

A Particle Filtering-Based Approach for the Prediction of the Remaining Useful Life of an Aluminum Electrolytic Capacitor

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ABSTRACT

This work focuses on the estimation of the Remaining Useful Life (RUL) of aluminum electrolytic capacitors used in electrical automotive drives under variable and non-stationary operative conditions. The main cause of the capacitor degradation is the vaporization of the electrolyte due to a chemical reaction. Capacitor degradation can be monitored by observing the capacitor Equivalent Series Resistance (ESR) whose measurement, however, is heavily influenced by the measurement temperature, which, under non-stationary operative conditions, is continuously changing. In this work, we introduce a novel degradation indicator which is independent from the measurement temperature and, thus, can be used for real applications under variable operative conditions. The indicator is defined by the ratio between the ESR measured on the degraded capacitor and the ESR expected value on a new capacitor at the present operational temperature. The definition of this indicator has required the investigation of the relationship between ESR and temperature on a new capacitor by means of experimental laboratory tests. The prediction of the capacitor degradation and its failure time has been performed by resorting to a Particle Filtering-based prognostic technique.

1. INTRODUCTION

The aluminium electrolytic capacitor is one of the most critical components of electric systems, leading to almost 30% of the total number of failures in such systems

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(Wolfgang, 2007). Its main failure mode is caused by the vaporization of the contained electrolyte, which involves a loss of functionality, and produces a reduction of the capacity and an increase of the Equivalent Series Resistance (ESR) of the component: for this reason, the ESR is typically used as degradation indicator. This degradation mechanism is driven by the temperature experienced by the component: higher the temperature, faster the degradation. Generally the failure threshold of the capacitor is defined as the double of the initial ESR value, and a physical model of the ESR evolution has been proposed for capacitors working at constant temperature (Perisse et al., 2006, Abdennadher et al., 2010, Gasperi, 1996).

In this work, we consider capacitors used in Fully Electrical Vehicles (FEVs), which are characterized by continuously changing operative conditions, also of temperature, so that the measured value of the capacitor ESR is continuously changing. Thus, we propose a new degradation index for the electrolytic capacitor, which is based on the ratio between the ESR measured on the degraded capacitor and the ESR expected value on a new capacitor at the present operational temperature. Its computation has required to perform a series of laboratory experiments for the identification of the relationship between the ESR and the temperature in a new capacitor. The main advantage of this new degradation index is that it is independent from the measurement temperature and, thus, can be used for real applications under variable operative conditions. The physical degradation model and the novel proposed degradation index have been exploited for the prediction of the RUL of a capacitor under non-stationary operative conditions by means of a particle filtering algorithm.

The remaining part of the report is organized as follows: in Section 2 the capacitor degradation model is presented; Section 3 shows the particle filtering model for the RUL estimation; in Section 4, the experimental test setup for the parameters estimation and the obtained results are presented; in Section 5 the developed methodology is applied to a case study; finally, in Section 6 some conclusions and remarks are drawn.

2. CAPACITOR DEGRADATION MODEL

The aluminum electrolytic capacitor is one of the most critical components of electric systems: thus, its failure modes and degradation mechanisms have been deeply investigated in literature (Perisse et al., 2006, Abdennadher et al., 2010, Ma & Wang, 2005, Gasperi, 1996, Celaya et al., 2011). In particular, in Abdennadher et al. (2010) a physical model describing the evolution of the health state of the component is presented.

2.1. Degradation indicator

The degradation of the capacitor is mainly due to the chemical reactions occurring inside the component, which cause the vaporization of the contained electrolyte, leading to a loss of functionality. Component degradation can be identified by monitoring the ESR: higher the degradation, higher the measured ESR value.

2.2. ESR evolution equation

According to Abdennadher et al. (2010), the ESR for a capacitor aging at constant temperature T^{ag} is given by:

$$ESR(t, T^{ag}) = ESR_0(T^{ag})e^{C(T^{ag})t} \quad (1)$$

where $ESR_0(T^{ag})$ represents the initial ESR value of the capacitor at temperature T^{ag} , t the age of the capacitor and $C(T^{ag})$ a temperature-dependent coefficient which defines the degradation speed of the capacitor. In particular, the temperature coefficient $C(T^{ag})$ can be expressed as:

$$C(T^{ag}) = \frac{\ln 2}{Life_{nom}(T_{nom}) \exp\left[\frac{E_a}{k} \left(\frac{T_{nom} - T^{ag}}{T_{nom} \cdot T^{ag}}\right)\right]} \quad (2)$$

where $Life_{nom}$ represents the nominal life of the capacitor aged at the constant nominal temperature (T_{nom}), and the temperatures are expressed in Kelvin degrees. A detailed description of the semi-empirical procedure adopted for the definition of the macro-level physical model of Eqs. (1) and (2) can be found in Perisse et al. (2006).

It has to be emphasized that the measured ESR value depends on the measurement temperature: this means that if we measure the ESR value on the same degraded capacitor at a temperature T^{me} different from that at which the capacitor is degrading (T^{ag}), the measured value of ESR will be different. The relationship between the initial ESR for a

new capacitor and the ESR measurements temperature T^{me} for a new capacitor is (Abdennadher et al., 2010):

$$ESR(0, T^{me}) = ESR_0(T^{me}) = \alpha + \beta e^{-T^{me}/\gamma} \quad (3)$$

where α , β and γ are parameters characteristics of the capacitor.

3. A PF APPROACH FOR RUL ESTIMATION

Unfortunately, the relationship defining the influence of the measurement temperature T^{me} on the ESR for a degraded capacitor is unknown. Thus, since the FEV capacitor typically works at variable temperatures, the ESR cannot be directly used as degradation indicator for a capacitor experiencing different operational conditions such as those of FEV. For this reason, in order to define a degradation indicator which is independent from the temperature, in the present work we introduce a new degradation indicator defined by the ratio between the ESR measured at temperature T^{me} and its initial value at the same temperature T^{me} :

$$ESR_{norm}(t) = ESR(t, T^{me}) / ESR_0(T^{me}) \quad (4)$$

where $ESR_0(T^{me})$ is computed by using Eq. (3). Notice that, according to this new degradation indicator, if we consider a degraded capacitor and we measure its ESR value at different temperature, we obtain exactly the same ESR_{norm} value, which is independent from the temperature of the measurement and it expressed as a percentage. The failure threshold, i.e. a value of ESR_{norm} such that if it is exceeded the capacitor is considered failed, is set equal to $ESR_{norm} = 200\%$. The rationale behind this choice is that the failure threshold for any capacitor is typically defined as the double of its initial ESR value (Venet et al., 1993). The new degradation indicator allows overcoming the lack of knowledge on the relationship between the temperature and the measured ESR for a degraded capacitor. Thus, it is now possible to represent the degradation process as a first order Markov Process between time steps t_{k-1} and t_k ; the new degradation equation is, then, defined as:

$$ESR_{norm}(t_k) = ESR_{norm}(t_{k-1})e^{C(T_{k-1}^{ag})} + \omega_{k-1} \quad (5)$$

where T_{k-1}^{ag} represents the aging temperature at time t_{k-1} and ω_{k-1} models the process noise.

Eq. (5) represents the degradation state evolution and is independent from the measurement temperature T^{me} . There is only a dependence from the temperature T^{ag} experienced by the capacitor in the coefficient $C(T^{ag})$ defining the speed of degradation, which can be computed by using Eq. (2).

The equation linking the measured ESR and ESR_{norm} is:

$$ESR(t_k, T_k^{me}) = ESR_{norm}(t_k) \cdot \left(\alpha + \beta e^{-\frac{T_k^{me}}{\gamma}} \right) + \eta_k \quad (6)$$

where T_k^{me} represents the measurement temperature at time t_k and η_k represents the measurement noise.

Figure 1 sketches the PF approach to prognostics based on the following three steps:

1. the estimation of the equipment degradation state at the present time based on a sequential Monte Carlo method; the state of the system is defined by the ESR_{norm} value. The PF approach requires the definition of a process equation, which in this case is given by Eq. (5), and a measurement equation, which is given by Eq.(6)
2. the prediction of the future evolution of the degradation state by Monte Carlo simulation
3. the computation of the equipment RUL.

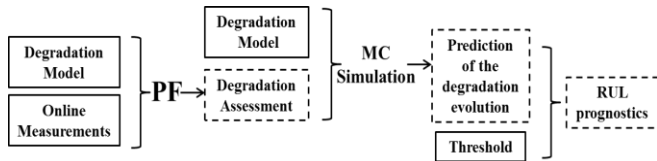


Figure 1. Sketch of the PF approach to fault prognostics

More details on the application of the PF approach to prognostics can be found in Baraldi et al., (2013).

Notice that we resort to a PF instead that to a classic Kalman Filter framework because in Eq. (5) we cannot express the noise as a Gaussian additive term. In practice, the Gaussian noise, to which the aging temperature T^{ag} is subject, affects the aging coefficient $C(T^{ag})$ (Eq. (2)) and, then, Eq. (5), thus becoming a non Gaussian additive term.

4. PARAMETER ESTIMATION

According to the Particle Filtering model described in Section 3 and used for the RUL prediction, we need the relationship between the initial ESR and the temperature for a new capacitor described by Eq. (3). Since the parameters α , β and γ of Eq. (3) are characteristic of the particular type of capacitor, we have performed experimental tests in order to identify the α , β and γ values for the considered capacitor.

4.1. Experimental Design

We considered a capacitor of the ALS30 series in pristine conditions. ESR measurements have been taken using a FLUKE PM6306 RLC meter directly connected to the capacitor in a Votsch Industrietechnik climatic chamber . The experimental test procedure has been based on the following three steps:

- Setting of the desired temperature
- Once the stationary conditions are reached in the chamber, the temperature is maintained for 20 minutes in order to allow the internal layers of the capacitor to heat up.
- The ESR is measured at different frequencies, between 10 kHz and 1 MHz.

The procedure has been repeated at different temperatures in the range $[12^\circ\text{C}, 110^\circ\text{C}]$, which is expected to be experienced by the FEV capacitor. The ESR measurements have been performed at steps of 15°C .

4.2. Results

The obtained experimental laboratory results are shown in Figure 2, where the ESR measurements performed on a new capacitor at different temperatures and frequencies are reported.

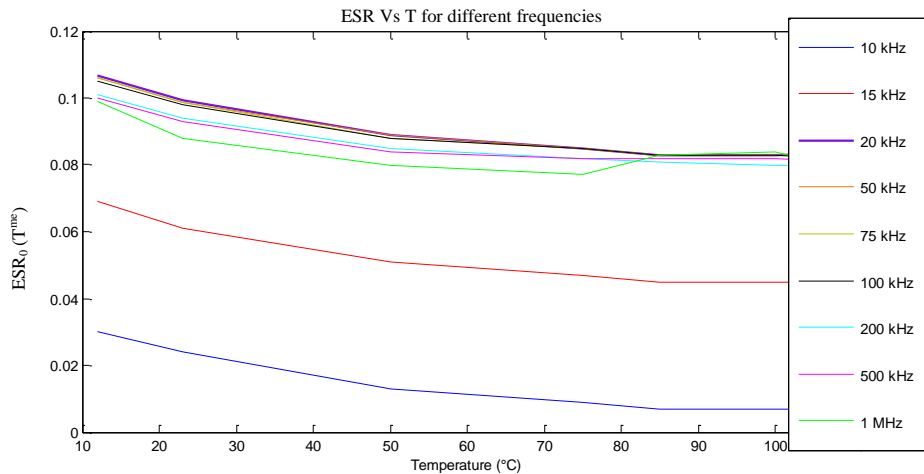


Figure 2. Experimental curve describing the variation of the initial ESR value $ESR_0(T^{me})$, in Ohm, at different measurement frequencies

Notice that the ESR at a given temperature tends to increase when the frequency is increased from 10 kHz to 20 kHz, whereas further increasing of the frequency does not modify numerically the ESR measurements. Since the degradation index ESR_{norm} defined in Eq. (4) is based on the ratio between the measured value of ESR and its initial value at the corresponding temperature, the most advantageous choice would be the measurement frequency with the highest associated absolute values of the ESR, which in this case corresponds to the 20 kHz curve. The rationale behind this consideration is that if we assume the same measurement noise, then its influence would be lower for the largest absolute values of the ESR.

Then, by resorting to an exponential regression method we have identified the following values for the experimental parameters α , β and γ :

$$\alpha=0.0817 \Omega \quad \beta=0.037 \Omega \quad \gamma=30.682^\circ\text{C} \quad (7)$$

Notice that these values can be used for modelling the degradation of the tested capacitor (ALS30 Series Electrolytic capacitors from KEMET) and cannot be employed on different types of capacitors.

5. CASE STUDY

In this Section, the application of the method described in Sections 3 and 4 to the degradation process of a capacitor used in a FEV is discussed. Since, at the present time, real ESR data collected on a degrading capacitor operating on a FEV are not available, the developed method has been applied to a numerically simulated capacitor life. Notice that laboratory experiments are being performed at CEIT facilities within the European Project HEMIS (www.hemis-eu.org), whose objective is the development of Prognostics and Health Monitoring System (PHMS) for the most critical FEV components. The objective of the tests is to collect data describing the capacitor degradation process in environmental conditions similar to those of a FEV (Celaya et al., 2012).

5.1. Simulation of the temperature profiles experienced by a FEV

Since real data describing the temperature profile experienced by a capacitor in a FEV are currently not available, we have simulated possible temperature profiles. According to the suggestions of motor experts, we have considered that the temperature variations experienced by the capacitor during its life are mainly caused by the variation of the environmental external temperature. The temperature profile simulations are based on the following assumptions:

- the FEV is operating 4000 hours in a year (1000 hours each season);

- the seasonal mean temperatures experienced by the FEV capacitor depend from the season and are: $T_{winter}=70^\circ\text{C}$, $T_{spring}=85^\circ\text{C}$, $T_{summer}=95^\circ\text{C}$, $T_{autumn}=80^\circ\text{C}$;
- in order to take into account temperature oscillations, the real temperature value experienced by the FEV is sampled from a Gaussian distribution with mean value equal to T_{winter} , T_{spring} , T_{summer} , T_{autumn} depending on the season, and standard deviation equal to 2°C for all cases.

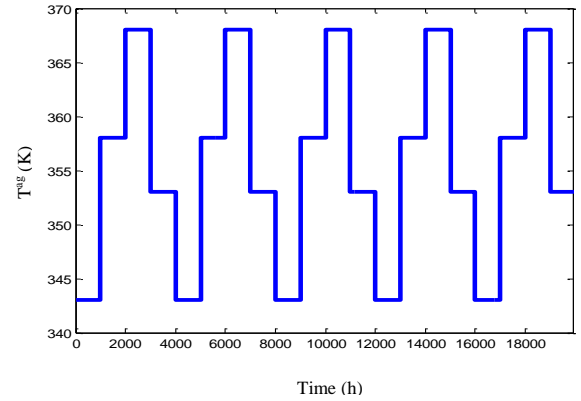


Figure 3. Average Temperature Profile

5.2. Simulation of a capacitor life

According to the above assumptions, considering the ALS30 Series electrolytic capacitor, whose nominal life at the nominal aging temperature of 85°C is reported to be of 20000 hours, we have simulated a capacitor life which will be considered as the “real” degradation trajectory. In practice, starting from the initial value $ESR_{norm}=100\%$, by using Eq. (5) and the simulated temperature profile we have numerically simulated the time evolution of the capacitor degradation (ESR_{norm}) until the failure time, i.e., according to Section 3, the time at which the ESR of the capacitor reaches the double of its initial value. In Eq. (5), the process noise ω_k is due to the intrinsic uncertainty of the physical degradation process, and it is a normally distributed random variable with mean set equal to zero and standard deviation set equal to 2%. Furthermore, we have simulated the values of 7 ESR and T^{me} measurements during the capacitor life (taken every 2500 hours, starting from $t=3000$ h to $t=18000$ h). The measured ESR values have been obtained by applying Eq. (6) to the numerically simulated degradation indicator values ESR_{norm} , considering the measurement noise η_k as a normally distributed random variable with mean equal to zero and standard deviation equal to 0.02Ω . The measurement temperature values T^{me} have been simulated by adding an artificial Gaussian noise ($\mu = 0^\circ\text{C}$; $\sigma = 2^\circ\text{C}$) to the expected temperature profile shown in Figure 3. Figure 4 shows the simulated values of the considered 7 ESR measurements. The obtained simulated capacitor life will be referred to as the “true” capacitor life, considering the

numerically simulated ESR measurements as the real available ESR measurements.

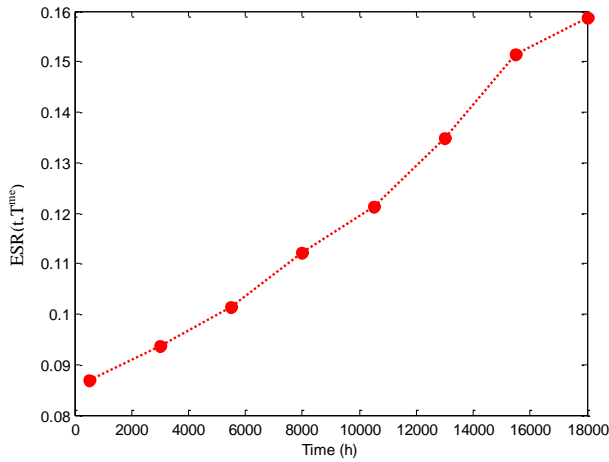


Figure 4. Numerical simulation of the measured ESR value $ESR(t, T^{me})$

5.3. Application of the method and results

The prognostic method described in Section 3 has been applied to the simulated capacitor life of Section 5.2 described by the 7 ESR and temperature measurements. The application of the PF method has been done with fixed number of particles equal to 1000; the process noise ω_k and the measurement noise η_k have been sampled from Gaussian distributions characterized by $(\mu = 0\%; \sigma = 2\%)$ and $(\mu = 0\Omega; \sigma = 0.02\Omega)$, respectively. The prognostic method provides a prediction of the RUL in the form of a probability density function.

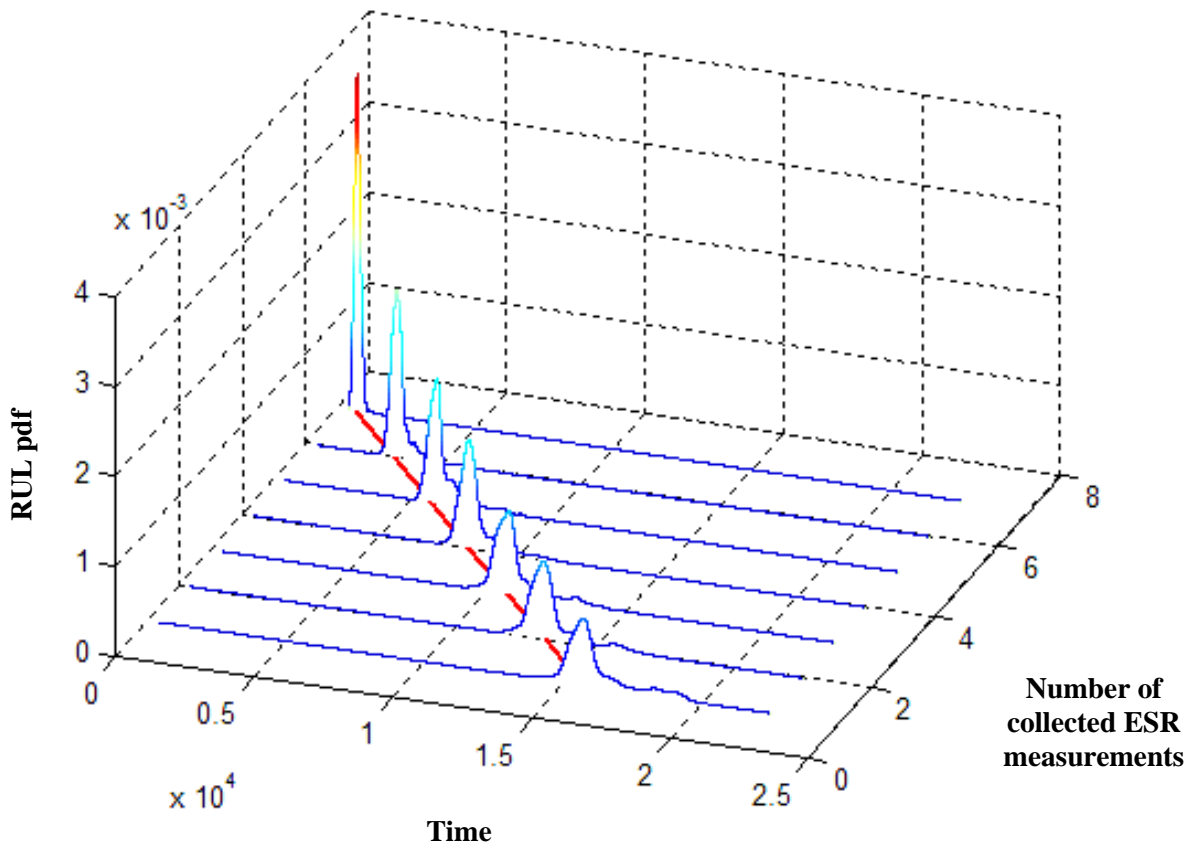


Figure 5. Evolution of the RUL prediction pdf according to the measurement number

In Figure 5, the real RUL of the component is represented by the solid line. Notice that the range of variability of the predicted RUL is clearly reducing from a large width at the first measurement ($t=3000$ h) to a narrow width at the last measurement ($t=18000$ h). This reduction of the RUL uncertainty is due to the acquired knowledge of the degradation provided by the ESR measurements, which allows updating the degradation probability distribution and leads to a more accurate assessment of the component degradation state. This can be clearly observed in Figure 5, where the evolution of the RUL pdf as time passes is shown. It is also interesting to notice in Figure 6 that the expected RUL value (dark solid line) remains close to the true RUL value (black dashed line), indicating the accuracy of the method, and that the true RUL value is always within the 10th and the 90th percentiles of the distribution (light solid lines). It is worth noting that the predicted RUL is closer to the 10th percentile than the 90th percentile: this is due to the fact that the Gaussian measurement noise to which the aging temperature T^{ag} is subject causes a non-symmetric non-gaussian effect on the coefficient $C(T^{ag})$ in Eq. (5).

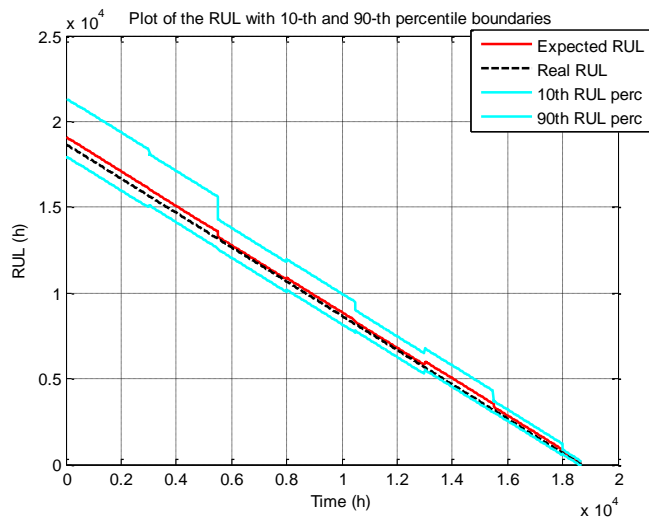


Figure 6 RUL prediction uncertainty representation

6. CONCLUSION

In this paper, we have addressed the problem of predicting the RUL of an aluminum electrolytic capacitor used in FEVs. Given the non-stationary operative conditions and the varying operational temperature experienced by capacitors in FEVs, we have proposed a new degradation index independent from temperature. The index is defined by the ratio between the ESR measured at temperature T^{me} and its initial value at the same temperature T^i . In order to compute the proposed degradation index ESR_{norm} , experimental tests have been expressly designed and

performed for the estimation of the parameters of the physical relationship between the temperature and the initial value of the ESR for a new capacitor. Resorting to the ESR physical evolution model, we have then applied a particle filtering framework to predict the capacitor RUL. The obtained results encourage a further development of the method in order to allow its application to the prediction of the RUL of a capacitor operating in FEVs. Once the proposed framework will be completely developed, we intend to compare its performance with respect to different machine learning techniques in order; finally, a sensitivity analysis will be performed for the complete characterization of the proposed method.

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