elements are used to identify the capacitance and parasitic resistance element.

We present here an empirical degradation model that is based on the observed degradation process during the accelerated life test. A model structure is suggested based on the observed degradation curves. Model parameters are estimated using nonlinear least-squares regression. A Bayesian framework is employed to estimate (track) the state of health of the capacitor based on measurement updates of key capacitor parameters. The Kalman filter algorithm is used to track the state of health and the degradation model is used to make predictions of remaining useful life once no further measurements are available. A discussion and physical interpretation of the degradation model is presented. An analysis of the frequency response guides the selection of the precursor of failure variable used in the RUL prediction framework. A first order capacitance and equivalent series resistance (ESR) model is employed and the capacitance value is used in the development of the algorithm.

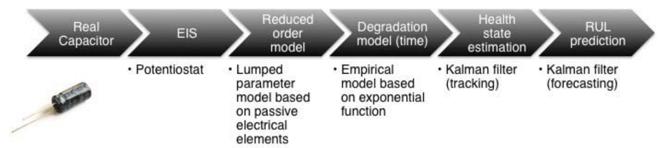

Figure 1. Model-based prognostics methodology for electrolytic capacitor.

1.3 Previous work

In earlier work (Kulkarni, Biswas, Koutsoukos, Goebel, & Celaya, 2010b), we studied the degradation of capacitors under nominal operation. There, work capacitors were used in a DC-DC converter and their degradation was monitored over an extended period of time. The capacitors were characterized every 100-120 hours of operation to capture degradation data for ESR and capacitance. The data collected over the period of about 4500 hours of operation were then mapped against an Arrhenius inspired ESR degradation model (Kulkarni, Biswas, Koutsoukos, Goebel, & Celaya, 2010a).

In following experimental work, we studied accelerated degradation in capacitors (Kulkarni, Biswas, Koutsoukos, Celaya, & Goebel, 2010). In that experiment the capacitors were subjected to high charging/discharging cycles at a constant frequency and their degradation progress was monitored. A preliminary approach to remaining useful life prediction of electrolytic capacitors was presented in (Celaya et al., 2011). This paper here builds upon the work presented in the preliminary remaining useful life prediction in (Celaya et al., 2011).

1.4 Other related work and current art in capacitor prognostics

The output filter capacitor has been identified as one of the elements of a switched mode power supply that fails more frequently and has a critical impact on performance (Goodman et al., 2007; Judkins et al., 2007; Orsagh et al., 2005). A prognostics and health management approach for power supplies of avionics systems is presented in (Orsagh et al., 2005). Results from accelerated aging of the complete supply were presented and discussed in terms of output capacitor and power MOSFET failures; but there is no modeling of the degradation process or RUL prediction for the power supply. Other approaches for prognostics for switched mode power supplies are presented in Goodman et al. (2007) and Judkins et al. (2007). The output ripple voltage and leakage current are presented as a function of time and degradation of the capacitor, but no details were presented regarding the modeling of the degradation process and there were no technical details on fault detection and RUL prediction algorithms.

A health management approach for multilayer ceramic capacitors is presented in Nie et al. (2007). This approach focuses on the temperature-humidity bias accelerated test to replicate failures. A method based on Mahalanobis distance is used to detect abnormalities in the test data; there is no prediction of RUL. A data driven prognostics algorithm for multilayer ceramic capacitors is presented in Gu et al. (2008). This method uses data from accelerated aging test to detect potential failures and to make an estimation of time of failure.

2. Accelerated aging experiments

Accelerated life test methods are often used in prognostics research as a way to assess the effects of the degradation process through time. It also allows for the identification and study of different failure mechanisms and their relationships with different observable signals and parameters. In the following section we present the accelerated aging methodology and an analysis of the degradation pattern induced by the aging. The work presented here is based on an accelerated electrical overstress. In the following subsections, we first present a brief description of the aging setup followed by an analysis of the observed degradation. The precursor to failure is also identified along with the physical processes that contribute to the degradation.

2.1 Accelerated aging system description

Since the objective of this experiment is studying the effects of high voltage on degradation of the capacitors, the capacitors were subjected to high voltage stress through an external supply source using a specially developed hardware. The capacitors are not operated within DC-DC converters; only the capacitors were subjected to the stress.

The voltage overstress is applied to the capacitors as a square wave form in order to subject the capacitor to continuous charge and discharge cycles.

At the beginning of the accelerated aging, the capacitors charge and discharge simultaneously; as time progresses and the capacitors degrade, the charge and discharge times vary for each capacitor. Even though all the capacitors under test are subjected to similar operating conditions, their ESR and capacitance values change differently. We therefore monitor charging and discharging of each capacitor under test and measure the input and output voltages of the capacitor. Figure 2 shows the block diagram for the electrical overstress experiment. Additional details on the accelerated aging system are presented in (Kulkarni, Biswas, Koutsoukos, Celaya, & Goebel, 2010).

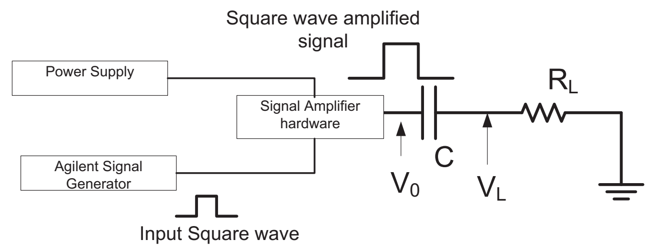

Figure 2. Block diagram of the experimental setup.

For this experiment six capacitors in a set were considered for the EOS experimental setup. Electrolytic capacitors of 2200μF capacitance, with a maximum rated voltage of $10V$, maximum current rating of $1A$ and maximum operating temperature of $105°C$ was used for the study. These were the recommended capacitors by the manufacturer for DC-DC converters. The electrolytic capacitors under test were characterized in detail before the start of the experiment at room temperature.

The ESR and capacitance values were estimated from the capacitor impedance frequency response measured using an SP-150 Biologic SAS electro-impedance spectroscopy instrument. A lumped parameter model consisting of a capacitor with a resistor in series was assumed to estimate the ESR and capacitance. The average pristine condition ESR value was measured to be $0.056\ m\Omega$ and average capacitance of $2123\ \mu$F individually for the set of capacitors under test.

The measurements were recorded every 8-10 hours of the total 180 plus hours of accelerated aging time to capture the rapid degradation phenomenon in the ESR and capacitance values. The ambient temperature for the experiment was controlled and kept at $25°C$. During each measurement the voltage source was shut down, capacitors were discharged completely and then the characterization procedure was carried out. This was done for all the six capacitors under test. For further details regarding the aging experiment results and analysis of the measured data refer to (Kulkarni, Biswas, Koutsoukos, Celaya, & Goebel, 2010; Celaya et al., 2011).

2.2 Physical interpretation of the degradation process

There are several factors that cause electrolytic capacitors to fail. Continued degradation, i.e., gradual loss of functionality over a period of time results in the failure of the component. Complete loss of function is termed a *catastrophic* failure. Typically, this results in a short or open circuit in the capacitor. For capacitors, degradation results in a gradual increase in the equivalent series resistance (ESR) and decrease in capacitance over time.

In this work, we study the degradation of electrolytic capacitors operating under high electrical stress, i.e., $V_{applied} \geq V_{rated}$. During the charging/discharging process the capacitors degrade over the period of time. A study of the literature indicated that the degradation could be primarily attributed to three phenomena (IEC, 2007-03; MIL-C-62F, 2008):

1. Electrolyte evaporation,
2. Leakage current, and
3. Increase in internal pressure

An ideal capacitor would offer no resistance to the flow of current at its leads. However, the electrolyte (aluminum oxide) that fills the space between the plates and the electrodes produces a small equivalent internal series resistance (ESR). The ESR dissipates some of the stored energy in the capacitor. In spite of the dielectric insulation layer between a capacitor's plates, a small amount of 'leakage' current flows between the plates. For a good capacitor operating nominally this current is not significant, but it becomes larger as the oxide layer degrades during operation. High electrical stress is known to accentuate the degradation of the oxide layer due to localized dielectric breakdowns on the oxide layer (Ikonopisov, 1977; Wit & Crevecoeur, 1974).

The literature on capacitor degradation shows a direct relationship between electrolyte decrease and increase in the ESR of the capacitor (Kulkarni, Biswas, Koutsoukos, Goebel, & Celaya, 2010b). ESR increase implies greater dissipation, and, therefore, a slow decrease in the average output voltage at the capacitor leads. Another mechanism occurring simultaneously is the increase in internal pressure due to an increased rate of chemical reactions, which are attributed to the internal temperature increase in the capacitor.

During the experiments, as discussed earlier, the capacitors were characterized at regular intervals. ESR and capacitance are the two main failure precursors that tipify the current health state of the device. ESR and capacitance values were calculated after characterizing the capacitors. As the devices degrade due to different failure mechanisms we can observe a decrease in the capacitance and an increase in the ESR.

ESR and capacitance values are estimated by using a system identification using a lump parameter model consistent of the capacitance and the ESR in series as shown in Figure 3. The frequency response of the capacitor impedance (measured with electro-impedance spectroscopy) is used for the parameter estimation. It should be noted that the lumped-parameter model used to estimate ESR and capacitance, is not the model to be used in the prognostics algorithm; it only allows us to estimate parameters which provide indications of the degradation process through time. Parameters such as ESR and capacitance are challenging to estimate from the *in-situ* measurements of voltage and current through the accelerated aging test.

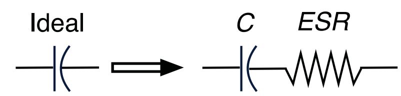

Figure 3. Lumped parameter model for a real capacitor.

Figure 4 shows percentage increase in the ESR value for all the six capacitors under test over the period of time. This value of ESR is calculated from the impedance measurements after characterizing the capacitors. Similarly, figure 5 shows the percentage decrease in the value of the capacitance as the capacitor degrades over the period under EOS test condition discussed. As per standards MIL-C-62F (2008), a capacitor is considered unhealthy if under electrical operation its ESR increases by $280-300\%$ of its initial value or the capacitance decreases by 20% below its pristine condition value. From the plots in Figure 4 we observe that for the time for which the experiments were conducted the average ESR value increased by $54\% - 55\%$ while over the same period of time, the average capacitance decreased by more than 20% (the threshold mark for a healthy capacitor) (see Figure 5). As a result, the percentage capacitance loss is selected as a precursor of failure variable to be used in the degradation model development presented next.

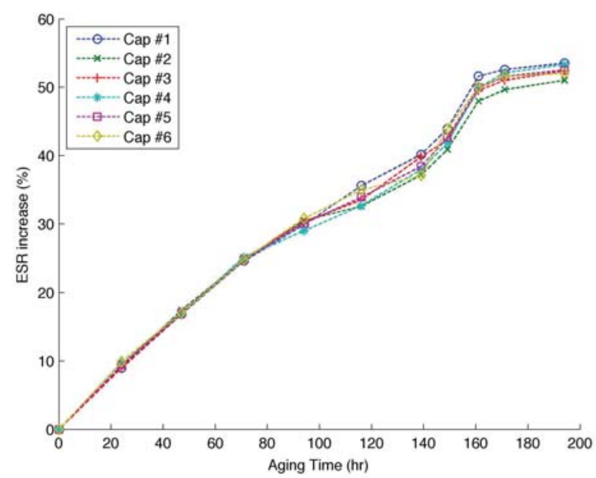

Figure 4. Degradation of capacitor performance, percentage ESR increase as a function of aging time.

3. Prediction of Remaining Useful Life

A model-based prognostics algorithm based on Kalman filter and a physics inspired empirical degradation model is presented. This algorithm is able to predict remaining useful life of the capacitor based on the accelerated degradation data

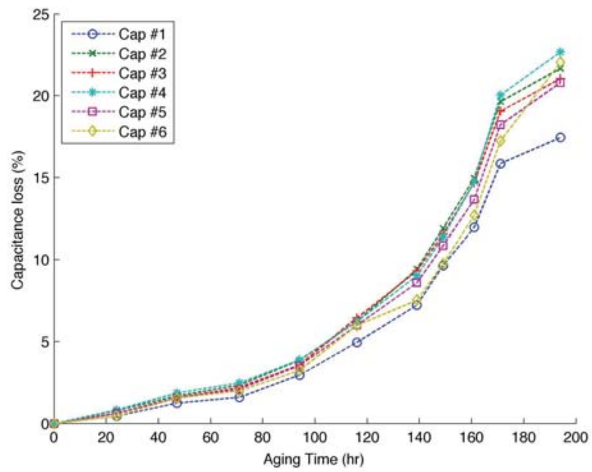

Figure 5. Degradation of capacitor performance, percentage capacitance loss as a function of aging time.

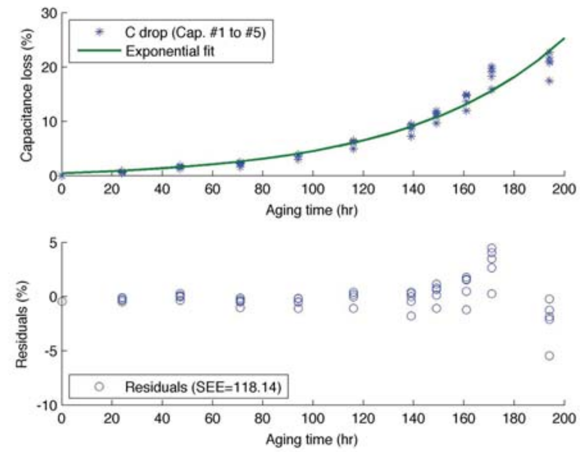

Figure 6. Estimation results for the empirical degradation model.

from the experiments described in previous sections. The percentage loss in capacitance is used as a precursor of failure variable and it is used to build a model of the degradation process. This model relates aging time to the percentage loss in capacitance and has the following form,

$$C_k = e^{\alpha t_k} + \beta, \tag{1}$$

where α and β are model constants that will be estimated from the experimental data of accelerated aging experiments. In order to estimate the model parameters, five capacitors are used for estimation (labeled capacitors #1 through #5), and the remaining capacitor (#6) is used to test the prognostics algorithm. A nonlinear least-squares regression algorithm is used to estimate the model parameters. Figure 6 shows the estimation results. The experimental data are presented together with results from the exponential fit function. It can be observed from the residuals that the estimation error increases with time. This is to be expected since the last data point measured for all the capacitors fall slightly off the concave exponential model. The estimated parameters are $\alpha = 0.0163$ and $\beta = -0.5653$.

The estimated degradation model is used as part of a Bayesian tracking framework to be implemented using the Kalman filter technique. This method requires a state-space dynamic model relating the degradation level at time t_k to the degradation level at time t_{k-1}. The formulation of the state model is described below.

$$\begin{aligned} \frac{dC}{dt} &= \alpha C - \alpha\beta \\ \frac{C_t - C_{t-\Delta t}}{\Delta t} &= \alpha C_{t-\Delta t} - \alpha\beta \\ C_t &= (1 + \alpha\Delta_t) C_{t-\Delta t} - \alpha\beta\Delta_t, \end{aligned} \tag{2}$$

$$C_k = (1 + \alpha\Delta_k) C_{k-1} - \alpha\beta\Delta_k. \tag{3}$$

In this model C_k is the state variable and it represents the percentage loss in capacitance. Since the system measurements are percentage loss in capacitance as well, the output equation is given by $y_k = hC_k$, where the value of h is equal to one. The following system structure is used in the implementation of the filtering and the prediction using the Kalman filter.

$$C_k = A_k C_{k-1} + B_k u + v, \tag{4}$$
$$y_k = hC_{k-1} + w, \tag{5}$$

where,

$$\begin{aligned} A_k &= (1 + \Delta_k), \\ B_k &= -\alpha\beta\Delta_k, \\ h &= 1, \\ u &= 1. \end{aligned} \tag{6}$$

The time increment between measurements Δ_k is not constant since measurements were taken at non-uniform sampling rate. This implies that some of the parameters of the model in equations (4)-(6) will change through time. Furthermore, v and w are normal random variables with zero mean and Q and R variance respectively. The description of the Kalman filtering algorithm is omitted from this article. A thorough description of the algorithm can be found in Stengel (1994), a description of how the algorithm is used for forecasting can be found in Chatfield (2003) and an example of its usage for prognostics can be found in (Saha et al., 2009). Figure 7 shows the results of the application of the Kalman filter to the test case (Cap. #6). The model noise variance Q was estimated from the model regression residuals. The residuals have a mean very close to zero and a variance of 2.1829. This variance was used for the model noise in the Kalman filter implementation. The measurement noise variance R is also required in the filter implementation. This variance was computed from the direct measurements of the capacitance with the electro-impedance spectroscopy equipment, the observed variance is $4.99E^{-7}$. Figure 7 shows the result of the filter tracking the complete degradation signal. The residuals show an increased error with aging time. This is to be expected given the results observed from the model estimation process.

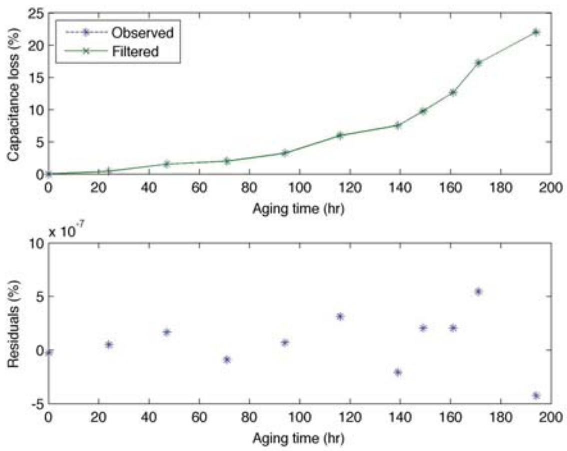

Figure 7. Tracking results for the Kalman filter implementation applied to test capacitor (capacitor #6).

The use of the Kalman filter as a RUL forecasting algorithm requires the evolution of the state without updating the error covariance matrix and the posterior of the state vector. The n step ahead forecasting equation for the Kalman filter is given below. The last update is done at the time of the last measurement t_l.

$$\hat{C}_{l+n} = A^n C_l + \sum_{i=0}^{n-1} A^i B \tag{7}$$

The subscripts from parameters A and B are omitted since a constant Δ_t is used in the forecasting mode (one prediction every hour). Figure 8 presents results from the remaining useful life prediction algorithm at time 149 (hr), which is the time at which an ESR and C measurements are taken. The failure threshold is considered to be a crisp value of 20% decrease in capacitance. End of life (EOL) is defined as the time at which the forecasted percentage capacity loss trajectory crosses the EOL threshold. Therefore, RUL is EOL minus 149 hours.

Figure 9 presents the capacitance loss estimation and EOL prediction at different points during the aging time. Predictions are made after each point in which measurements are available. It can be observed that the predictions become better as the prediction is made closer to the actual EOL. This is possible because the estimation process has more information to update the estimates as it nears EOL. Figure 10 presents a

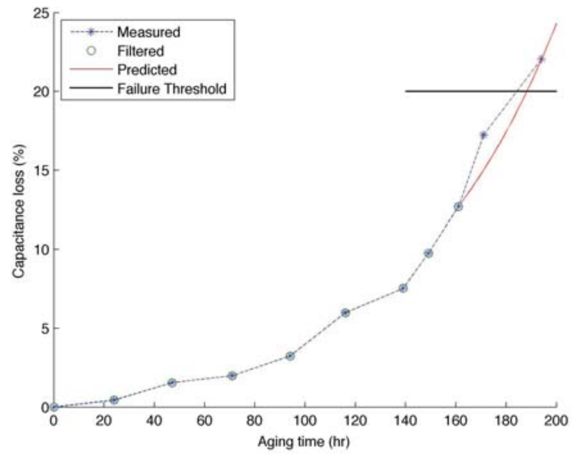

Figure 8. Remaining useful life prediction at time 149 (hr).

zoomed-in version of figure 9 focusing in the area close to the failure threshold.

Table 1 summarizes results for the remaining life prediction at all points in time where measurements are available. The last column indicates the RUL prediction error. The magnitude of the error decreases as the prediction time gets closer to EOL. The decrease is not monotonic which is to be expected when using a the tracking framework to estimate health state because the last point of the estimation is used to start the forecasting process. An α-λ prognostics performance metric is presented in Figure 11. The blue line represents ground truth and the shaded region is corresponding to a 30% ($\alpha = 0.3$) error bound in the RUL prediction. This metric specifies that the prediction is within the error bound halfway between first prediction and EOL ($\lambda = 0.5$). In addition, this metric allows us to visualize how the RUL prediction performance changes as data closer to EOL becomes available.

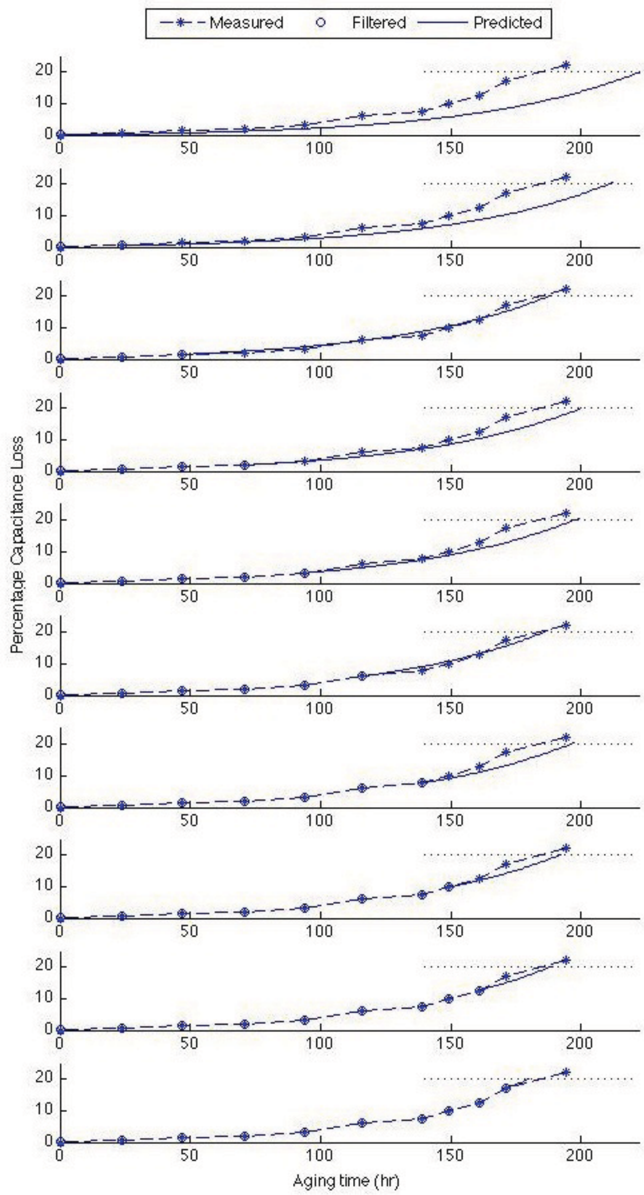

Figure 9. Health state estimation and forecasting of capacitance loss (%) at different times t_p during the aging time; $t_p = [0, 24, 47, 71, 94, 116, 139, 149, 161, 171]$.

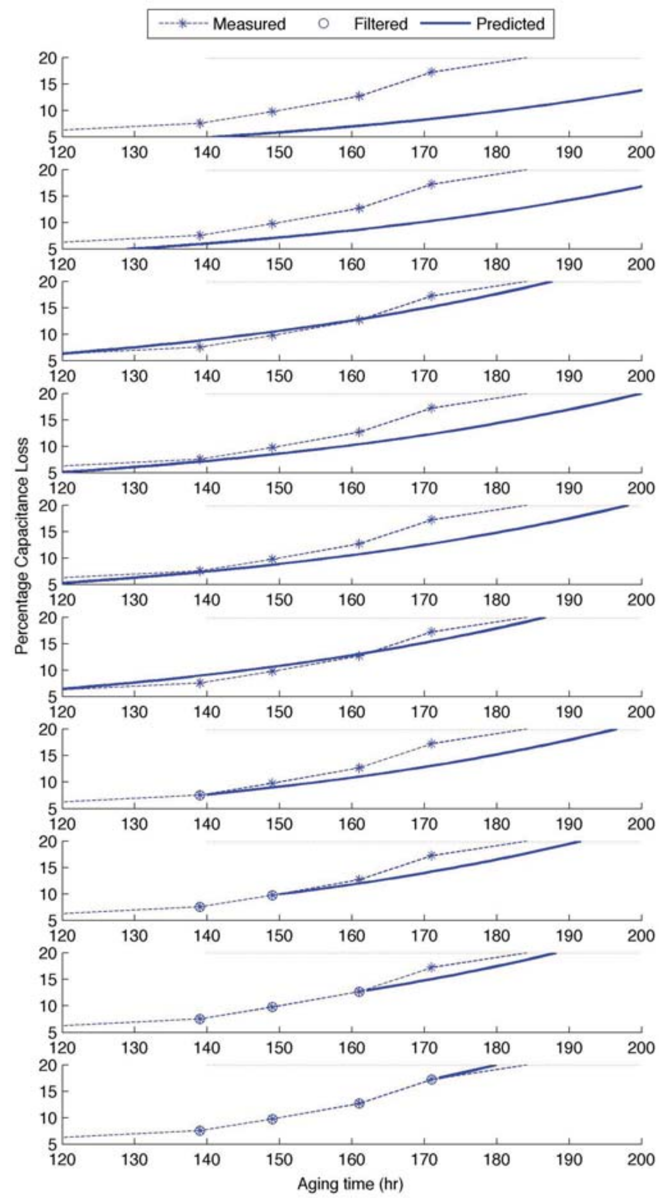

Figure 10. Detail of the health state estimation and forecasting of capacitance loss (%) at different times t_p during the aging time; $t_p = [0, 24, 47, 71, 94, 116, 139, 149, 161, 171]$.

4. Conclusion

This paper presents a RUL prediction algorithm based on accelerated life test data and an empirical degradation model. The main contributions of this work are: a) the identification of the lumped-parameter model (Figure 3) for a real capacitor as a viable reduced-order model for prognostics-algorithm development; b) the identification of the ESR and C model parameters as precursor of failure features; c) the development of an empirical degradation model based on accelerated life test data which accounts for shifts in capacitance as a func-

RUL forecasting time (hr)	RUL estimate (hr)	Ground truth (hr)	Error (hr)
0	222.2	184.24	37.96
24	186.55	160.24	26.31
47	140.66	137.24	3.42
71	128.98	113.24	15.74
94	104.18	90.24	13.94
116	70.71	68.24	2.47
139	57.58	45.24	12.34
149	42.61	35.24	11.37
161	27.20	23.24	3.96
171	8.94	13.24	-4.3

Table 1. Summary of RUL forecasting results.

tion of time; d) the implementation of a Bayesian based health state tracking and remaining useful life prediction algorithm based on the Kalman filtering framework. One major contribution of this work is the prediction of remaining useful life for capacitors as new measurements become available.

This capability increases the technology readiness level of prognostics applied to electrolytic capacitors. The results presented here are based on accelerated life test data and on the accelerated life timescale. Further research will focus on development of functional mappings that will translate the accelerated life timescale into real usage conditions time-scale, where the degradation process dynamics will be slower, and subject to several types of stresses. The performance of the proposed exponential-based degradation model is satisfactory for this study based on the quality of the model fit to the experimental data and the RUL prediction performance as compared to ground truth. As part of future work we will also focus on the exploration of additional models based on the physics of the degradation process and larger sample size for aged devices. Additional experiments are currently underway to increase the number of test samples. This will greatly enhance the quality of the model, and guide the exploration of additional degradation-models, where the loading conditions and the environmental conditions are also accounted for towards degradation dynamics.

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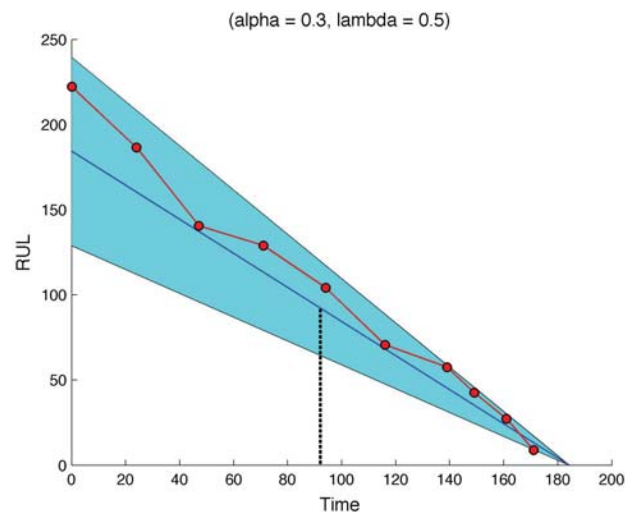

Figure 11. Performance based on α-λ performance metric.

Nomenclature

C_p	Pristine state measured capacitance
ESR	Equivalent series resistance of the electrolytic capacitor
ESR_p	Pristine state measured equivalent series resistance
C_k	Measured capacitance at time t_k
RUL	Remaining useful life

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José R. Celaya is a research scientist with SGT Inc. at the Prognostics Center of Excellence, NASA Ames Research Center. He received a Ph.D. degree in Decision Sciences and Engineering Systems in 2008, a M. E. degree in Operations Research and Statistics in 2008, a M. S. degree in Electrical Engineering in 2003, all from Rensselaer Polytechnic Institute, Troy New York; and a B. S. in Cybernetics Engineering in 2001 from CETYS University, México.

Chetan S Kulkarni is a Research Assistant at ISIS, Vanderbilt University. He received the M.S. degree in EECS from Vanderbilt University, Nashville, TN, in 2009, where he is currently a Ph.D student.

Sankalita Saha is a research scientist with Mission Critical Technologies at the Prognostics Center of Excellence, NASA Ames Research Center. She received the M.S. and PhD. degrees in Electrical Engineering from University of Maryland, College Park in 2007. Prior to that she obtained her B.Tech (Bachelor of Technology) degree in Electronics and Electrical Communications Engineering from the Indian Institute of Technology, Kharagpur in 2002.

Kai Goebel received the degree of Diplom-Ingenieur from the Technische Universitt Mnchen, Germany in 1990. He received the M.S. and Ph.D. from the University of California at Berkeley in 1993 and 1996, respectively. Dr. Goebel is a senior scientist at NASA Ames Research Center where he leads the Diagnostics and Prognostics groups in the Intelligent Systems division. In addition, he directs the Prognostics Center of Excellence and he is the technical lead for Prognostics and Decision Making of NASAs System-wide Safety and Assurance Technologies Program. He worked at General Electrics Corporate Research Center in Niskayuna, NY from 1997 to 2006 as a senior research scientist. He has carried out applied research in the areas of artificial intelligence, soft computing, and information fusion. His research interest lies in advancing these techniques for real time monitoring, diagnostics, and prognostics. He holds 15 patents and has published more than 200 papers in the area of systems health management.

Gautam Biswas received the Ph.D. degree in computer science from Michigan State University, East Lansing. He is a Professor of Computer Science and Computer Engineering in the Department of Electrical Engineering and Computer Science, Vanderbilt University, Nashville, TN.