

A SIMPLE *ESR* IDENTIFICATION METHODOLOGY FOR ELECTROLYTIC CAPACITORS CONDITION MONITORING

A. Vicente T. Leite¹, Henrique J. A. Teixeira¹,
A. J. Marques Cardoso² and Rui M. Esteves Araújo³

¹ Escola Superior de Tecnologia e de Gestão, Instituto Politécnico de Bragança, Campus de Santa Apolónia, Apartado 1134, 5301-857 Bragança, Portugal, avtl@ipb.pt and hteixeira@ipb.pt.

² Departamento de Engenharia Electrotécnica e de Computadores, Universidade de Coimbra, Pólo II - Pinhal de Marrocos. P - 3030-290 Coimbra, Portugal, ajmcardoso@ieee.org.

³ Faculdade de Engenharia, Universidade do Porto, Porto, Portugal, Rua Dr. Roberto Frias, s/n 4200-465 Porto, Portugal, raraujo@fe.up.pt.

ABSTRACT

Electrolytic capacitors are usually used in power electronic systems for smoothing, energy storage or filtering. They have the best overall performance for these objectives being a critical element in the design of these systems, in several applications, with different requirements. But, unfortunately, in most cases, they are the most life-limiting device. The expected life of electrolytic capacitors depends on their internal temperature and is determined by the ratio of the electrolyte solution evaporation used in their fabrication. The deterioration caused by this evaporation is reflected in electrical parameters, mainly the equivalent series resistance (*ESR*). As the volume of the electrolyte decreases, *ESR* increases and capacitance decreases. Additionally, the increase in *ESR* has a positive feedback effect since it leads the temperature to increase and this in turn leads to further evaporation of the electrolyte leading to the *ESR* increase and so forth.

This paper presents a simple *ESR* identification methodology for electrolytic capacitors condition monitoring in view of preventive maintenance to signal the need of maintenance and or replacement. The identification methodology is based on a simple continuous-time model and some recursive prediction error methods, namely, Kalman filter, gradient and forgetting factor approaches. Simulation and experimental data acquired from a step down converter were used with these algorithms. The identification methodology is also suitable for different power converter topologies.

KEYWORDS

Equivalent series resistance, electrolytic capacitors, condition monitoring, identification methodology, recursive prediction error methods.

INTRODUCTION

Electrolytic capacitors are widely used in power electronic systems due to factors such as: cost and space effectiveness, as well as performance as referred by Stevens *et al.* (2002). However, they are among the

most expensive components in power electronic circuits and, according to MIL-HDBK 217F standard (1995 cited Lahyani *et al.* 1998, Venet *et al.* 2002 and Imam *et al.* 2005), they have the highest probability of failure at ambient temperature of 25°C and under rated conditions, and are also responsible for more than half of the breakdowns. Unfortunately, the expected life of electrolytic capacitors is limited and determined by their internal temperature. In fact, among several factors that can cause electrolytic capacitors to fail, the most influential factor on their operational life is heat and the life of electrolytic capacitors is strongly dependent on the operating temperature as described in the technical note (Evox Rifa, a). Failure mechanisms of non-solid electrolytic capacitors have been described in the literature by researchers: Harada *et al.* (1993), Gasperi (1996), Stevens *et al.* (2002), Imam *et al.* (2005) and Parler (a). The internal failure mechanisms are multiple and complex in their interactions and must be considered as a complete system (Stevens *et al.*, 2002), but in simple terms the life of electrolytic capacitors depends on the operating temperature and is determined by ratio of the electrolyte solution evaporation used in their fabrication. The deterioration caused by this evaporation is reflected in electrical parameters such as capacitance, leakage current and the equivalent series resistance (*ESR*). Actually, as the volume of the electrolyte decreases, *ESR* increases and capacitance decreases. Additionally, the increase in *ESR* has a cumulative effect since the increase in *ESR* leads to temperature increased and this in turn leads to further evaporation of the electrolyte (Sankaran *et al.*, 1997). Thus, the rise of temperature depends on the *ESR* value and rms current of the capacitor apart from other factors. Hence, the current through the capacitor causes power loss due mainly to the *ESR* and the temperature inside the capacitor rises linearly with this power loss which is given by $(I_{\text{rms}})^2 \times \text{ESR}$. Therefore, among others parameters, *ESR* is of paramount importance as far as the end of life of electrolytic capacitors is concerned. Although an old-rule-of-thumb referred in a technical paper by Lauber (1985 cited Gasperi, 1996), has described that the end of life is when the capacitor has lost about 40% of its electrolyte, the rise of the *ESR* value is usually used to define the end of life of an electrolytic capacitor. For instance, Evox Rifa (a) defines end of life of their electrolytic capacitors when *ESR* becomes higher than two times the initial value. According to (Parler, b), Cornell Dubilier uses EIA standard IS-749 which specifies capacitor lifetime as that time at which 10% of the capacitors have failed due to parametric failure and no more than 10% due to open or short circuit which means, as far as the parametric failure is concerned, that the life time of the capacitor is over, when the *ESR* is above 200% its initial value (Cornell Dubilier). Furthermore, life is generally defined in (Parler a) as the time to which a certain level of parametric degradation occurs and, as a practical matter, this is usually the time required for the *ESR* to reach double or triple its initial value or limit. Typical values of *ESR* range from 10 mΩ to 1 Ω, and *ESR* is inversely proportional to capacitance for a given rated voltage. Furthermore, not only *ESR* increases (and capacitance decreases) as the capacitor ages, but also it varies with frequency. *ESR* frequency and temperature variation is described in (Parler, a) and also shown in (Evox Rifa, b) and (Aeloíza *et al.*, 2005). At frequencies above few kHz, *ESR* is the predominant factor in the capacitor's impedance according to (Evox Rifa, b), (Venet *et al.*, 2002) and (Aeloíza *et al.*, 2005).

Due to all it was said so far, special attention has been paid to fault diagnosis and conditioning monitoring of this critical component being the works achieved by Aeloíza *et al.* (2005), Imam *et al.* (2005), Maddula and Balda (2005), Amaral and Cardoso (2004b), Ondel *et al.* (2004) and Venet *et al.* (2002) just some recent examples. The electrolytic capacitor conditioning has been investigated by several methods. Most of them are based on the *ESR* evaluation (Harada *et al.*, 1993), (Gasperi, 1996), (Gasperi, 1997), (Sankaran *et al.*, 1997), (Lahyani *et al.*, 1998), (Venet *et al.*, 2002), (Amaral and Cardoso, 2004a) and (Aeloíza *et al.*, 2005) among others. Venet *et al.* (2002) realized a circuit to signal the worn-out state of electrolytic capacitors online, based on *ESR* evaluation and in (Aeloíza *et al.*, 2005) a real time diagnostic method is presented to estimate their deterioration condition. A method based on an adaptive filter modelling using the LMS algorithm is described in (Imam *et al.*, 2005).

This paper presents a simple *ESR* identification methodology for electrolytic capacitors condition monitoring in view of preventive maintenance to signal the need of maintenance and or replacement. The identification methodology is based on a continuous-time model and some recursive prediction error methods, namely, Kalman filter, gradient and recursive least squares algorithms.

THE IDENTIFICATION METHODOLOGY

The Model

The model used for the *ESR* estimation of electrolytic capacitors is very simple and is derived directly from the simplified equivalent circuit of an electrolytic capacitor shown in figure 1.

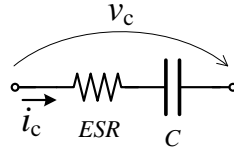


Figure 1: Simplified equivalent circuit of an electrolytic capacitor.

An equation for this equivalent circuit can be written as follows:

$$v_c(t) = ESR \times i_c(t) + \frac{1}{C} \int i_c(t) dt \quad (1)$$

The above equation can also be written as:

$$\frac{dv_c(t)}{dt} - \frac{i_c(t)}{C} = ESR \times \frac{di_c(t)}{dt} \quad (2)$$

or, in a general form:

$$y(t) = \varphi(t)^T \theta \quad (3)$$

where: $y(t) = \frac{dv_c(t)}{dt} - \frac{i_c(t)}{C}$, $\varphi(t) = \frac{di_c(t)}{dt}$ and $\theta = ESR$.

The model given by (3) is called linear regression and would be a very simple single-input single-output model if the input and output could be measured. In fact this virtual input and virtual output can not be measured directly because they depend on the first derivatives of the voltage and current of the capacitor. Nevertheless, even though they can not be measured they can be computed as described below and this fact is used to develop a new identification methodology for *ESR* estimation.

In the continuous-time model described by (2) the first derivatives of the capacitor voltage and current are computed by using a recursive filter which can be obtained from the following formula (Harrison and Stoten, 1995):

$$\left. \frac{dx}{dt} \right|_{t=t_k} = \frac{1}{T_s} \sum_{i=0}^{n-1} C_i x(t_k - iT_s) \quad (4)$$

A particular filter is derived from (4) when a set of weighing coefficients, C_i , is chosen. These weights can be found in (Harrison and Stoten, 1995) which are determined after Taylor's series expansion of (4) to $m+1$ terms with $m = \{1, 2, \dots, n\}$, with m being the order of the filter and n the number of points used in the computation. Harrison and Stoten (1995) also present the minimum error and optimum $\{n, m\}$ for a range of f_s/f_p and $X/\delta x$. f_s and f_p are the sampling frequency and signal frequency whereas X is the signal magnitude and δx denotes the size of the quantum to which x is subject. In the tests carried out in this work the coefficients $[11 \ -18 \ 9 \ -2]/6$ were used successfully with very good results. Thus, considering these coefficients, the output and linear regression of (3) are given as follows:

$$y(k) = \frac{1}{6T_s} (11v_c(k) - 18v_c(k-1) + 9v_c(k-2) - 2v_c(k-3)) - \frac{i_c(k)}{C} \quad (5)$$

$$\varphi(k) = \frac{1}{6T_s} (11i_c(k) - 18i_c(k-1) + 9i_c(k-2) - 2i_c(k-3)) \quad (6)$$

The Algorithms

A recursive prediction error method, which is well described, for instance, in (Ljung, 1999) was used and can be summarized as follows:

$$1. \psi(k+1) = \left. \frac{\partial \hat{y}(k, \theta)}{\partial \theta} \right|_{\theta = \hat{\theta}(k)} \quad (7a)$$

$$2. L(k+1) = \frac{P(k)\psi(k+1)}{\psi^T(k+1)P(k)\psi(k+1) + R_m} \quad (7b)$$

$$3. \hat{\theta}(k+1) = \hat{\theta}(k) + L(k+1)(y(k+1) - \hat{y}(k+1)) \quad (7c)$$

$$4. P(k+1) = P(k) - L(k+1)\psi^T(k+1)P(k) + R_s \quad (7d)$$

5. Go to 1

In this general recursive prediction error algorithm, $\psi(k+1)$ is the gradient of the predicted output, \hat{y} , with respect to a parameter vector, θ , and $L(k)$ is the gain matrix that affects both the adaptation gain and the direction in which the updates of parameters θ are made and can be chosen following several approaches as referred in (Ljung, 1999).

A typical approach to the adaptation issue is to assume a model for the parameters variation in which the parameters vary with the time in a random way, that is:

$$\theta(k+1) = \theta(k) + r_s(k) \quad (8)$$

$r_s(k)$ is assumed to be white Gaussian noise with covariance matrix, $R_s = E\{r_s(k)r_s(k)^T\}$. Thus, $R_s(k)$ denotes the covariance matrix of the system noise and expresses the lack of confidence in the estimated parameters, essentially, due to errors in the system model. $P(k) = E\{(\theta(k) - \hat{\theta}(k))(\theta(k) - \hat{\theta}(k))^T\}$ can be interpreted as the covariance matrix of the estimation error.

Let us consider a single-output system described by a linear regression which can be written as:

$$y(k) = \varphi^T(k)\theta(k) + r_m(k) \quad (9)$$

$\varphi(k)$ is the regression vector and $r_m(k)$ is the measurement noise. In this case $R_m = E\{r_m(k)^2\}$ is a scalar. If the system has more than one output $\varphi(k)$ is the regression matrix and $r_m(k)$ is the measurement noise vector being $R_m = E\{r_m(k)r_m(k)^T\}$ the covariance matrix of the measurement noise vector and expresses the lack of confidence in the new measurements. The natural prediction of the output is $\hat{y}(k+1) = \varphi^T(k+1)\hat{\theta}(k)$ and its gradient with respect to θ , $\psi(k+1)$, becomes exactly $\varphi(k+1)$. Although a linear regression has been used for the algorithm explanation, it can also be applied to the general case (Ljung, 1999).

Taking into account the above considerations, the recursive prediction error method corresponds to the Kalman filter approach to the referred adaptation and is known as Kalman filter (KF) algorithm.

Another approach to the adaptation issue is to allow the gain to be computed as follows:

$$L(k+1) = \gamma I \psi(k+1) \text{ or } L(k+1) = \frac{\gamma I}{|\psi(k+1)|^2} \quad (10)$$

where I is the identity matrix. In these cases the recursive prediction error method given by (7) corresponds to the (unnormalized or normalized) gradient method (UG or NG) with gain γ .

A third approach is obtained when old measurements are exponentially discounted with a memory horizon given by $\tau = 1/(1-\lambda)$, where λ is called forgetting factor. In this case, with $R_m = \lambda$, $R_s = 0$ and dividing $P(k+1)$ by λ in step 4, of the recursive prediction error method given by (7) is the forgetting factor approach and also correspond to the recursive least squares (RLS).

The three algorithms described above (KF, UG or NG, and RLS) are used in this work for the *ESR* estimation of electrolytic capacitors.

The Experiment and Experimental Setup

A step down converter was used to carry out the experiments regarding the *ESR* estimation of electrolytic capacitors. In the step down converter, shown in figure 2, the load was held constant, the switching frequency was set to 10 kHz and the duty cycle was adjusted to 0.63 in order to obtain a 24 V output voltage for a 40 V input voltage. A 50 V, 4700 μF electrolytic capacitor was used. The current and voltage across the electrolytic capacitor were acquired with a sampling frequency of 100 kHz. Before the estimation procedure, using the algorithms referred above, these signals are reconstructed off line with linear interpolation with a step of 1 μs to perform precise computations of their first derivatives.

In order to simulate the *ESR* increase (aging) of the electrolytic capacitor additional resistance was introduced in series with the capacitor which is represented by $ESR_{\text{additional}}$ in figure 2.

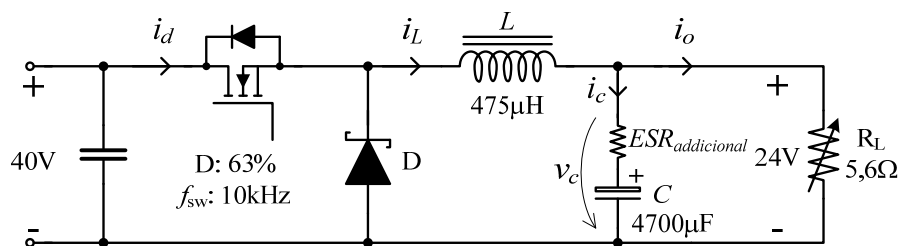


Figure 2: Step down converter used in simulation and experimental results.

The Model Validation

The model validation was carried out by means of several simulations and experimental tests implemented in MATLAB with Simulink[®]. This section presents some simulation results for validation purposes. Figure 3 shows the *ESR* estimation using Kalman filter (KF), unnormalized gradient (UG) and recursive least squares with a forgetting factor (RLS) algorithms. Providing that the computation step of the derivatives is small the results are very good as can be seen in figure 3 for (a) $ESR = 20\text{m}\Omega$, (b) $ESR = 40\text{m}\Omega$, (c) $ESR = 80\text{m}\Omega$ and (d) $ESR = 160\text{m}\Omega$.

The algorithms were initialized as shown in table 1.

KF	UG	RLS
$R_s = 1\text{e-}18$		$\lambda = 0.995$
$R_m = 1$	Gain = $1\text{e-}10$	$\theta(0) = 0$
$\theta(0) = 0$	$\theta(0) = 0$	$P(0) = 1\text{e-}10$
$P(0) = 1\text{e-}10$		

Table 1: Initialization of the algorithms.

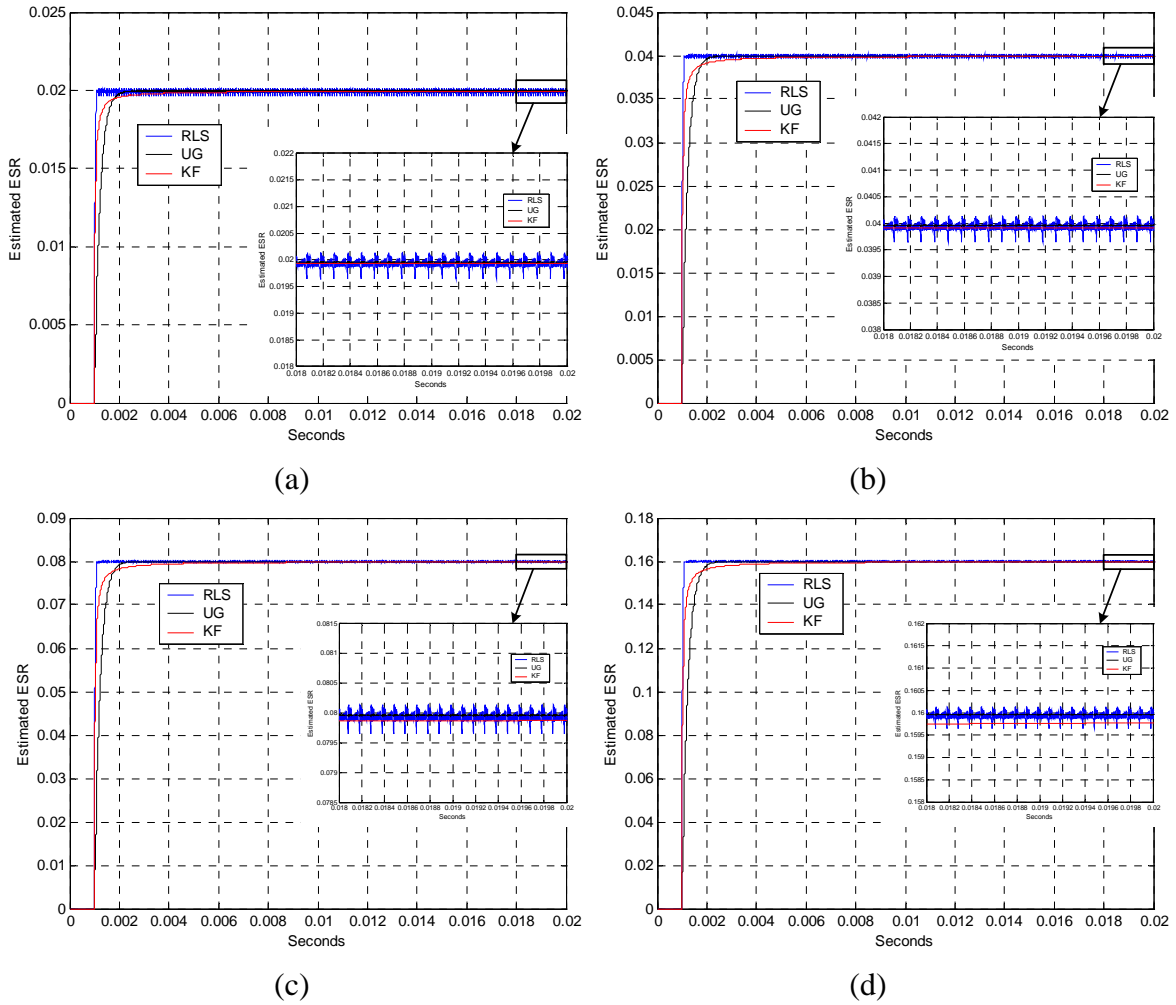


Figure 3: ESR estimation using KF, UG and RLS algorithms: (a) $ESR=20\text{ m}\Omega$, (b) $ESR=40\text{ m}\Omega$, (c) $ESR=80\text{ m}\Omega$ and (d) $ESR=160\text{ m}\Omega$.

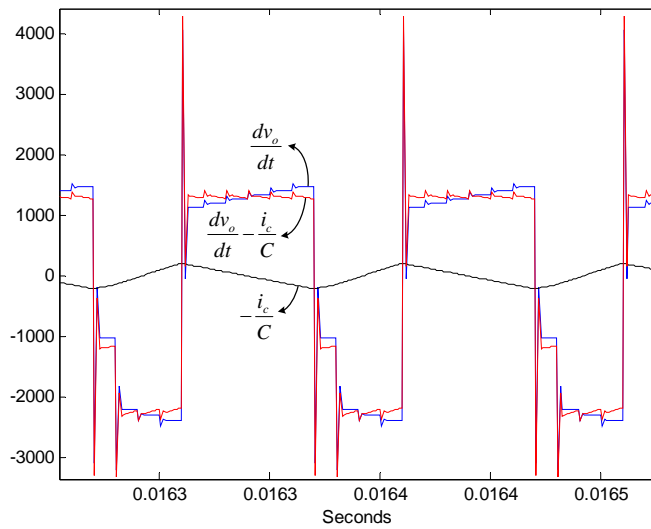


Figure 4: Illustration of the sensitivity of estimated ESR with respect to errors in C.

Actually, the gain of the unnormalized gradient starts with $1e-10$, as indicated in table 1, but decreases exponentially to $1e-12$. This is done to improve the dynamic of the algorithm during the convergence period, on the one hand, and to reduce the noise in the estimated ESR after that period, on the other hand.

Beforehand, an important drawback of the model given by (2) could be the sensitivity of the *ESR* estimation with respect to errors in the capacity. Fortunately, this do not happen since the second term of the first member of (2), that is $-i_c(t)/C$, contributes with just a small amount to the output of the model when compared with the first term, $dv_c(t)/dt$. This is illustrated in figure 4.

The Experimental Results

When experimental data is used for *ESR* estimation in view of electrolytic capacitor conditioning monitoring as describe in the introduction section, there are two aspects to be considered. First, the convergence time of the algorithms becomes much longer and, second, the estimation using the RLS algorithm with a forgetting factor less than 1 is too noisy, even with a high value of the forgetting factor as shown in figure 5. The data was acquired with an additional resistance (*ESR*) of 50 m Ω . Due to this, and since the forgetting factor approach with $\lambda=1$ corresponds to Kalman filter algorithm as shown previously, only the estimations obtained with gradient and Kalman filter algorithms are presented with experimental data. Hence, in figure 6, the estimation of the *ESR* with an additional resistance of 50 m Ω , using the Kalman filter algorithm, is shown for different starting instants of computation. Both algorithms, KF and UG have similar behaviour. However, even though the UG is simpler it requires an initial gain higher to have similar convergence to the KF.

Several tests were achieved regarding *ESR* estimation with the UG and KF algorithms. To simulate the electrolytic capacitor aging (*ESR* increase) additional resistance was introduced in series with the capacitor. Table 2 shows the results of several tests performed for this purpose. The values presented correspond to the average of the estimated values during the last 100 ms.

Most of the results are also illustrated in figure 7. Although the real value of the *ESR* is unknown both algorithms show a good consistency. Moreover, the estimation error decrease as the *ESR* increases which is better for the electrolytic capacitor aging monitoring.

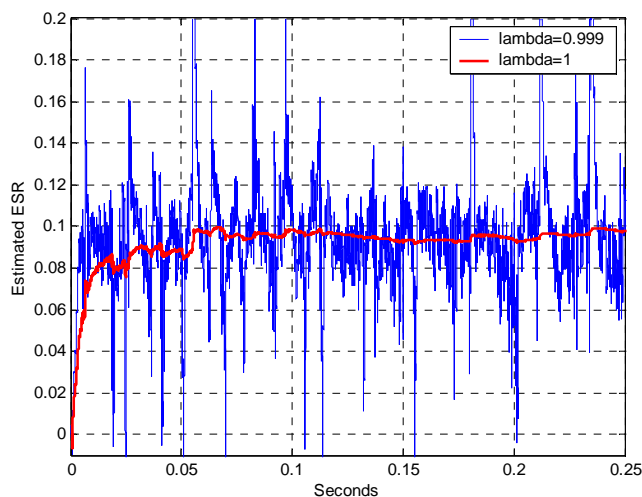


Figure 5: Illustration of the *ESR* estimation with forgetting factors 0.999 and 1 (RLS).

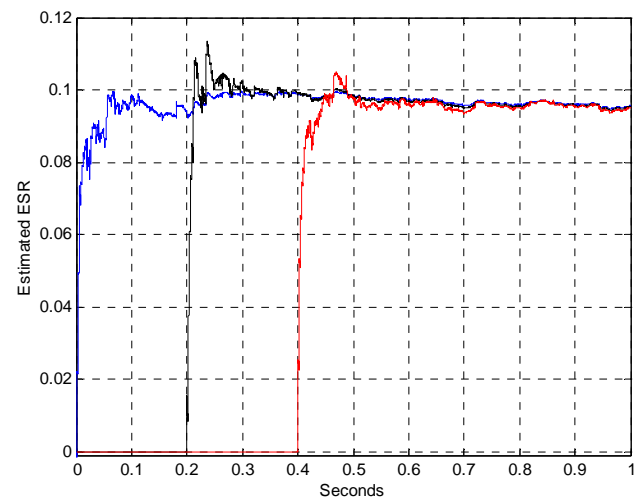
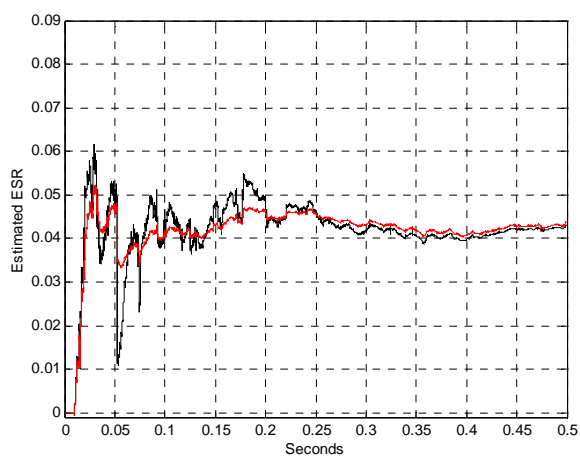


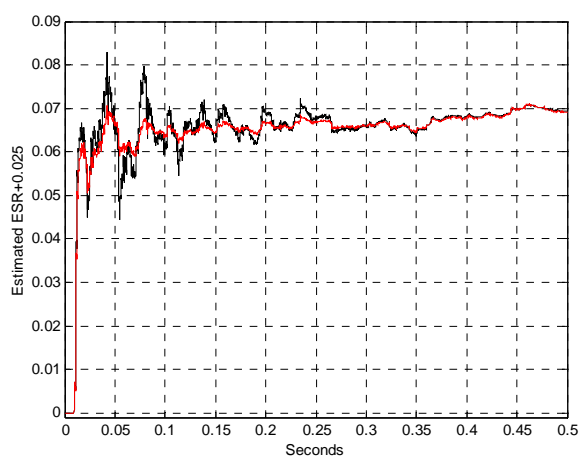
Figure 6: Illustration of the *ESR* estimation with KF for different starting instants.

<i>ESR</i> +Additional resistance (m Ω)	<i>ESR</i> estimated with UG (m Ω)	<i>ESR</i> estimated with KF (m Ω)
<i>ESR</i> +0	41.6	42.4
<i>ESR</i> +25	69.3	69.2
<i>ESR</i> +50	98.9	98.6
<i>ESR</i> +70	120.0	120.2
<i>ESR</i> +90	132.5	133.9
<i>ESR</i> +164	193.9	193.4
<i>ESR</i> +267	289.2	289.4
<i>ESR</i> +322	344.4	344.1
<i>ESR</i> +544	606.9	606.1
<i>ESR</i> +820	912.5	912.4

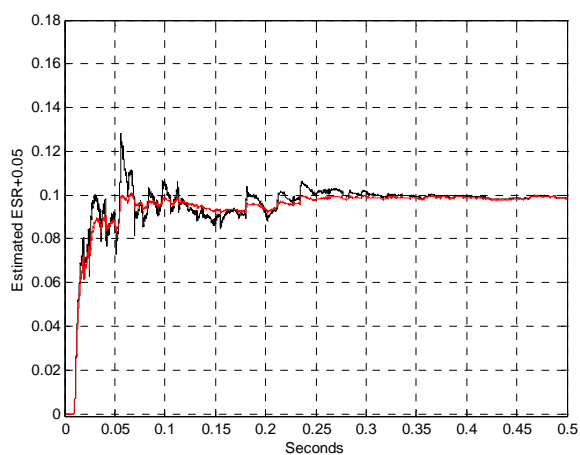
Table 2: *ESR* estimation (with additional resistance - *ESR*) using unnormalized gradient (UN) algorithm and Kalman filter (KF) algorithm.



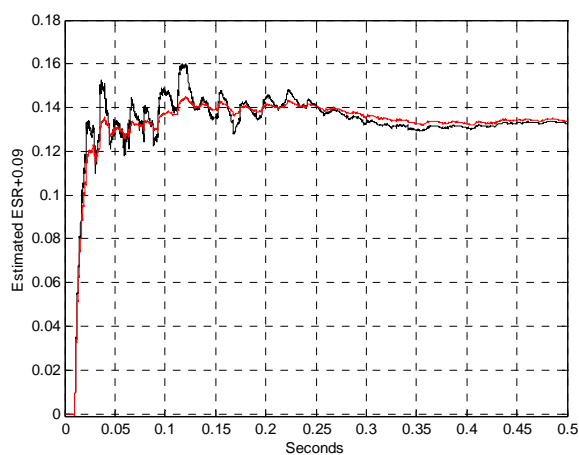
(a)



(b)



(c)



(d)

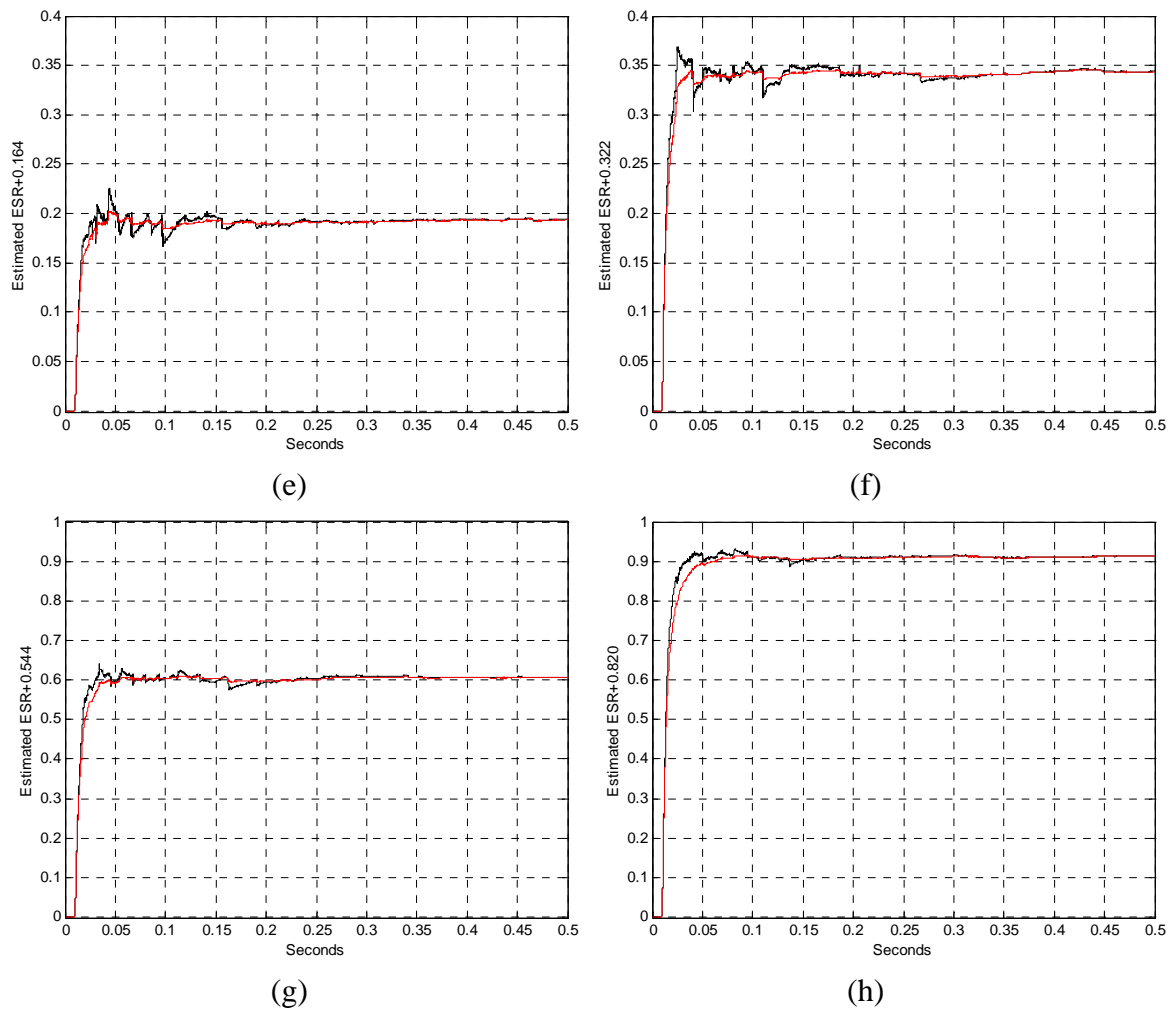


Figure 7: *ESR* estimation using KF and UG algorithms: (a) *ESR*+0 m Ω , (b) *ESR*+25 m Ω , (c) *ESR*+50 m Ω , (d) *ESR*+90 m Ω , (e) *ESR*+164 m Ω , (f) *ESR*+322 m Ω , (g) *ESR*+544 m Ω and (h) *ESR*+820 m Ω .

CONCLUSIONS

Electrolytic capacitors are a critical element in power electronic systems. In most cases, despite of their advantages, they are the most life-limiting device. The deterioration caused by evaporation of the electrolyte is reflected by the increase of the equivalent series resistance (*ESR*). This leads to the temperature increased and this in turn leads to further evaporation and increase of *ESR*.

This paper presented a simple *ESR* identification methodology for electrolytic capacitors condition monitoring in view of preventive maintenance. The identification methodology is based on a very simple continuous-time model given by (2), and some recursive prediction error methods. As far as the estimation algorithms is concerned, the Kalman filter, gradient and forgetting factor approaches were investigated. Kalman filter and unnormalized gradient algorithms proved to be suitable with experimental data. The forgetting factor approach requires a forgetting factor 1 (which corresponds to the RLS) and gives the same results of Kalman filter algorithm. Even though the model uses the computation of first derivative of the capacitor's voltage and current, by means of suitable filters, the identification methodology produces very good results with experimental data.

The proposed identification methodology only uses the capacitor's voltage and current measurements. Even though it was validated for a step down converter, it is also suitable for different power converter topologies and can be used as a condition monitoring procedure in preventive maintenance or can be implemented for the same purpose as part of the control.

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