A Comprehensive Review on Energy Management Strategies for Electric Vehicles Considering Degradation Using Aging Models

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ABSTRACT Electrification in the transportation industry is becoming more important to face global warming and replace fossil fuels in the future. Among the available energy sources Li-ion battery and proton exchange membrane fuel cell (PEMFC) are the most promising energy sources. Therefore, employing them in fuel cell hybrid electric vehicles (FCHEVs) to combine their advantages is one of the favorable solutions. However, they still face a major challenge residing in their aging that cause the drop of system performance. On one hand, the degradation is the result of the interaction between several aging mechanisms that react differently with various operating conditions. On the other hand, a hybrid system requires an essential energy management strategy (EMS) for fuel economy and optimal power share. At the end, this EMS has an important impact on the lifetime of sources in term of reducing or favorizing the degradation. Therefore, it is important to consider the degradation in the objectives of the designed EMS. Since the degradation is usually neglected when designing an EMS, this paper tends to review the possible methods for designing a health-conscious EMS. Hence, this paper presents a summary of the main fuel cell (FC) and Li-ion battery aging mechanisms as well as the useful degradation models for state of health estimation. In addition, the existing works that consider the degradation of on-board energy sources in their approaches for increasing their durability are classified and analysed. Remaining challenges are detailed along with a discussion and outlooks about current and future trends of health-conscious EMS.

INDEX TERMS Battery and PEMFC aging, degradation modeling, energy management strategy, reliability.

I. INTRODUCTION

Global concerns over greenhouse emission, environmental awareness increase, and stringent vehicle emission regulations have encouraged the use of sustainable and greener solutions in the automobile industry. Therefore, the traction system has been electrified and many automotive manufacturers are offering hybrid electric vehicles (HEVs) and full electric vehicles with different powertrain topologies as shown in Fig. 1 [1]. This would reduce fuel consumption and CO_2 emissions [2]. Battery electric vehicles (BEVs) are proposed as a zero emission solution to replace the conventional internal combustion engine (ICE). However, they still have

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long charging time, and high price of their energy storage system. While, HEVs permit a good driving range as they are still equipped with an ICE. However, their emissions depend on their usages as they have a short electric driving range. In this context, hydrogen which can be produced through a water electrolysis process can be used as a form of energy storage to store generated renewable energy. Then it can be reused to produce electricity using fuel cell. Consequently, FCHEVs are gaining interest for their zero emissions and good driving range compared to ICE and HEVs. In addition to their high-driving range and quick refueling time (minutes) compared to battery based EVs. Fuel cell has high performance at stable loading conditions, while its sensitivity to high dynamic loading, as in automotive sector, is regarded as a weakness. Therefore, fuel cell is hybridized with battery
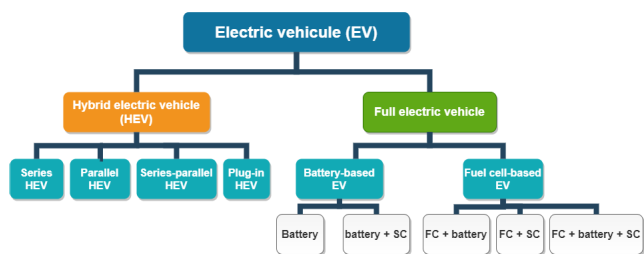
FIGURE 1. Classification of powertrain topologies for EVs.

and/or supercapacitor (SC) to overcome the weaknesses of FC [3]. The FC is regarded as the primary energy source for the requested energy while the battery and/or the supercapacitor is regarded as the secondary energy source providing the peak power demand and storing regenerated energy. Among the available types of batteries, Li-ion batteries are the most promising one that are being used in electric vehicles. Compared to other types as lead-acid, sodium, lithium and nickel, they have long cycle life, high energy and power density, and low self-discharge [4], [5]. Therefore, this paper focus on Li-ion battery based multi-source vehicles.

Relying on more than one source of energy rises up the issue of managing their power. Hence, the EMS has an important function in allocating the power share for each source along the operation of the system while meeting several operating constrain. In addition, the EMS could include many objectives to fulfill as total fuel consumption, emissions, degradation and durability...Ideally, all the objectives are met, but in reality meeting all of them could be complicated and a compromise should be achieved [6]. Despite all the advantages of Li-ion batteries and FCs they still suffer from performance degradation, accelerated by many factors, during their lifetime. This is a major challenge because the vehicle performance depends on its source's performance. Therefore, the importance of designing a health-conscious energy management that take the degradation of sources into consideration [7]. In this case, the EMS would give good performance, improve the reliability and the lifetime of the on-board sources so electric vehicles could compete in the market. Fig. 2 shows an example of a powertrain topology of a FCHEV with a fuel cell/battery system. Where the battery management strategy (BMS) and the FC controller estimate the state of health (SOH) of the battery and the FC respectively. Different estimation methods exist that can be grouped into three main categories namely experimental, model-based or machine learning method. Noting that model-based and machine learning based are the only one suitable for real time applications while the model-based method shown in Fig. 2. The interaction between the EMS control layer and both the BMS and the FC controller to communicate the SOH estimation is crucial to have a health-conscious EMS.

Several methods are applied to quantify the degradation as prognostics and health management (PHM), machine learning, modelization and identification. The PHM could assess

the health of energy sources and estimate their SOH and remaining useful life (RUL) but the post decision still need more study [8]–[10]. Machine learning based methods as support vector machine [11] and neural network (NN) [12], [13] are suitable for complex nonlinear systems, as they are model-free. They build the degradation by mapping external characteristics into battery capacity loss. However, they require huge high-quality data sets that take time for training. On the other hand, a health management that consider a trade-off between the complexity and accuracy can be based on integrating a quantitative degradation model. They are formulated based on conducted accelerated aging experiments that emulate the driving conditions of electric vehicles. However, it is still challenging because despite all the effort made there is still no accurate degradation model that combine all the aging factors. Several literature reviews focused on classifying and comparing EMSs for EVs but the degradation effect is neglected [1]–[14], [15]. In addition, others focused on battery degradation modeling [16]–[19]. However, this work focus on useful degradation model in terms of EMSs. Moreover, it differs from existing works by reviewing also FC degradation models that could be used for health-conscious EMSs in vehicular applications. The methods and works that took into consideration the sources degradation in their strategy are also discussed.

The rest of the paper is organized as follows: first in part II a brief review on batteries and fuel cells degradation is presented while based on their analysis different degradation models that could be used for the health management are reviewed in part III. In addition, different health-conscious EMSs that took the degradation into consideration are reviewed and classified in part IV. Finishing by a discussion and conclusion sections.

II. LI-ION BATTERY AND FUEL CELL DEGRADATION
A. A BRIEF REVIEW OF LI-ION BATTERY DEGRADATION
Li-ion batteries have been developed and improved for many years to reach a better performance than other types of batteries such as sodium, nickel and lead [20]. Making them suitable for different application such as EVs. Despite their advantages they still suffer from challenges such as cost, safety [21], recycling [22], and degradation. They have different degradation level under various external (environmental) and internal (electrochemical) operating conditions. In addition, monitoring their aging state is still considered challenging as the parameter indicating the degradation level, SOH, is difficult to measure during the battery operation. Therefore, the BMS estimate/calculate the battery degradation indicator, capacity and/or internal resistance, from the continuous monitoring of cell charge/discharge current, voltage, and temperature using lifetime models or estimation methods. Then they are correlated to the battery SOH. Consequently, besides charge control, thermal management, cell balancing, and battery diagnosis, the BMS provide a reasonable assessment of the battery SOH and transfer it to the EMS for designing a
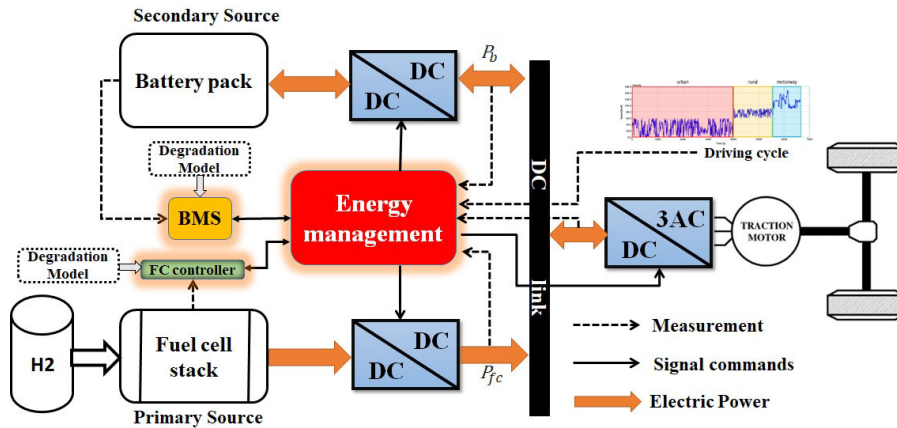
FIGURE 2. One of the multi-energy sources configurations.

health-conscious EMS with better reliability. The degradation of the battery affects its ability to store energy and meet the requested power [23]. In fact, many factors affect its degradation such as the battery temperature, current magnitude, SOC, and depth of discharge (DOD) [17]–[24], [25]. These factors cause different aging mechanisms that interact as they are not independent causing capacity fade and/or resistance growth. This interaction make it difficult to understand the aging process [24]. In addition, it should be distinguished between two origins of aging, the calendar aging and the cycle aging [26]. They refer to deterioration caused by different uses of the battery. In reality, they always occur in combination as the calendar aging always occurs no matter if the cell is in use or not, while the cycle aging is related to the usage of the cell [27].

For vehicular applications, the battery is considered unusable and should be replaced when its capacity fade reaches 20% [25]. The main components of a battery cell are the anode, cathode, electrolyte, and separator. They are interconnected and subjected to aging [28]. The aging of one component affects the other components operation leading to cell aging. Therefore, cell aging leads to the battery pack aging composed of modules combining number of cells. The aging mechanism origin is chemical or mechanical degradation[30]. The reaction between the anode and the electrolyte at the electrode/electrolyte interface produces with time a protective layer. It covers the surface of the electrode and it is considered as the main aging source of the anode electrode [31]. The protective layer known as Solid Electrolyte Interface (SEI) is naturally created mainly during the first charges [32], [33]. The reaction causes the electrolyte decomposition as well as the consumption of the Li^+. Initially, the SEI layer role consists of protecting the negative electrode from corrosion and the electrolyte from further reductions. However, the steady growth of the SEI during the life of the cell lead to the loss of an active area of the electrode due to its penetration into the pores of the electrode. It will result in internal resistance increase associated with power fade and

capacity fade [32]. The SEI may also form at the cathode side. However, it is much thinner than the one formed on the anode.

Lithium plating is also a very known degradation mechanism for Li-ion batteries that occur at low temperature [34] or at high-charging rates [35]–[30]. Slow diffusion of lithium ions into the graphite or/and in the electrolyte, or high lithium ions transport to the surface of the electrode overlay the electrode with metallic lithium plating [36]. In addition, dendrite growth of the metallic lithium can cause internal short circuit and the failure of the battery by tearing the separator and reaching the positive electrode [37]. SEI formation and growth beside the lithium plating are accountable for the loss of cyclable lithium [34]. The effect of temperature on the performance and the aging of the battery is significant specially at low temperature (subzero) and at high temperature as they accelerate the degradation rate of batteries [37]. The thermal management system controlled by the BMS is important to regulate the temperature of the battery to guarantee a good operation condition. Hence, several methods of heating such as internal and external heating for fuel cells [38] and batteries [39]–[40] are considered.

There are other anode aging phenomena as current collector corrosion, contact loss...In addition, the cathode side faces aging despite the fact that the aging of the negative electrode is predominant [17]. Fig. 3 presents an overview of all the aging mechanisms inside a Li-ion cell. They are not independent and according to the electrode materials they may interact differently. Consequently, the complexity of the aging and the interaction of several factors make the estimation and the modeling of the degradation even more complex.

B. A BRIEF REVIEW OF PEMFC DEGRADATION
Fuel cells differ in their operating temperature, efficiency, costs...etc, but among the different type of FCs proton exchange membrane fuel cell is now extensively used in FCHEVs [41]. It is characterized by low operating temperature (< 90°C), low pressure (from ambient to 5 atm),
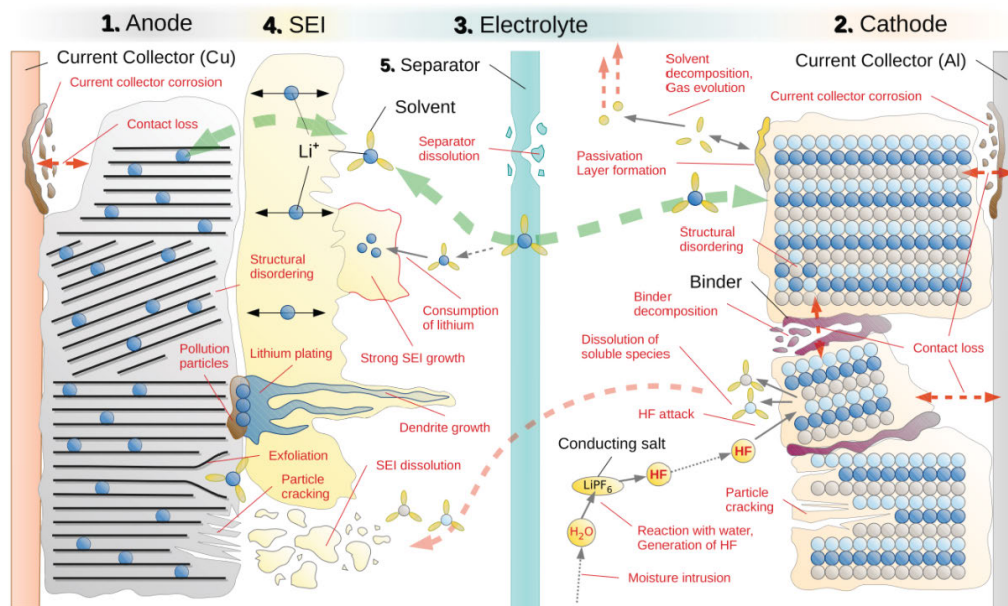
FIGURE 3. Degradation mechanisms in Li-ion cells [29].

high efficiency, and high starting speed [42]–[43]. Its integration will increase the vehicle autonomy while refueling hydrogen takes only several minutes. A fuel cell has several components from polymer membrane electrolyte, electrodes, bipolar plates, gas diffusion layers (GDL), and active catalyst layers. Similarly to the battery, all those components could suffer from different rates of degradation. A brief review of their degradation mechanisms is described in this section.

First, catalyst degradation is affected by the reduction of the electro-chemical active surface area (ECASA) that depends on the degree of dispersion and the particle sizes [44]. Over time, the ECASA will decrease through the sintering and/or dissolution of some platinum particles and the corrosion of the carbon support [45]. This process could be more prevalent at fuel starvation [46]. It happens under transient load changing, during the shutdown/start-up procedures or when failing to supply enough reactant at high loading. In addition, running at very low current will cause the catalyst layer degradation.

Second, the membrane that separates the fuel from the air, transport the protons and support the anode and cathode catalyst layer [47]. It will face mechanical degradation due to mechanical stress and/or thermal stress. In addition, the membrane could break down under a chemical attack caused by the chemical reaction of foreign elements like the precipitated platinum [48]. Its degradation could be reduced by limiting the high temperature operation and operating the fuel cell at its best operating point and conditions. Other actions could also be done as improving the water management [45].

Third, the GDL that allows the reactant and the product gases to diffuse to and from the catalysts respectively. Also it forms an electrical connection for electrons transfer between the catalyst layer and the bipolar plates [45]. Its degradation

is difficult to differentiate for that of membrane-electrode assembly. However, its degradation includes deterioration in water management due to the loss of hydrophobicity and surface change. In addition, the loss of conductivity caused by the carbon corrosion, thermal expansion or shrinking [49]–[47]. Finally, regarding other components degradation as the bipolar plate that collect the generated current, isolate the individual cells, separate reactants and coolants, and uniformly distribute reactant and product streams [45]. Its typical degradation consists of corrosion and formation of a resistive surface layer on the plates leading to higher ohmic resistance and loss of conductivity [48]. While over long operating time the thickness of gaskets will reduce leading to more pressure on the GDl thus causing its porosity loss and higher reactant transport resistance. In addition, they may cause damage to the membrane due to their crossover leakage [47], [48]. In addition, the electrodes will suffer from loss of performance due to the loss of active area caused by the degradation of carbon support and catalyst layer.

The EMSs decisions contribute to some of these degradations directly or indirectly. Therefore, the EMSs should target the unfavorable operating conditions contributing to the degradation. Especially the fuel cell loading which are start-up/shutdown, very low or high requested power, and large transient power change rates as shown in Fig. 4, that contribute to mentioned aging mechanisms.

III. DEGRADATION MODELING
A. BATTERY DEGRADATION MODELING
Based on the analysis of different battery aging mechanisms, the type of battery life to be considered (calendar or cycle life), and the performance to be studied (resistance increase
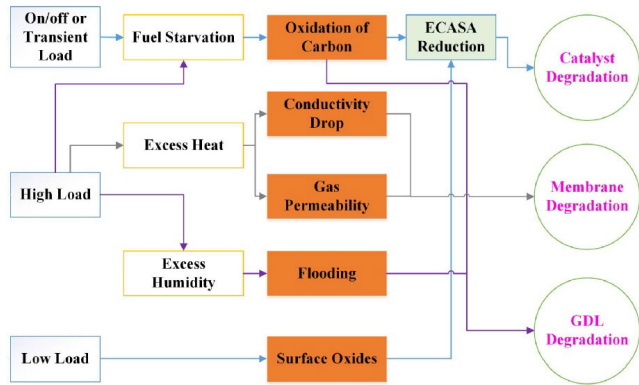
FIGURE 4. Degradation mechanisms regarding to PEMFC loading [50].

or capacity fade) there are different ways to model and estimate the degradation of Li-ion batteries [16]. Usually, they are divided into three types. Electrochemical models which are accurate as they depend on understanding the internal chemical reaction, but they are complex for real application implementation. Empirical models are based on fitting collected experimental aging data. Although their simplicity, they require a significant amount of time and data sets which are valid only under some experimental conditions. To overcome the disadvantages and combine the advantages of those two models semi-empirical models are introduced. They combine some of the theoretical principal with the collected experimental results. Therefore, they are simpler and more implementable than the electrochemical models and they are more accurate than the empirical models for a wider range of conditions. In the following subsections, battery degradation models that can be integrated in the EMS are reviewed.

1) ELECTROCHEMICAL MODEL

The SEI film growth due to the irreversible side reactions between the electrolyte and the electrode cause the loss of lithium ions to the SEI which is the common source of capacity fade. Therefore, the SEI film growth model could be used to model the battery's degradation [51], [52]. The change in the film thickness, δ_{film}, during charging is calculated by [53]:

$$\frac{\partial \delta_{film}}{\partial t} = -\frac{M_p}{a_n \rho_P F} J_S \quad (1)$$

where M_p is the average molecular weight of the constituent compounds of the SEI layer, ρ_P is the average density of the constituent compounds, a_n is the specific surface area, F is the Faraday's constant and J_S is the side reaction current density described using the Tafel equation as:

$$J_S = -a_n i_{os} \exp\left(-\frac{\alpha_c F}{R_g T} \eta_s\right) \quad (2)$$

where i_{os} is the exchange current density, T is the temperature, R_g is the universal gas constant, R_{film} is the overall film

resistance, and η_s the side reaction over-potential calculated as:

$$\eta_s = \phi_s - \phi_e - U_{ref,s} - \frac{J_{total}}{a_n} R_{film} \quad (3)$$

where ϕ_s, ϕ_e represent the solid and the electrolyte potentials respectively; and the local volumetric transfer current density J_{total} is given by a sum of the intercalation current density J_I and the side reaction current density J_S as follows:

$$J_{total} = J_I + J_S \quad (4)$$

J_I is calculated as:

$$J_I = a_n i_{0,n} \left[\exp\left(\frac{\alpha_{a,n} F}{R_g T} \eta_n\right) - \exp\left(\frac{\alpha_{c,n} F}{R_g T} \eta_n\right)\right] \quad (5)$$

finally, this would allow the overall film resistance to be calculated as:

$$R_{film} = R_{SEI} + \frac{\delta_{film}}{\kappa_p} \quad (6)$$

where R_{SEI} is the initial film resistance, and κ_p is the conductivity of the film. The complexity of this model imposes challenges for its implementation on real-time applications. To overcome these challenges simplifying the model is proposed [54], [55] without losing the accuracy.

2) SEMI-EMPIRICAL MODELS

These models are based on mathematical relationships that links some stress factors as the discharge rate, Ah-throughput, DOD, temperature, and SOC to the capacity loss or internal resistance increase. In these degradation models, some parameters are fitted to the experimental battery aging data. Wang *et al.* introduced a cycle life model for lithium iron phosphate ($LiFePO_4$) that take into account the discharge C-rate, temperature, and charge throughput after running several aging test while varying three parameters, temperature (-30 to $60°C$), DOD (90 to 10%), and C-rate (C/2 to 10C) [56]. However, the model needs more validation at subzero temperature and it is represented by:

$$Q_{loss} = B \cdot \exp\left(\frac{-31700 + 370.3 \cdot C_{rate}}{R_g \cdot T}\right) \cdot (A_h)^{0.55} \quad (7)$$

where Q_{loss} represent the percentage of capacity loss, B is a pre-exponent factor that depends on the C-rate, T is the absolute temperature, R is the gas constant, and A_h is the total charge throughput. The model is also validated under different C-rates and temperatures in [57]. However, this model dismiss the effect of the battery SOC as an aging factor. Hence, this model is improved for predicting the battery's degradation in the field of HEV [58]. The pre-exponent factor B is introduced as a function of the SOC as shown in (8) below:

$$Q_{loss} = (\alpha \cdot \text{SOC} + \beta) \cdot \exp\left(\frac{-E_a + \eta \cdot I_c}{R_g(273.15 + \theta)}\right) \cdot Ah^{\bar{z}} \quad (8)$$

where α and β define the SOC dependence presented in the Table 1, and $\bar{z}$ is the average value of power law exponent.

TABLE 1. Optimal values of α and β [58].

	$\alpha(SOC)$	$\beta(SOC)$
$SOC[\%] < 45$	2896.6	7411.2
$SOC[\%] \geq 45$	2694.5	6022.2

To show better the degradation of the battery a severity factor could be used to quantify the aging effects under different operating conditions [59] based on the battery ageing model [58] giving by:

$$\sigma(t) = \frac{Ah_{nom}\left(SOC_{nom}, C_{rate,n\,om}, T_{K,n\,om}\right)}{Ah_{cyc}\left(SOC, C_{rate}, T_K\right)} \quad (9)$$

It represents the ratio of the total Ah-throughput under nominal cycles conditions, Ah_{nom}, to the total Ah-throughput, Ah_{cyc}, under given pattern of SOC, C_{rate}, and T until the end of life (EOL) is reached. Therefore a severity map could be estimated as shown in Fig.5.
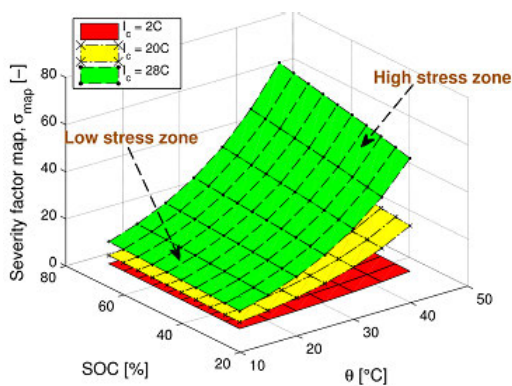

FIGURE 5. Severity factor map for the battery under three different current rate [59].

Similarly, Cui et al. tried to build a cycle lifetime model that couples muti-stress factors for Li-ion batteries under shallow-depth discharge [60]. It considers temperature T, time t, charge/discharge rate C, DOD and the tapper voltage V_t as stress factors to extend the model applicability represented by:

$$A\left(DOD, C, V_t\right)$$
$$= -157.671 + 3.624\,DOD + 14.190\,C$$
$$+ 2.721\exp\left(0.938\,V_t\right) \quad (10)$$

$$Q_{loss}\left(T, C, D\,OD, V_t, t\right)$$
$$= A\left(DOD, C, V_t\right)\exp\left(-\frac{E_a(C)}{8.314T}\right)t^{0.740} \quad (11)$$

When considering the calendar aging three main factors (battery SOC, temperature, and storage time) are considered in the model. Sarasketa-Zabala et al. proposed a semi-empirical model for the calendar aging validated under dynamic operating conditions [61]:

$$Q_{loss} = \alpha_1 \cdot \exp\left(\beta_1 \cdot T^{-1}\right) \cdot \alpha_2 \cdot \exp\left(\beta_2 \cdot SOC\right) \cdot t^{0.5} \quad (12)$$

where α_1, β_1, α_2, β_2 are fitting parameters, T is the temperature, and t is the storage time in days. Also, they proposed a

cycle life model that take into account the charge throughput and the DOD as shown below [62]:

$$Q_{loss}$$
$$= \left(\gamma_1 \cdot DOD^2 + \gamma_2 \cdot DOD + \gamma_3\right) \cdot k \cdot Ah^{0.87}$$
$$\text{for } 10\% \leq DOD \leq 50\%$$

$$Q_{loss}$$
$$= \left(\alpha_3 \cdot \exp\left(\beta_3 \cdot DOD\right) + \alpha_4 \cdot \exp\left(\beta_4 \cdot DOD\right)\right) \cdot k \cdot Ah^{0.65}$$
$$\text{for } DOD < 10\% \text{ and } DOD > 50\% \quad (13)$$

where γ_1, γ_2, and γ_3 are fitting parameters while k is a correction factor for the dynamic operating conditions and it is considered 1 for constant DOD.

On the other hand, Ah-throughput representation could lead to mistakes in separating the two battery life model (cycle and calendar life) [63]. Therefore, based on the Dakin's degradation approaches a total degradation model is proposed by Baghdadi et al. after running several aging experiments test. For the calendar aging, three different temperatures (30, 45, and 60°C) with three different SOCs (30, 65, and 100%) are considered. While for power cycling aging four aging factors (magnitude of the current, charge throughput, cell temperature, and DOD) are considered. The total degradation rate k_{tot} consider the power cycle as an amplification to the calendar aging:

$$k_{tot} = k_{cyc} \cdot k_{calendar} \quad (14)$$

$$k_{tot} = \underbrace{\exp^{(a(T)I)}}_{\text{Cycle part}} \cdot \underbrace{\exp(\frac{cSOC}{a}) \cdot \exp(\frac{d}{a}) \cdot \exp(\frac{-b}{aT})}_{\text{Calendar part}} \quad (15)$$

the instantaneous performance studied is calculated by:

$$\xi(t) = \xi(0)\exp^{(\pm kt^{\alpha})} \quad (16)$$

where ξ represents the battery capacity or resistance, the negative sign is for the battery capacity while the positive is for the resistance, t is the aging time (days), and α is a time-dependent factor determined by fitting the double logarithms of capacity fade and resistance according to:

$$\ln\left(\pm\ln\left(\frac{\xi(t)}{\xi_0}\right)\right) = \alpha\ln t + \ln k \quad (17)$$

The two battery life models are also considered separately, where the contribution of the calendar aging is subtracted from the total aging to have the power cycling [64]–[65]. Schmalstieg et al. considered for the calendar aging only one temperature 50°C for 12 different SOCs ranging from 0% to 100% and 3 temperatures (35, 40, 50°C) for 50% SOC. While for the cycle aging, only one current magnitude (1C) and one temperature (25°C) with different variations of SOC are considered [65]. They express capacity and internal resistance using the following equations:

$$C = \underbrace{1 - \alpha_{cap} \cdot t^{0.75}}_{\text{Calendar part}} - \underbrace{\beta_{cap} \cdot \sqrt{Q}}_{\text{Cycle part}}$$

$$R = 1 + \alpha_{res} \cdot t^{0.75} + \beta_{res} \cdot Q \quad (18)$$

where α and β are ageing coefficients related to (voltage, temperature) and (DOD, average voltage $\overline{V}$) respectively, t is time in days, and Q is the charge throughput (Ah). Besides, Wang *et al.* also build a complete degradation model considering 5 different DODs (10 to 90%), four different temperatures (10 to 43°C), and five discharge rates (0.5 to 6.5C) for the cycle test in their studies. However, they considered the cycling at low conditions (current at 0.5C and 10% of DOD) for approximating the calendar loss which is a huge assumption. Hence, they build a single equation [64] to model the battery degradation as:

$$
\begin{aligned}
Q_{\text{loss}} &= \left(a \cdot T^2 + b \cdot T + c\right) \exp\left[(d \cdot T + e) \cdot I_{\text{rate}}\right] \cdot \text{Ah}_{\text{throughput}} \\
&\quad + f \cdot t^{0.5} \cdot \exp\left[-E_{\text{a}}/RT\right]
\end{aligned} \tag{19}
$$

where the model parameter and coefficient values are presented in table 2. Despite the fair accuracy of semi-empirical model and incorporating some physical interpretation, they still depend on the designed accelerated aging experiment.

TABLE 2. The model coefficient values and units[64].

	Coefficient values and units				
a	8.61×10^{-6}	$1/\text{Ah} - \text{K}^2$	I_{rate}	C-rate	
b	-5.13×10^{-3}	$1/\text{Ah} - \text{K}$	t	Days	
c	7.63×10^{-1}	$1/\text{Ah}$	E_{a}	24.5	kJmol^{-1}
d	-6.7×10^{-3}	$1/\text{K} - (C)$	R	8.314	$\text{Jmol}^{-1}\text{K}^{-1}$
e	2.35	$1/(C - \text{rate})$	T	K	
f	14.876	$1/\text{day}^{1/2}$			

3) EMPIRICAL MODELS

In prognostics and health management, they are used to estimate the SOH which could be defined as the ratio between the actual capacity to the initial capacity and estimate the RUL defined as the time left from the present observation to the EOL when the full battery capacity reaches 80% of its initial value [66]. The empirical model is established based on fitting large amount of collected battery degradation data. As example two empirical regression models, a polynomial model (20) and an exponential model (21), are established by fitting the experimental degradation data [67]–[68].

$$
Q_{pk} = \beta_1 \cdot k_{cyc}^2 + \beta_2 \cdot k_{cyc} + \beta_3 \tag{20}
$$

$$
Q_{ek} = \alpha_1 \cdot \exp\left(\alpha_2 \cdot k_{cyc}\right) + \alpha_3 \cdot \exp\left(\alpha_4 \cdot k_{cyc}\right) \tag{21}
$$

k is the cycle number, α_i and β_i are the model parameters. The exponential model showed a better fit compared to the polynomial. Additionally, Xing *et al.* [67] proposed an ensemble model from the previous models that showed a better regression characteristic over the entire battery life.

$$
Q_{Ck} = \gamma_1 \cdot \exp\left(\gamma_2 \cdot k\right) + \gamma_3 \cdot k^2 + \gamma_4 \tag{22}
$$

Instead of predicting the capacity fade, Eddahech *et al.* used the increase of the internal resistance of the battery

during calendar ageing to estimate the RUL considering the SOC, temperature and storage time [69] using:

$$
\text{Re}(t, T, \text{SOC}) = A(T, \text{SOC}) \cdot t^{1/2} + B(T, \text{SOC}) \tag{23}
$$

In addition, recursive filtering methods are appropriate for online parameter identification [70]. Therefore they are used to estimate and track the changes of the internal resistance based on the equivalent circuit model [71]. However, they depend on the accuracy of the battery model.

4) PARTIAL SYNTHESIS

As it is explained, the battery aging is hard to quantify due to the complexity of the battery, interaction of several factors, and diversity of operating modes during the battery life. This aging cause a significant decay in the battery performance. In addition, the laboratory controlled conditions and the accelerated aging experiments (time consuming) cannot guarantee the same use and behavior of the battery as the operating conditions and the load profile are completely random and constantly changing for automotive applications. Therefore, a well-designed model and a good degradation estimation are critical for developing a health-conscious EMS. Table. 3 represents the performance comparison between the different degradation estimation based on different criteria such as their precision, their applicability in real application, and their complexity. The different models can be complementary as none of the models can perform enough while respecting all the constraints. However, semi-empirical models seem to be the most promising models for battery health-conscious EMSs due to their fair accuracy, complexity, and applicability in real applications.

B. FUEL CELL DEGRADATION MODELING

Proton exchange membrane fuel cell, the prominent technology used in the automotive industry face different degree of degradation compared to batteries. Currently, they suffer from low lifetime duration around 3000h whereas a 5000h lifetime duration is required to compete in the vehicle markets [46]–[73]. Dynamic operating conditions in transportation applications compared to constant load operations in stationary applications impose difficulties in water, gas and thermal management leading to fuel cell degradation [74]. Therefore, adding a secondary source for example a battery to the fuel cell powertrain can improve the dynamic performance. In addition, the degradation is affected by the powertrain design and the control strategy. To avoid this effect a control strategy that limit the FC system power change and the number of start-stop can increase the system durability [75].

1) EMPIRICAL MODELS

Regarding the SOH indicators for fuel cell, the variation of the output voltage, internal resistance and output power are considered as reliable indicators. However, most of the researchers use the FC voltage, as it is simple to measure, for estimating its degradation. The best-known model is based

TABLE 3. Comparison of different battery lifetime models (5 stars: excellent, 1 star very poor).

	Applicability	Physical/chemical knowledge	Complexity	Precision	Experimental data requirement
SEI film growth model [51]-[52]-[53]	★★★☆☆	★★★★★	★★★★★	★★★★☆	★★☆☆☆
Semi-empirical model [56]-[58]-[59]-[60]-[61]-[62]-[63]-[64]-[65]	★★★★☆	★★☆☆☆	★★☆☆☆	★★★☆☆	★★★☆☆
Empirical model [67]-[68]-[69]	★★★★★	★★☆☆☆	★★☆☆☆	★★☆☆☆	★★★★☆
Data-driven model [72]	★★★★☆	☆☆☆☆☆	★★★★☆	★★★★☆	★★★★★
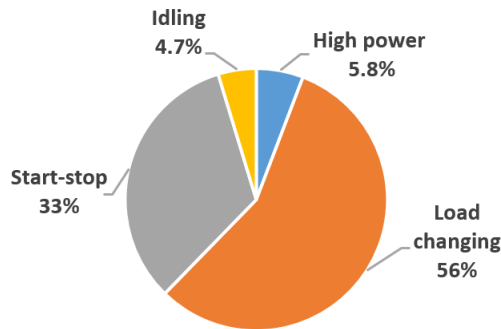
FIGURE 6. Performance degradation rate of PEMFC caused by different operation conditions [74].

on the actual operating condition that causes degradation as shown in Fig. 6. Pei *et al.*, developed an empirical model that used the output voltage decay as a degradation indicator, where a 10% drop is considered the end of life, presented as [76]:

$$T_f = \frac{\Delta P}{k_p \left(P_1' n_1 + P_2' n_2 + P_3' t_1 + P_4' t_2 \right)} \qquad (24)$$

where ΔP is the limited performance decrease, P_1', P_2', P_3' and P_4' are the performance deterioration rate respectively caused by large-range load change cycling, start–stop cycling, idle condition and high power load condition while n_1, n_2, t_1 and t_2 are their cycle time respectively per hour. In addition to the decay suffered under undesired conditions, a normal decay caused by the normal operating condition is added to the previous model presented as [77]:

$$\begin{aligned} \Delta \phi FC_{\text{degrad}} &= \Delta \phi FC_{\text{addition}} + \Delta \phi FC_{\text{nomal}} \\ &= Kp \left((k_1 t_1 + k_2 t_2 + k_3 t_2 + k_3 t_4) + \beta \right) \end{aligned} \qquad (25)$$

where $\Delta \phi FC_{\text{degrad}}$ donates the performance decline in percentage, $\Delta \phi FC_{\text{addition}}$ is the performance degradation under unpleasant operating conditions, while $\Delta \phi FC_{\text{nomal}}$ is a constant value for normal decay under normal operating conditions; t_1, t_2, t_3, and t_4 are idling time, the number of start-stop, duration of heavy loading, and heavy load time, respectively. Idling is where the output power is lower than 5% of the maximum power, heavy loading is a variation greater than 10% of maximum power per second, while high power is considered when it exceeds 90% of maximum power. The model coefficients are presented in table 4.

TABLE 4. Coefficient of the degradation model [76].

Coefficient	Values (unit)
k_1	0.00126 (%/h)
k_2	0.00196 (%/cycle)
k_3	0.0000593 (%/h)
k_4	0.00147 (%/h)
β	0.02 (%/h)

In the same concept, Fletcher *et al.* also considered penalty coefficient related to the operating conditions and more precisely linked to the requested power [46]. The degradation due to operating at low/high current and transient operations are considered as a function of the fuel cell operating power and the rate of power change respectively.

$$D_{\text{power}} = f \left(P_{\text{FC}} \right), \ \& \ D_{\text{transients}} = f \left(\frac{dP_{FC}}{dt} \right) \qquad (26)$$

In addition, start/stop degradation is presented by:

$$D_{\text{cycle}} = \begin{cases} \dfrac{1}{n_{\text{max}}}, & \text{if } P_{FC,t+1} \geq 0 \wedge P_{FC,t} < 0 \\ 0, & \text{otherwise} \end{cases} \qquad (27)$$

where n_{max} represent the maximum number of start/stop switches estimated by the manufacturer. The sum of these degradation metrics, that represents a proportion of performance drops, will penalize the stack voltage depending on the power change.

In the same context, but considering only the frequent overload as the main reason for fuel cell degradation. Lin *et al.*, used the standard deviation of the five-second sequence of output power to calculate the output voltage decay rate in order to limit and restrict the FC power to reduce the degradation. Based on test results, the decay rate per standard deviation of output power is 225 $\mu v h^{-1}$ and 10 $\mu v h^{-1}$ under steady-state condition. Therefore the voltage decline rate $\partial u_{\text{decay}} / \partial t (\mu \text{V/s})$ is calculated as [78]:

$$\begin{aligned} &\frac{\partial u_{\text{decay}}}{\partial t} \\ &= \frac{225 \times \text{stdev} \left(P_{fc}^k, P_{fc}^{k-1}, P_{fc}^{k-2}, P_{fc}^{k-3}, P_{fc}^{k-4} \right) + 10}{3600} \end{aligned} \qquad (28)$$

afterward the FC output power is adjusted dynamically using the following equation:

$$\Delta P_f = \left(1 - \frac{\frac{\partial u_{\text{decay}}}{\partial t}}{\max \frac{\partial u_{\text{decay}}}{\partial t}}\right) \Delta P_{f\,\max} \qquad (29)$$

where $\Delta P_{f\,\max}$ is the maximum change in the output power and ΔP_f is the increment of fuel cell working power.

2) OTHER MODELS AND TECHNIQUES

Beside the empirical models, FC degradation models are also classified into electrochemical models [79] and data driven models [80]. As for electrochemical models Wang *et al.* as example quantified the fuel cell degradation by building an electrochemical surface area (ECSA) decay model [81]. Hence, the FC degradation is included in the formulated objective function while the DP is used to solve the optimization problem. As for the data driven methods, this category focus on the trend of FC aging and based on its operating data the degradation model is established [82]. They don't require a full understanding of FC aging mechanisms. However, they face some limitation because of their need for large experimental data-sets. For example based on wavelet analysis, extreme learning machine and genetic algorithm (GA) a novel PEMFC degradation model is proposed in [83]. This model considers the influence of several factors from PEMFC load current, relative humidity, temperature, to hydrogen pressure. Moreover, it can be combined with the EMS durability improvement. Additionally, the electrochemical impedance spectroscopy (EIS) is a powerful tool to assess and evaluate the state of health of fuel cell [84] and battery [69]. The impedance spectra can show the effect of different levels of degradation [85], [86].

3) PARTIAL SYNTHESIS

Most of the available FC degradation models are empirical models based on experimental data. This is due to the difficulties in modeling the FC and its complexity. Therefore, their accuracy is questioned under different operating conditions. Regardless of the care given to the aging test bench, the accelerated aging test that cannot fully emulate the actual behavior in real field conditions. For example, air pollution and vibrations accelerate the fuel cell degradation. While other approaches as PHM for FC could solve the degradation modeling problem. Therefore, assess its SOH and estimate the RUL but the post-decisions still need more investigations in the field of energy management.

IV. ENERGY MANAGEMENT STRATEGIES

Optimal power splitting between the multi-sources is the main task of the supervisory control also known as energy management strategy. In addition, other objectives could be included such as the reduction of degradation especially considering the high prices of FCs and batteries. Generally, in the literature EMSs are classified into two main categories, rule-based (RB) and optimization based [87], [88]. Today,

the majority of the efficient EMSs are going toward optimization based [15]. Therefore, the interest in this section is to review the existing works and strategies that consider the degradation of sources mainly for FCHEVs using optimization based methods. They can be performed off-line to have a global optimal solution or extract and tune other rule-based methods. Moreover, they can be applied on-line to have a local optimal solution. Regardless of the type of EMS used, from the energetic point of view if the sources degradation aspect is neglected the performance would be the best only for given state of health. Moreover, the lifespan of sources could be highly affected.

A. RULE-BASED: EFFICIENT CONDITION OF OPERATIONS

To mitigate the degradation of energy sources RB methods could target the unfavorable operating conditions based on human expertise from SOC and current for batteries to startups/shutdown, low/high power and high power change rate for FCs. They promote good operating condition as in the safe zone for FC shown in Fig.7. Thermostat (on/off), power followers control strategy, state machines [89], frequency-based approach, and fuzzy logic control (FLC) are popularly used RB strategies [87]. They are formulated in terms of preset fixed rules and operations to split the requested power. Frequency decoupling using low-pass filter (LPF) [90] or time-frequency representation tool like wavelets transform (WT) [7] mitigate the FC degradation by assigning the high frequency content of the requested power to the battery. While the low frequency is assigned for the fuel cell to increase its lifetime as it has a slow dynamic response [91], [92]. FLC are well known especially for real-time applications as they are model free and suitable for handling complex nonlinear systems. They can consider the SOH as input beside the SOC and the requested power for durability improvement. Yue *et al.* used the SOH, estimated by the means of particle filter, beside the SOC and the requested power as input for the FLC [94]. Therefore, the battery degradation is reduced by limiting its current and SOC. Similarly, Noura *et al.* used the recursive least square (RLS) to estimate the battery internal resistance and its SOH based on the thevenin equivalent circuit model
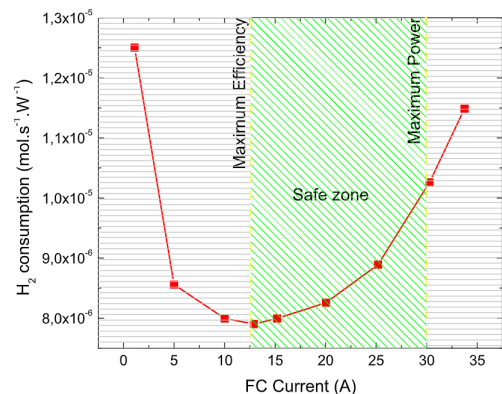
FIGURE 7. Hydrogen flow (mol.$s^{-1}.W^{-1}$) of a 20 h aged PEMFC [93].

leading for an appropriate FLC [71]. The optimality of FLC could be improved by optimizing the membership functions offline using for example GA [10]. The tuned controllers showed a good performance compared to the optimal solution of dynamic programming (DP) that took into account the degradation cost of the battery and the fuel cell in their cost function [95]. Further improvement could be achieved using traffic conditions prediction. In [96], neural network is used for driving pattern recognition. Other optimization algorithms could be utilized as the particle swarm optimization (PSO) [97] or bees algorithm [98] as an example.

B. OPTIMIZATION: INDIRECT AND EXPLICIT CONSCIOUS DEGRADATION

Optimization based strategies are having more attention in research with 56.7% in comparison with 32.9% for rule-based strategies and 10.4% for reviews and analysis in the last recent years [15]. Their objective is to minimize the operating cost over a considered time span while meeting some inequality and equality constraints. The objectives are quantified by a cost function that can differ by taking into consideration fuel consumption, hydrogen consumption, degradation…etc. They are divided into two categories indirect and direct integration of degradation.

1) INDIRECT CONSCIOUS OF DEGRADATION

The degradation is not calculated and introduced in the formulated cost function for indirect methods. However, the constraints of optimization play part in operating the sources in the safe zone and limiting the degradation factors that trigger their degradation. Therefore, the constraints tend to target the parameters that cause electrical abuses such as min/max SOC, DOD, power, and current. For example, the lifetime of the battery is improved by imposing constraints on its SOC and current while reducing the fuel consumption using the Pontryagin's minimum principle (PMP) [99]. In the same context, the battery degradation is limited by putting constraints on its SOC and for FC by setting a minimum FC power threshold and a time limit between its startup and shutdown while the model predictive control (MPC) track the power demanded of the FCHEV [100]. In addition, the FC current change rate is limited to reduce the degradation caused by high and frequent load change [101]. Such approach has a non-optimal solution as the degradation behavior is not modeled. Therefore, the explicit conscious method is becoming more and more employed.

2) EXPLICIT CONSCIOUS OF DEGRADATION

Having a degradation model or SOH estimation help to estimate the cost of degradation depending on its aging factors and operating condition. Therefore, in addition to the cost of fuel consumption, the degradation is included in the objective function as an economic cost to minimize. Normally, it is based on the replacement cost at their end of life.

For example, the objective function J is defined by

$$J = \sum_{k=0}^{N} \left(C_{H2} + C_{\delta_b} + C_{\delta_{FC}} \right) \tag{30}$$

where C_{H2} represent the fuel cost based on hydrogen consumption rate and cost, C_{δ_b} & $C_{\delta_{FC}}$ represent the battery and FC degradation cost based on their replacement cost and degradation rate. On the other hand, instead of allocating an economic cost equivalent for degradation, the objective function can be formulated based on equivalent hydrogen consumption for degradation, defined as follows

$$J = \sum_{k=0}^{N} \left(\Delta m_{H_2} + \Delta m_{H_2equ3} + \Delta m_{H_2equ2} + \Delta m_{H_2equ1} \right) \tag{31}$$

where first and second part, Δm_{H_2} & Δm_{H_2equ3}, are for hydrogen consumption and equivalent hydrogen consumption of the battery. While the third and fourth part, Δm_{H_2equ2} & Δm_{H_2equ1}, account for the equivalent hydrogen consumption of the performance degradation as shown in (32) [102]–[77]. It is based on the price of FC and battery M_{FC} and M_{Bat}, the price of hydrogen C_{H_2}, in addition to the degradation level of the Fc and battery $\Delta\phi_{FC_{degrad}}$ and $\Delta\phi_{Bat_{degrad}}$.

$$\Delta m_{H_2equ2} = \frac{\Delta\phi_{FC_{degrad}} M_{FC}}{10\% C_{H_2}} \quad \Delta m_{H_2equ1} = \frac{\Delta\phi_{Bat_{degrad}} M_{Bat}}{20\% C_{H_2}} \tag{32}$$

a: OFFLINE OPTIMIZATION

Dynamic programming is the most famous algorithm for having a global optimization. The cost-to-go function is calculated for each sample time and the optimal control policy is achieved by proceeding backward. It has a high computational burden and requires prior road information but it can serve as a benchmark solution. First, for health-conscious energy management, where the cost function consider only the battery degradation based on its severity factor, it has been used to reduce the battery degradation for a battery/ultra-capacitor hybrid system [103]. The same concept is applied but using the battery dynamic degradation based on the Ah-throughput model and according to the cumulative damage theory [6], [104] as follows:

$$Q_{\text{loss},p+1} - Q_{\text{loss},p} = \Delta A_h z A^{\frac{1}{z}} e^{-\left(\frac{Ea + BC_{\text{Ratex}}}{zRT_{\text{bat}}} \right)} Q_{\text{loss},p}^{\frac{z-1}{z}} \tag{33}$$

where $Q_{\text{loss},p+1}$ and $Q_{\text{loss},p}$ are the accumulated capacity loss at time t_{p+1} and t_p, and ΔA_h is the Ah throughput from t_{p+1} to t_p which is defined as:

$$\Delta A_h = \frac{1}{3600} \int_{t_p}^{t_{p+1}} |I_{\text{bat}}| \, dt \tag{34}$$

Therefore, the cost function contains the cost of accumulated capacity loss. Secondly, the cost function consider the total operating cost. Therefore, a trade-off between fuel

TABLE 5. Advantages and disadvantages of EMS algorithms.

	Advantages	Disadvantages
RB	On/offline strategy; relatively simple and practical; easy to design; good performance	Sub-optimal solution; rely on human expertise and threshold values;
DP	Global optimal solution; benchmark for other strategies	Long computation time; offline strategy; need prior power demand knowledge
ECMS	relatively low computation time and burdens; on-line strategy;	Local optimality doesn't guarantee global optimality
NN	Near global optimal solution for real driving conditions	Depend on trained data and prediction accuracy
SDP	Global optimal solution for predicted drive cycles	Depend on the availability of Markov decision problem; time consuming
MPC	Real time implementation; ability to tackle constraints into the control actions	Depend on prediction accuracy; rarely to achieve global optimal solution

consumption and battery degradation is considered using DP [105]–[106]. Similarly, for battery/fuel cell system a trades off will be between the hydrogen consumption and the degradation of the energy sources. Martel et al., considered the degradation of the fuel cell based on the voltage loss model and also introduced their battery degradation model for calendar and cycle life. Lastly, building the cost function based on hydrogen. Hu et al. considered the system durability and fuel economy for a FCHEV using DP [77]. Degradation models (7) and (25) are employed to convert the sources degradation into equivalent hydrogen consumption based on the price of FC, battery and hydrogen as shown in Equ. 32.

On the other hand, as a benchmark Song et al. used the DP solution, considering the battery degradation, during two different driving cycles in order to extract control rules from them and to propose a near-optimal rule-based strategy [104]. However, the DP is highly sensitive for changing the driving cycle as a 13% change in the optimal lifetime is obtained when the driving cycle is changed in [108] as an example. Therefore, the extracted rules are applicable only for specific driving cycle and may not guarantee a high level of optimality for different driving cycles. Furthermore, regarding training other methods, DP results are used to train an intelligent artificial neural networks for real time implementation that extends the battery life compared to rule-based method [109].

Stochastic dynamic programming (SDP) is used to allow real-time implementation where future conditions are predicted using Markov chain models or neural networks [87]–[110]. For example, Fletcher et al. used the SDP to minimize the fuel consumption, fuel cell and battery degradation by setting voltage constraints on the battery and penalizing the FC stack voltage depending on its power change [46]. Other SDP application for PHEV considering battery degradation and consumption is found in [51] and for HEV in [111].

b: ONLINE OPTIMIZATION

A prior knowledge of the upcoming driving cycle is not required. The global optimization problem is reformulated and its cost function is replaced with an instantaneous cost function to overcome the computation time limitation, memory resources in addition to the driving cycle knowledge

in advance. Equivalent cost minimization strategy (ECMS), PMP, and MPC are the best known strategies for online implementation in health management.

The ECMS was first introduced for hybrid electric vehicle working under charge-sustaining [112]. The energy used during discharging the battery must be replenished at a later stage using the engine. Hence, virtual or equivalent fuel consumption is associated with the electric energy, using an equivalent factor (EF), to obtain an instantaneous equivalent fuel consumption that should be minimized [14]. Optimization based ECMS with a constant EF is presented in [113] considering battery degradation using the SEI film growth model leading for longer lifetime while sacrificing fuel consumption. In addition, sequential quadratic programming (SQP) and PMP are the most common used in ECMS approach. The EF and the fuel cell dynamic change rates are changed based on the SOH of the battery and the fuel cell to insure charge sustenance and prolong fuel cell lifetime [114]. In addition, Zhou et al. showed how the penalty factor, of the ECMs based on PMP, using the severity factor model (8) can affect the battery degradation [115]. He concluded that a proper penalty factor can significantly extend the battery lifetime while sacrificing a slight fuel efficiency in a hybrid electric vehicle. Zhang et al. considered the lifetime of the battery and the fuel cell using SQP based ECMs for a fuel cell hybrid ship with a battery/ultra-capacitor as an energy storage system [102]. The multi-objective function is formulated considering fuel consumption, battery and UC equivalent hydrogen consumption in addition to battery and fuel cell degradation equivalent hydrogen consumption. The strategy showed better performance compared to wavelet-based and rule-based control strategy. Similarly, only the lifetime of the fuel cell is considered along with the fuel consumption for a range extender FCHEV in [116].

The PMP is based on a local minimization of the Hamiltonian function characterized by an electrical usage factor the co-state also known as adjoint state. The first attempt to investigate the capacity degradation of the battery in energy management for HEVs was presented in [117]. Where a battery degradation cost interpretation based on a severity factor map is added to the Hamiltonian function of the PMP for balancing the fuel consumption and the battery degradation.

However, experimental validation is missing especially for the aging model so additional improvement is made using the severity factor map based on the Ah-throughput capacity degradation model [118]. In the same concept, experimental data corresponding to HEV driving conditions are used to parameterize the aging model that takes into account the SOC dependency (Equ.8) [58]–[119]. Then, the objective cost function include the fuel and degradation cost while the optimal control is solved by the means of PMP. Even fuel cell performance drift caused by the degradation could be tracked and integrated in the objective function to formulate the Hamiltonian of the PMP. In [120], the fuel cell power fluctuation was penalized by adding a damping factor to the Hamiltonian function. Thereby, the lifetime is improved with just scarifying slight hydrogen consumption raise. Moreover, Jiang *et al.* considered the degradation cost of the battery and the fuel cell using (Equ.7 & Equ.24) with the energy consumption cost in their objective function [121]. The optimized solution is obtained using two-dimensional DP and PMP. On the other hand, hybridization can play a role to improve the lifetime and reduce the total operating cost. The performance of a plug-in hybrid electric bus and a single battery bus are presented in [122]. The PMP is used to find a trad-off between the equivalent battery life loss cost and the energy consumption.

The MPC anticipate future events and take accordingly the best control action. It is an optimization based on receding horizon control strategy using three main steps: (i) calculate the optimal control input over a prediction horizon that minimize the cost function subjected to constraints (ii) implement the first element of the derived optimal inputs to the physical plant, and (iii) move the entire prediction horizon one step forward and repeat from step (i) [1]. Therefore, the computational burden compared to DP and PMP is reduced but the solution becomes sub-optimal due to dividing the problem into several time steps. In this regard, an appropriate size of prediction horizon should be adapted as it can affect the accuracy and the computational burden. For health-conscious EMS, the MPC is used to extend the lifetime of the battery by limiting the rate of change of the current and insuring operating within the operating constraints for a battery/ultra-capacitor system [123], [124]. Instead of using the battery degradation in the objective function, a novel MPC is proposed considering the optimal DOD [125]. Therefore the total cost is reduced including fuel consumption and degradation cost. On the other hand, the first attempt to consider both fuel cell and battery degradation explicitly in a cost-optimal predictive manner for a FCHEV is presented in [50]. The SQP is used in the spectrum of MPC to minimize the total operating cost including the cost of degradation sources.

c: OTHER METHODS: FILTERS AND MACHINE LEARNING

Extremum seeking could be used to find the best operating points in real time. For fuel cells, as an example, their energetic performance change depending on the operating conditions and aging. Hence, the best performance should be
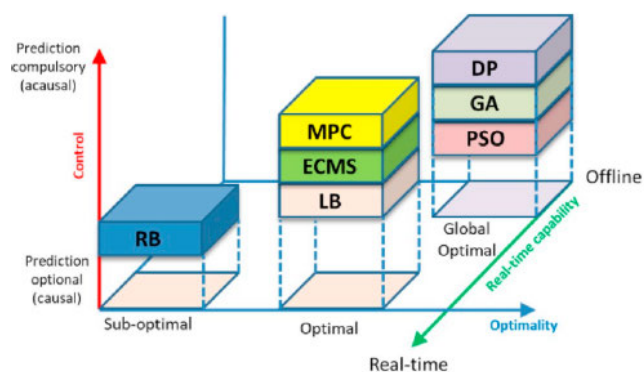

FIGURE 8. General comparison of EMSs [1].

tracked by determining the maximum efficiency and power range. This will lead to efficiency, performance and durability improvement for the fuel cell system and decrease the equivalent hydrogen consumption of the battery [126], [127]. For example, Ettihir *et al.* tracked the fuel cell performance deterioration caused by its degradation using an adaptive recursive least square algorithm [93]. Therefore, the updated performance is integrated in the PMP for fuel consumption and degradation reduction. Similarly, a new novel degradation model was proposed combine the polarization curves and FC efficiency with different state of health [128]. Therefore, the power distribution is adaptively tuned during the whole lifetime of the stack. On the other hand, learning based strategies (LB) are intelligent control strategies that use massive historical data and real-time information to obtain an optimal control law. They don't rely on a precise model as an advantage to be used for complex nonlinear systems, but they could be time consuming for training data sets. There are several LBS as neural network learning, supervised/unsupervised learning, reinforcement learning, support vector regression (SVR). Higher DOD of the battery induces more degradation. Therefore, defining an optimal DOD for a plugin hybrid vehicle with different initial SOC of the battery can reduce the total cost of operating including the degradation equivalent cost. Xie *et al.* used the generated data of the PMP during different initial battery SOC to train an artificial neural network (ANN) for better power distribution [129]. The ANN has comparative results to the PMP that include the battery degradation and with much improvement compared to rule-based method. In addition, reinforced learning methods are gradually used in real-time application as in HEVs for their optimality compared to DP [130]. Some of the mentioned strategies are compared in Table 5 and Fig. 8. Despite the difficulty to describe the evolution and differences between these methods, they present an explicit evolution in their way to consider the degradation and improving the durability as shown in Fig. 9.

C. PARTIAL SYNTHESIS
The EMS is regarded as a high supervisory control that meet the requested power by distributing the power on the available sources while respecting safety constraints. However,
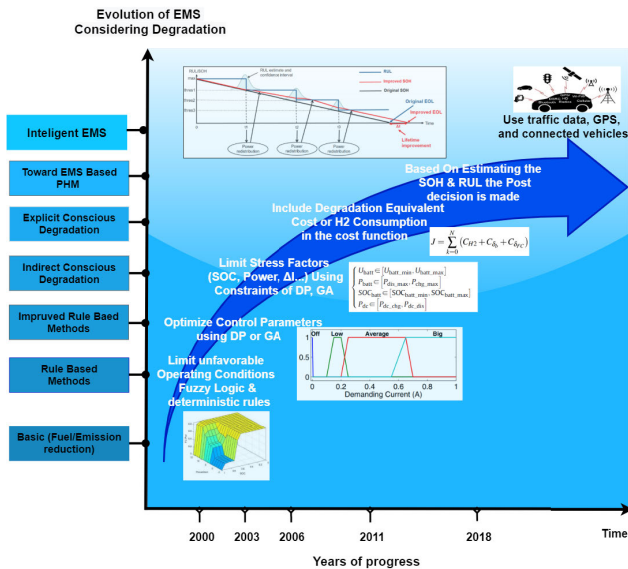
FIGURE 9. Tentative evolution of EMS considering degradation reduction.

multi-objectives EMS could be formulated to improve the system reliability and durability. Consequently, it is gaining interest to develop a health-conscious EMS as shown in Fig. 9. It started with simple rule-based methods (FLC & deterministic rules) that reduce the degradation based on safety constraints and limiting the degradation factors based on human expertise. They were improved by the mean of optimization algorithm (DP, GA…) to tune some parameters off-line. For their simplicity and online implementation, they were and are still used in vehicular applications. Then the indirect conscious degradation continued with the offline optimization-based methods using their constraints to target the degradation factors. They have the advantage of finding a global solution. However, they require a prior knowledge of the driving cycle. As result, the real time application is limited unless the driving cycle is predicted (railway applications as example). Lately, the interest increased into considering the degradation explicitly in the formulated cost function. Therefore, the degradation equivalent cost or hydrogen consumption is directly included in the cost function. On one hand, global optimizations are used to have the optimal solution as a benchmark to evaluate other solutions. On the other hand, online optimization (PMP, ECMS…) are used to overcome the limitation of global solution and allow real time implementation. The next trend could go towards investigating the post decision of the PHM as it still lack investigation for both batteries and FCs. In addition, the connected vehicles, the availability of traffic data, and GPS could improve the driving cycles prediction in addition to the use of machine learning based methods.

V. CHALLENGES AND OUTLOOKS
Developing an optimum FCHEV, capable of competing with conventional ICEs, requires many considerations especially

source reliability as they have high cost for replacement. In addition, an appropriate sizing of the energy sources is important not only to reduce the initial capital cost but also to reduce the running cost and achieve a higher lifetime. However, this is still challenging as they are highly depending on the type of driving cycle which leads to more investigation under any arbitrary drive cycle. Furthermore, system to system degradation is another challenge that still need more investigation. As reducing the degradation of one source cannot guarantee that the degradation of the second source will not be accelerated. Besides extending the developed EMSs from simulation level to experimental setup or hardware in the loop.

Considering multi-objective cost function that incorporates fuel consumption minimization, sources health, emissions, thermal management…is one of the future research directions. Therefore, the challenge relies in proposing a reliable model that describes those concerns without increasing significantly the computational burdens as some hardware and time limits are imposed for real-time implementation. For example, the temperature is an important factor that affect the performance of the energy sources and yet it is not well investigated in terms of the EMS. Therefore, incorporating the thermal management in addition to the degradation in the design of a health-conscious EMS has the potential of improving both performance of the vehicle and the lifetime of the energy sources.

As example, despite all the effort made in the degradation modeling there isn't a single degradation model that consider all the aging mechanisms that occur in automotive application. However, each model can perform well under its own particular controlled conditions. In addition, most of the studies focus on one aging effect at a time either capacity fade or internal resistance raise. While both have different impact on the performance of the system related to the available energy and the deliverable power. Moreover, the accelerated aging experiments helped in understanding the different aging mechanisms and collecting aging data. However, they have their own drawbacks related to neglecting the real environmental variables that occurs in real life. For example, investigating how the degradation of the FC is affected by air pollution and vibration. Therefore, the accelerated aging test cannot emulate fully the actual behavior in real field conditions leading to some errors. Other aspects should be considered are the complexity of the developed model and its precision to overcome the on-board computational limits and enable online implementation. Temperature is another important factor that affect the performance of the energy sources and yet it is not well investigated in terms of the EMS. Therefore, incorporating the thermal management in addition to the degradation in the design of a health-conscious EMS has the potential of improving both performance of the vehicle and the lifetime of the energy sources.

Besides, the difficulty of having a Pareto optimization solution increases as the objectives are normally conflicting.

Therefore, less important objectives could be replaced by some constraints. Another promising opportunity rise from the rapid development of intelligent transportation system, accessibility to traffic data, global positioning systems (GPS) and geographical information. Hence, EMS based artificially intelligent can learn from past scenarios and adapt to new changes for better real-time performance. Additionally, cloud computing based EMS can process massive collected data and solve the on-board hardware limitation while using the internet for communicating.

VI. CONCLUSION

FCHEVs are a hot subject today for their zero emissions, fast hydrogen refilling time and high efficiency. However, the degradation of their energy sources is inevitable and it is accelerated by the operating conditions as well as the control strategy causing drop in the system performance and durability. Therefore, firstly the aging mechanisms of the battery and the fuel cell are presented. Their complexity and interaction justify the variety of degradation model described secondly. In this context, a special focus was made toward finding and analyzing models that can be incorporated with the EMSs for a health-conscious energy management. In addition to highlighting the useful degradation models and their characteristics, a review and an analysis of the existent health conscious energy management strategies that took the degradation of energy sources in their approach is presented. Consequently, this work tries to give an insight on improving source durability issue and developing a health management strategy. While challenges and issues are highlighted from degradation modeling, validation and evaluation, optimality to real-time implementation. In addition to a future research direction based on multi-objective problem using practical models, estimation methods or intelligent based EMSs.

NOMENCLATURE
ABBREVIATIONS

ANN	Artificial neural network.
BMS	Battery management strategy.
DOD	Depth of charge.
DP	Dynamic programming.
ECASA	Electro-chemical active surface area.
ECMS	Equivalent cost minimization strategy.
EF	Equivalent factor.
EMS	Energy management strategy.
FC	Fuel cell.
FCHEV	Fuel cell hybrid electric vehicle.
FLC	Fuzzy logic control.
GA	Genetic algorithm.
GDL	Gas diffusion layer.
GPS	Global positioning systems.
HEV	Hybrid electric vehicle.
ICE	Internal combustion engine.

LB	Learning based.
LPF	Low pass filter.
MPC	Model predictive control.
NN	Neural network.
PEMFC	Proton exchange membrane fuel cell.
PHM	Prognostics and health management.
PMP	Pontryagin's minimum principle.
PSO	Particle swarm optimization.
RB	Rule-based method.
RLS	Recursive least square.
RUL	Remaining useful life.
SC	Supercapacitor.
SDP	Stochastic dynamic programming.
SEI	Solid Electrolyte Interface.
SOC	State of charge.
SOH	State of health.
SQP	Sequential quadratic programming.
SVR	Support vector regression.
WT	Wavelets transform.

VARIABLES

ΔP_f	FC power variation.
V_t	Tapper voltage.
$\alpha, \beta, \eta, \bar{z}$	Battery degradation coefficients.
$\alpha_{1\ldots4}, \beta_{1\ldots4}$	Fitting degradation parameters.
$\alpha_{\text{cap}}, \alpha_{\text{res}}$	Aging coefficient.
α_a, α_c	Anodic and cathodic transfer coefficients of electrochemical reaction.
$\Delta\phi FC_{\text{degrad}}$	Total FC performance decline.
$\Delta\phi FC_{\text{nomal}}$	Natural FC performance decay.
$\Delta m_{\text{H}_2\text{equ}_i}$	Degradation's equivalent hydrogen consumption.
Δm_{H_2}	Cost of hydrogen consumption.
Δm_{H_i}	Equivalent hydrogen consumption.
ΔP	FC percentage decay at EOL.
$\Delta\phi FC_{\text{addition}}$	FC performance drop for specific conditions.
δ_{film}	SEI film thickness.
a	Activation energy.
η	Local over potential.
γ_i	Fitting degradation parameters.
κ_p	Conductivity of the film.
$\partial u_{\text{decay}}$	FC voltage decline.
ϕ_s, ϕ_e	Solid and the electrolyte potentials.
ρ_P	Density of active material.
$\sigma(t)$	Severity factor for the battery degradation.
$\xi(t)$	Battery capacity or internal resistance.
a_n	Specific surface area of porous electrode.
C_{δ_b}	Battery degradation cost.
$C_{\delta_{FC}}$	Fuel cell degradation cost.
C_{H2}	Cost of consumed hydrogen.
D_{cycle}	FC degradation during switching.
D_{power}	FC degradation under high power.
$D_{\text{transients}}$	FC degradation under transient loading.

i_{os}	Exchange current density.
J_I	Current density for intercalation reaction.
J_S	Current density for side reaction.
J_{total}	Sum of the current density.
K_{cyc}	Number of cycles.
$k_{cyc}, k_{\text{calendar}}$	Cycle and calendar degradation rate.
k_{tot}	Total degradation rate.
n_i, t_i	FC operating time during various conditions.
P_{fc}^k	FC power at instant time t.
Q_{Ck}	Combined capacity fade models.
Q_{pk}, Q_{ek}	Combined capacity fade models.
R_{film}	Overall film resistance.
R_g	Universal gas constant.
R_{SEI}	Initial film resistance.
P'_i	FC degradation coefficient.
T_f	FC degradation percentage.
Ah	Amper hour throughput.
F	Faraday's constant.
I_{rate}	Rated current.
J	The objective cost function.
K	Correction factor.
k_p	Accelerating coefficient.
Q	Charge throughput Ah.
Q_{loss}	Capacity loss.
Re	Internal battery resistance for calendar aging.
T	Temperature.
t	Time.
U	Local equilibrium potential.
z	Value of power law exponent.

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