Overview and Benchmark Analysis of Fuel Cell Parameters Estimation for Energy Management Purposes

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ABSTRACT

Proton exchange membrane fuel cells (PEMFCs) have become the center of attention for energy conversion in many areas such as automotive industry, where they confront a high dynamic behavior resulting in their characteristics variation. In order to ensure appropriate modeling of PEMFCs, accurate parameters estimation is in demand. However, parameter estimation of PEMFC models is highly challenging due to their multivariate, nonlinear, and complex essence. This paper comprehensively reviews PEMFC models parameters estimation methods with a specific view to online identification algorithms, which are considered as the basis of global energy management strategy design, to estimate the linear and nonlinear parameters of a PEMFC model in real time. In this respect, different PEMFC models with different categories and purposes are discussed first. Subsequently, a thorough investigation of PEMFC parameter estimation methods in the literature is conducted in terms of applicability. Three potential algorithms for online applications, Recursive Least Square (RLS), Kalman filter, and extended Kalman filter (EKF), which has escaped the attention in previous works, have been then utilized to identify the parameters of two well-known semi-empirical models in the literature, Squadrito et. al and Amphlett et. al. Ultimately, the achieved results and future challenges are discussed.

Keywords: Online identification, Extended Kalman filter, Semi-empirical modeling, Parameter estimation, Proton exchange membrane fuel cell

1. Introduction

The harmful discharges from the conventional vehicles, running on fossil fuels, play a significant part in the growth of CO_2 emissions. Therefore, the requisite energy of future vehicles should be supplied by cleaner sources [1, 2]. Among the various technical solutions, i.e. electric vehicles, hybrid electric vehicles etc., a fuel cell vehicle (FCV) is one of the most promising due to no local emissions, high driving range, and very short refuelling duration [3]. FCVs mainly utilize proton exchange membrane fuel cells (PEMFCs) as the prime power source because of their low temperature and pressure operating range as well as their high power density in comparison to other fuel cell types such as carbon dioxide and solid membrane [4]. PEMFCs show satisfactory durability in slow dynamic applications. The intrinsic slow dynamic characteristic of a PEMFC and its incapability in storing extra energy make the utilization of a secondary power source, such as battery, necessary to satisfy the fast dynamic load in some applications like vehicles. Hybridization of the sources creates a multi-source system in which an energy management strategy (EMS) is in demand for splitting the power [5]. The majority of the existed EMSs in the literature, namely rule-based, and optimization-based, are premised on PEMFC models, especially static models [6-8]. In this respect, PEMFC modeling is of vital importance and a wise selection of the model should be made with regard to the particular goals of the project. However, some factors such as dependency of PEMFC energetic performance on its operating conditions (temperature, pressure, and current), impact of aging and degradation phenomena on its performance, and so forth have made the design of a comprehensive PEMFC model immensely complicated. In this regard, utilization of identification algorithms has been suggested to deal with the problems caused by operating conditions change, degradation and aging by adjusting online the models parameters [9]. It should be noted that the careful selection of identification method is as important as the choice of model since it can complement the model and even compensate for its lack of details and considerations.

This paper provides an extensive review of identification methods for estimating PEMFC models parameters and introduces the suitable ones for EMS purposes. Moreover, an experimental benchmark study that compares three promising online identification techniques by using two renowned PEMFC models is conducted. It should be noted that in this work, online identification refers to the processing of the data in real time, i.e. the data is evaluated immediately after each sample. The remainder of this article is structured as follows:

A general description of the proposed article methodology is presented in section 2. An overview of the existed PEMFC models in the literature along with a broad review of identification algorithms, utilized for PEMFC parameter estimation, is provided in section 3. Section 4 deals with a benchmark study on online identification techniques. Finally, the conclusion is given in section 5.

2. Overall process

In a multi-source system, the operating points of the components can be determined by the EMS in a way to maximize the output power, system efficiency, lifetime, and autonomy. However, determining the operating point in a PEMFC, which is a multiphysics system and its energetic performances are operating conditions dependent, is very difficult and the desired operating point constantly moves through the operating space. Regarding the FCVs, it is very interesting to keep PEMFC running at its best power. Nevertheless, the power versus current curve of the PEMFC is moving with temperature and aging. Moreover, comprehensive modeling of a PEMFC, including the effect of degradation and operation points drift, is very difficult, time-consuming and still a study limitation.

Maximum power or efficiency point tracking (MPPT) could be a good solution for this problem if they were not limited to a single specific objective. Perturbation and observation (P&O) and incremental conductance are MPPT algorithms that vary the current to get the maximum power point from the power curve; this process is known as hill climbing. Those variations increase the hydrogen consumption. These algorithms are sensitive to rapid changes, and they might be trapped in a local maximum [10, 11]. Moreover, the implementation of such techniques in PEMFC systems is highly challenging due to different electrochemical, fluidic, and thermal time constants that vary from milliseconds to minutes.

In order to address these issues, the employment of a global energy management, as shown in Fig. 1, is vital to reach a good compromise between energetic efficiency and durability under various operating conditions. The whole process is performed online during the operation of the PEMFC. The global energy management strategy is composed of three steps, namely parameter identification, information extraction, and power split strategy. The main idea is to perform a real time model identification to find the best operating points through an information extraction. Subsequently, the power split strategy can use the provided data from the updated PEMFC model to optimally distribute the power flow. As shown in Fig. 1, the information extraction step, which is maximum power (P_{max}) in this work, is one example out of several possibilities, such as maximum efficiency point (η_{max}), minimum voltage (V_{min}), maximum current (I_{max}), and so forth. This step provides the power split strategy with essential information based on which it can decide how to share the power among the components. It should be noted that this paper mainly takes care of the choice of identification method and PEMFC model, which are the core of the presented global energy management. The parameter estimation of PEMFC models is really challenging due to their complex behavior. Next section provides a broad review of PEMFC modeling and identification techniques. The future works can extend the information extraction step and use such basis to design online power split strategies.

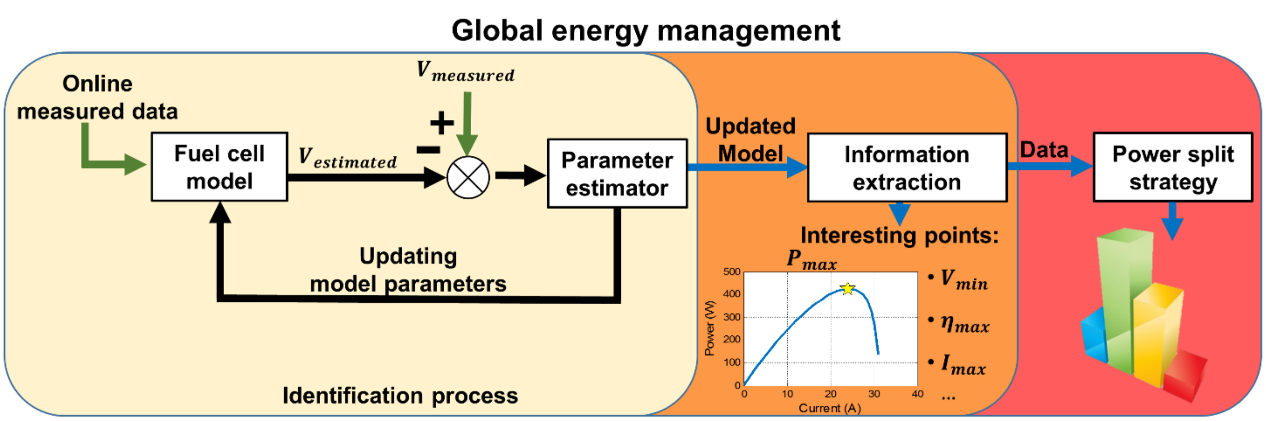

Fig. 1. Global EMS representation

3. Review

3.1. Modeling

Modeling has a significant part to play in the technological evolution of PEMFCs. Several applications, such as automotive industry [12-14], portable applications [15], distributed generation [15], military [16] , etc., and objectives, such as multiphysics modeling, diagnosis, monitoring, energy management, control, etc., can be counted for modeling of PEMFCs. The existed PEMFC models in the literature can be fallen into three categories of white box, black box, and grey box [17-23], as shown in Fig. 2. White box models, known as mechanistic or theoretical models, consist of algebraic and differential equations which are based on thermodynamics, electrochemistry, and fluid mechanics [24-28].

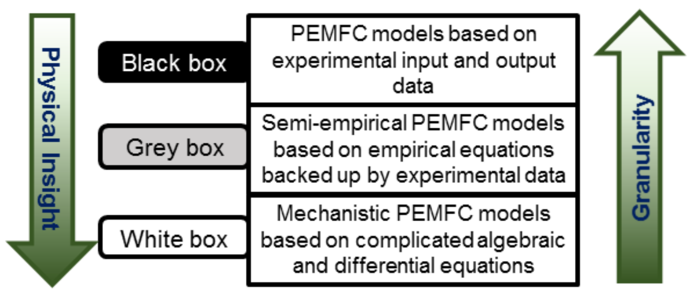

Fig. 2. PEMFC models categories

They are designed to investigate various phenomena, such as polarization influences, catalyst employment, water management, and so forth, and have different spatial dimensions. As opposed to the white box models, black box models are obtained by means of observations and do not go through the details of physical relationships inside the PEMFC [29-35]. Since the computational effort of black box models is very low, they are very interesting for online applications like vehicles. However, the uncertainties of such models increase when confronting new operating conditions. Artificial neural networks, fuzzy logic, and their combination are perceived as prevalent approaches in developing PEMFC black box models [36]. Grey box models, known as semi-empirical models, offer an acceptable compromise between complexity and simplicity [37-

43]. These models are premised upon the physical relationships which are supported by experimental data and demonstrate the fundamental electrochemical aspects of the PEMFCs (polarization curve). One of the interesting practical applications of grey box PEMFC models is in the area of energy management design. The physical insight provides significant information about polarization curve effects such as cell reversible voltage, activation drop, ohmic loss, and concertation overvoltage, which are highly valuable to investigate the relevance of the outcomes. Table 1 gives a brief summary of the discussed PEMFC models.

Table 1
Comparison of PEMFC models

Features	White box (Mechanistic)	Grey box (Semi-empirical)	Black box
Experimental data dependency	Low	Average	High
Computational time effort	High	Average	Low
Precision	High	Satisfactory	Satisfactory
Granularity	High	Average	Low
Physical insight	High	Satisfactory	Very low
Application area	Cell level understanding, Emulators design, Diagnosis purposes	Energy management, Control, Diagnosis studies	Energy management, Control, Diagnosis studies
Online applicability	Not applicable	OK	OK

In the light of the previously discussed models, grey and black box models seem to be the fittest types for control and energy management purposes. Next section provides a thorough review of the utilized identification methods for parameters estimation of PEMFC models, which are based on grey and black box models.

3.2. Identification

System identification utilizes a black box or a grey box model to estimate a dynamic system features. Appropriate parameter identification of PEMFC models can strikingly increase the accuracy and compensate for the lack of details. However, the parameter estimation of PEMFC models is really demanding owing to their complicated features. A number of approaches have been reported in the literature to optimize and identify the parameters of a PEMFC model, namely metaheuristic based methods (GA, PSO…) [37-66], Electrochemical impedance spectroscopy

(EIS) based methods (Frequency, Nyquist…) [67-72], black box based methods (ANN, SVM…) [73-89], Adaptive filter based methods (RLS, SRUKF…) [90-93], and some other methods such as current change, parametric table etc. [94-100], which fit to none of the categories. Table 2 summarizes the advantages and disadvantages of these methods. It should be noted that all of these methods have different convergence time, i.e. the required time for the algorithm to reach an acceptable value of the identified parameter. This convergence time mainly depends on their implementation and complexity. However, some of them such as recursive and black box based methods have been reported to be much faster than the others.

Table 2
Identification methods characteristics

Approach	Advantage	Disadvantage
Metaheuristic based	• Extracting an acceptable model regardless of the number of parameters • Revealing the defects of the device	• High computational burden • No online implementation reported
EIS based	▪ Suitable for different parts modeling and diagnosis objectives	▪ Expensive and time-consuming ▪ Parameters are solely valid in the vicinity of the tested points ▪ Ambiguous relation between the estimated and real parameter in fractional models
Black box based	• Accurate output • Online applicability	• No physical interpretation • Demanding training process • Unreliable in new conditions
Recursive filter based	▪ Matched with semi-empirical models ▪ Providing good internal insight ▪ Appropriate for online applications	▪ Choice of filter is very sensitive ▪ Challenging Initialization and customization

3.2.1. Metaheuristic-based optimization techniques:

Numerous manuscripts have proposed metaheuristic-based optimization techniques to identify the linear and nonlinear parameters of an electrochemical PEMFC model without trapping in local optima. Regarding the metaheuristic-based methods, the majority of them [44-66] are amazingly based upon the proposed model by Amphlett et al. [41, 43], which is a semi-empirical model and is able to imitate the behavior of the PEMFC to a satisfactory extent. All of these works revolve around the idea of introducing a new optimization algorithm to estimate the physical parameters of the static semi-empirical PEMFC model. Table 3 introduces the range of the identified parameters in the mentioned articles.

Table 3
Boundaries of the parameters

Parameters	ξ_1	$\xi_2 \times 10^{-3}$	$\xi_3 \times 10^{-5}$	$\xi_4 \times 10^{-4}$	λ	$R_C \times 10^{-4}$ (Ω)	b (V)	J_{max} (Acm^{-2})
Maximum	-0.80	5	9.8	-0.954	24	8	0.5	1.5
Minimum	-1.2	1	3.6	-2.6	10	1	0.0135	0.5

It should be noted that the utilized model in these articles describes the polarization curve and is based on the thermodynamic potential of the cell and three voltage drops (activation, ohmic, and concentration). In this respect, the parameters $\xi_n (n = 1 \ldots 4)$ are related to the activation drop, λ and R_C are related to the ohmic drop, and b, and J_{max} are related to the concentration drop. Table 4 provides data on the type of proposed algorithms and obtained values for the parameters in the mentioned articles.

Table 4
Metaheuristic-based algorithms utilized for parameters estimation of the PEMFC model in [41, 43]

Reference	Method	FC power (W)	Parameters							
			ξ_1	$\xi_2 \times 10^{-3}$	$\xi_3 \times 10^{-5}$	$\xi_4 \times 10^{-4}$	λ	$R_C \times 10^{-4}$	b	J_{max}
[44]	ABSO	250	-0.9519	3.0850	7.8	−1.880	23	1	0.02789	0.84478
[45]	AC-POA	250	-0.8997	2.5468	5.4432	-1.3650	14.206	0.8261	0.01	-
[46]	AIS	250	-0.9469	3.0271	7.4944	-1.8845	18.996	6.429	0.02896	0.85279
[47]	ARNA-GA	250	-0.8806	2.9451	8.4438	-1.2883	13.4860	1.0068	0.03167	-
[48]	BIPOA	250	-0.8016	2.6673	8.1288	-1.2713	13.5158	0.8	0.0324	-
[49]	DE	250	-0.9878	2.6167	3.6	-1.5694	24	1	0.0355	-
[50]	HABC	250	-0.8540	2.8498	8.3371	-1.2940	14.2873	1	0.0340	-
[51]	HADE	250	-0.8532	2.8100	8.0920	-1.2870	14.0448	1	0.03353	-
[52]	MPSO	250	-0.944	3.0037	7.4	-1.945	23	1	0.0272	0.85228
[53]	Simple GA	250	-0.8020	2.9521	6	-1.5812	13	2.47	0.0261	-
[54]	STLBO	250	-0.9520	2.9400	7.8000	-1.8800	23	1	0.0328	-
[55]	TLBO-DE	250	-0.8532	2.6432	7.9960	-1.4050	10.0068	1.0498	0.0299	1.15843
[59]	TRADE	SR-12 500	-0.9373	3.465	9.308	-0.954	23.9999	1	0.2375	0.50045
[61]	ADE	BCS 500	-1.0291	3.6	8.2495	-2.600	18.6921	7.9	0.0287	1495.40
		SR-12 500	-0.8955	2.46	3.9074	-0.954	24	1.1	0.2113	753.05
[62]	GWO	BCS 500	-1.018	2.3151	5.24	-1.2815	18.8547	7.5036	0.0136	-
		SR-12 500	-0.9664	2.2833	3.40	-0.954	15.7969	6.6853	0.1804	-
[63]	IGHS	BCS 500	-1.0098	3.3	6.93	-2.59	21.25	7.6	0.0489	1.41915
		SR-12 500	-1.0368	2.9	4.07	-0.954	22.53	2.4	0.2029	0.74453
[65]	Rank	BCS 500	-1.0269	3.2749	6.40	-2.60	22.0226	8	0.0138	1.49985
		SR-12 500	-0.9987	3.2155	7.09	-0.954	23.9999	1	0.1861	0.71224

It should be noted that in [45] ten parameters of a new semi-empirical model, which is based on [43] with an additional cathode inlet pressure actor, are estimated by an AC-POA, but only its common parameters with other manuscripts is reported in Table 4. The other manuscripts, which are based on optimization algorithms, have worked on the models with more dynamic properties [67-73]. A summary of the methods employed in these papers is given in Table 5.

Table 5
Features of the estimation approaches

Reference	Method	Parameters and considered areas	Real time applicability
[67]	Hybrid stochastic strategy (PSO+DE)	12 parameters. Activation, Ohmic, Concentration	No
[68]	PSO	5 parameters. Activation, Ohmic	No
[69]	Evolution strategy	22 parameters. Activation, Ohmic, Concentration, Thermal model	No
[70]	Quantum-based optimization	3 parameters. Activation, Ohmic, Concentration	Yes
[71]	Hybrid optimization (PSO+ Big Bang-Big Crunch)	7 parameters. Activation, Ohmic, Concentration	No
[72]	PSO and DE	5 parameters. Activation, Ohmic, Concentration	No
[73]	PSO	8 parameters. Activation, Ohmic, Concentration	No

3.2.2. Electrochemical impedance spectroscopy:

Another category of methods, applied in the parameter estimation of PEMFC models, is the works based on EIS technique. EIS is a frequency-based approach, which has been well established in PEMFC filed in recent years. The application of this approach covers a wide range of studies such as temperature and humidity effects, sub-zero condition, catalyst layer, and so on [74]. Taleb et al. have employed EIS method to validate a PEMFC fractional order impedance model, which imparts a good level of physical parameters comprehension. They have used the EIS data for estimating the parameters of the model by means of a frequency identification method based on nonlinear optimization. Subsequently, they have used Taylor series to obtain a third-order transfer function and applied least square and recursive least square methods for parameter estimation of the fractional order model. Their method is applicable in online application although the relationship between the physical parameters and the online identified parameters remains ambiguous [75]. In [76], a comparative study is conducted for three cases of Dicks-Larminie dynamic model, EIS model, and equivalent circuit model. The parameter estimation is performed with the help of least square and recursive least square methods for the load resistances of the electrical equivalent circuit model and the impedance of Dicks-Larminie and EIS models. It is concluded that both EIS and electrical equivalent circuit model offer better precision than the Dicks-Larminie dynamic model. However, they cannot be applied in vehicular applications due to their level of complexities and computational time. In [77], the EIS technique is utilized to obtain the impedance model and frequency identification methods are used to estimate the fractional order transfer function impedance model's parameters. In this regard, least square methods, as a time domain approach, estimate the initial values for coefficients of the derivation operators and a nonlinear optimization, as a frequency domain approach, finalizes the values. In [78], the Nyquist and Bode diagrams computed from EIS are used to estimate the PEMFC catalyst layer parameters. In [79], an equivalent circuit model of PEMFC, which is based on non-integer derivatives for diffusion modeling, is introduced and its parameters are extracted by means of EIS technique.

3.2.3. Black box based identification:

The next group of works are premised upon the black box based identification of PEMFC models. In this regard, some manuscripts are based on artificial neural networks (ANNs) employment [80-84]. linear regression technique, which uses gradient descent algorithms for updating the parameters, is compared with an ANN approach, which uses Levenberge-Marquardt algorithm for training, to model a 250-W PEMFC for an electric bicycle application in [80], and is concluded that ANN model benefits from more accuracy as well as convenience in modeling. In [81], two neural structures of nonlinear auto regressive with exogenous input (NARX) and nonlinear output error (NOE) are utilized to develop a PEMFC stack voltage model and NARX is recommended for real time applications while NOE is suggested for off-line applications. In [82], radial basis function neural network is utilized to develop a PEMFC metamodel for the data obtained from design of experiment approach. In [83], Gaussian radial basis function variable ANN is employed to identify the PEMFC model parameters online. In [84], the capabilities of PSO, for global search, and Levenberg–Marquardt algorithm neural network, for fast convergence around the global optimum, are combined to obtain a voltage and thermal model for the PEMFC. In [85, 86], nonlinear autoregressive moving average model with exogenous inputs (NARMAX) is employed to obtain a temperature model and a voltage model of PEMFC respectively. In [85], orthogonal least mean square is used to obtain the parameters of NARMAX temperature model first, then the selection is modified by GA. In [86], time domain and frequency domain NARMAX model of PEMFC are compared and the time domain is preferred. In [87, 88], support vector machine (SVM) principle is utilized. Mathematical modeling of a laboratory PEMFC air supply system is dealt with by a novel Wiener model identification based on SVM in [87]. In [88], SVM is employed to model a PEMFC for real time and monitoring applications. Fuzzy logic control (FLC) principle is utilized in [89, 90], in which an adaptive neuro-fuzzy inference system (ANFIS) is proposed for voltage modeling of PEMFC in high temperature condition and an adaptive FLC is used for adding the control of gas flow to a PEMFC model respectively. In [91], a black box approach is compared with a white box one and it is concluded that the black box model has higher accuracy. In [92], the Volterra and Wiener model methods are utilized to obtain a linear PEMFC model for vehicular applications. In [93], the nonlinear black box time series model of [94] and the proposed PEMFC control approach of [95] are combined to follow the optimum operating points of the fuel cell.

3.2.4. Recursive filter based methods:

Next category of the articles belongs to the application of recursive filters for estimating the parameters of a PEMFC semi-empirical model. This category, which had escaped the attentions for many years, seems to be very interesting for energy management purposes. As previously mentioned, PEMFC is a very complicated, nonlinear, and multiphysic device, which is not easy to be comprehensively modeled. Furthermore, the performance of the PEMFC is influenced on the one hand by its operating conditions alteration and on the other hand by aging and degradation. All of the mentioned complexity, dependency, and phenomena widen the gap between the performance of a PEMFC model and the real device. Proper tuning of a PEMFC model parameters, by means of parameter identification techniques, can narrow the existed gap in the modeling to a great extent and integrate the influence of different factors into the model. Ettihir et al. have proposed the employment of adaptive recursive least square (RLS) in [96-98], and square root unscented Kalman filter (SRUKF) in [99], to estimate the parameters of a semi-empirical model, proposed by Squadrito et al. [42]. They have concluded that the classical power split approaches may result in mismanagement due to the fact that they are not capable of tracing the performances alteration arising from aging and operating condition variations. Their proposed adaptive EMS can meet the power demand while sustaining the battery state of charge. Moreover, it is able to track real behavior of the PEMFC and to request a relevant power. It should be noted that the selected model in these works is solely a function of PEMFC operating current and they have proposed the extension of their work by adding more operating parameters such as temperature and pressure.

3.2.5. Other methods:

There are some other methods that have been utilized in the PEMFC model identification. In [100], a parametric table, obtained from experimental test, is utilized to optimize the operating conditions of a one-dimensional analytical model. Although the proposed method of this work has shown interesting results, the process of obtaining such data to form a map seems to be highly time-consuming. In [101, 102], two online methods for PEMFC model identification are proposed based on data-driven schemes to be used in model predictive control and adaptive control respectively. However, both of the suggested methods require data storage and high memory capacity for identifying the parameters online. In [103], least square methods are employed to fit the parameters of three models, Amphlett [43], Larminie-Dicks [4] and Chamberlin-Kim [4], and the obtained models have been compared regarding their levels of accuracy. In [104], current change technique is proposed to estimate the parameters of an equivalent circuit PEMFC model, in which waveform measurement analysis of current change tests is employed for parameter extraction. In [105], static and dynamic modeling of PEMFC based on data measurement is introduced, in which a simple Matlab curve fitting method is utilized for the identification of static model parameters and Pspice Optimizer is used for the dynamic one. In [20], a dynamic model of PEMFC is developed in the gPROMS modeling environment and the parameters are extracted based on experimental data. In [106], nonlinear least squares based on Lagrangian approach is developed to estimate the parameters of a one-dimensional PEMFC model.

3.3. Synopsis of the modeling and identification review

In the light of the discussed sections, it can be inferred that the recursive filter based methods appear to be very fit for online applications and energy management purposes. This is partly due to the fact that the semi-empirical PEMFC models, which increase the internal comprehension about the device, are used with these approaches and partly due to the fact that they are suitable for applications in which the desired parameters change over time. However, special attention should be paid to the choice of filter and its design, in terms of initialization and customization, to achieve satisfactory outcomes. It should be noted that the thing which makes the recursive based methods more preferable than black box based methods in this work is that the former easily enables one to investigate the relevance of the results (physical meaning) and it also makes the power and efficiency curve plots really convenient (polarization curve).

4. Benchmark Study

Unlike the aforementioned techniques, this paper presents a comparative study of online recursive methods with the purpose of facilitating the energy management design. To do so, extended Kalman filter (EKF) is suggested for the process of parameter identification. To the best of our knowledge, this is the first attempt to identify the linear and nonlinear parameters of a PEMFC semi-empirical model online. As discussed in the preceding section, the recursive filter based methods are highly appropriate for online applications and global energy management designs. In this respect, three potential recursive filters (RLS, Kalman filter, and EKF) are utilized to identify the parameters of two famous semi-empirical models, in the literature, in this section. Apart from the fact that the selected PEMFC models are well-known in the literature, they provide a good opportunity to make a comparison between a multi-input model (Amphlett et. al.) and a single input model (Squadrito et. al.). Fig. 3 represents the experimental test bench utilized for testing the PEMFC models as well as identification algorithms in this work. Regarding the test bench, it should be noted that a 500-W air breathing Horizon PEMFC, described in Table 6, is connected to a National Instrument CompactRIO through its controller. A programmable DC electronic load is used to ask some load profiles from the PEMFC. According to the manufacturer, the difference between the atmospheric pressure in the cathode side and the pressure of the PEMFC in the anode side should be adjusted to about 50.6 kPa. The pressure in the anode side is set to 55.7 kPa. The measured data (temperature, voltage, current) from the real PEMFC is transferred to the PC, by means of the CompactRIO, to be used in the selected model for identification process. Concerning the energy management, it is worth reminding that this paper only deals with the implementation of the models and algorithms to pave the way towards designing an EMS. As an example of information extraction, the real maximum power of the PEMFC is obtained at each moment, in this work. Therefore, a power split strategy can be easily added to this work in future to benefit from a global energy management.

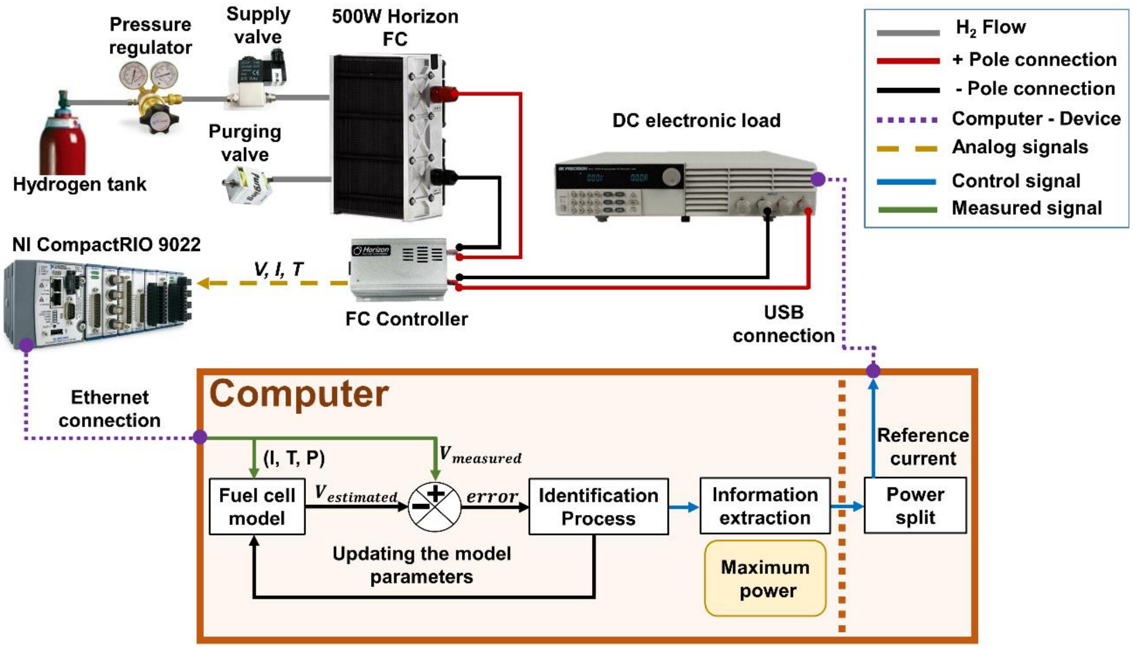

Fig. 3. Test bench and intended methodology representation

Table 6
PEMFC characteristics

PEMFC Technical specification	
Type of FC	PEM
Number of cells	36
Active area	52 cm^2
Rated Power	500 W
Rated performance	22 V @ 23.5A
Max Current	42 A
Hydrogen pressure	50-60 kPa (0.5-0.6 Bar)
Rated H_2 consumption	7 l/min
Ambient temperature	5 to 30 °C
Max stack temperature	65 °C
Cooling	Air (integrated cooling fan)

4.1. PEMFC models introduction

The general formulation of the electrochemical PEMFC model proposed by Amphlett et. al [41, 43], which is for a number of cells connected in series, is as follows. This model takes several operating conditions into account, as it is seen in (1-5) and opens up a good opportunity to compare the effect of linear and nonlinear parameter identification due to its structure in the concentration loss calculation.

$$V_{FC} = N(E_{Nernst} + V_{act} + V_{ohmic} + V_{con}) \tag{1}$$

$$E_{Nernst} = 1.229 - 0.85 \times 10^{-3}(T - 298.15) + 4.3085 \times 10^{-5}T[\ln(P_{H2}) + 0.5\ln(P_{O2})] \tag{2}$$

$$\begin{cases} V_{act} = \xi_1 + \xi_2 T + \xi_3 T ln(CO_2) + \xi_4 T ln(i) \\ CO_2 = \frac{P_{O2}}{5.08\times10^6 \exp(-498/T)} \end{cases} \tag{3}$$

$$V_{ohmic} = -iR_{internal} = -i(\zeta_1 + \zeta_2 T + \zeta_3 i) \tag{4}$$

$$V_{con} = Bln(1 - \frac{J}{J_{max}}) \tag{5}$$

Where V_{FC} is the output voltage (V), N is the number of cells, E_{Nernst} is the reversible cell potential (V), V_{act} is the activation loss (V), V_{ohmic} is the ohmic loss (V), V_{con} is the concentration loss (V), T is the stack temperature (K), P_{H2} is the hydrogen partial pressure in anode side (N m^{-2}), P_{O2} is the oxygen partial pressure in cathode side (N m^{-2}), $\xi_n(n = 1 \dots 4)$ are the semi-empirical coefficients based on fluid mechanics, thermodynamics, and electrochemistry, CO_2 is the oxygen concentration (mol cm^{-3}), i is the PEMFC operating current (A), $R_{internal}$ is the internal resistor (Ω), $\zeta_n(n = 1 \dots 3)$ are the parametric coefficients, B is a parametric coefficient (V), J is the actual current density (A cm^{-2}), and J_{max} is the maximum current density (A cm^{-2}).

It should be noted that the utilized ohmic loss calculation is based on the formula introduced in [43] rather than [41], because it is a more general formula, which can be used for different commercial fuel cells like Horizon, and more importantly it does not need any specific data like thickness and active area of membrane, which are only available for a limited number of fuel cells. The electrochemical PEMFC model suggested by Squadrito et. al [42] is presented below.

$$V_{FC} = N[V_O - b\ log(J) - R_{internal} J + \alpha J^{\sigma} \ln(1 - \beta J)] \tag{6}$$

Where N is the number of cells, V_{FC} is output voltage (V), V_O is the reversible cell potential (V), b is the Tafel slope, J is actual current density (A cm^{-2}), $R_{internal}$ is cell resistance (Ω), α is a semi-empirical parameter related to the diffusion mechanism, σ (between 1 and 4) is a dimensionless number which is related to the water flooding phenomena, and β is the inverse of the limiting current density (cm^2 A^{-1}). Table 7 presents the parameters to be identified by the recursive algorithms. Indeed, the increased number of parameters bring more accuracy about at the cost of increasing the computational time. However, the utilized methods in this paper have no problem in this regard due to the fact that the identifiable parameters are linear in structure, except in one case which is dealt with EKF. It should be noted that the parameter J_{max}, which is not linear in the structure and assumed to be constant in most of the previous articles, is estimated online by EKF to draw an analogy between the linear and nonlinear parameters estimation methods. This parameter changes over time due to the influence of degradation and is highly sensitive regarding voltage and polarization curve estimation, as reported in [107].

Table 7
Targeted parameters for estimation

Algorithm	PEMFC model	Parameters vector
RLS and Kalman filter	Amphlett et. al	$[\xi_1, \xi_2, \xi_3, \xi_4, \zeta_1, \zeta_2, \zeta_3, B]$
RLS and Kalman filter	Squadrito et. al	$[V_O, b, R_{internal}, \alpha]$
EKF	Amphlett et. al	$[\xi_1, \xi_2, \xi_3, \xi_4, \zeta_1, \zeta_2, \zeta_3, B, J_{max}]$

4.1.1. Resistor measurement

So as to check the appropriateness of the parameter identification process and relevance of the obtained values with the physical meaning some clues about the real values of the device are required. Regarding the Amphlett et. al model, the range of all the parameters is available according to the reported values in Table 3. However, as explained in the previous section, the employed resistor formulation in this paper is different with the demonstrated resistor parameters of Table 3 due to the fact that specific information about membrane type of the 500-W commercial air-breathing Horizon fuel cell is not accessible. Thus, in this paper, the current interrupt method, which is a well-known electrochemical technique [108-111], is used to measure the evolution of resistor with respect to the temperature and current. This measurement clarifies the range of the resistor for the whole stack and is a helpful tool to check the accuracy of the achieved results by both PEMFC models. The effectiveness of utilizing current interrupt method for measuring the ohmic resistor has been already proved in [111]. The principle behind the current interrupt method is that ohmic losses fade almost immediately after current interruption and activation losses decrease to the open circuit voltage at a strikingly slower pace. Thus, rapid acquisition of the measured voltage is essential for splitting the ohmic from activation loss. The advantages of current interrupt method to other electrochemical techniques is that data analysis is highly straightforward. However, one of the difficulty of this method is the determination of the exact point in which the voltage jumps and a fast oscilloscope is in demand to solve this issue. In this paper, the procedure for performing the current interrupt test is strictly according to [111]. Table 8 presents the various stack temperature and currents while conducting the test. It should be noted that the stack was given enough time to achieve a stable temperature at each current level before conducting the current interrupt measurement and all the measurements are performed for the forced convection condition.

Table 8
Current levels and PEMFC stack temperature during ohmic measurement

Current (A)	Temperature (K)
3	297.55
6	297.95
9	299.55
12	300.45
15	301.95
18	304.15
21	306.35
24	309.95
26	312.15

Fig. 4 indicates the result of resistor measurement. Fig. 4a shows the evolution of the PEMFC resistor with respect to the increase of current and Fig. 4b presents the temperature related evolution. These results are obtained from the conducted current interrupt test. The main purpose of conducting current interrupt test is to realize the variation range in the value of resistor for the employed 500-W PEMFC and utilize this range as a tool to check the evolution of the resistor in the PEMFC model.

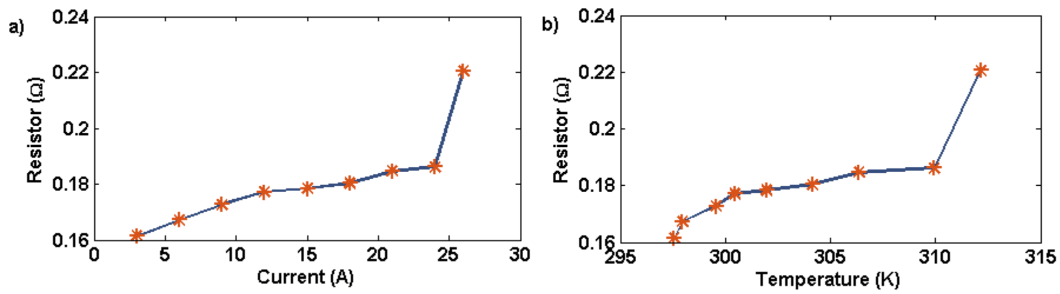

Fig. 4. Resistor alteration with respect to current (a) and temperature (b)

4.2. Recursive filters

As previously mentioned, the parameters of a PEMFC model are time-varying since the device is affected by degradation and operating conditions. The focus of this section is to introduce and compare the performance of three recursive algorithms. These algorithms are utilized for online identification of the parameters and they are independent of saving data because they benefit from recursive structures, in which new measurement data can be analyzed as they arrive. RLS and Kalman filter are utilized to estimate the parameters, which are linear in the structure, while EKF is utilized to estimate linear and nonlinear parameters.

4.2.1.Recursive least square

RLS algorithm is premised upon the concept of minimizing the error related to input signal. RLS gives excellent performance when operating in time varying conditions. The enhanced performance is achieved at the cost of increased computational cost and some stability problems. The structure of the employed RLS in this work is as follows:

$$\theta(t) = \theta(t-1) + k(t)e(t) \tag{7}$$

$$k(t) = \frac{\Gamma(\mathrm{t})^{-1}p(t-1)\phi(t)}{(1+\Gamma(\mathrm{t})^{-1}\phi^T(t)p(t-1)\phi(t))} \quad (8)$$

$$p(t) = \Gamma(\mathrm{t})^{-1}p(t-1) - \Gamma(\mathrm{t})^{-1}k(t)\phi^T(t)p(t-1) + bI \quad (9)$$

$$\begin{cases} \Gamma(t) = \Psi - \frac{1-\Psi}{\phi^T(t)p(t-1)\phi(t)}; & if\ \phi^T(t)p(t-1)\phi(t) > 0 \\ \Gamma(t) = 1; & if\ \phi^T(t)p(t-1)\phi(t) = 0 \end{cases} \quad (10)$$

$$e(t) = u(t) - \phi^T(t)\theta(t-1) \quad (11)$$

Where t denotes discrete time, $\theta(t)$ is the parameter vector, $k(t)$ is the gain vector, $e(t)$ is the error, $\Gamma(\mathrm{t})$ is the directional forgetting factor, $\phi(t)$ is the regression vector, $p(t)$ is the covariance matrix, b is a nonnegative scalar, which increases covariance matrix and prevents estimation faults due to big changes, I is the identity matrix, Ψ is the forgetting factor ($0 < \Psi < 1$), and $u(t)$ is the measured output, which is obtained from the test bench. The parameters vector of each model ($\theta(t)$) has been already shown in Table 7 and the corresponded regression vector of each model is defined as below.

$$\phi(t) = [1, T, Tln(CO_2), Tln(i), -i, -iT, -i^2, ln(1 - \frac{J}{J_{max}})] \text{ (Amphlett et. al model)} \quad (12)$$

$$\phi(t) = [1, log(J), -J, J^\sigma \ln(1 - \beta J)] \text{ (Squadrito et. al model)} \quad (13)$$

4.2.2.Kalman filter

Kalman filter is considered as an optimal estimator and it can conclude the parameters of interest from imprecise and uncertain observations. This filter estimates the current state variables firstly and then updates them when the next measurement is received. The structure of Kalman filter is as follows:

$$\begin{cases} x(t+1) = F(t+1|t)x(t) + w(t) \\ y(t) = H(t)x(t) + v(t) \end{cases} \text{ (State-space model)} \quad (14)$$

$$\hat{x}^-(t) = F(t|t-1)\hat{x}^-(t-1) \text{ (State estimate propagation)} \quad (15)$$

$$P^-(t) = F(t|t-1)P(t-1)F^T(t|t-1) + Q(t-1) \text{ (Error covariance propagation)} \quad (16)$$

$$G(t) = P^-(t)H^T(t)[H(t)P^-(t)H^T(t) + R(t)]^{-1} \text{ (Kalman gain matrix)} \quad (17)$$

$\hat{x}(t) = \hat{x}^{-}(t) + G(t)(y(t) - H(t)\hat{x}^{-}(t))$ (State estimate update) (18)

$P(t) = (I - G(t)H(t))P^{-}(t)$ (Error covariance update) (19)

Where t is the discrete time, $x(t)$ is the state vector, which is unknown and here it can be called parameters vector as well, $\hat{x}(t)$ is the estimate of the state vector, $\hat{x}^{-}(t)$ denotes priori estimate of the state vector, $F(t+1|t)$ is the transition matrix, which takes the state vector from time t to time $t+1$, $w(t)$ is the process noise, $y(t)$ is the output, $H(t)$ is the measurement matrix, $v(t)$ is the measurement noise, $P(t)$ is the error covariance matrix, $Q(t)$ is the process noise covariance matrix, $G(t)$ is the Kalman gain, $R(t)$ is the measurement noise covariance matrix, and I is the identity matrix. It should be noted that the state vector is exactly like the parameter vectors shown in Table 7, the measurement matrix is the same as (12) and (13), and the transition matrix is assumed to be an identity matrix.

4.2.3. Extended Kalman filter

The EKF is the nonlinear version of the Kalman filter which linearizes the state space model at each time instant with respect to the latest state estimate. The structure of the EKF is defined as follows:

$$\begin{cases} x(t+1) = f\big(t, x(t)\big) + w(t) \\ y(t) = h\big(t, x(t)\big) + v(t) \end{cases} \quad \text{(State-space model)} \tag{20}$$

$$F(t+1|t) = \frac{\partial f(t,x)}{\partial x}\Big|_{x=x(t)} \tag{21}$$

$$H(t) = \frac{\partial h(t,x)}{\partial x}\Big|_{x=x^{-}(t)} \tag{22}$$

$\hat{x}^{-}(t) = f(t, \hat{x}(t-1))$ (State estimate propagation) (23)

$P^{-}(t) = F(t|t-1)P(t-1)F^{T}(t|t-1) + Q(t-1)$ (Error covariance propagation) (24)

$G(t) = P^{-}(t)H^{T}(t)[H(t)P^{-}(t)H^{T}(t) + R(t)]^{-1}$ (Kalman gain matrix) (25)

$\hat{x}(t) = \hat{x}^{-}(t) + G(t)y(t) - h(t, \hat{x}^{-}(t)))$ (State estimate update) (26)

$P(t) = (I - G(t)H(t))P^{-}(t)$ (Error covariance update) (27)

Where, $f(t, x(t))$ is a nonlinear transition matrix function, and $h(t, x(t))$ is a nonlinear measurement matrix function. The state vector is already presented in Table 7 for EKF. It should be noted that in this work, the $f(t, x(t))$ is not nonlinear and it is assumed to be an identity matrix. However, $h(t, x(t))$ is a nonlinear function and its derivation is as below.

$$\begin{cases} V_{FC}(t) = N[\xi_1 + \xi_2 T + \xi_3 T ln(CO_2) + \xi_4 T ln(i) - i(\zeta_1 + \zeta_2 T + \zeta_3 i) + B ln(1 - \frac{J}{J_{max}})] \\ x(t) = [\xi_1, \xi_2, \xi_3, \xi_4, \zeta_1, \zeta_2, \zeta_3, B, J_{max}] \\ H(t) = \frac{\partial h(t,x)}{\partial x} = \left[1, T, T ln(CO_2), T ln(i), -i, -iT, -i^2, ln\left(1 - \frac{J}{J_{max}}\right), \frac{BJ}{J_{max}(J_{max} - J)}\right] \end{cases} \tag{28}$$

4.3. Results and Discussion

The obtained results from the performed comparative study is presented in this section. All the mentioned algorithms and PEMFC models, introduced in the previous section, are tested on the presented test bench in Fig. 4 to assess the performance of the proposed methodology, in terms of estimating the behaviour of the real PEMFC to be used in EMS designs. In the first stage of the analysis, RLS and Kalman filter algorithms are utilized to estimate the demonstrated parameters in Table 7 for both of the models. This analysis enables one to form a primary opinion about the accuracy of the models. The entire estimated parameters are linear at this stage. Further analyses are performed in the first stage to compare the results of RLS and Kalman filter. In the second stage of the investigation, the linear and nonlinear parameters of Amphlett et. al model are estimated and the results are compared with the linear estimation of the same model. The aim of this analysis is to investigate the influence of J_{max}, which is a nonlinear parameter, in the process of model identification. This parameter is usually considered constant in the other similar works although it changes over time owing to the effect of degradation and operating conditions.

Fig. 5a represents the employed current profile to conduct the test. This current profile varies between the minimum and maximum operating current of the utilized 500-W Horizon PEMFC. Fig. 5d shows the corresponded temperature evolution to the current profile. The current profile is applied to the PEMFC system and the output voltage of the real PEMFC is recorded. The current and temperature data as well as the regulated pressure are concurrently sent to the PEMFC model and the output voltage of the model is calculated after estimation of the parameters by the identification methods. It should be noted that the whole explained process happens online. The estimated output voltage of the two introduced PEMFC models is compared with the real PEMFC voltage in Fig. 5b in which the parameters are identified by means of RLS algorithm and this estimation seems to be satisfactory for both models. The relative error estimation of the output voltage by RLS, shown in Fig. 5c, also confirms that the both PEMFC models demonstrate acceptable voltage approximation. The same test regarding voltage estimation and relative error have been done for Kalman filter, as shown in Fig. 5e and Fig. 5f, respectively. It is observed that both of the models and algorithms are able to estimate the output voltage with almost the same accuracy and that is why further analyses regarding the performance comparison of models and algorithms are required as hereinafter provided.

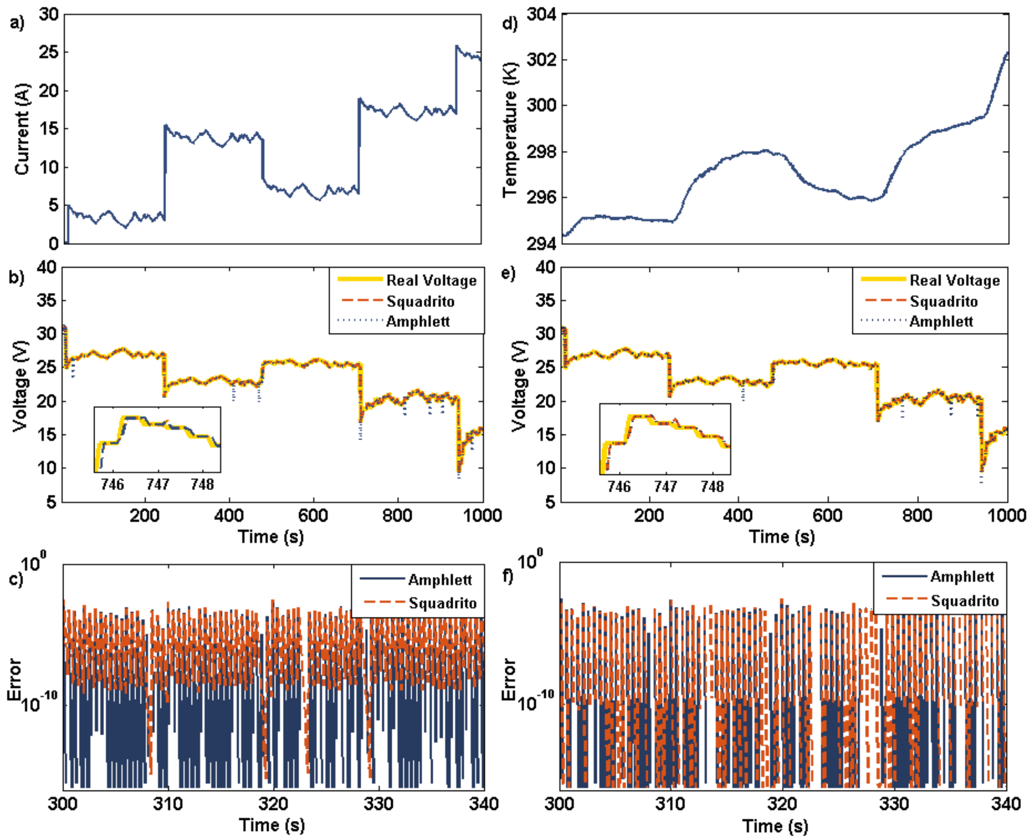

Fig. 5. Accuracy comparison of the two PEMFC models with RLS and Kalman filter algorithms, (a) the employed current profile, (b) voltage estimation by RLS, (c) RLS relative error ($|V_{measured} - V_{estimated}|/|V_{estimated}|$), (d) temperature evolution due to current profile, (e) voltage estimation by Kalman filter, (f) Kalman filter relative error.

Fig. 6 provides a comparison of the achieved polarization curves by RLS and Kalman filter for the both discussed PEMFC models. As it is observed in Fig. 6, regardless of the identification techniques, the obtained polarization curves by Squadrito et. al model are noticeably different with the reference polarization curve, which belongs to the real PEMFC. This difference infers that the model proposed by Amphlett et. al gives more accurate polarization curves and results than Squadrito et. al model. It also shows that only accurate voltage estimation does not guaranty that the model benefits from enough precision because the physical relevance of the results should be investigated through the polarization curves. Moreover, when an identification technique is utilized, it tries to minimize the voltage estimation error for one single point irrespective of how the parameters fluctuate or the system behaves. Thus, the employment of another tool like a polarization curve seems to be vital for the process of PEMFC model parameters identification. The difference in the accuracy level of the two models for polarization curve prediction can be attributable to the difference in the consideration of operating conditions in the two models and it sheds light on the positive influence of including temperature and pressure, in addition to the current, to the PEMFC model. Another worth discussing observation apropos of Fig. 6 is the performance comparison of the two employed identification algorithms. Looking more closely at the polarization curves implies that in the case of using Squadrito et. al model, which has four parameters to be estimated, RLS and Kalman filter show to a great extent similar performances. However, in the case of Amphlett et. al model, which has eight parameters to be estimated for linear estimation, the Kalman filter seems to outperform RLS to some extent. The increase in the number of parameters, the original difference in the structure of Kalman filter and RLS, and the model uncertainties can all contribute to make the distinction between the performance of the RLS and Kalman filter in this particular application. It should be noted that the R-squared value, which indicates how well the observed outcomes are replicated by the model, are reported in the caption of Fig. 6 for all the combinations to clarify the amount of error.

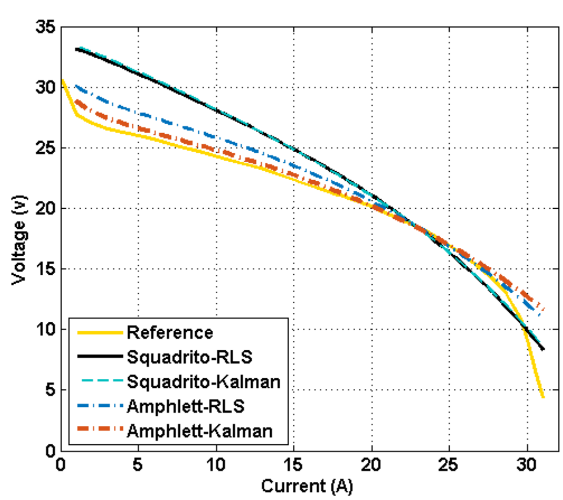

Fig. 6. Polarization curves comparison for linear cases (R^2 values: Squadrito-RLS: 0.7993, Squadrito-Kalman: 0.8440, Amphlett-RLS: 0.9001, Amphlett-Kalman: 0.9215)

Fig. 7 presents the results concerning the effectiveness investigation of estimating the nonlinear parameter, J_{max}, in addition to the other parameters for the Amphlett et. al model. In this case, since the structure in one of the targeted parameters for estimation is nonlinear, RLS and Kalman filter cannot be used for identification process and instead of them EKF is tested. Fig. 7a compares the obtained polarization curve by EKF with Kalman filter. As it can be seen in this figure, EKF is capable of predicting a better polarization curve than the Kalman filter and its polarization curve is closer to the reference. Fig. 7b shows the corresponded power curve to each polarization curve. As is clear in this figure, there is a clear relationship between the starting point of concentration region and maximum power of the PEMFC. Obtaining this maximum power can be considered as an example of the information extraction step as shown in Fig. 4 and it can easily be integrated into a power split strategy for a global energy management design of FCVs.

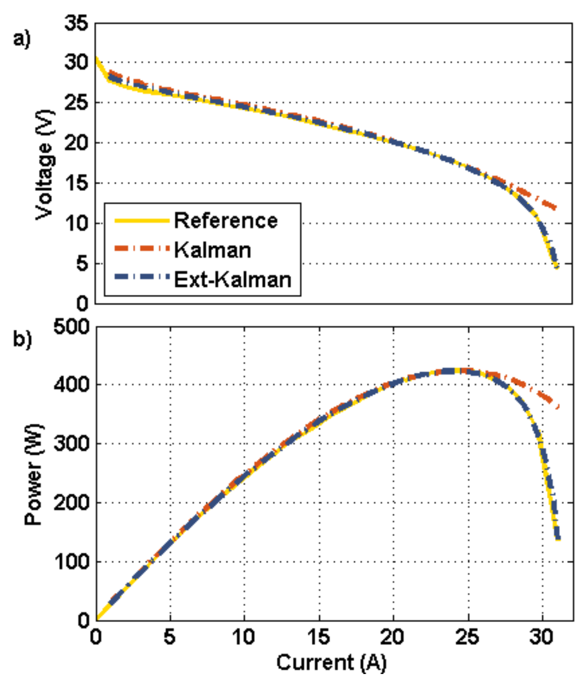

Fig. 7. Comparison of linear and nonlinear identification cases, a) Polarization curves, b) Power curves (R^2 values: Kalman: 0.9215, Extended Kalman: 0.9984)

Fig. 8 represents the resistor evolution of the Amphlett et. al model with different identification methods. As is seen in this figure, the estimated resistors by all the identification methods are almost in the same range as the conducted current interrupt test, shown in Fig. 4, although the results of EKF and Kalman filter are more accurate than RLS. It should be reminded that so far it has been observed that employment of the suggested identification techniques results in not only precise voltage estimation but also accurate polarization curve and resistor. To put the finishing touches to the validation of the relevance of the achieved results to the physical meaning of the PEMFC, the average values of the activation and concentration related parameters of the Amphlett et. al model are reported in Table 9 for all of the three identification algorithms. It should be noted that these parameters are not constant and constantly evolve over time. However, their evolution range is almost in the same range as Table 3.

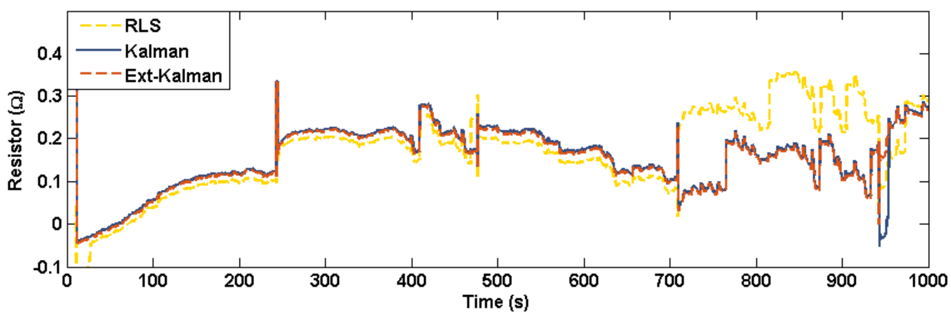

Fig. 8. Resistor evolution obtained by Amphlett et. al model

Table 9
Average values of the activation and concentration parameters

Method	ξ_1	$\xi_2 \times 10^{-3}$	$\xi_3 \times 10^{-5}$	$\xi_4 \times 10^{-4}$	B	J_{max}
RLS	-0.9950	2.1285	2.1881	-1.2379	0.4970	1.2381
Kalman	-0.9950	2.1228	2.1264	-1.1337	0.4970	1.2381
EKF	-0.9950	2.1300	2.1423	-0.9785	0.0130	1.6250

4.4. Synopsis of the benchmark study

The benchmark study is composed of a two-stage analysis. In the first stage, the linear case comes under scrutiny, in which the performance of RLS and Kalman filter is examined for each of the models. It is inferred from the first stage of analysis that Amphlett et. al model relatively outperforms Squadrito et. al model. Concerning RLS and Kalman filter, it is observed that both of them give similar performances for Squadrito et. al model. However, Kalman filter performs to some extent better than RLS for the case of Amphlett et. al model. In the second stage, the performance of EKF for identifying linear and nonlinear parameters of the superior model in the first stage is investigated and compared with the results of the superior identification technique in the first stage. It is observed that EKF is capable of improving the estimation process to a certain extent. It should be noted that in the estimation process the accuracy of voltage estimation, polarization curve prediction, and resistor evolution is considered as the means of validation.

5. Conclusion

A thorough review of necessary steps from modeling to employing identification techniques for online energy management design of FCVs is carried out in this paper. In this respect, firstly, PEMFC modeling approaches are investigated in which semi-empirical models are singled out as one the most suitable models for online purposes. Secondly, PEMFC parameter identification methods, related to the last five years, are discussed and one of the categories which is highly appropriate for real time energy management design is selected for further analysis. Finally, an in-depth comparative study of three potential parameter identification techniques, RLS, Kalman filter, and EKF, is conducted by utilizing two renowned semi-empirical PEMFC models. The obtained results of the benchmark study indicate that in case of linear analysis, the integration of Kalman filter with the suggested model by Amphlett et. al, which is a multi-input model, has a superior performance compared to other combinations. More importantly, it is observed that the proposed nonlinear identification method of this work, by means of EKF and Amphlett et. al model, results in the most precise polarization curve estimation for the utilized PEMFC.

The results of this paper suggest the following directions for future researches:

- Integrating the introduced model and identification technique into the energy management design of a FCV, since this work has paved the way in this direction.
- Integrating a thermal model in addition to the introduced voltage model of PEMFC to increase the accuracy of polarization curve prediction.

Acknowledgements

This work was supported by the Natural Sciences and Engineering Research Council of Canada (NSERC). This research was undertaken, in part, thanks to funding from the Canada Research Chairs program.

Nomenclature

ABSO	Artificial Bee Swarm Algorithm
AC-POA	Aging and Challenging P Systems Based Optimization Algorithm
ADE	Adaptive Differential Evolution
AIS	Artificial Immune System-Based
ANFIS	Adaptive neuro-fuzzy inference system
ANN	Artificial neural network
ARNA-GA	Adaptive RNA Genetic Algorithm
BIPOA	Bio-Inspired P Systems Based Optimization Algorithm
BMO	Bird Mating Optimizer
DE	Differential Evolution
EIS	Electrochemical impedance spectroscopy
EKF	Extended Kalman filter
EMS	Energy Management Strategy
FCV	Fuel Cell Vehicle
FLC	Fuzzy logic control
GA	Genetic Algorithm
GGHS	Grouping-Based Global Harmony Search
GWO	Grey Wolf Optimizer
HABC	Hybrid Artificial Bee Colony

HADE	Hybrid Adaptive Differential Evolution
IGHS	Innovative Global Harmony Search
MPPT	Maximum power point tracking
MPSO	Modified Particle Swarm Optimization
NARMAX	Nonlinear autoregressive moving average model with exogenous inputs
NARX	Nonlinear auto regressive with exogenous input
NOE	Nonlinear output error
PEMFC	Proton exchange membrane fuel cell
P&O	Perturbation and observation
PSO	Particle Swarm Optimization
Rank-MADE	Improved Multi-Strategy Adaptive Differential Evolution
RLS	Recursive least square
SOA	Seeker Optimization Algorithm
SRUKF	Square root unscented Kalman filter
STLBO	Simplified Teaching-Learning Based Optimization
SVM	Support vector machine
TLBO-DE	Teaching Learning Based Optimization-Differential Evolution
TRADE	Transferred adaptive differential evolution

Symbols

V_{FC}	Output voltage (V)

N	Number of cells
E_{Nernst}	Reversible cell potential (V)
V_{act}	Activation loss (V)
V_{ohmic}	Ohmic loss (V)
V_{con}	Concentration loss (V)
P_{max}	Maximum power (W)
η_{max}	Maximum efficiency point (%)
V_{min}	Minimum voltage (V)
I_{max}	Maximum current (A)
T	Stack temperature (K)
P_{H2}	Hydrogen partial pressure in anode side (kPa)
P_{O2}	Oxygen partial pressure in cathode side (kPa)
CO_2	Oxygen concentration (mol cm^{-3})
i	PEMFC operating current (A)
$R_{internal}$	Internal resistor (Ω)
B	Concentration loss related parametric coefficient (V)
J	Actual current density (A cm^{-2})
J_{max}	Maximum current density (A cm^{-2})
V_O	Reversible cell potential (V)

b	Tafel slope
t	Discrete time
$k(t)$	Kalman gain
$e(t)$	Error
$p(t)$	Covariance matrix
c	Nonnegative scalar
I	Identity matrix
$u(t)$	Measured output
$x(t)$	State vector
$\hat{x}(t)$	Estimate of the state vector
$\hat{x}^{-}(t)$	A priori estimate of the state vector
$F(t+1\|t)$	Transition matrix
$w(t)$	Process noise
R_C	Contact resistance to electron conduction
$y(t)$	Output
$H(t)$	Measurement matrix
$v(t)$	Measurement noise
$P(t)$	Error covariance matrix
$Q(t)$	Process noise covariance matrix,

$G(t)$ Kalman gain

$R(t)$ Measurement noise covariance matrix

$f(t, x(t))$ Nonlinear transition matrix function

$h(t, x(t))$ Nonlinear measurement matrix function

Greek symbols

$\xi_n (n = 1 \dots 4)$ Activation loss related semi-empirical coefficients

$\zeta_n (n = 1 \dots 3)$ Ohmic loss related parametric coefficients

α Semi-empirical parameter related to the diffusion mechanism

σ Dimensionless number related to the water flooding phenomena

β Inverse of the limiting current density (cm^2 A^{-1})

$\theta(t)$ Parameter vector

Γ(t) Directional forgetting factor

$\phi(t)$ Regression vector

Ψ Forgetting factor

λ Water content of the membrane

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