Online Lifetime Estimation of Supercapacitors

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***Abstract*—This paper proposes an online lifetime estimation methodology for supercapacitors. The online technique uses a Lyapunov-based adaptation law to estimate online the supercapacitor's parameters. Unlike offline time- or frequency-domain characterization techniques that require discontinuation of the system's normal operation, the proposed approach is more suitable for real-time applications, such as electric/hybrid vehicles, as it provides online lifetime estimation. Furthermore, convergence and stability analysis is provided by Lyapunov's stability theory as opposed to many online estimators available in the literature. The effectiveness of the proposed strategy is validated through experiments along with comparison against two different methods.**

***Index Terms*—Aging indicator, lifetime estimation, Lyapunov, parameter identification, supercapacitors.**

NOMENCLATURE

BOL	Beginning of life.
EIS	Electrochemical impedance spectroscopy.
EKF	Extended Kalman filter.
EOL	End of life.
LS	Least square.
RLS	Recursive least square.
SOC	State of charge.

I. INTRODUCTION

SUPERCAPACITORS present an attractive energy storage alternative for high-performance applications, thanks to their compact size and high power density [1]–[6]. This is mainly due to their compact size and high power density, which makes them more appropriate for absorbing and delivering higher current in short periods of time such as in regenerative breaking and acceleration conditions [3], [7]. Similar to other energy storage devices, their performance depends heavily on their aging stage, which is mainly impacted by number of cycles and temperature [8]–[10]. Therefore, online lifespan estimation of supercapacitors is one of the important aspects that guarantees high performance and predict their failure. The definition of the EOL of a supercapacitor varies from one application to another. In transportation applications, the limit is usually set to 80% of the nominal capacitance or when the internal resistance reaches twice its nominal value. In real-world applications, supercapacitors are exposed to charge/discharge cycles of high current intensities, which yield important temperature variations.

The negative consequences of aging under temperature effects are illustrated in [11] and [12]. Thus, charge/discharge cycles have a substantial impact on the aging of supercapacitors. Classical diagnostic techniques such as alternating current signal injection and EIS are known for their simplicity [13], [14]. But, these procedures often require supplementary instrumentation. More importantly, they are usually performed offline disrupting of the system's operation [15], [16]. Several offline capacitance and resistance characterization techniques are based on frequency domain [11], [12], [17], [18]. The advantages and limitations of the characterization in the time domain have been reported in [19] and [20]. This method is used for its simplicity, but suffers from poor precision since voltage drop is difficult to measure with precision. Moreover, resistance often has low values, and hence, noisy measurements have a significant impact on the approximation's accuracy. This raises the urgency to consider alternative online lifespan prediction methodologies for supercapacitors.

Adaptive filtering is seriously considered as an alternative for online estimation. For instance, an EKF is widely used for state estimation of a variety of nonlinear dynamic systems. In [21], the EKF is used for the SOC estimation of supercapacitors. In an effort to estimate both temperature and SOC of supercapacitors, the EKF is utilized in [22] to estimate the *RC* circuit parameters. Moreover, the supercapacitor's capacitance and resistance are both estimated in [23] using the EKF and an interconnected observer. This technique also uses the classical first-order *RC* transmission line model. In [24], the EKF is again used for ultracapacitors. But, the considered model is linear, which limits the performance of the observer. The EKF is arguably very popular for state estimation of nonlinear systems. However, it is based on a nonlinear systems' linearization around an operating point of the states, which does not guarantee the performance and stability in all operating conditions. Another filtering approach is used in [25] for real-time parameter estimation of supercapacitors. In this technique, the RLS method identifies both the equivalent series capacitance and resistance without temperature sensing to estimate the state of energy. Also, the RLS algorithm with a time-varying forgetting factor is applied in [26] for online identification. In [27], an online identification procedure is presented for embedded applications. This procedure takes into account the nonlinear behavior of supercapacitors by considering a series of fractional linear differential equations for multiple points. Then, a global nonlinear model is deduced and the LS method is used as an identification procedure. In [23],

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two state-space observers are designed to estimate online the capacitance and the resistance. However, the aforementioned techniques presume a constant capacitance, although it is known to vary with the voltage [28]. More importantly, they lack convergence and stability analysis, which is a crucial aspect in online applications [29].

On another aspect, soft-computing techniques, such as neural networks and fuzzy logic, have been credited in different applications with uncertainties [30], [31]. Several neural network models have been proposed at the cost of higher computational complexity [32], [33], which have delivered a good performance. The nonlinear dynamic model of the supercapacitors are approximated online using a multilayer neural network in [32] and [33]. The backpropagation algorithm is then used for learning. However, capacitance is again assumed to be constant during charge/discharge phases. In reality, capacitance varies as a function of the voltage [28]. Additionally, these methods also lack stability proof and convergence analysis. Moreover, despite the success of neural networks, they remain incapable of incorporating any human-like expertise already acquired about the dynamics of the system in hand, which is considered one of the main weaknesses of such soft-computing methodologies. Moreover, these tools suffer from a heavy computation and tuning may not be trivial since they are based on heuristics. In [34], a neuro-fuzzy architecture is proposed to overcome these limitations. Therefore, the multiple-input nonlinear observer uses offline training, which yields computational simplicity. But, this requires offline experimental data, which limits its use in online applications. Furthermore, an increase of the root-mean-square errors of both resistance and capacitance estimates is reported with aging, which limits the performance of the observer.

In this paper, the proposed approach achieves online lifetime estimation of supercapacitors, which eliminates the need of offline data. For that, an online identification method is used for parameter estimation. Several online estimation strategies are available in the literature. Linearized-based techniques, such as EKF and state-space observers, cannot guarantee good performance in all operating conditions. Yet, numerous nonlinear estimators do not have this problem, since they preserve the nonlinear characteristics of the system in hand. But, they fail short when it comes to their convergence and stability proof. Additionally, intelligent estimators offer good performance at the cost of higher computational complexity. Unlike the aforementioned methods, the proposed online estimation strategy guarantees convergence and stability with implementation simplicity, which makes it more suitable for real-time applications with respect to other online estimation approaches. Since the supercapacitor's capacitance is directly correlated with its aging condition, the online identification strategy aims to estimate this parameter by using a Lyapunov-based estimation and adaptation law. As such, the stability and convergence are guaranteed by Lyapunov's direct method. Moreover, it is practically realizable at a lower cost due to a significant computational burden's reduction as opposed to machine-learning-based techniques. This paper is one of the first attempts to guarantee convergence and stability for online lifetime estimation of supercapacitors. The effectiveness of the proposed method is verified by experiments. Additionally, the proposed approach is compared against both the well-known dc characterization method and Kalman filter. The rest of this paper is organized as follows: Section II outlines the circuit model for supercapacitors along with their dynamics. The proposed adaptive estimation technique along with convergence and stability analysis is detailed in Section III. In Section V, experimental results are reported and discussed. Finally, a conclusion reports some remarks pertaining to this problem.

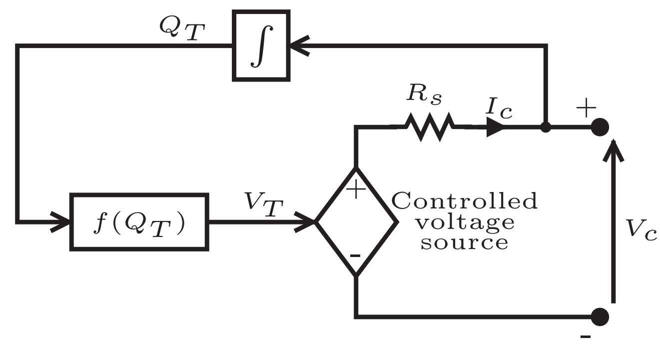


Fig. 1. Supercapacitor model [35].

II. Supercapacitors Dynamics

The behavior of supercapacitors is captured in Fig. 1. As shown experimentally in [35], the supercapacitor can be represented by the Stern model, which is a combination of Helmholtz and Gouy-Chapman model [36].

Therefore, the supercapacitor is governed by the following dynamics [35]:

$$V_c = \frac{1}{C_T}\int I_c\,dt - R_s I_c. \tag{1}$$

The goal is to estimate the supercapacitor's capacitance C_T, since it is directly correlated with the aging condition. In this paper, the supercapacitor's parameters are considered to be *a priori* unknown. The supercapacitor voltage V_c and current I_c are used as the system's measurable states.

III. Online Parameter Identification

In this section, an online parameter estimator is designed to predict the supercapacitor's resistance and capacitance. Using (1), the supercapacitor's model can be written as a regression model

$$V_c = \frac{1}{C_T}\int I_c\,dt - R_s I_c = \Psi^T\Theta \tag{2}$$

where $\Psi \in \mathbb{R}^2$ is a vector of known functions (regressor), and $\Theta \in \mathbb{R}^2$ is a vector of parameters:

$$\theta_1 = \frac{1}{C_T}$$

$$\theta_2 = R_s.$$

Define the supercapacitor's voltage estimation error as

$$e = V_c - \hat{V}_c. \tag{3}$$

Hence, the supercapacitor's voltage estimation law is stated as

$$\hat{V}_c = \frac{1}{\hat{C}_T}\int I_c\,dt - \hat{R}_s I_c^* \tag{4}$$

where $\hat{\bullet}$ denotes the estimate and

$$I_c^* = I_c - K_p e - K_i \int e - K_d \dot{e} \tag{5}$$

where K_p, K_i, and K_d are the proportional, integral, and derivative gains, respectively. Substituting I_c^* from (5) into (4) leads to

$$\hat{V}_c = \frac{1}{\hat{C}_T}\int I_c\,dt - \hat{R}_s I_c - \hat{R}_s\left(K_p e + K_i \int e + K_d \dot{e}\right). \tag{6}$$

Subtracting (2) from (6) and using the linear regression yields

$$(K_p + \hat{\eta})e + K_i \int e + K_d \dot{e} = \hat{\eta}\Psi^T \tilde{\Theta} \tag{7}$$

where $\tilde{\Theta} = \Theta - \hat{\Theta}$ is the vector of parameter estimation errors and $\eta = {}^{1}/_{R_s}$. This can be formulated in the following state-space form:

$$\dot{X} = AX + BU \tag{8}$$

where $X \in \mathbb{R}^2 = [\int e,\, e]^T$ is the state vector and $U \in \mathbb{R} = \Psi^T \tilde{\Theta}$ is the state-space input. $A \in \mathbb{R}^{2\times 2}$ is a stable matrix and $B \in \mathbb{R}^2$, which are given by

$$A = \begin{bmatrix} 0 & 1 \\ -\bar{K}_i & -(\bar{K}_p + \hat{\beta}) \end{bmatrix}$$

$$B = \begin{bmatrix} 0 \\ \hat{\beta} \end{bmatrix}$$

where $\bar{K}_p = {}^{K_p}/_{K_d}$, $\bar{K}_i = {}^{K_i}/_{K_d}$, and $\beta = {}^{\eta}/_{K_d}$. Henceforth, the estimator's gains K_p, K_i, and K_d can be chosen by using a pole placement technique to place the closed-loop poles at their desired locations or by solving the algebraic Riccati equation in (10), as detailed in [37]. Convergence and stability are important aspects in online estimators. Many recursive algorithms are based on the gradient descent technique, which lacks stability proof. Unlike these methods, the adaptive estimator's stability and convergence are guaranteed by Lyapunov's direct method.

Theorem 1: Given a nonlinear system in the form of (1), the adaptive estimator's stability and the estimation error's asymptotic convergence to zero are guaranteed with the estimation law (4) and the following adaptation law:

$$\dot{\hat{\Theta}} = -\Gamma \Psi B^T P X \tag{9}$$

where $\Gamma = [\gamma_1, \gamma_2]$ and γ_i is a positive constant gain (adaptation rate). P is a positive-definite symmetric matrix selected to satisfy the following algebraic Riccati equality:

$$A^T P + PA = -Q \tag{10}$$

with Q is a positive-definite matrix.

Proof: Define a Lyapunov candidate as

$$V = X^T P X + \tilde{\Theta}^T \Gamma^{-1} \tilde{\Theta}. \tag{11}$$

Taking its derivative leads to

$$\dot{V} = \dot{X}^T P X + X^T P \dot{X} + 2\tilde{\Theta}^T \Gamma^{-1} \dot{\tilde{\Theta}}. \tag{12}$$

The estimation algorithm sampling frequency is high enough such that the variation of the supercapacitor's parameter vector Θ between two samples is negligible. Therefore, $\dot{\tilde{\Theta}} = \dot{\hat{\Theta}}$. Substituting $\dot{X}$ from (8) implies that

$$\dot{V} = [AX + BU]^T P X + X^T P [AX + BU] + 2\tilde{\Theta}^T \Gamma^{-1} \dot{\hat{\Theta}}. \tag{13}$$

Thus, setting $U = \Psi^T \tilde{\Theta}$ yields

$$\dot{V} = X^T [A^T P + PA] X + 2\tilde{\Theta}^T \Psi B^T P X + 2\tilde{\Theta}^T \Gamma^{-1} \dot{\hat{\Theta}}. \tag{14}$$

Setting $A^T P + PA = -Q$ as in (10) implies that

$$\dot{V} = -X^T Q X + 2\tilde{\Theta}^T [\Psi^T B^T P X + \Gamma^{-1} \dot{\hat{\Theta}}]. \tag{15}$$

Setting the adaptation law as defined in (9) leads to

$$\dot{V} = -X^T Q X < 0. \tag{16}$$

Therefore, $X = 0$ is a globally asymptotically stable equilibrium point since Q is positive definite which makes $\dot{V} < 0\,\forall X \neq 0$. A positive Lyapunov function V, which is decreasing ($\dot{V} < 0$), is bounded since it converges to a finite limit. Hence, the system is asymptotically stable in the sense of Lyapunov. Therefore, X and so e, $\int e$, and $\tilde{\Theta}$ are also bounded and converge to finite values. Since Ψ is bounded, it implies from (8) that $\dot{X}$ is also bounded. Henceforth, $\ddot{V}$ is also bounded.

Lemma 1 (Barbalat): If the differentiable function $V(t)$ has a finite limit as $t \to \infty$, and if $\dot{V}(t)$ is uniformly continuous, then $\dot{V}(t) \to 0$ as $t \to \infty$.

From Lemma 1, V has a finite limit as $t \to \infty$ and $\dot{V}$ is uniformly continuous. Accordingly, $\lim_{t\to\infty} \dot{V} = 0$, and thus, $\lim_{t\to\infty} X = 0$. It shows that $\lim_{t\to\infty} e = 0$ and $\lim_{t\to\infty} \dot{e} = 0$. Consequently, $\lim_{t\to\infty} \hat{V}_c = V_c$.

IV. Lifetime Estimation

The electrodes of the supercapacitor investigated in this work consists of an aluminum metallic collector with a high surface area coated on both sides with an active carbon powder material. A porous membrane separates the two electrodes to prevent electronic conduction by physical contact between the electrodes while allowing the ionic conduction between them. Therefore, its maximum voltage is governed by the electrolyte decomposition voltage, which is mainly impacted by the operating temperature and the current strength. Temperature variations reduce the electrolyte's viscosity and change the accessibility of the surface for the ions to reach deeper carbon areas. The variation in the accessible surface area results in a varying supercapacitor's series resistance and capacitance, which are directly correlated with its degradation.

Lifetime estimation can be obtained from either the supercapacitor's internal resistance or capacitance. Studies have reported a supercapacitor's internal resistance increase and capacitance decline for reduced lifespan [38]. Therefore, The

Algorithm 1: Online parameter identification.

begin
- **Step 1:** Initialize the error e to zero and the vector of parameters $\hat{\Theta}$ to a set of predefined values.
- **repeat**
  - **Step 2:** Evaluate the estimation law in (4).
  - **Step 3:** From (3), calculate the error e.
  - **Step 4:** Compute the vector of parameters' update, i.e., $\Delta\hat{\Theta} = \dot{\hat{\Theta}}$ from (9).
  - **Step 5:** Update the vector of parameters using, $\hat{\Theta}(k) = \hat{\Theta}(k-1) + \Delta\hat{\Theta}$.
- **until** *stop request is received.*

supercapacitor's parameters can be extracted by using

$$C_T = \frac{1}{\theta_1}$$

$$R_s = \theta_2.$$

The estimation of parameters θ_1 and θ_2 leads to the supercapacitor's capacitance and resistance estimation, respectively. Thus, a supercapacitor's EOL resistance (R_{EOL}) can be taken as 200% brand new supercapacitor's internal resistance (R_{new}), i.e., $R_{\mathrm{EOL}} = R_{\mathrm{new}} * 200\%$. Therefore, the lifespan indicator is expressed as [39]

$$Ł(\%) = \frac{R_{\mathrm{EOL}} - R_s}{R_{\mathrm{EOL}} - R_{\mathrm{new}}} * 100\%. \quad (17)$$

In real-life applications, the estimation of the parameter θ_2 is a difficult task to undertake because of the combination of low resistance values with low sensors' precision and measurements' noise. Therefore, the estimation of the parameter θ_1, i.e., capacitance C_T, seems to be rational choice for the supercapacitor's lifespan estimation. Henceforth, the lifespan indicator is determined by [39]

$$Ł(\%) = \frac{C_{\mathrm{EOL}} - C_T}{C_{\mathrm{EOL}} - C_{\mathrm{new}}} * 100\% \quad (18)$$

where $C_{\mathrm{EOL}} = 0.8 * C_{\mathrm{new}}$.

Algorithm 1 describes the iterative parameter identification procedure.

V. Experimental Results

A. Setup

Various 350-F supercapacitors in different SOC stages are exposed to various temperatures, and their capacitance is measured periodically. Before beginning the aging procedure, the supercapacitors' characterization is carried out by charging and discharging the supercapacitors under a predefined current profile. Then, the supercapacitors are laid in different climate chambers whose temperatures are, respectively, set to 55, 60, 65, and 70 °C. The supercapacitors' aging calendar is carried out by connecting the supercapacitors to voltage sources for several days. Then, the supercapacitors are removed from the climate chamber and characterized again at ambient temperature with the same current profile. This procedure continues until the aging limit is attained. It is important to note that the supercapacitors are characterized after each aging stage, and four aging milestones are selected for validation, i.e., 0 h (brand new), 115 h, 230 h, and 390 h (EOL). These milestones are labeled C_0, C_1, C_2, and C_3, respectively. In this paper, 350-F, 2.7-V supercapacitors are used in a hardware-in-the-loop system for validation. The adaptive observer algorithm is implemented in MATLAB/Simulink software with a sampling period of 0.1 s. The adaptation rate vectors and parameter estimate are initialized to (5×10^{-7}, 1×10^{-7}) and (4×10^{-3}, 1×10^{-4}), respectively.

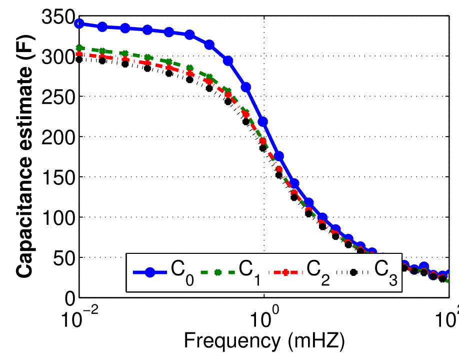


Fig. 2. Capacitance frequency response for different milestones.

Fig. 3. Experimental setup.

To study the supercapacitors' aging, the well-known capacitance characterization technique [40] is used in this paper as a benchmark to validate the performance of the proposed online observer. Although this parameter identification method can be used online, it is usually performed using offline experimental cycling data obtained by using constant discharge/charge current. As such, the temporal response is used to identify the supercapacitor's capacitance C. Therefore, using experimental

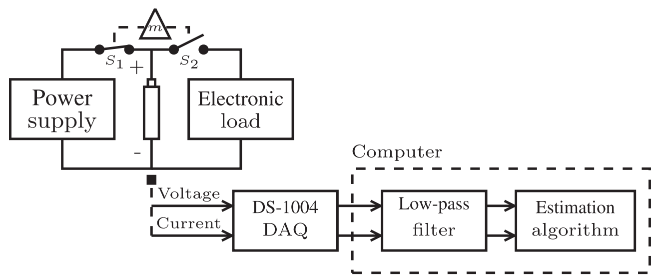


Fig. 4. Illustration of the experimental setup.

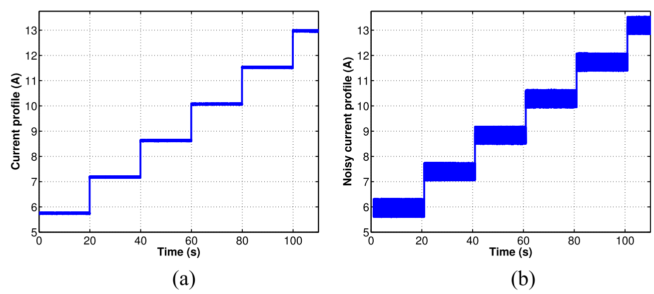


Fig. 5. Current profile. (a) Normal. (b) Noisy.

data at constant current, the capacitance is computed as follows:

$$C = I_c \frac{\Delta t}{\Delta V_c}. \tag{19}$$

The capacitance C is determined by measuring the depleted charge $I_c \Delta t$ when the voltage decreases by ΔV_c under a constant charge/discharge current. This method does not require the initial charge value. But, it suffers from sensitivity to noise because of the derivative operation. Moreover, it needs a considerable number of samples to generate a filtered estimate.

Fig. 2 shows the frequency response obtained using spectroscopy, where C_0 and C_3 correspond to the initial and EOL states, respectively. It is important to note that the capacitance is maximum at a low frequency ($f < 0.1$ Hz) since the ions have the necessary time to travel deeper in the carbon pores and reach the electrode surface. As the frequency increases, the ions cannot follow the applied electric field anymore and do not reach the needed depth of the electrode pores.

B. Results

Several experiments are carried out to validate the proposed identification strategy. A test bench has been designed, as illustrated in Fig. 3, to validate various types of estimation algorithms. It consists of a power supply and a data acquisition system to measure the voltage and the current. The experimental setup block diagram is depicted in Fig. 4. During these experiments, the supercapacitors are subjected to a charge process (i.e., S_1 closed and S_2 open) using the piecewise current profile in Fig. 5(a) for around 2 min. Fig. 6(a) shows the supercapacitor's voltage under charging for the four selected aging milestones, i.e., C_0, C_1, C_2, and C_3. As can be observed, the supercapacitor at an EOL stage (C_3) is the first to reach the rating

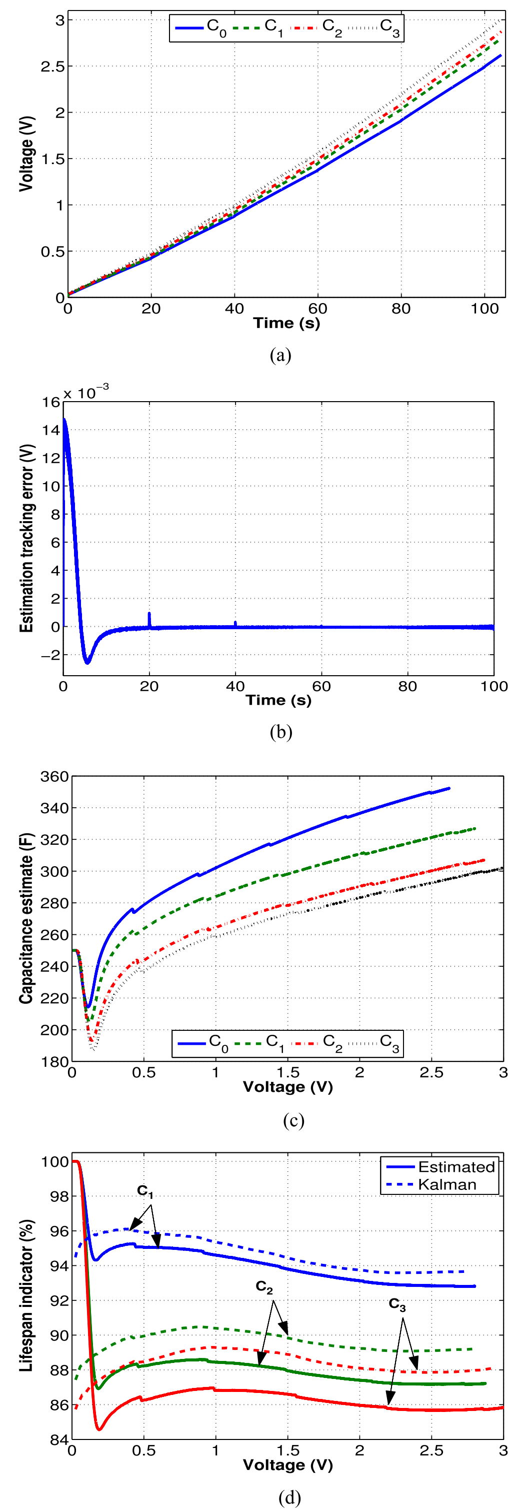
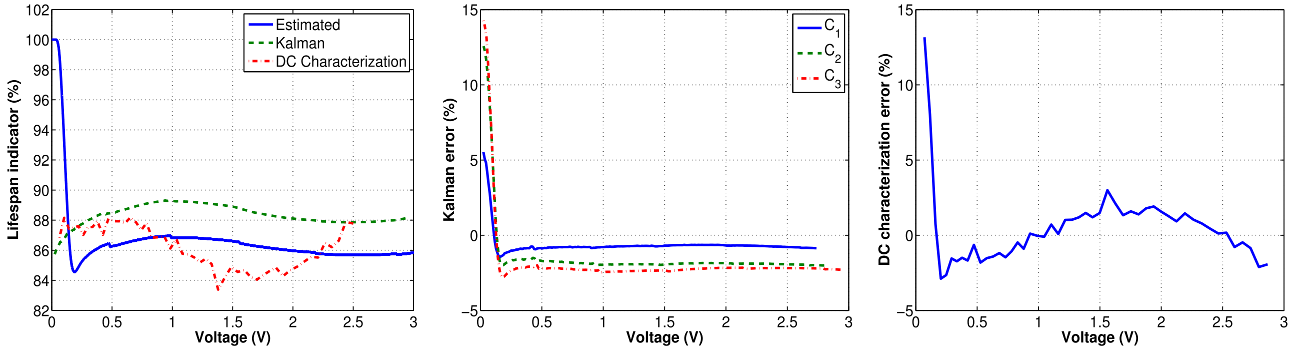


Fig. 6. Experimental results. (a) Voltage. (b) Estimation tracking error. (c) Capacitance estimate. (d) Lifespan indicator.

voltage of 3 V since supercapacitors with lower capacitance are expected to charge and discharge quicker. On the contrary, the supercapacitor at the BOL stage (C_0) takes the longest time to fully charge. As illustrated in Fig. 6(b), the estimation tracking error converges gradually and stays at zero despite of the current step nonlinearities. Estimation results for the selected



(a) (b) (c)

Fig. 7. Experimental comparison results. (a) Lifespan indicator. (b) EKF error. (c) DC characterization error.

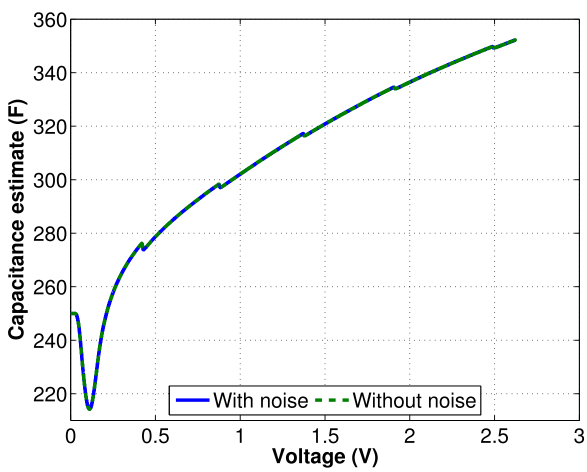


Fig. 8. Capacitance estimate.

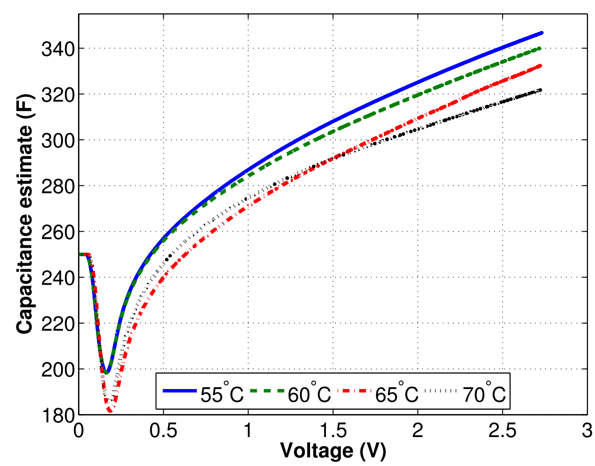


Fig. 9. Supercapacitor's experimental results for various temperatures.

milestones are shown in Fig. 6(c). As illustrated, thecapacitance estimates for all aging milestone show smooth convergence from their initial value, i.e., 250 F. As expected, the capacitance of the supercapacitors varies with the voltage and decreases with aging. Then, the EKF proposed in [41] is implemented and used as a benchmark for comparison. For each procedure, the aging indicator is evaluated in $(\%)$ for different aging milestones with respect to their respective initial milestone (BOL, i.e., C_0). The comparative results are depicted in Fig. 6(d). As expected, the capacitance's estimate of the supercapacitors for both methods decreases after each aging milestone. But, an offset is also observed along with a higher drift at C_3 aging milestone. To investigate the source of these effects, the well-known dc characterization technique is used as a second benchmark technique, and comparison results for the EOL supercapacitor (C_3) are depicted in Fig. 7(a). Although the supercapacitor's capacitance varies with the voltage, its lifespan indicator for a given aging stage should remain constant over a voltage range. As revealed, the dc characterization technique exhibits more than 4% variation, while the proposed method's variation is kept within less than 2%. This is expected since dc characterization technique is known for sensitivity to noise. But more importantly, the proposed methodology generates a filtered estimate of the lifespan indicator with less variations. On the other hand, the estimate obtained by the EKF seems to have an offset with respect to both the proposed technique and the dc characterization. As shown in Fig. 7(c), the difference between the two methods is $\pm 2\%$. On the other hand, the difference between the proposed technique and the EKF shows in Fig. 7(b) an increasing offset with aging of up to 2.5%. It is noteworthy that, although the characterization method is known for its sensitivity to sensors' noise, it is sufficient to provide an approximation of a supercapactior's aging to validate the proposed method. Therefore, the effectiveness of the proposed identification strategy is clearly shown in these experiments. Moreover, the asymptotic convergence and stability is guaranteed unlike EKF and many other online estimation strategies.

Next, the adaptive estimator's performance is evaluated under disturbance. Since noise is inherent in practical applications such as electric vehicles, the supercapacitors are subjugated to a noisy current profile, as shown in Fig. 5(b). For that, a noisy excitation signal with an amplitude of ± 0.4 A is injected manually to the piecewise current profile. The capacitance estimate of the BOL supercapacitor is revealed in Fig. 8. As observed, the proposed observer is able to cope with measurement uncertainties and provide a smooth and accurate estimate. This is mainly due to the presence of the integral of the current in the supercapacitor's dynamics (1), which damps any high-frequency noise or disturbance.

Finally, the effect of temperature variations is studied. For that, various supercapacitors are aged in different temperature conditions (55, 60, 65, and 70 °C). It is noteworthy that aging accelerates when supercapacitors are subjected to high temperatures, which results in higher capacity losses. Fig. 9 reveals the performance under these conditions. As expected, the adaptive estimator is able to capture these effects.

VI. Conclusion

An online parameter identification method is introduced for lifetime diagnostic and failure prognostic of supercapacitors. The proposed estimation scheme capitalizes on the capabilities of adaptive control theory to achieve online parameters estimation with guaranteed convergence and stability. It is easier to be implemented as opposed to other estimation approaches with similar performance, which makes it more suitable for real-time applications. Experimental results for supercapacitors at various aging stages highlight the performance of the proposed estimator in determining the aging indicator. Moreover, comparison is performed against the dc characterization technique and a Kalman filter, which confirms the effectiveness of the adaptive estimation approach. Unlike these two methods, the proposed method achieves online parameter estimation with guaranteed stability and higher accuracy.

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