Real-Time Parameter Estimation of a Fuel Cell for Remaining Useful Life Assessment

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***Abstract*—This article presents a real-time parameter estimation of a proton exchange membrane fuel cell (PEMFC). The proposed strategy estimates online the PEMFC's resistance, since it is directly correlated to its remaining useful life assessment. The estimation of the PEMFC's parameters is a difficult task to undertake due to various uncertainties, like temperature and aging, that lead to a drift in parameters and limit the performance of the overall energy system. Therefore, online system identification is essential to track online the PEMFC's time-varying parameters. Unlike other identification techniques, the proposed strategy is based on a simple yet accurate PEMFC's model and adjusts its parameters in real-time using a Lyapunov-based adaptation law, which yields guaranteed stability. Experiments are conducted on a 500-W Horizon PEMFC and results along with a comparison against the well-known Kalman filter highlight the effectiveness of the proposed approach, which is instrumental for its numerous applications, such as the energy management of hybrid fuel cell vehicles.**

***Index Terms*—Fuel cell, Lyapunov stability, online identification, parameter estimation, remaining useful life (RUL).**

I. Introduction

THE proton exchange membrane fuel cell (PEMFC) is widely used in power and energy conversion applications due to its high energy and power density, making it a popular choice in vehicular applications [1], [2]. It extracts electric energy from the chemical energy stored in hydrogen and operates in various temperature conditions, which impact its lifespan [3]. The PEMFC's degradation can be caused by the dehydration of the polymer membrane or the corrosion of the plates that leads to higher gas crossover due to cracks [3]. Thus, performance becomes heavily dependent on its state-of-health, which is mainly affected by operating conditions. Although a loss of performance over time is unavoidable, online lifetime diagnosis and prognosis tools are instrumental to avoid early failure. For that, remaining useful life (RUL) prediction can help in minimizing the rate of degradation and in detecting faults before they occur. The definition of the end-of-life (EOL) of the PEMFC varies from one application to another; but, it generally comes with an increase of the internal resistance leading to a power decrease [4]. This work focuses on an online estimation of the PEMFC's resistance for real-time RUL prediction.

In real-life, the PEMFC is subjected to high power cycles, which result in significant temperature variations and reduce its lifespan. Also, the PEMFC's lifetime may be shortened by other factors such as imperfection in the manufacturing process and the presence of impurities. Classical RUL assessment methods, such as high-frequency resistance measurement, polarization curve analysis, cyclic voltammetry, current interrupt, electrochemical impedance spectroscopy (EIS), and nonlinear frequency response analysis, are known for their simplicity [5]–[8]. However, they are not suitable for real-time applications and require additional hardware and costly analysis instrumentation. For instance, the EIS measurement procedure can take several minutes to complete as it induced separately each frequency harmonic to limit disturbance. Additionally, EIS is shown in [6] to be limited when testing under extreme nonlinear conditions. On the other hand, real-time RUL estimation of the PEMFC is a difficult task to undertake since voltage drop due to resistance increase is difficult to measure with an acceptable level of precision. Moreover, the PEMFC's resistance has a low value and hence, estimation accuracy is heavily affected by noisy measurements. This raises the urgency to consider online approaches capable of providing the needed robustness to achieve precise RUL prediction.

To perform real-time estimation, existing methods based on the PEMFC's physical model face a tradeoff dilemma between model complexity and accuracy [9]–[12]. While complex models can improve estimation precision, it is however achieved at the expense of increased computation burden. Other techniques are based on empirical data and feature less computational complexity [13]–[16]. In either case, these methods yield static models that are only representative of the original test conditions. The impact on the PEMFC's performance due to varying operating

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conditions, aging and degradation phenomena, and so forth have made the design of a comprehensive PEMFC model immensely complicated. Consequently, online identification algorithms are good candidates to cope in real-time with such uncertainties.

A number of methodologies have been proposed to identify the parameters of the PEMFC model, namely, metaheuristic-based methods [17]–[20], adaptive filtering [21], [22], and other techniques [23], [26]. In [17], two well-known metaheuristics, namely particle swarm optimization (PSO) and differential evolution (DE) are proposed. In order to improve the inherent drawbacks of PSO, an adaptive PSO algorithm with better equilibrium characteristic between global search and local search is proposed in [18]. In [19], a global harmony search algorithm-based parameter identification method is proposed and a comparison is carried-out against other harmony search algorithms, PSO algorithms, bee swarm optimization algorithm, and seeker optimization algorithm. In [20], evolutionary algorithms are also explored for the estimation of the PEMFC's equivalent circuit-based model parameters. But, stochastic optimization methods and evolutionary algorithms in general, like neural-network-based approaches [23]–[26], are associated with high computational burden due to the high number of objective function evaluations needed for convergence. Thus, they are not suitable for low-cost real-time applications. In [21], recursive least-squares (RLS) estimation is applied to track the unknown time-varying parameters of a third-order polynomial used to fit the PEMFC's data. Modeling complex systems with an appropriate accuracy requires a high-degree polynomial, which makes the convergence of the large number of parameters to estimate difficult. More importantly, the estimated polynomial gains cannot be related to the PEMFC's physical parameters that are essential to its RUL assessment. In [22], extended Kalman filter (EKF) is used to estimate both the states and parameters simultaneously with unknown noise. EKF is also used in [28] to estimate directly the state-of-health (SOH) of the PEMFC. The performance of the two well-known recursive filters, i.e., Kalman filter (KF) and RLS, is presented in [29] and the KF algorithm is used in [2] as an online parameter identification method for hybrid electric vehicle energy management. But, these algorithms are presented without stability proof and convergence analysis. In [30], a real-time adaptive parameter estimation method is presented. The PEMFC's nonlinear model is linearized using Taylor series expansion and exponential parameter convergence is derived using Lyapunov stability theory. However, linearization does not guarantee performance and stability in all operating conditions.

The PEMFC's real-time prognosis requires a simple and reliable model that is able to accurately predict and track the time-varying parameters associated with aging. Unlike the aforementioned techniques, the proposed strategy achieves real-time RUL prediction through online estimation of the PEMFC's resistance. For that, a simple yet accurate equivalent circuit model is used to emulate the PEMFC's dynamics and a Lyapunov-based adaptation law is proposed to track online the PEMFC's time-varying parameters. As such, the proposed approach learns online the PEMFC's dynamics with significantly less computational burden with respect to machine learning based methods making it suitable for lower-cost applications. Moreover, unlike many online estimation techniques, the stability and convergence are guaranteed by Lyapunov's direct method. In addition, the proposed estimation procedure requires only the measurement of voltage and current, which reduces the number of sensors as opposed to other techniques. To the authors' best knowledge, this article is one of the first attempts, if any, to guarantee asymptotic stability and convergence for the PEMFC's real-time RUL prediction. Experiments carried-out on a 500-W Horizon PEMFC show the effectiveness of the proposed approach in achieving accurate estimation. Moreover, comparison against the well-known KF highlights the performance of the method. The rest of this article is organized as follows. Section II outlines the PEMFC's circuit model along with its dynamics. The proposed adaptive estimation technique and the convergence and stability analysis are outlined in Section III. In Section IV, experimental results are reported and discussed. Finally, Section V conclude with some remarks.

II. Modeling of a PEMFC

The PEMFC's behavior has been thoroughly studied in both time and frequency domain, which led to several models [4], [5], [17], [31]. Basically, the PEMFC is subjected to three major irreversibilities: 1) activation losses, where a proportion of the voltage is lost in the chemical reaction taking place on the surface of the electrodes; 2) ohmic losses where the voltage drop is caused by the resistance to the flow of electrons; and 3) mass transport or concentration losses that result from the change in concentration of the reactants at the surface of the electrodes. Essentially, the most important losses are due to the activation and ohmic losses [30]. Both losses have similar magnitudes at low temperature and the activation losses become less significant compared to ohmic losses at high temperatures [5]. The general formulation of a PEMFC can be written as [4]

$$V_{\text{FC}} = E - V_{\text{act}} - V_{\text{ohmic}} - V_{\text{con}} \tag{1}$$

where V_{FC} is the PEMFC's voltage (V), E is the reversible potential also called open circuit voltage (V), V_{act} is the activation voltage loss (V), V_{ohmic} is the ohmic voltage loss (V), and V_{con} is the concentration voltage loss (V) expressed as

$$V_{\text{act}} = A \ln\left(\frac{I_{\text{FC}}}{b}\right) \tag{2}$$

$$V_{\text{ohmic}} = R_r I_{\text{FC}} \tag{3}$$

$$V_{\text{con}} = m \exp(n I_{\text{FC}}) \tag{4}$$

where I_{FC} is the PEMFC's current and R_r is the internal resistance. A, b, m, and n are constants that depend on the PEMFC's condition.

The PEMFC's dynamics can be represented by an electric transmission line model, where the charge propagation along the electrode surface is characterized by RC circuits [3], [4], [20], [31]–[34]. As such, a series of RC branches corresponding to a series expansion of the transmission line model offer a good accuracy in a wide frequency range. Each RC branch, also called RC network, corresponds to a given time-constant. The number of RC networks depends on the transient response's time span to

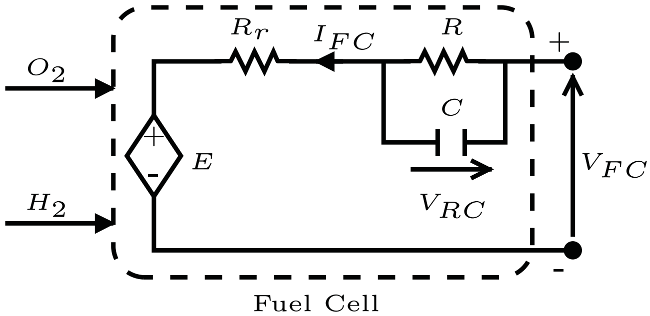


Fig. 1. Equivalent electric circuit model of a PEMFC [4].

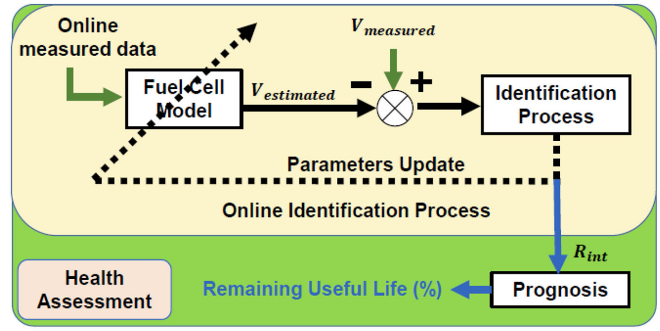


Fig. 2. RUL assessment scheme.

be covered from slow to fast dynamics. It is noteworthy that such a model results in a drastic increase in the system's nonlinear complexity. As it is shown experimentally in [4] and [5], and references therein, the PEMFC's model can be represented by the equivalent circuit model depicted in Fig. 1, where a single RC network generally provides an accurate representation of the PEMFC's dynamics. As it is depicted, a resistor R_r is used to illustrate the ohmic loss phenomenon.

Using Kirchhoff's second law on the equivalent circuit model in Fig. 1 yields

$$V_{\text{FC}} = E + V_{RC} + R_r I_{\text{FC}} \tag{5}$$

with the voltage across the RC network as

$$V_{RC} = \frac{1}{C}\int I_C \tag{6}$$

where the current flowing through the capacitor, from Kirchhoff's first law, is $I_C = I_R - I_{\text{FC}}$, and I_R being the current through the equivalent parallel resistor R. Substituting I_C in (6) leads to

$$V_{RC} = \frac{1}{C}\int (I_R - I_{\text{FC}})\,. \tag{7}$$

Using Ohm law on the equivalent parallel resistor R yields

$$V_{RC} = \frac{1}{C}\int \left(\frac{V_{RC}}{R} - I_{\text{FC}}\right). \tag{8}$$

Taking the derivative of V_{RC} and using Kirchhoff's second law equation in (5) leads to the following voltage–current characteristic dynamic mathematical model:

$$\dot{V}_{RC} = \frac{1}{RC}V_{RC} - \frac{1}{C}I_{\text{FC}} \tag{9}$$

$$V_{\text{FC}} = E + V_{RC} + R_r I_{\text{FC}} \tag{10}$$

A. Problem Statement

This article aims to estimate the PEMFC's resistance, since it is directly correlated to its RUL assessment. In this work, parameters R, C, and R_r are assumed to be *a priori* unknown and V_{RC} is not measurable. The system's measurable states are the PEMFC's voltage V_{FC} and current I_{FC}.

Assumption 1: The PEMFC's voltage V_{FC} and current I_{FC} along with their derivatives $\dot{V}_{\text{FC}}$ and $\dot{I}_{\text{FC}}$ are continuous, bounded, and persistently excited.

Assumption 2: The estimation algorithm sampling frequency is high enough with respect to the slowly time-varying PEMFC's parameters such that, $\dot{E} \approx \dot{R}_r \approx \dot{R} \approx \dot{C} \approx 0$.

Since the PEMFC's parameters vary with various factors, such as temperature and aging, an online parameter estimation is then required to track in real-time their variation. The proposed estimation scheme is outlined in Fig. 2. As such, an adaptive parameter identification strategy estimates online the PEMFC's resistance using the voltage V_{FC} and current I_{FC}. Then, the estimated resistance is fed to a prognosis algorithm to determine the PEMFC's RUL. Next, the proposed online parameter estimation approach is described in details with its stability proof.

III. Online Parameter Estimation

Substituting V_{RC} from (10) into (9) and using assumption 2

$$\dot{V}_{\text{FC}} - \frac{1}{RC}V_{\text{FC}} - R_r\dot{I}_{\text{FC}} + \frac{R_r}{RC}I_{\text{FC}} + \frac{1}{C}I_{\text{FC}} + \frac{1}{RC}E = 0.$$

Multiplying by RC yields

$$V_{\text{FC}} = RC\dot{V}_{\text{FC}} - R_r RC\dot{I}_{\text{FC}} + (R + R_r)I_{\text{FC}} + E = \Psi^T\Theta$$

where $\Psi \in \mathbb{R}^4$ is a vector of known functions (regressor), and $\Theta \in \mathbb{R}^4 = [RC,\ -R_r RC,\ R + R_r,\ E]$ is a vector of parameters.

Studies have reported a PEMFC's equivalent series resistance ($R_{\text{int}} = R + R_r$) rise as an indication of increased degradation [4]. Therefore, the proposed approach achieves real-time health assessment of the PEMFC with the estimation of its equivalent series resistance R_{int}. For that, an accurate estimation of parameter Θ_3 would lead to a precise RUL prediction. The PEMFC's EOL equivalent series resistance (R_{EOL}) is usually taken as 200% brand new PEMFC's equivalent series resistance (R_{new}), i.e., $R_{\text{EOL}} = R_{\text{new}} * 200\%$. Thus, RUL estimation can be achieved using

$$RUL(\%) = \frac{R_{\text{EOL}} - R_{\text{int}}}{R_{\text{EOL}} - R_{\text{new}}} * 100\%. \tag{11}$$

Define the estimation error as

$$e = \int V_{\text{FC}} - \int \hat{V}_{\text{FC}} \tag{12}$$

and the estimation law as follows:

$$\hat{V}_{\text{FC}} = \Psi^T\hat{\Theta} + K_d e \tag{13}$$

where $\hat{V}_{\rm FC}$ is the voltage estimate, $\hat{\Theta}$ is the vector of parameter estimates, and K_d is a strictly positive constant gain. Taking the time derivative of (12) yields

$$\dot{e} = V_{\rm FC} - \hat{V}_{\rm FC}.$$

Setting the estimation law as defined in (13) leads to the desired error dynamics

$$\dot{e} = \Psi^T \tilde{\Theta} - K_d e \tag{14}$$

where $\tilde{\Theta} = \Theta - \hat{\Theta}$ is the vector of parameter estimates error. Thus, the estimation error asymptotic stability and convergence to zero are achieved with the following adaptation law:

$$\dot{\hat{\Theta}} = -\Gamma \Psi e \tag{15}$$

where $\Gamma = [\gamma_1, \gamma_2, \ldots, \gamma_4]$ and γ_i is a positive constant gain. Convergence and stability are important aspects in online estimators. Many recursive algorithms available in literature for PEMFC's parameter estimation are presented without stability proof. Unlike these methods, the proposed online estimator's convergence and stability are guaranteed by Lyapunov's direct method.

Theorem 1: Consider a nonlinear system in the form of (9)–(10) with the estimation law (13). The adaptation law (15) guarantees the estimation error's asymptotic stability and convergence to zero.

Proof: Choose the following Lyapunov candidate:

$$V = \frac{1}{2}e^2 + \frac{1}{2}\tilde{\Theta}^T \Gamma^{-1} \tilde{\Theta}. \tag{16}$$

Taking the derivative of *V* yields

$$\dot{V} = e\dot{e} + \tilde{\Theta}^T \Gamma^{-1} \dot{\tilde{\Theta}}. \tag{17}$$

Since parameters Θ are considered to be slowly time-varying (assumption 2), therefore, $\dot{\tilde{\Theta}} = \dot{\hat{\Theta}}$. Substitute $\dot{e}$ from (14) into (17):

$$\dot{V} = \Psi^T \tilde{\Theta} e + \tilde{\Theta}^T \Gamma^{-1} \dot{\hat{\Theta}} - K_d e^2. \tag{18}$$

Setting the adaptation law as defined in (15) leads to

$$\dot{V} = -K_d e^2 < 0 \quad \forall\, K_s > 0. \tag{19}$$

Setting $K_d > 0$ yields $\dot{V} < 0, \forall\, e \neq 0$, so that $e = 0$ is a globally asymptotically stable equilibrium point. A positive Lyapunov function V, which is decreasing ($\dot{V} < 0$), must converge to a finite limit. Therefore, the system is asymptotically stable in the sense of Lyapunov. Hence, signals e, $\tilde{\Theta}$, and $\hat{\Theta}$ are also bounded and converge to finite values. It follows from (13) that $\hat{V}_{\rm FC}$ is also bounded, which implies from (14) that $\dot{e}$ is also bounded.

For nonautonomous systems, finding a Lyapunov function V with a negative definite derivative ($\dot{V} < 0$) does not lead to a conclusion about the asymptotic stability. Therefore, Barbalat's lemma is applied for the time-varying system in hand to prove its asymptotic stability and convergence.

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 $t \to \infty$.

Algorithm 1: Online System Identification.

Initialize $\hat{\Theta}$ to a set of predefined values
Set K_d and Γ to positive predefined values
Set the error to zero, i.e., $e \leftarrow 0$
while $Stop \neq 1$ **do**
  Evaluate the estimation law in (13):
  $\hat{V}_{FC} \leftarrow \Psi^T \hat{\Theta} + K_d e$
  Update the error using (12):
  $e \leftarrow \int V_{FC} - \int \hat{V}_{FC}$
  Compute the vector of parameters' update from (15):
  $\Delta\hat{\Theta} \leftarrow \dot{\hat{\Theta}} \leftarrow -\Gamma \Psi e$
  Update the vector of parameters:
  $\hat{\Theta}(k+1) \leftarrow \hat{\Theta}(k) + \Delta\hat{\Theta}$
  Update the stop condition:
  $Stop \leftarrow$ user input, $0|1$
end while

Taking the derivative of $\dot{V}$ yields

$$\ddot{V} = -2e\dot{e}.$$

Therefore, $\ddot{V}$ is also bounded.

From Lemma 1, V has a finite limit as $t \to \infty$ and $\dot{V}$ is uniformly continuous. Therefore, $\lim_{t\to\infty} \dot{V} = 0$, and hence, $\lim_{t\to\infty} e = 0$. From Lemma 1, e has a finite limit as $t \to \infty$ and $\dot{e}$ is uniformly continuous. Therefore, $\lim_{t\to\infty} \dot{e} = 0$. Hence, $\lim_{t\to\infty} \hat{V}_{\rm FC} = V_{\rm FC}$. Algorithm 1 describes the iterative procedure to estimate the fuel cell's parameters.

Remark 1: The convergence of the tracking error is an important aspect in adaptive systems [35]–[37]. But, it does not guarantee parameter convergence that is only achieved if the following persistent excitation condition:

$$\alpha_0 I_n \leq \int_{t_0}^{t_0+\beta} \Psi \Psi^T dt \leq \alpha_1 I_n$$

is met for all t_0, where α_0, α_1, and β are all positive. It is important to note that the integral of $\Psi\Psi^T$ must be positive definite and bounded over all intervals of length β. In other word, Ψ must vary sufficiently over the interval β to span the entire dimensional space.

Remark 2: In order to make recursive estimation algorithms more robust, various modifications are available in the literature as summarized in [38]. These adjustments aim to keep the parameter estimates bounded. In a lack of persistent excitation, maintaining the parameter estimates bounded does not solve the parameter drift issue due to the noise and other disturbances. To overcome this, a dead-zone is used to disable parameter adaptation when the estimation error is smaller than the disturbance bound that is assumed to be known. More details on this aspect can be found in [38].

IV. Experimental Validation

To validate the performance of the proposed prognostic approach, an experimental test bench has been developed. Hereinafter, the setup is explained first. Subsequently, experimental

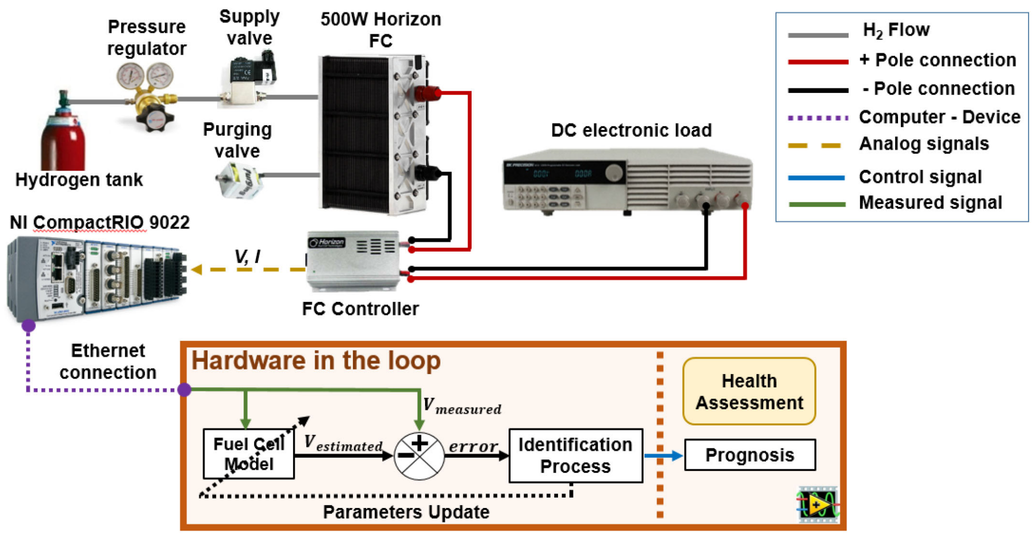


Fig. 3. Experimental setup.

TABLE I
PEMFC's SPECIFICATIONS

Parameter	Value	Unit
Power	500	(W)
Number of cells	36	
Hydrogen pressure	$0.5-0.6$	(Bar)
Cathode pressure	1	(Bar)
Ambient temperature	$5-30$	$(^{\circ}C)$
Maximum temperature	65	$(^{\circ}C)$
Hydrogen purity	99.999	(%)
Size	130X220X122	(mm)

results of the internal resistance estimation are presented and discussed.

A. Setup

The illustration of the experimental setup is shown in Fig. 3. This setup is mainly composed of an open-cathode fuel cell (Horizon H-500), a CompactRIO (NI cRIO-9022), and a dc electronic load (8514 BK Precision). The specifications of the fuel cell are given in Table I. It has two fans installed on the stack housing with a dual role of providing the process air and regulating the stack temperature. The hydrogen supply subsystem consists of a hydrogen tank and supply valve, a pressure regulator, and a mass flowmeter. The hydrogen partial pressure is sustained between 0.5 and 0.6 bar, as advised by the manufacturer.

The purging valve expels the extra water, hydrogen, and nitrogen out of the flow channels every 10 s for a duration of 100 ms. The fuel cell is linked to the CompactRIO via its controller, which has control over the operation of the valves and the axial fan. The communication between the CompactRIO and the computer is made through an Ethernet connection. Current, temperature, and voltage of the PEMFC stack are recorded and used for the purpose of this article. LabVIEW software is installed in the computer to program the proposed algorithm and upload it in the CompactRIO controller and to control the electronic load (8514 BK Precision), which is used to request current profiles from the PEMFC stack. Voltage and current are measured, respectively, using the CompactRio module 9221 (12-b resolution) and the electronic load internal sensor with a 10 mA resolution. The internal temperature sensor of the fuel cell is a thermistor with the following characteristics: 1076 Ω @ 20 °C with a Δresistance of $\pm 3.8\ \Omega$ for ± 1 °C. It is connected to NI CompactRio module 9205 (16-b resolution). The algorithm is developed and tested first using a MATLAB script. Then, it is implemented in CompactRIO controller via the MathScript RT Module of LabVIEW. The sampling time for both the adaptive and KF algorithms is set to 100 ms.

For the purpose of this article, two 500-W fuel cells with different degradation levels are employed. The first fuel cell has a rated power of 400 W and is referred to as FC400 and the second one, referred to as FC300, has a rated power of 300 W. To show the aging extent of each fuel cell, their polarization and power curves are presented in Fig. 4 as an indicator of their present health state. The polarization curves are obtained by applying a fixed current to the fuel cells and their output voltage is observed and recorded at each rising current level. The fuel cells are given a rest time of 15–25 min after each increase in the current level to allow them to reach equilibrium. The adaptive estimation algorithm is implemented with a sampling frequency of 10 Hz. The proposed estimation approach is compared against the KF algorithm presented in [2].

B. Results

Several experiments are carried out to validate the proposed estimation approach. During these experiments, both fuel cells are subjected for about 10 min to the current profile shown in Fig. 5. It is important to note that this profile corresponds to a city driving behavior known as urban dynamometer driving

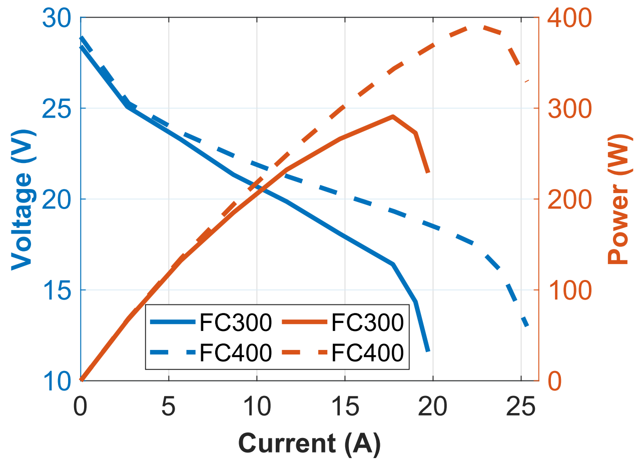


Fig. 4. Experimental characteristics of the PEMFCs.

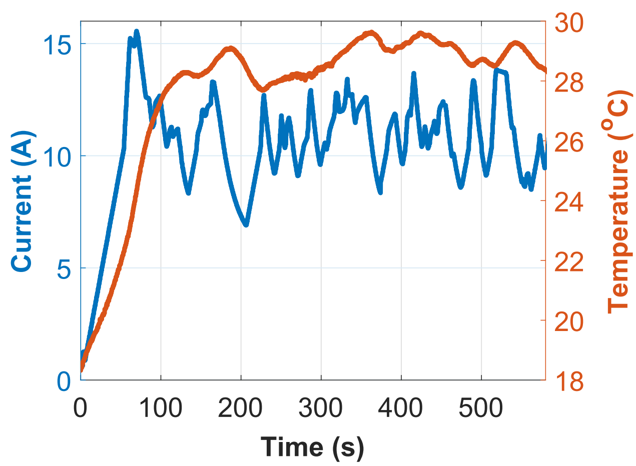


Fig. 5. Applied current profile.

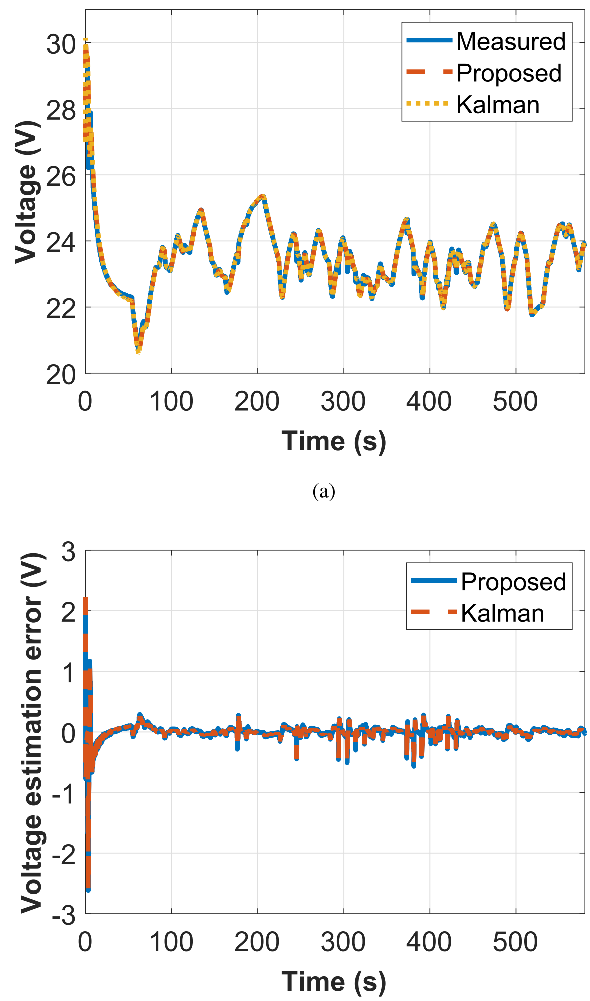
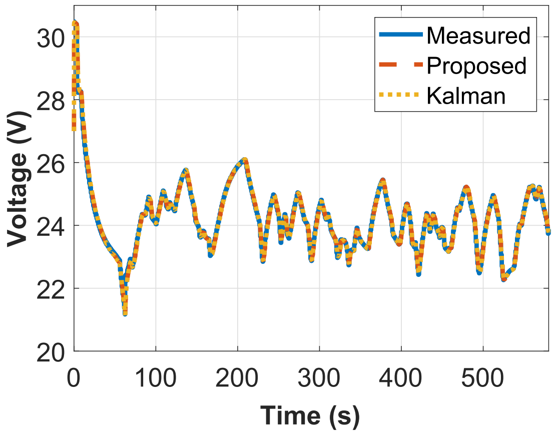


Fig. 6. Experimental results for FC300: (a) voltage; and (b) estimation error.

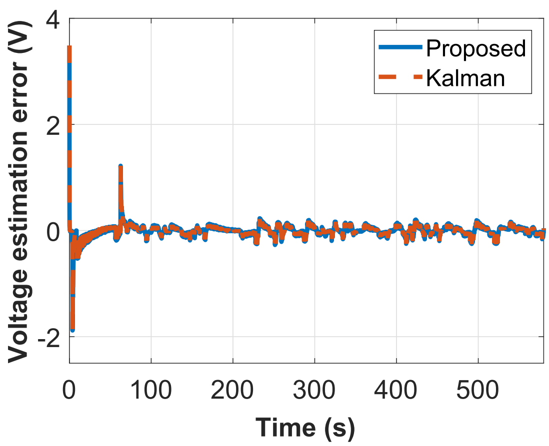
schedule (UDDS), which is an open source.[1] As it is illustrated in Figs. 6 and 7, accurate voltage tracking is achieved by both the proposed method and KF algorithm as the estimation tracking error converges quickly and stays within a negligible magnitude. As it is depicted in Fig. 8, the resistance estimates for both fuel cells show smooth convergence from their initial value. It is noteworthy that the estimates obtained with the proposed method are very close to those of KF. As it is expected, a resistance's estimate increase is observed for both methods at each aging milestone. The effectiveness of the proposed online estimator in tracking in real-time resistance changes through aging is clearly shown in these experiments. Moreover, it yields less complexity and computational burden as opposed to KF, which is an important factor in real-time applications, such as in electric vehicles, where the on-board computation power is limited. KF algorithm needs to perform various time-consuming arithmetic manipulations, such as matrix operations. This complexity has been studied in [39]. As it is illustrated, KF has six steps running to 12 matrix multiplications, 7 matrix additions/subtractions, a matrix inversion, and 3 matrix transpose operations. Unlike this burdensome process, the proposed algorithm has no time-consuming matrix operation. Instead, it has two vector multiplications, two scalar multiplications, one vector addition, two scalar additions/subtractions, and one vector transpose operation. Furthermore, the asymptotic convergence and stability is guaranteed unlike KF and several other online estimation strategies. Accurate parameter estimation is essential for all PEMFC's operation range, since it is usually used to extract polarization power characteristic curves for an energy management purpose in vehicular applications. To quantitatively adjudge the performance, the integral of the tracking error is introduced as a performance metric which is calculated as, $\eta = \int_{t_0}^{t_f} e^2 \, dt$, where t_0 and t_f are initial and final time instants, respectively. The obtained numerical values for both estimation methods are displayed in Table II. While both methods show a similar performance, the proposed estimation method yields a slightly higher tracking accuracy.

It is also important to note that the drift higher in the parameter estimates from 200 s until the end the experiment is due to temperature increase. To validate this aspect, the piecewise current profile shown in Fig. 9(a) is applied to the FC400 fuel

[1][Online] Available. http://www.uqtr.ca/VTSMotorVehiclesChallenge17



(a)



(b)

Fig. 7. Experimental results for FC400: (a) voltage; and (b) estimation error.

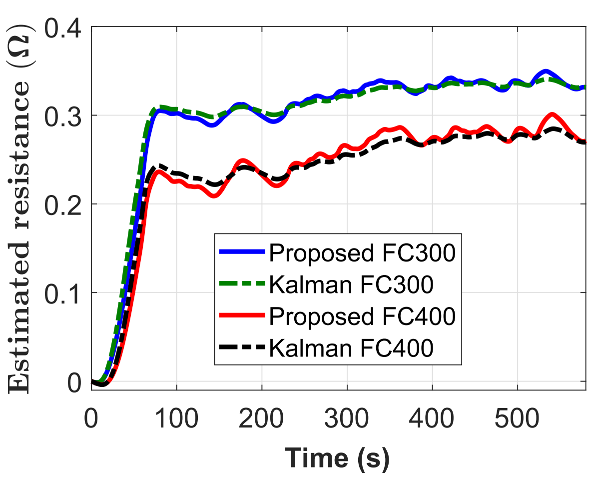
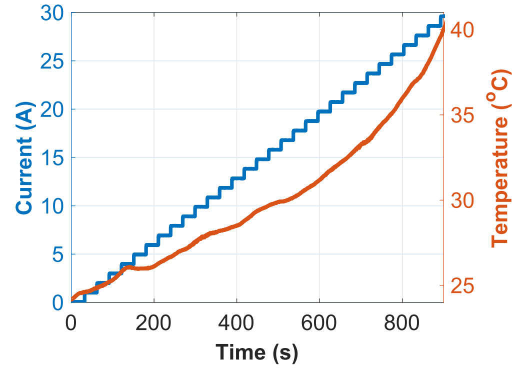


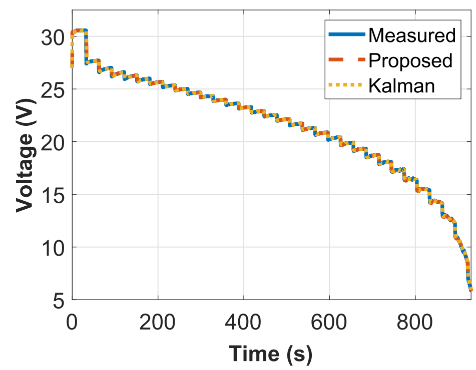
Fig. 8. Estimated resistance.

TABLE II
PERFORMANCE COMPARISON

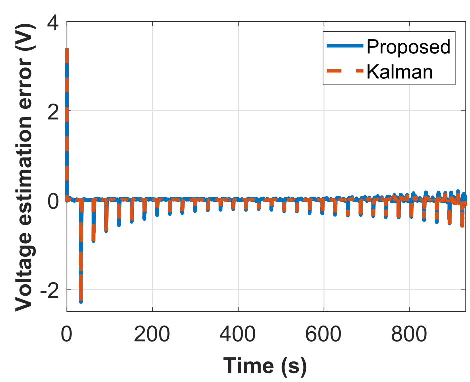
η	Proposed method	KF
FC300	93.03	93.95
FC400	73.57	74.09



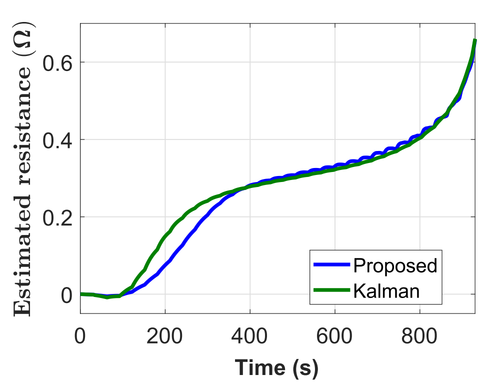
(a)



(b)



(c)



(d)

Fig. 9. Experimental results for FC400 under piecewise current profile: (a) current; (b) voltage; (c) estimation error; and (d) estimated resistance.

TABLE III
CURRENT AND TEMPERATURE LEVELS FOR CURRENT INTERRUPT TEST

Current (A)	Temperature ($^{\circ}C$)
3	24.4
6	24.8
9	26.4
12	27.3
15	28.8
18	31.0
21	33.2
24	36.8
26	39.0

cell. It consists of 1 A step increase each 30 s for about 900 s. It is worthwhile noting that the selected piecewise current profile results in an exponential increase in temperature as revealed in Fig. 9(a). Experimental results, under such condition, are depicted in Fig. 9. As current increases, the fuel cell's voltage decreases in steps from 30 to around 5 V [see Fig. 9(b)]. The proposed estimation technique as well as the KF algorithm are able to track the voltage with high accuracy [see Fig. 9(c)]. The resistance estimation performance of both methods are shown in Fig. 9(d). Similar performance is achieved by both estimators; but more importantly, they were able to track the resistance's change with temperature. The PEMFC's time-varying parameters due to factors like temperature and aging reduce significantly its performance. Henceforth, the proposed real-time methodology is instrumental in coping with such uncertainties to maintain the high performance needed in vehicular applications. It is noteworthy that internal resistance can be measured with respect to current and temperature using a well-known characterization technique called current interrupt [40]–[43]. In the current interrupt test, fast acquisition of the voltage signal is necessary to separate activation loss from ohmic loss, since this latter fades away instantly after the interruption of current, whereas activation loss converges to the open circuit voltage at a much slower rate. One significant advantage of current interrupt method compared to other electrochemical techniques is the convenience of data analysis. Yet, capturing the exact point, where the voltage jumps is not trivial and requires a fast oscilloscope. In this article, the current interrupt test is conducted based on the procedure explained in [43]. Table III shows different stack temperature and current levels while performing this test. It is worth noting that before performing the current interrupt test, enough time is given to the PEMFC stack to reach a stable temperature at each current level. Moreover, all the measurements are made for the forced convection condition. The current interrupt test is stopped at 26 A to avoid damaging the PEMFC stack with a continuous operation in the concentration zone.

Although this method is not suitable for online applications, since it is performed offline, it is usually used to provide a rough estimate of the internal resistance at various operating conditions. This test is applied to the FC400 fuel cell and results are revealed in Fig. 10. As it can be seen, the internal resistance range is consistent with the estimates obtained by both recursive methods [see Fig. 9(d)]. After convergence, both algorithms yield internal resistance values in the 0.15–0.4 Ω range in the linear current–voltage region. In the high current region which is also consistent with the results obtained by both offline and online methods. Future work envisions aging multiple fuel cells for the development of prognosis and health management tools. For that, extensive experiments will be conducted to accurately establish the relationship between various operating conditions. Other methods, like signal injection and EIS, can also be considered to measure the resistance of the fuel cell stack in different current and temperature operating conditions using additional measurement and analysis instrumentation.

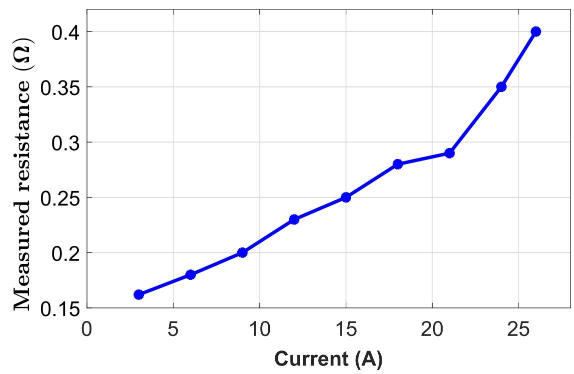


Fig. 10. Measured resistance for FC400 using current interrupt test.

V. CONCLUSION

An online parameter estimation strategy is proposed for real-time RUL assessment of a PEMFC. The proposed approach is based on a simple yet accurate PEMFC's model and tracks in real-time its time-varying parameters using a Lyapunov-based adaptation law. Hence, asymptotic stability and convergence are guaranteed as opposed to several existing techniques. Experimental validation carried out on a 500-W Horizon PEMFC along with a comparison against KF demonstrates the effectiveness of the proposed methodology in estimating the PEMFC's time-varying resistance with reduced implementation complexity with respect to KF, which makes it more suitable for real-time applications. This makes the proposed approach a good candidate for lower-cost implementation in applications like electric vehicles, where the on-board computation capability is limited.

REFERENCES

[1] M. Kandidayeni, A. O. M. Fernandez, A. Khalatbarisoltani, L. Boulon, S. Kelouwani, and H. Chaoui, "An online energy management strategy for a fuel cell/battery vehicle considering the driving pattern and performance drift impacts," *IEEE Trans. Veh. Technol.*, vol. 68, no. 12, pp. 11 427–11 438, Dec. 2019.

[2] A. M. Fernandez, M. Kandidayeni, L. Boulon, and H. Chaoui, "An adaptive state machine based energy management strategy for a multi-stack fuel cell hybrid electric vehicle," *IEEE Trans. Veh. Technol.*, vol. 69, no. 1, pp. 220–234, Jan. 2020.

[3] J. Kim, J. Lee, and B. H. Cho, "Equivalent circuit modeling of PEM fuel cell degradation combined with a LFRC," *IEEE Trans. Ind. Electron.*, vol. 60, no. 11, pp. 5086–5094, Nov. 2013.

[4] J. Larminie and A. Dicks, Eds., *Fuel Cell Systems Explained*. Hoboken, NJ, USA: Wiley, 2000.

[5] A. Forrai, H. Funato, Y. Yanagita, and Y. Kato, "Fuel-cell parameter estimation and diagnostics," *IEEE Trans. Energy Convers.*, vol. 20, no. 3, pp. 668–675, Sep. 2005.

[6] C. de Beer, P. Barendse, and P. Pillay, "Fuel cell condition monitoring using optimized broadband impedance spectroscopy," *IEEE Trans. Ind.*

[7] P. Lindahl, S. Shaw, and S. Leeb, “Fuel cell stack emulation for cell and hardware-in-the-loop testing,” *IEEE Trans. Instrum. Meas.*, vol. 67, no. 9, pp. 2143–2152, Sep. 2018.

[8] H. Homayouni, J. DeVaal, F. Golnaraghi, and J. Wang, “Voltage reduction technique for use with electrochemical impedance spectroscopy in high-voltage fuel cell and battery systems,” *IEEE Trans. Transp. Electrific.*, vol. 4, no. 2, pp. 418–431, Jun. 2018.

[9] R. F. Mann, J. C. Amphlett, M. A. Hooper, H. M. Jensen, B. A. Peppley, and P. R. Roberge, “Development and application of a generalised steady-state electrochemical model for a PEM fuel cell,” *J. Power Sour.*, vol. 86, no. 1–2, pp. 173–180, Mar. 2000.

[10] G. Maggio, V. Recupero, and L. Pino, “Modeling polymer electrolyte fuel cells: An innovative approach,” *J. Power Sour.*, vol. 101, no. 1–2, pp. 275–286, Oct. 2001.

[11] L. Pisani, G. Murgia, M. Valentini, and B. D’Aguanno, “A new semi-empirical approach to performance curves of polymer electrolyte fuel cells,” *J. Power Sour.*, vol. 108, no. 1–2, pp. 192–203, Jun. 2002.

[12] C. Maxoulis, D. Tsinoglou, and G. Koltsakis, “Modeling of automotive fuel cell operation in driving cycles,” *Energy Convers. Manage.*, vol. 45, no. 4, pp. 559–573, Mar. 2004.

[13] D. Feroldi, M. Serra, and J. Riera, “Energy management strategies based on efficiency map for fuel cell hybrid vehicles,” *J. Power Sour.*, vol. 190, pp. 197–401, May 2009.

[14] J. Bernard, S. Delprat, T. M. Guerra, and F. N. Bchi, “Fuel efficient power management strategy for fuel cell hybrid powertrains,” *Control Eng. Pract.*, vol. 18, pp. 408–417, Apr. 2010.

[15] S. Kelouwani, K. Adegnon, K. Agbossou, and Y. Dube, “Online system identification and adaptive control for PEM fuel cell maximum efficiency tracking,” *IEEE Trans. Ind. Electron.*, vol. 27, no. 3, pp. 580–592, Sep. 2012.

[16] L. Xu, J. Li, and M. Ouyang, “Energy flow modeling and real-time control design basing on mean values for maximizing driving mileage of a fuel cell bus,” *Int. J. Hydrogen Energy*, vol. 40, pp. 15 052–15 066, Nov. 2015.

[17] P. Alotto and M. Guarnieri, “Stochastic methods for parameter estimation of multiphysics models of fuel cells,” *IEEE Trans. Magn.*, vol. 50, no. 2, pp. 701–704, Feb. 2014.

[18] Q. Li, W. Chen, Y. Wang, S. Liu, and J. Jia, “Parameter identification for PEM fuel-cell mechanism model based on effective informed adaptive particle swarm optimization,” *IEEE Trans. Ind. Electron.*, vol. 58, no. 6, pp. 2410–2419, Jun. 2011.

[19] A. Askarzadeh and A. Rezazadeh, “An innovative global harmony search algorithm for parameter identification of a PEM fuel cell model,” *IEEE Trans. Ind. Electron.*, vol. 59, no. 9, pp. 3473–3480, Sep. 2012.

[20] C. Restrepo, T. Konjedic, A. Garces, J. Calvente, and R. Giral, “Identification of a proton-exchange membrane fuel cell’s model parameters by means of an evolution strategy,” *IEEE Trans. Ind. Inform.*, vol. 11, no. 2, pp. 548–559, Apr. 2015.

[21] B. Somaiah and V. Agarwal, “Recursive estimation-based maximum power extraction technique for a fuel cell power source used in vehicular applications,” *IEEE Trans. Control Syst. Technol.*, vol. 28, no. 10, pp. 4636–4643, Oct. 2013.

[22] S.-W. Tong, G.-P. Liu, X. G. Wang, and M. Tan, “Real-time implementation of adaptive state feedback predictive control of PEM fuel cell flow systems using the singular pencil model method,” *IEEE Trans. Control Syst. Technol.*, vol. 17, no. 3, pp. 697–706, May 2009.

[23] H. Liu, J. Chen, M. Hou, Z. Shao, and H. Su, “Data-based short-term prognostics for proton exchange membrane fuel cells,” *Int. J. Hydrogen Energy*, vol. 42, no. 32, pp. 20791–20808, Aug. 2017.

[24] R. Ma, T. Yang, E. Breaz, Z. Li, P. Briois, and F. Gao, “Data-driven proton exchange membrane fuel cell degradation predication through deep learning method,” *Appl. Energy*, vol. 231, pp. 102–115, Dec. 2018.

[25] K. Chen, S. Laghrouche, and A. Djerdir, “Degradation model of proton exchange membrane fuel cell based on a novel hybrid method,” *Appl. Energy*, vol. 252, pp. 1–10, Oct. 2019.

[26] J. Liu, Q. Li, W. Chen, Y. Yan, Y. Qiu, and T. Cao, “Remaining useful life prediction of PEMFC based on long short-term memory recurrent neural networks,” *Int. J. Hydrogen Energy*, vol. 44, no. 11, pp. 5470–5480, Feb. 2019.

[27] H. Chaoui and C. Ibe-Ekeocha, “State of charge and state of health estimation for lithium batteries using recurrent neural networks,” *IEEE Trans. Veh. Technol.*, vol. 10, no. 66, pp. 8773–8783, Oct. 2017.

[28] M. Bressel, M. Hilairet, D. Hissel, and B. O. Bouamama, “Remaining useful life prediction and uncertainty quantification of proton exchange membrane fuel cell under variable load,” *IEEE Trans. Ind. Electron.*, vol. 63, no. 4, pp. 2569–2577, Apr. 2016.

[29] M. Kandidayeni, A. Macias, A. Amamou, L. Boulon, S. Kelouwani, and H. Chaoui, “Overview and benchmark analysis of fuel cell parameters estimation for energy management purposes,” *J. Power Sour.*, vol. 380, pp. 92–104, Mar. 2018.

[30] Y. Xing, J. Na, and R. Costa-Castell, “Real-time adaptive parameter estimation for a polymer electrolyte membrane fuel cell,” *IEEE Trans. Ind. Inform.*, vol. 15, no. 11, pp. 6048–6057, Nov. 2019.

[31] C. de Beer, P. Barendse, P. Pillay, B. Bullecks, and R. Rengaswamy, “Online diagnostics of HTPEM fuel cells using small amplitude transient analysis for CO poisoning,” *IEEE Trans. Ind. Electron.*, vol. 62, no. 8, pp. 5175–5186, Aug. 2015.

[32] S. C. Page, A. H. Anbuky, S. P. Krumdieck, and J. Brouwer, “Test method and equivalent circuit modeling of a PEM fuel cell in a passive state,” *IEEE Trans. Energy Convers.*, vol. 22, no. 3, pp. 764–773, Sep. 2007.

[33] A. M. Dhirde, N. V. Dale, H. Salehfar, M. D. Mann, and T.-H. Han, “Equivalent electric circuit modeling and performance analysis of a PEM fuel cell stack using impedance spectroscopy,” *IEEE Trans. Energy Convers.*, vol. 25, no. 3, pp. 778–786, Sep. 2010.

[34] C. de Beer, P. Barendse, P. Pillay, B. Bullecks, and R. Rengaswamy, “Classification of high-temperature PEM fuel cell degradation mechanisms using equivalent circuits,” *IEEE Trans. Ind. Electron.*, vol. 62, no. 8, pp. 5265–5274, Aug. 2015.

[35] H. Chaoui and H. Gualous, “Adaptive state of charge estimation of lithium-ion batteries with parameter and thermal uncertainties,” *IEEE Trans. Control Syst. Technol.*, vol. 2, no. 25, pp. 752–759, Mar. 2017.

[36] A. E. Mejdoubi, H. Chaoui, H. Gualous, and J. Sabor, “Online parameter identification for supercapacitor state-of-health diagnosis for vehicular applications,” *IEEE Trans. Power Electron.*, vol. 12, no. 32, pp. 9355–9363, Dec. 2017.

[37] H. Chaoui and H. Gualous, “Online lifetime estimation of supercapacitors,” *IEEE Trans. Power Electron.*, vol. 9, no. 32, pp. 7199–7206, Sep. 2017.

[38] M. de Mathelin and R. Lozano, “Robust adaptive identification of slowly time-varying parameters with bounded disturbances,” *Automatica*, vol. 35, no. 7, pp. 1291–1305, Jul. 1999.

[39] C. Montella, “The kalman filter and related algorithms: A literature review,” 2011.

[40] A. Husar, S. Strahl, and J. Riera, “Experimental characterization methodology for the identification of voltage losses of PEMFC: Applied to an open cathode stack,” *Int. J. Hydrogen Energy*, vol. 37, no. 8, pp. 7309–7315, Apr. 2012.

[41] J. Wu, X. Yuan, H. Wang, M. Blanco, J. Martin, and J. Zhang, “Diagnostic tools in PEM fuel cell research: Part I electrochemical techniques,” *Int. J. Hydrogen Energy*, vol. 33, no. 6, pp. 1735–1746, Mar. 2008.

[42] K. R. Cooper and M. Smith, “Electrical test methods for on-line fuel cell ohmic resistance measurement,” *J. Power Sour.*, vol. 160, no. 2, pp. 1088–1095, Oct. 2006.

[43] T. Mennola, M. Mikkola, M. Noponen, T. Hottinen, and P. Lund, “Measurement of ohmic voltage losses in individual cells of a PEMFC stack,” *J. Power Sour.*, vol. 112, no. 1, pp. 261–272, Jul. 2002.

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