Towards Health-Aware Energy Management Strategies in Fuel Cell Hybrid Electric Vehicles: A Review

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Abstract

An energy management strategy (EMS) is responsible for distributing the power between the electrochemical power sources of a fuel cell hybrid electric vehicle (FCHEV) with a view to minimizing the hydrogen consumption and maximizing the lifetime of the system. However, the energetic characteristics of the electrochemical devices (fuel cell, battery, and supercapacitor) are time-varying due to the influence of ageing, and different ambient and operating conditions. Any drift in the characteristics of the power sources can lead to the mismanagement of an EMS. According to the literature, ignorance of health adaptation can increase the hydrogen consumption from almost 6.5% to 24% depending on the EMS. Therefore, it is necessary to develop a strategy which is aware of the actual state of the components while conducting the power split. Health monitoring techniques are potential candidates to deal with the uncertainties arising from the mentioned factors. In this respect, this paper first puts forward a concise review of the general modeling techniques which are essential for developing precise health monitoring techniques and in turn EMSs. Subsequently, the utilized methods for prognosis, diagnosis, and health state tracking of each of the mentioned power sources in a FCHEV are introduced. Then, a new taxonomy for the classification of the EMSs based on their health-awareness is proposed based on which three categories of prognostic-based, diagnostic-based, and systemic EMSs are formed. Each category is thoroughly explained, and a state-of-the-art review of these health-aware EMSs is presented. Finally, future perspectives of this new line of research and development are discussed before drawing a conclusion.

KEYWORDS: Diagnostic methods; Energy management strategy; Fuel cell; Health-conscious; Parameter estimation; Prognostic; State of health; Systemic management

1. **Introduction**

Transportation sector is perceived as one of the main contributors to greenhouse gas emissions around the world chiefly owing to its dependency on fossil fuels [1, 2]. Vehicle electrification, which covers a wide range of technological advancements, such as hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), battery electric vehicles (BEVs), and fuel cell hybrid electric vehicles (FCHEVs), is considered as a practical solution to make the current transportation system environmentally-friendly [3]. The increase of environmental concern, public awareness, governmental regulations for air quality enhancement, and initial investment in infrastructure are making the automakers turbocharge their attempts to reply to this transportation transformation towards sustainability. Among the existing technological solutions, HEVs, PHEVs, and BEVs could be proper substitutes for conventional vehicles which run on internal combustion engines (ICEs). However, HEVs and PHEVs still depend on fossil fuels, and BEVs struggle with long recharging time. These shortfalls have indeed paved the way for the emergence of fuel cells (FCs), as a new power source, in vehicular application. Table 1 compares different electrified vehicles.

Table 1: A brief comparison of the electrified vehicles (B: battery)

Technology	Strength	Weakness
HEV (ICE + B): Toyota: Prius Hyundai: Sonata Honda: Accord	• Convenient refueling • Energy recovery ability • High endurance • Long battery lifespan	• Little air pollution • Reduced millage over long trips • No all-electric mode while driving
PHEV (ICE + B): Mercedes: GLC360e Honda: Clarity BMW: i8	• Less emission than HEV • Convenient charging • All-electric mode • Lower fuel cost than HEV	• Complex powertrain configuration • Higher battery cost than HEV • No fuel saving over long trips
BEV (B): Tesla: Model S Nissan: Leaf Kia: Soul	• Zero exhaust emission • Convenient charging • Relatively Mature technology • Smooth propelling with no noise	• Long recharging time • Shorter battery lifespan than hybrid • Expensive and heavy owing to overloaded batteries
FCHEV (FC + B and/or SC): Toyota: Mirai Hyundai: NEXO Honda: Clarity	• Zero-emission and noise • Smooth propelling with no noise • Fast refueling • High driving autonomy	• Immature technology • Limited infrastructures • High cost

Forklifts have already given FC technology a welcome boost as the early adopters of this energy system with around 12000 FC units deployed in the US and a handful elsewhere [4, 5]. Moreover, FCHEVs are presenting a steady growth in the division of the road vehicles market to the extent that a large number of prototypes of different brands and sizes have been developed, such as Hyundai Nexo, Honda Clarity, Mercedes-Benz F-Cell, and Toyota Mirai.

Among various types of FCs, proton exchange membrane fuel cell (PEMFC) is the most potential to be employed in vehicular applications due to its low-temperature operation, high power density, and solid electrolyte [6]. However, the sole employment of a PEMFC cannot satisfy all the requirements of a vehicle owing to the inherent limitations (slow dynamic, energy storage incapability, etc.) of this device. Consequently, utilizing a secondary power source with more power density (W/kg), such as battery, supercapacitor (SC), etc., is necessary in order of satisfying the fast dynamic load in vehicles, reducing degradation rate of the PEMFC by absorbing the power peaks, increasing the fuel economy, powering the load during cold start, and energy recovery. Common structures for hybridization of hydrogen vehicles are FC-battery, FC-SC, and FC-battery-SC [7, 8]. A vehicle with such structures is known as a FCHEV where a PEMFC stack acts as the primary energy source and a battery pack or/and SC bank will be the secondary one. Fig. 1 presents a typical powertrain configuration for a FCHEV. Several topologies with respect to the arrangement of the energy sources and converters can be obtained for this vehicle. Table 2 lists the configuration types of a FCHEV.

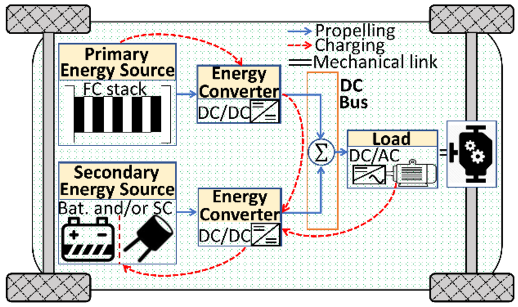

Fig. 1. Powertrain configuration of a FCHEV

Table 2: Types of powertrain configuration in a FCHEV [7].

Energy converter	Energy source		Configuration type
	PEMFC	Battery and/or SC	
Connection (DC/DC converter)	Yes	Yes	Full-active
	Yes	No	Semi-active
	No	No	Passive
	No	Yes	Not common

With all the favorable attributes of hybridizing the sources with different topologies, the performance of a FCHEV is impacted by several interrelated factors due to different nature of the utilized energy sources in terms of power delivery and energy efficiency. These factors put the design of an energy management strategy (EMS) in a critical position to enhance the performance and reduce the cost [9]. The term energy management or power management refers to the development of a higher-level control scheme for determining an appropriate amount of power for each of the sources in a FCHEV.

Several review papers have discussed the design of EMSs for the above-mentioned topologies in a FCHEV. In [10], different powertrain topologies along with the EMSs are discussed with a focus on the comparison of different DC/DC converter types and the required equipment to adjust the energy storage system (ESS) output voltage. In [11], latest EMSs of FCHEVs in heavy-duty applications are presented and a co-optimization framework is proposed for simultaneous optimization of the driving condition, auxiliary management, thermal management, and the power split. The authors have also stated that due to the limited lifetime of PEMFC and battery, a new insight into aging processes of these power sources is needed to have optimized operation. In [12], a particular attention is paid to the topological classifications, powertrain converters, and motor drive types. Moreover, the authors have identified the durability of the powertrain components, specifically FC, as one of the existing technical challenges and mentioned the need of fault diagnosis in this line of work. In [13], the optimization algorithms for developing EMSs in FCHEVs are reviewed based on their optimization objectives. Regarding the objectives, mainly hydrogen consumption and lifetime of PEMFCs are discussed without analyzing the battery pack durability. In [14], a comprehensive review of EMSs designed by means of genetic algorithm (GA) is conducted. In [15], a review of health-conscious EMSs for FCHEVs is performed. This paper mainly surveys the degradation models of PEMFCs and batteries as well as the papers that have utilized them for developing an EMS. However, the essential role of health monitoring techniques that use these degradation models and even other adaptation techniques to track the health state has not been discussed in this paper. Moreover, it has not studied the adaptive EMSs which are based on parameter estimation methods, extremum seeking, and systemic management to track the health state rather than the degradation models. In [16], different combination of FC, battery, and SC along with examples of EMSs are discussed. This paper has specifically highlighted the use of classical and fractional order-modeling of batteries and SCs. In [17], a study on the most common EMSs, such as proportional–integral–derivative controller, operational or state mode, rule-based or fuzzy logic, and equivalent consumption minimization strategies (ECMSs), is performed. Moreover, optimization methods, like linear programming, dynamic programming (DP), Pontryagin's minimum principle (PMP), GA, particle swarm, etc., come under scrutiny. In [18], the performance of the FC–battery–SC with different kinds of

EMSs and experimental investigations has been explored, and in [19], a meticulous study of the hybrid power systems for FCHEVs along with their corresponding EMSs is conducted. In [20], different methodologies for co-optimization of energy management and components sizing are discussed.

From the discussed manuscripts, one significant standpoint that has almost escaped the attention of most review papers is the weaknesses of using invariable models for developing an EMS irrespective of its type. In fact, the electrochemical power sources in a FCHEV have multivariate nature and their energetic characteristics vary and attenuate through time. The cause of this variation can be the change of ambient conditions, the fluctuation of operating parameters, and ageing of components which is a complex phenomenon. When it comes to performance drifts, most of the papers focus on the effect of driving cycles variation [21, 22]. It is indeed an important factor to be considered. However, there are also other causes for performance drifts, such as health state and operating conditions variation of the power sources, that need to be taken into consideration. In [23], an EMS based on quadratic programming (QP) is developed to decide on the required power from a FC stack (H-500 Horizon) and a simultaneous current and cooling fan duty cycle control is performed to supply this amount of power with the highest efficiency. This paper shows the ignorance of health adaptation increases the hydrogen consumption around 6.5%. In [24], the performance of a rule-based EMS and an optimal EMS based on DP is investigated. This paper shows that health unawareness in the FC system increases the hydrogen consumption up to nearly 24%. In this respect, this paper attempts to offer a new perspective on the design of EMSs in which the health-awareness is the pivotal point. Unlike the other existing review papers where the main focus is the review of conventional EMSs along with the powertrain configurations and fundamentals of the power sources, this manuscript mainly pays attention to the inclusion of the methodologies that can enhance the lifetime of the power sources which in turn increases the durability of a FCHEV. In this context, any EMS that considers a degradation model or any sort of adaptation technique to trace the performance attenuation/variation of the power sources is referred to as a health-aware EMS.

Section 2 provides a brief review of modeling approaches for electrochemical power sources. Subsequently, the available techniques for health monitoring of PEMFCs, lithium-ion batteries, and SCs are concisely reviewed in Section 3. Section 4 gives some explanation about conventional EMSs, discusses the existing health-aware EMSs, introduces new categories for developing health-aware EMSs, and explains different ways for including health monitoring algorithms in the design of a health-aware strategy. The shortcomings of the existing strategies are identified and potential topics for future studies are suggested in Section 5. Finally, a brief conclusion is given in Section 6.

2. Modeling of power sources

Proper functioning of any supervisory control system, such as an EMS, in a FEHEV depends on assessing and observing the performance of the electrochemical power sources (FC, battery, and SC) through precise characterization in different conditions. However, the direct measurement of some parameters/states of interest, like FC membrane water content, and battery/FC internal resistance, are very challenging and sometimes impossible specifically in real-time. In this regard, modeling has become an integral part of an EMS to indirectly monitor the operation of electrochemical power sources through the measurement of their terminal voltage, current, surface temperature, and other available states [25]. The existing modeling approaches of electrochemical power sources are broadly fallen into three categories of white-box, black-box, and grey-box, as shown in Fig. 2.

In brief, developing white-box models require in-depth knowledge about the underlying phenomena. Since they are developed based on partial differential equations (PDEs) for describing different concepts, they are very accurate at the cost of high computational burden. These models are suitable for analyzing different phenomena. However, their online application is not convenient [26].

Alternatively, black-box models are developed using the observed data and do not struggle with the underlying physical and theoretical relationships. Black-box models normally employ intelligent modeling methods, such as machine learning algorithms, artificial neural network (ANN), and fuzzy logic, to predict the performance of an electrochemical power source. As they have low computational complexity, they have

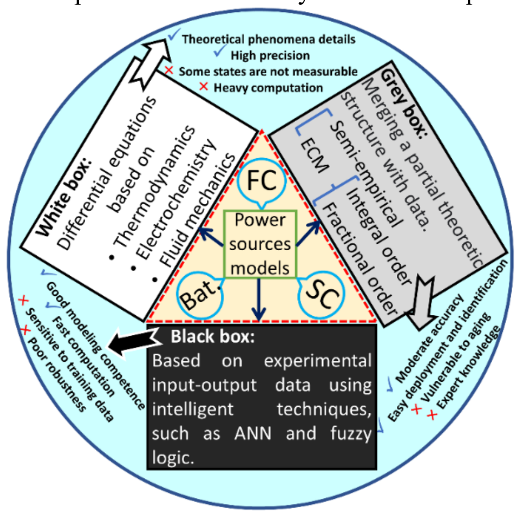

Fig. 2. Different approaches for modeling electrochemical power sources. FC: fuel cell, SC: supercapacitor, Bat.: battery, ECM: equivalent circuit model, and ANN: artificial neural network.

been used in online and real-time onboard applications [27]. To give some examples, Ma et al. [28] and Liu et al. [29] suggested applying long short-term memory (LSTM) recurrent neural networks (NNs) to predict the degradation trends of PEMFCs. In [30], a compact convolutional NN is proposed to estimate the battery capacity. In [31], ANN is trained using experimental data and an optimization algorithm, and the trained model is used to estimate the battery state of charge (SOC). Zhou et al. [32] employed LSTM NN for the life prediction, and Houlian et al. [33] combined Kalman filter (KF) and ANN for estimating the SOC of SCs. On the other hand, access to extensive and high-quality training data is indispensable to assure the model accuracy and generality. Another worth noting point is that these models are black box. Hence, accessibility to some internal parameters and states is restricted which can affect some operational measures like maintenance.

Grey-box models make a compromise between the complexity of white-box models and simplicity of the black-box ones and can be generally divided into two main categories of semi-empirical models and equivalent circuit models (ECMs). The semi-empirical models are in fact a simplified version of the white-box models in which some complicated mathematical equations are replaced by empirical ones or even map tables [34]. In FCs, semi-empirical models normally demonstrate the fundamental electrochemical characteristics, such as polarization behavior. An ideal polarization curve represents standard reversible potential and three irreversible losses, namely activation, ohmic, and concentration. It can demonstrate the influence of some parameters, such as humidity, temperature, flow rate, and composition, on the cell/stack performance. So far, several semi-empirical models have been proposed for FCs, and have been utilized for designing EMSs. In [35], Srinivasan et al. propose a model without considering the concentration zone. This model has been improved by adding the mass transport phenomenon in [36, 37]. Squadrito et al. in [38] has introduced an amplification term to increase the accuracy of the concentration zone, and Pisani et al. [39] added a flooding parameter. There are also more complicated semi-empirical models in the literature, such as the one proposed by Amphlett et al. [40] which is temperature dependent and the one introduced by Williams et al. [41] that is focused on cathode side. Regarding the battery, semi-empirical models are normally employed to illuminate the relationships among different parameters, such as terminal voltage, throughput current, surface temperature, SOC and so on. One of the primary semi-empirical battery models has been designed by Shepherd in [42]. This model provides the cell potential during discharge as a function of discharge time, current density, and other factors. A modified version of this model is proposed in [43] in which a term regarding the polarization voltage is included to better characterize the open circuit voltage (OCV) and the polarization resistance is slightly revised. In [44], another model is put forward which separates the kinetic and diffusive components of the total overpotential as opposed to other discussed models. In [45], a simple but precise heat estimation model is developed for lithium-ion batteries. Although these models are straightforward and easy for deployment, they suffer from imprecision of 5 to 20% according to the literature [46]. It should be noted that there are not a lot of semi-empirical models for SCs in the literature. In fact, ECMs are more popular for modeling SCs and batteries. The ECMs are grouped into integral-order ECMs (IO-ECMs) and fractional-order ECMs (FO-ECMs). IO-ECMs employ lumped elements, such as resistors, capacitors, and voltage source, to illustrate the complete dynamic behavior of an electrochemical power source. These models benefit from simple implementation as they are formulated by ordinary differential equations (ODEs). The most popular IO-ECM for PEMFCs is the one suggested by Larminie et. al [47]. This model is composed of an ideal voltage source representing the OCV, a series ohmic resistance, and one series-connected RC branch. As opposed to FCs, IO-ECM is one of the most promising methods for modeling a lithium-ion battery behavior especially for online battery parameter/state estimation in BEV and FCHEV applications. The most common IO-ECMs for lithium-ion batteries are Rint model, Randles model, and RC model [48]. Rint is the simplest IO-ECM for lithium-ion batteries that contains an ideal voltage source, which is OCV, and a series resistor describing internal ohmic losses [49]. The values of both elements in an Rint model depend on the SOC, health state, and temperature. Moreover, hysteresis effect (the value of relaxed voltage being different with the true OCV during charging and discharging) needs to be considered for an accurate SOC estimation. For instance, in [50], a zero-state hysteresis model is combined with an Rint model leading to better results than a sole Rint model. Anyhow, an Rint model provides a crude estimate of the terminal voltage and can result in large uncertainties in SOC estimates. Randles model was initially used for lead acid battery until Gould et. al used it for the estimation of state-of-function in lithium-ion batteries [51]. In this model, battery is perceived as a large capacitor. This model is composed of a capacitor to store the charge in parallel with a self-discharge resistor and an RC branch to represent the small time-constant electrochemical transitions. A series resistance (internal resistance) is also connected to the RC branch. To achieve more accurate transient response, more parallel RC branches can be included in the original model. The RC model is a modification of the Rint model. It is composed of an ideal voltage source to characterize OCV as a function of SOC, a series ohmic resistance and a number of parallel RC branches. Depending on the required accuracy, the number of parallel RC branches varies from 1 (known as Thevenin ECM) to n. RC models have been abundantly utilized in energy management and estimation of SOC and health state [46].

The most common IO-ECMs of SCs are shown in Fig. 3 [52]. Fig. 3a shows the classical model which is composed of an equivalent resistor (R_s) connected in series with a parallel RC branch ($R_p C$) and is sufficient for presenting SC dynamics over a time scope of several seconds. The capacitor imitates the canonical capacitance effect, R_s represents the overall resistance, and R_p accounts for self-discharge phenomenon [53]. In [54], the model shown in Fig. 3b has been utilized in which the application is for power electronics. This model comprises three RC branches (immediate branch, delayed branch, and long-term branch) to characterize the SC behavior over diverse timescales. A nonlinear capacitance is included in the immediate branch as a voltage-dependent capacitor connected with a constant capacitor in parallel. Moreover, a variable resistor is used to further describe the self-discharge process. The model shown in Fig. 3c contains a series resistor, a capacitor, and two RC branches. This model has been used in [55] to represent the dynamics of a SC in a BEV under a dynamic profile and its parameters have been extracted by extended KF. Fig. 3d illustrates a model based on transmission lines introduced in [56]. This model considers transient and long-term behavior by emulating the distributed capacitance and electrolyte resistance of the porous electrodes. It should be reminded that the discussed models have been utilized in different studies and combined with other approaches that their complete review is not in the scope of this work.

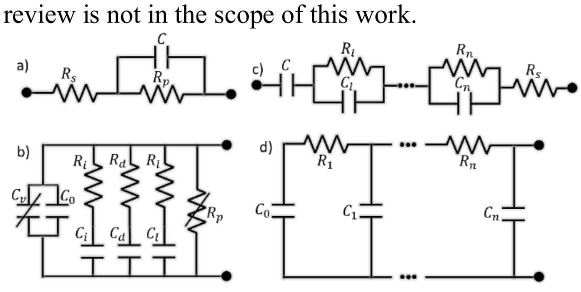

Fig. 3. Commonly used IO-ECMs for SCs [52]. (IO-ECM: integral-order equivalent circuit model)

However, several studies in batteries, PEMFCs, and SCs have shown that in a specific frequency range, for instance middle-frequency in a lithium-ion battery [57, 58], the Nyquist curve will not be a standard semicircle. This means that classical RC networks will not be suitable to emulate the behavior on the whole frequency range and constant phase elements (CPEs) should replace the capacitors in RC networks. Hence, the FO-ECMs have been suggested to convert polarization processes into electrical equivalents containing resistors, capacitors, inductors, and Warburg elements. Several FO-ECMs have been developed for electrochemical power sources. In [59], six most commonly used FO-ECMs for PEMFCs are introduced. These models have different level of accuracies. FO-ECMs have been also extensively used for estimating the battery states and reliability evaluation. For instance, Xiong et al. [60] and Ling et al. [61] have utilized FO-ECMs and KF to calculate the SOC of the lithium-ion batteries. Hu et al. [62] and Tian et al. [63] have investigated the use of these models for estimating the health state and degradation rates. Yang et al. [64] have employed this type of modeling approach for performing fault diagnosis through battery external short circuit. In the same way, several studies have proposed FO-ECMs for SCs. In [65], an innovative half-order model is proposed for SCs which has an acceptable accuracy and computational time. However, the potential of enhancing the precision of the model is limited since the fractional differentiation order is fixed. In [66], a FO-ECM is utilized to accurately estimate the SOC of SCs. Overall, the FO-ECMs are based on non-integer ODEs and normally have a higher potential in capturing the dynamic behavior compared to integer-order ECMs. However, this better representation of characteristics will be at the cost of higher complexity and computation time compared to IO-ECMs. Moreover, each electrical element must have its own definition in terms of the analytical process, otherwise they can lead to uncertainty in understanding the EIS data.

Considering the discussed approaches, semi-empirical models, IO-ECMs, and black-box models have great potentials for online applications and consequently have been used for EMS design several times.

3. Health monitoring techniques in electrochemical power sources

This section provides a concise review of the utilized health monitoring techniques, namely prognostic, diagnostic, and state estimation measures, in the electrochemical power sources. It should be noted that the main purpose of this section is to briefly introduce the techniques and highlight the role and portion of online estimation techniques (OETs) which have a great potential to be used in the design of EMSs. Therefore, the detailed analysis and more information about these techniques can be found in the relevant references cited throughout the manuscript.

3.1. Performance attenuation in fuel cells and batteries

PEMFC is considered as a propitious candidate to be used as the main power source in FCHEVs [67]. Lithium-ion battery is also the dominant choice, as the secondary power source, mainly due to its high energy and power density as well as low self-discharge rate [68]. However, under the dynamic conditions in automotive applications, the energetic performance of these components is attenuated. It should be reminded that while designing an EMS for FCHEVs, ageing and state of health (SOH) of a SC are normally negligible. This is in large due to the fact that SC lifetime is much longer than that of the vehicle and also the other power sources (FC and battery) [52, 69].

In a PEMFC, a single cell is composed of a polymer membrane, two electrodes, two gas diffusion layers (GDLs), and two bipolar plates (BPPs) [70]. Each of the mentioned components has their own degradation mechanism, as explained in [15, 71]. A FC stack is composed of several cells. Each cell and the corresponding components might go under degradation throughout the time. Moreover, the auxiliary system becomes degraded. Its degradation and its interrelation with components add to the complexity of the issue. Hence, the degradation is generally studied on the stack level in PEMFCs since focusing on the component level and discovering the relation and effects on the other components are highly difficult. Several attempts based on black-box, grey-box, and white-box modeling approaches have been done for simulating the degradation mechanisms. However, the degradation process in vehicular application is very complex and this is still an open problem in the literature. Some of the common PEMFC degradation models for energy management applications have been discussed in [15]. Battery degradation has its roots in both physical mechanisms (e.g., thermal stress and mechanical stress) and chemical mechanisms (e.g., side reactions) [72]. The main degradation modes derived from different mechanisms are lithium inventory loss and active material loss, which are completely associated with material. In addition to the material factor, degradation mechanisms significantly differ under various operating conditions and battery designs. For instance, fast charging is one of the main reasons for lithium plating, while it does not happen during discharge. Full description of battery degradation mechanism can be found in [73]. Some of the common battery degradation models for EMS design have been described in [15].

The multivariate nature, working under various operating conditions, material difference, design techniques all lead to unique degradation mechanisms in these electrochemical devices. These factors make the diagnostic, which is vital for fault handling, and prognostic, which is necessary for remaining useful life (RUL) prediction, extremely challenging but vital tasks. Consequently, health monitoring techniques, including prognostic and diagnostic, are considered as key measures to provide some preventive actions to extend the lifetime, enhance the performance, and decline repairing works which are among the bottlenecks in these power sources. Hereinafter, each of prognostic and diagnostic actions is briefly explained for FCs and batteries. SCs are excluded as their lifespan is much longer than that of the vehicle. Moreover, state estimation techniques are briefly reviewed for FCs, batteries, and SCs.

3.2. Prognostic methods in fuel cells and batteries

The principle of prognostic is to predict the RUL of the system based on its actual SOH and prior to its failure. This process comprises two steps of learning and prediction. In the learning step, a degradation model is developed through measuring particular parameters. The degradation model is tuned to estimate the current SOH of the system using health indicators (HIs). When the degradation model is well-tuned, it is used to predict the system evolution in the second step. Fig. 4 represents the whole prognostic process. HIs are required for precise prognostics of PEMFCs and batteries. According to [74], in PEMFCs, HIs can be divided into two main groups of measurement-based indexes (voltage, power, polarization curve based indexes, Electrochemical Impedance Spectroscopy (EIS) based indexes, and degradation model parameters) and component indexes (PEM indexes, the electrode indexes, the Bipolar plate indexes, the GDL indexes, and the sealing gasket indexes). The most applicable PEMFC HIs in the EMS design are the measurement-based ones specifically voltage, power, and polarization curves as they signify the macro-scale health states. The most used HI for a FC system in energy management application is the voltage failure threshold defined by the US Department of Energy (DOE). According to DOE MYRD&D 2020, a target of 5000 hours with less than 10% of voltage drop is set for the durability of a FC stack used in a passenger vehicle [75]. This measure changes to 8500 hours with less than 10% voltage degradation in FC electric buses [76]. The main HIs in batteries are capacity and internal resistance. In this regard, the most common used failure thresholds are reaching 80% of the initial capacity or 1.3 times increase in the resistance value. It is worth noting that since online measurement of these HIs, especially capacity, is challenging and requires a specific process, the use of some statistic indicators, such as mean or variance of discharge voltage changes, has also been practiced [77]. In this case, the degradation model should create a relationship between the main HI and the statistic one.

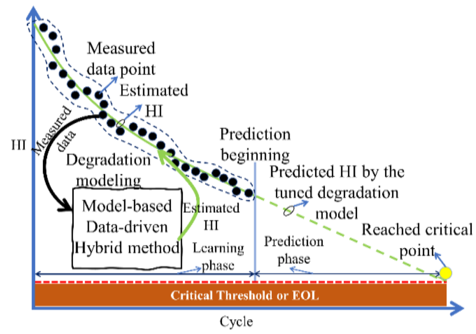

Fig. 4. Prognostic process

The utilized prognostic methods of PEMFCs and batteries in automotive application broadly fall into three categories of model based, data-driven based, and hybrid methods, as shown in Fig. 5. Model-based prognostic methods are based on mechanistic models, semi-empirical models (including ECMs), and fused models. The main principles of mechanistic and semi-empirical models have been previously explained. Concerning the fused models, they attempt to combine different model-based approaches to extract more information. In [78], a mechanistic multi-physic FC model for membrane degradation is proposed and tested with the New European Driving Cycle (NEDC). Simulation of the membrane degradation with this model has taken about 30 h under NEDC driving profile. In [79], a fused battery model is proposed by combining a capacity fade model with an internal resistance growth one based on ECM. It is shown that this model can better handle prediction uncertainties while having higher precision level compared to a classical degradation model.

Data-driven methods employ historical data to predict the degradation trend instead of getting involved with complexity of analyzing mechanisms for developing a model. They take advantage of intelligent techniques, such as ANN, and even statistical analysis, and signal processing to develop a degradation model and predict the ageing trend of the devices. They only need good amount of raw data to perform the prediction which is a great advantage. However, they might not be robust while confronting new conditions that had not been seen in their training phase. In [80], an attention-based recurrent NN model is put forward to enhance the prediction accuracy of the output voltage degradation in a PEMFC under the original long-term dynamic loading cycle durability test data. This method provides accurate results as long as it is fed with rich raw data. In [81], a discrete wavelet transform, as a signal processing method, has been used to decompose the raw signals into estimated and detailed signals to form a model for RUL prediction in a lithium-ion battery.

Hybrid methods merge the physical properties of a model-based approach with some experimental data using the intelligent techniques or even adaptive techniques to exploit the advantages of both methods while avoiding their weaknesses. Therefore, whenever an opportunity is seen to combine the two model-based and data-based categories, a new hybrid method is introduced. For instance, in [82], the non-linear and time-varying characteristics of the PEMFC are modeled by a number of linear-parameter-varying models and the prognostic task is performed by an echo state network using the voltage as a HI. In [83], the battery RUL prediction is performed by providing the future residual sequence by a data-driven method that is employed to update the state variables in an unscented KF. In [84], a semi-empirical model based on polarization curve of the PEMFC is utilized as the degradation model and an extended KF estimates the actual SOH and the dynamic of the degradation.

Considering the discussed points, particular concerns in data-driven methods are that biased and inadequate training data can result in incorrect predictions and confronting new conditions causes uncertainties. Nevertheless, model-based methods need fewer data and are much less sensitive to external uncertainty although their development require expert knowledge. From the revealed features, it seems that fused models (semi-empirical models and ECMs combined with OETs) and hybrid techniques have a great potential to be used in the design of EMSs as they can provide the control scheme with a precise RUL prediction. OETs, such as the family of KF, are normally used with these approaches and compensate for the lack of measured data. Moreover, they can conveniently adapt to performance drifts imposed by the variation of states.

Although the prognostic techniques have experienced considerable progress, there are still several real challenges to overcome. For instance, most of the researchers working on prognosis in FCs and batteries do not employ field-based data. They only utilize the measured data in laboratory condition. Consequently, FC and battery degradation data under dynamic load profiles and realistic working conditions is highly required. Another worth noting challenge is the need of algorithms that can perform a primary prediction with less measured data. The existing methods require between 40% to 70% of the whole lifecycle data to tune the parameters of the model or train the hybrid or data-driven models. Hence, devising new algorithms or methodologies with less reliant on measured data is needed. The other research gap in this domain is the development of a multi-physic model but with less computational burden to be used in onboard applications. This is very interesting for analyzing newly developed FCs and batteries where there are not sufficient experimental data.

Model-based methods:

Mechanistic: Using a complete physical model for RUL prediction.

Semi-empirical: Creating the model based on automotive conditions for predicting RUL.

Fused: Combining different model-based approaches.

Data-driven methods:

Machine learning: Building a degradation model by an intelligent method and predicting the RUL.

Statistical: Constructing a stochastic process model within a probabilistic framework.

Signal-processing: extracting practical information from the raw data

Hybrid methods:

Tuning a physical degradation model by intelligent techniques and predicting the RUL.

Fig. 5. Prognostic methods in FCs and batteries

3.3. Diagnostic methods in fuel cells and batteries

The main idea behind the diagnosis is to monitor the current SOH to detect and isolate any malfunctions/faults before the system comes to a halt. The significance of diagnosis and handling a fault has been frequently shown in various instances [85]. The diagnostic methods in FC and battery can be fallen into two main categories of model-free and model-based methods, as shown in Fig. 6. Model free methods are subdivided into two groups of measurement-based and data driven-based approaches. The measurement-based methods include regular measured variables (stack/cell voltage, flow rate, stack temperature, etc.) and special measurements (polarization curve, EIS, cyclic voltammetry (CV), current interruption). Data-driven methods take the advantage of machine learning (ANN, support vector machine, etc.), fusion methods, fuzzy logic, and signal processing to accomplish the diagnosis process. The model-based diagnostic methods consist of parameter identification, observer-based, and structural analysis. The parameter identification methods normally utilize an analytical or a semi-empirical model in which the values of some parameters will be used as indicators of specific faults or performance. For instance, in [86], dual extended KF is utilized to identify the high and low frequency parameters of a linear first-order RC model representing the behavior of a FC system under EIS tests. Observers are virtual sensors developed by a model, measurable peripheral signals, and an algorithm. Since the hermetic structures of PEMFC and battery make the measurement of some internal states difficult or even impossible, observers are used for subsystem management and internal state monitoring. In [87], a nonlinear internal state observer based on cubature KF is proposed to estimate the oxygen and nitrogen mass in the cathode side of an automotive PEMFC system. Regarding the structural analysis, instead of an observer, the parity relation is utilized to generate the residual. In [88], the parity relations are obtained from an eight-state representation. Some faults, such as flooding, drying, and compressor over-voltage, could be detected and isolated.

Considering the discussed methods, it can be inferred that parameter identification and observer-based techniques from the model-based category are the most used methods in this domain. This is due to the fact they do not require neither collecting rich fault data like data-driven methods nor performing precise interpretation like the structural analysis. The procedure for incorporating these techniques in designing EMSs will be discussed in detail later in a subsequent section.

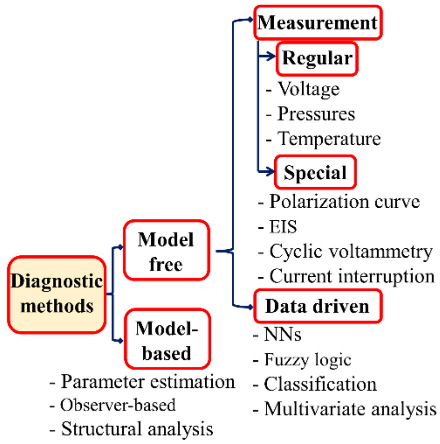

Fig. 6. Diagnostic methods in FCs and batteries

Similar to the prognostic methods, there are several challenges that remain concerning the diagnosis of FCs and batteries. Some of these challenges are as follows:

- The intrinsic internal mechanisms and their relations with outputs or operational parameters should come under a close scrutiny. Various conditions could result in the same fault. However, the coupling or interrelation between them is completely vague in FCs and batteries.
- A mathematical model to simulate the faults behavior from micro time to macro system level is still one of the open problems in FCs and batteries.
- The general measured data from batteries and FCs are voltage, current, and temperature. However, they are not a plain source of information about the internal electrochemical phenomena. Therefore, determining the proper characteristics to describe the internal states of the electrochemical power sources is still a challenge.

3.4. States estimation in fuel cells, batteries, and supercapacitors

State estimation has progressed as a substantial research area for electrochemical power sources. In FCs, the inappropriate internal state levels under dynamic situations can lead to the attenuation of the performance and lifespan. Therefore, monitoring the internal states is necessary in order to keep them within the desired ranges. However, considering the hermetic structure of the FC, measuring the states in the automotive application is strongly challenging. In this regard, the design of observers for estimating the internal states of a FC system has gained a lot of attention. As discussed in [89], there are eight crucial internal states in a FC system that are normally estimated by an observer. These states include membrane water content, liquid saturation in porous media and in gas channel, oxygen partial pressure, hydrogen partial pressure, nitrogen partial pressure at anode and cathode sides, water vapor partial pressure at anode and cathode sides, and the internal temperature of the FC. Observer design falls under the model-based category of diagnosis methods, as shown in Fig. 6. Model-based observers provide quantitative internal information which is essential for designing controllers. Most of the existing observers for a FC system can be classified as KF observers, Luenberger observers, and sliding mode observers. In [90], a state observer based on relative humidity sensor and unscented KF is proposed to estimate four key internal states (water vapor pressure, hydrogen and nitrogen pressure, average liquid water saturation ratio). The authors conclude that by controlling the purge valve based on the liquid water saturation ratio, it is possible to avoid water flooding on the anode side. In [91], internal gas pressure is estimated by a Luenberger observer and compared with the estimation by the

KF. It is indicated that KF has a faster convergence. In [92], a second-order sliding-mode observer is developed for estimating gas partial pressures and air stoichiometry. Despite the made progress in the estimation of internal states in a FC system, more innovative ideas need to be encouraged in this domain to develop highly reliable observers. For instance, KF and Luenberger algorithms require the linearization of the model. However, FC is a multi-physic nonlinear component with strong coupling between different phenomena, and hence model linearization in this component would not be very easy. On the other hand, sliding mode observers, which have shown good robustness, need an observation matrix that is highly complicated to calculate. All these algorithms are influenced by the noise and electromagnetic interference that exist in the automotive application. Therefore, increase of robustness and ease of deployment need to be further explored in the design of observers.

In batteries, state estimation includes ample techniques already reported in the literature [93]. This is largely due to the fact that comprehensive information about the states (SOC, state of energy (SOE), SOH, and state of power (SOP)) is a necessity for efficient health management, charging, and thermal management, of batteries. Fig. 7 presents a general category for the existing techniques to estimate the states of a battery as well as the two important parameters whose estimation are necessary for calculating the states. From this figure, capacity and resistance are two key parameters for estimating different battery states. In [94], recursive least square (RLS) is used to update the parameters of the battery model in real time, and dual KF is employed to estimate the SOC. In [95, 96], two model-based estimators, using unscented KF and the combination of RLS and cubature KF, are proposed to estimate the SOE with high accuracy. In [97] dual extended KF is employed to estimate the SOH and SOC of a battery using a downstream of capacity and internal resistance estimation. In [98], the battery SOP is calculated by means of extended KF considering different surface temperatures In fact, combination of OETs with model based-methods to estimate different states of a battery pack is a popular method in the literature. These methods can be easily integrated into the EMS design in FCHEVs to provide reliable states estimation. For instance, battery SOC is one of the most important parameters in all the EMSs and its imprecise estimation can disturb the efficient performance of the vehicle. In spite of the presence of numerous techniques for battery state estimation, more pioneering measures can be taken to enhance the precision in this domain. For instance, the most precise approach to realize a state is to measure it, on condition that the required sensor is available. Therefore, the use of cutting-edge technologies, such as acoustic, ultrasonic etc., to measure different internal states is demanding. Another suggestion could be promoting the design of joint estimation techniques as battery states are interrelated and impact one another. Estimating one individual state with the assumption of knowing the other ones can only lead to acceptable results under specific conditions. The last suggestion is to validate the applicability of the existing techniques in terms of precision, security, and computational burden when used in a real vehicle which is composed of a battery module or pack.

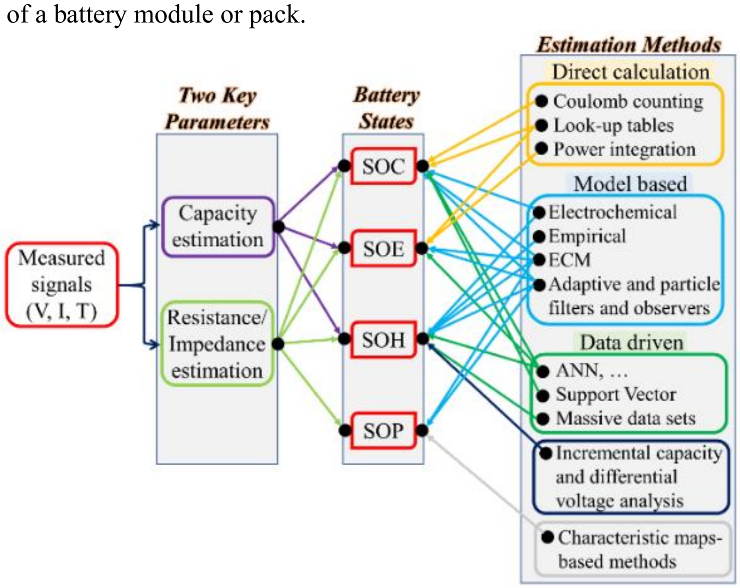

Fig. 7. Summary of battery states estimation methods

In SCs, a precise state estimation is also vital, owing to the presence of model uncertainties and noise, to assure a reliable, robust, and efficient operation. Two common studied states estimation for SCs in this regard are SOC and SOH. However, while designing an EMS for FCHEVs, ageing and SOH tracking of a SC are normally ignored. Therefore, the only discussed state variable for SCs will SOC herein. Compared to rechargeable batteries, the SOC in a SC is straightly associated with its terminal voltage. This is due to its distinct electrostatic characteristic for storing energy. Yet, the SOC determination using terminal voltage measurement can result in a substantial bias from its true value. This bias is mainly blamed for the presence of leakage currents, self-discharge, and side-effect reactions, such as pseudocapacitance, inside SCs [99]. In this respect, some studies have been performed to provide superior solutions for SOC estimation. The methods in these studies are principally based on electrochemical models, data-driven methods, and model-based techniques. Among them, the model-based techniques normally incorporate the OETs, such as KF, into the design of an accurate SOC estimator. For instance, in [100], an observable ECM for the SC is developed which captures the leakage effect and then an unscented KF SOC estimator is proposed for the ECM. In fact, compared to batteries and FCs, there are not a lot of estimation techniques for SCs in the literature. Therefore, the lessons learned from the estimation of states in FCs and batteries can be deployed in this line of work.

4. Health-aware energy management strategy design:

Considering the level of complexity in FCHEVs, EMSs are typically developed as a hierarchical supervisory control scheme for determining the reference signals of the power demand from the powertrain main components. The consequent set points are then imposed to the control loops of the component level using classic PID controllers or even more advanced approaches. Several EMSs have been developed for FCHEVs. Conventionally, these strategies are divided into three groups of rule-based, optimization-based, and intelligent-based methods. The rule-based methods depend on the operation modes defined by some rule tables to accomplish the requirements of the vehicle and are subdivided into deterministic and Fuzzy rule-based strategies. Although the rule-based strategies are easily applicable in online applications, their heuristic nature can lead to limited and sub-optimal solutions. In this regard, the researchers have directed attentions to the optimization-based EMSs, which guarantee optimal or near-optimal solutions in theory. Furthermore, they can provide new guidelines for refining the rule-based methods. Optimization-based EMSs are subdivided into offline and online methods that are all about minimizing a constrained cost function. The former employs the cost function over a fixed driving cycle known in advance and is helpful for understanding the optimal policy. The latter, nonetheless, performs an instantaneous optimization based on the system's variables. The most common offline optimization-based EMS is DP, which is a direct optimization approach used as a benchmark in most energy management studies. Regarding the online optimization-based EMSs, depending on the formulation of the optimization problem, several methods, such as ECMS, model predictive control (MPC), extremum seek methods, etc., have been introduced. Instantaneous optimization methods have a heavy computational burden compared to the rule-based ones. Moreover, some of the parameters in these methods, like the estimation of the equivalent factor in ECMS and the initialization of the co-state in PMP, are sensitive to transient dynamic and the driving condition. In this regard, the use of intelligent-based strategies that exploit data mining techniques to produce optimum performance has come under attention. These strategies mainly utilize the car navigation data and history of motion for recognizing and predicting the driving condition, and the intelligent techniques, such as reinforcement learning, clustering learning, and NN learning, to manage the energy/power flow among the powertrain components. The details about developing these conventional EMSs with different techniques are available in the previously discussed review papers in the introduction section [10-20].

The described conventional EMSs would normally take into account some constraints, such as variation of battery SOC, maximum efficiency (ME) and maximum power (MP) points of the FC system, and dynamic fluctuation of PEMFC system. However, these constraints cannot guarantee the endurance enhancement of electrochemical power sources as their characteristics change through time. Moreover, there is no clear understanding of the performance drifts in real-time vehicular applications. Therefore, the recent papers have tried to take things to a further step regarding the inclusion of health management techniques in their design.

In fact, health state consideration is becoming an integral part of EMSs in FCHEVs. Fig. 8 shows the number of papers regarding the design of an EMS for FCHEVs from 2014 to present. According to this figure, it is obvious that from 2019 onwards, the researchers have realized the importance of health awareness and increasingly started including this factor into the EMS design. In fact, the concept of health-awareness can be integrated into all the three ruled-based, optimization-based, and intelligent-based EMSs and enhance their efficiency and robustness. The existing strategies that have attempted to enhance the performance of a FCHEV through incorporating the health awareness can be fallen into three categories of prognostic-based, diagnostic-based, and systemic EMSs. This classification for health-aware EMSs is a new taxonomy introduced in this manuscript. Prognostic-based and diagnostic based EMSs, as is clear by the names, attempt to improve the performance by utilizing the health monitoring techniques. Systemic EMSs have a more holistic viewpoint and try to include some local control and management schemes, such as thermal control, water management, and so on, into the design of an EMS. Fig. 9 represents the explained conventional EMSs alongside the defined categories for health-aware EMSs. Hereinafter, each category of health-aware strategies is described, and their pros and cons are discussed.

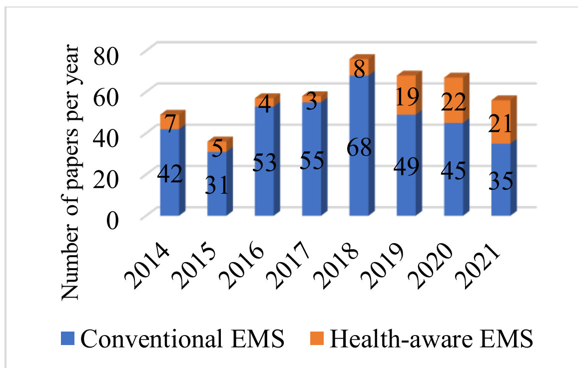

Fig. 8. The trend of conventional and health-aware EMSs in the literature

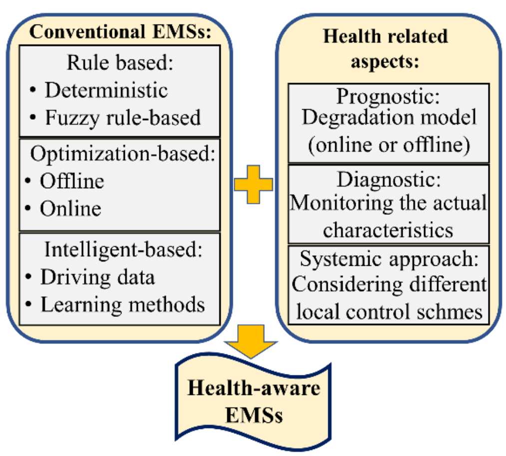

Fig. 9. Different types of conventional and health-aware EMSs

4.1. Prognostic-based energy management strategies

Normally, the objective of prognosis is to tune or develop a degradation model and then predict the performance attenuation accordingly. In this regard, all the EMSs that are based on prognostic methods or at least have used a degradation model for any of the sources are fit into prognostic-based EMSs. Fig. 10 shows the complete process of a prognostic-based EMS. From this figure, it is observed that some measured data are collected from the FC system and the ESS online or offline in phase 1. These measured data have two important usages. First, they can be used to directly calculate some parameters that the EMS requires (P_{Req}: requested power, battery SOC and SOP). Second, they are sent to a prognostic process, or just used to tune a degradation model already developed in the literature. In phase 2, the prognostic method or only the degradation models use the measured data and estimate the SOH of the sources, battery SOC and SOP, and the RUL. Battery SOC and SOP can also be directly calculated from measured data. The difference between the papers that use prognostic methods for estimating the required information and the ones that only use a degradation model or just measurement lies in the estimation accuracy of the characteristics. In fact, prognostic methods have been greatly improved and can lead to interesting and precise estimation in this respect. Finally, in phase 3, the calculated and estimated characteristics are fed into the EMS to distribute the power between the sources. Several papers have only used degradation models to enhance the durability of their strategies [101-139]. To take some examples, in [101], a MPC strategy is proposed to minimize the hydrogen consumption and degradation of power sources. In this work, the influence of on-off cycling, high loading, low loading, and transient loading are considered for the FC system degradation and a control-oriented model is used to estimate the capacity fade of battery pack. In [104], a predictive-based EMS is proposed by solely considering the battery degradation. A semi-empirical degradation model is used in this study to estimate the capacity fade. A number of manuscripts have also focused on the development of an EMS combined with online prognostic methods [140-145]. For instance, in [140], a sliding mode control EMS is proposed for a FC-SC hybrid system where the degradation of the FC system is quantified by a simple empirical model based on resistance and limiting current variations. The parameters of this model are estimated online by Cubature KF. In [141], particle filter is used to predict the RUL of the FC system. An EMS based on fuzzy logic and decision fusion is then used to distribute the power between the FC system and battery pack.

Table 3 summarizes the features of all the existing prognostic-based EMSs which have been designed in the literature so far.

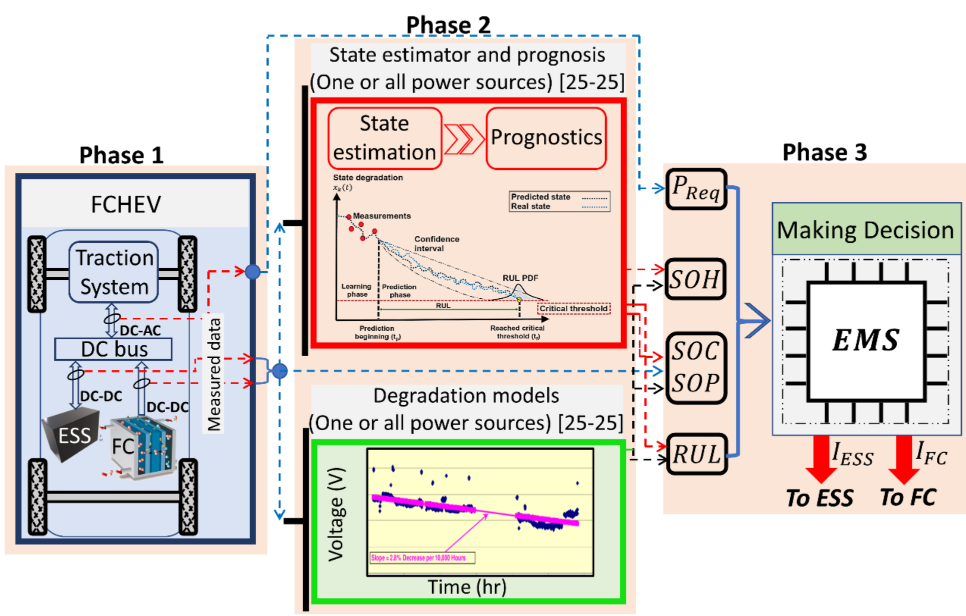

Fig. 10. The general structure of prognostic-based EMSs.

Table 3. Review of the prognostic-based EMSs (B.: battery)

EMS	Cost function	Health-awareness aspect (SOH)
MPC [101, 111, 112]	[101]: H2 & FC+B degradation [111]: System economy & FC+B degradation [112]: H2 & FC+B degradation & SOC penalty	[101, 111, 112]: FC+B degradation models (Offline)

Instantaneous optimization [102, 118]	[102]: Power loss of power sources [118]: H2 & FC+B degradation & SOC penalty	[102]: FC degradation model (Offline) [118]: FC+B degradation models (Offline)
PMP [103] [109] [122] [132]	[103]: H2 consumption [109]: H2 & FC power variation [122]: H2 & FC+B degradation & electricity consumption [132]: H2 & FC power variation & SOC penalty	[103, 109, 122]: FC+B degradation models (Offline) [132]: FC degradation model (Offline)
ECMS [105] [113] [139] [142] [143] [145]	[105]: H2 & FC+B degradation [113]: H2 & B equivalent consumption [139]: H2 & FC+B degradation & B equivalent consumption [142, 143]: H2 & FC+B degradation & SOC penalty [145]: H2 & B+SC equivalent consumption	[105, 113, 139]: FC+B degradation models (Offline) [142, 143, 145]: FC+B degradation models (Online by unscented KF)
Droop Control [107]	Voltage control	FC degradation model (Offline)
Game theory [108]	FC efficiency and SOC variation	FC degradation model (Offline)
Rule learning-based EMS [110]	H2 & FC+B degradation	FC+B degradation models (Offline)
Convex programming [115, 131]	[115]: Total energy cost & FC+B cost [131]: H2 & B+SC equivalent consumption	[115, 131]: B degradation model (Offline)
DP [116, 117, 127-130, 136]	[116, 117, 127]: H2 & FC+B degradation [128]: H2 & FC+B degradation & SOC penalty [129]: H2 & FC degradation & B equivalent consumption [130]: H2 & B degradation & B equivalent consumption [136]: H2 & FC degradation & SC+DC-DC costs	[116, 117, 127, 129]: FC+B degradation models (Offline) [128, 136]: FC degradation model (Offline) [130]: B degradation model (Offline)
Dual mode (optimization based) [119]	H2 & B equivalent consumption	FC+B degradation models (Offline)
Rolling optimization-based EMS [120]	H2 & FC degradation & B equivalent consumption	FC degradation model (Offline)
Optimized FLC [123] [138] [141] [144]	[123, 138]: H2 & FC+B degradation [141]: H2 & FC degradation & SOC penalty [144]: FC nominal power point and SOC penalty	[123, 138]: FC+B degradation models (Offline) [141, 144]: FC degradation model (Online by particle filter)
Heuristic EMS [124, 133]	[124, 133]: No cost function	[124]: B degradation model (Offline) [133]: FC degradation model (Offline)
Sliding mode control [140]	Current and voltage reference values	FC degradation model (Online by Cubature KF)
Performance consensus strategy [135]	[135]: Uniform FC performance state	[135]: FC degradation model (Offline)
LSTM [134]	H2 & FC+B degradation & B equivalent consumption	FC+B degradation models (Offline)
No EMS (Passive structure) [137]	No cost function	FC degradation model (Offline)

With all the favorable attributes of prognostic-based EMSs, they still remain challenging to be used in the FCHEVs. This is mainly due to the fact that these strategies are dependent on the degradation/ageing model of the electrochemical devices specifically PEMFC. Although researchers have made enormous efforts to model the degradation process in PEMFCs, this area needs further attentions particularly in dynamic conditions, such as vehicular applications.

4.2. Diagnostic-based energy management strategies:

As opposed to the prognostic-based EMSs in which the degradation model has a vital role, the key idea in diagnostic-based EMSs is to monitor the actual health state and make a decision accordingly. In this respect, all the EMSs that attempt to monitor the actual characteristics of the electrochemical devices online, rather than predicting them using degradation models, fall into the category of diagnostic-based EMSs. Fig. 11 illustrates the process of designing a diagnostic-based EMS. As is seen in this figure, the required characteristics for an EMS are provided using one of the three shown approaches (online state/parameter estimation, extremum seeking using perturb and observe (P&O), and NN-based models) and forwarded to the EMS to ascertain reliable reference signals. Some attempts have been made to estimate the behavior of the PEMFC using NNs and then use these characteristics in an EMSs [146, 147]. However, these models may become unreliable while facing new conditions and their online updating/retraining requires great amount of data. To overcome these shortcomings, the employment of an extremum seeking algorithm (ESA) based on P&O has been suggested in some studies to find the ME and/or MP points of a PEMFC system [148-151]. The extremum value is sought after by imposing the system input to a periodic perturbation signal, and then adjusting the input toward the extremum value based on the system input-output slope. In [148], different schemes (first-order, high-pass filter, and band-pass filter) of ESA are compared and concluded that the performance of the band-pass filter based ESA is preferred to enhance both the performance and durability of ESS. In [149], the authors put forward a multi-objective optimization problem based on extremum seeking to obtain the required levels of voltage regulation, ME, and MP. In [150], a fractional-order ESA is proposed to locate an extremum value of a static nonlinear system using a gradient optimization process. In [151], a global ESA is suggested to carry out a bidimensional optimization taking FC system net power and hydrogen consumption efficiency into account. Overall, the ESA-based strategies are interesting largely due to their simple application in an EMS formulation. However, when the concurrent identification of several operating points is needed, which is the case in online EMS applications, the complexity of these algorithms also rises. To evade the discussed issues regarding the black box models and ESA-based methods, a new paradigm has been suggested for an EMS formulation based on online state/parameter estimation algorithms. The leading notion is to employ a semi-empirical or ECM of the electrochemical device and update its parameters in real-time while the vehicle is under operation. The required characteristics, which are needed for the distribution of the power flow, are then extracted from the updated model and used in the EMS. Several manuscripts have introduced online estimation algorithms and used them in the design of EMSs [152-168]. To give some examples, in [167], Ettihir et al. have proposed the use of RLS method to extract the parameters of a current-dependent FC model, suggested by Squadrito et al. [38]. The voltage and power characteristics can be extracted from this model. In [159], the same estimation algorithm is used to update the parameters of a polynomial function representing the efficiency vs. current of the PEMFC and extract the ME point. It is concluded that compared to P&O, the proposed method leads to reduced tracking time and hydrogen consumption while making the PEMFC output power smoother. In [162], a comparative study of recursive maximum likelihood algorithm (RML) and RLS is performed using a semi-empirical PEMFC model, proposed by Amphlett et al. [169, 170], and concluded that RML is more robust against additive measurement noise. In [161], different PEMFC models and estimation methods are studied for EMS application. Furthermore, using RLS and KF, the performance of Squadrito and Amphlett models are compared and concluded that the multi-input model (Amphlett) is more accurate than the single-input one (Squadrito), and KF is slightly more precise than RLS. In [168, 171], online parameter estimation methods based on Lyapunov theory are derived to estimate the parameters of PEMFC models while guaranteeing the system's stability. The discussed papers in [159, 161, 162, 167, 168, 171] only show the potential of the online estimation algorithms for EMS application without integrating them into a strategy. To provide a systematic idea of the designed EMSs with online estimation algorithms, Table 4 gives a summary of the existing methods.

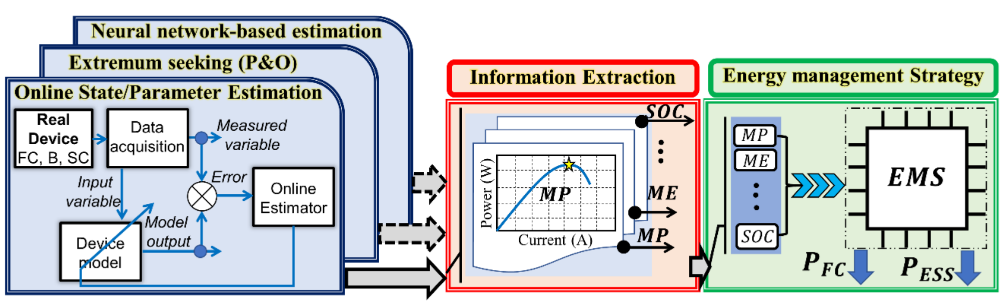

Fig. 11. The general structure of diagnostic-based EMSs.

Table 4. Summary of the designed diagnostic-based EMSs using online estimation algorithms (B: battery, Pol: polynomial, QP: quadratic programming).

EMS type	Power Sources	Online estimator	Estimated characteristics	Cost function	Reference
ECMS	FC, SC	RLS	FC (Pol): ME and MP points	H2 & SC equivalent consumption	[152]
ECMS	FC, Bat.	RLS	FC (Pol): ME range	H2 & B equivalent consumption	[153]
ECMS	FC, Bat.	KF	FC (Pol): H2 vs. power curve	H2 & B equivalent consumption	[154]
QP	FC, Bat.	KF	FC (semi-empirical): ME and MP points Bat.: $R_{internal}$, OCV	FC efficiency	[156]
Rule based	Multiple FCs, Bat.	KF	FC (semi-empirical): ME and MP points	--	[157]
Rule based	Multiple FCs	RLS	FC (Pol): H2 vs. power curve	--	[158]
Optimized FLC	FC, Bat.	KF	FC (semi-empirical): ME and MP points	H2 and FC degradation	[160]
PMP	FC, Bat.	Square root unscented KF	FC (semi-empirical): ME and MP points	H2 consumption	[163]
PMP	FC, Bat.	RLS	FC (semi-empirical): ME and MP points	H2 consumption	[164]
Rule based	FC, Bat.	RLS	FC (semi-empirical): ME and MP points	--	[165]
Optimal control	FC, Bat.	RLS	Vehicle mass estimation	Total energy	[166]

4.3. Systemic energy management strategies:

The main idea behind the systemic EMSs is to change the general component-level perception of researchers about FC while designing an EMS and direct to systemic design. In fact, the performance of a FC stack, in terms of power delivery and efficiency, relies on different operating points, such as power, temperature, pressure, humidity, and so forth. Perceiving the FC as a system provides several degrees of freedom for delivering the requested power since the stated operating parameters can be controlled in this manner. Several local management strategies for controlling each of the mentioned parameters can be developed to enhance the energetic performance of the system to the utmost. Therefore, a particular level of demanded power from FC can be provided by various combinations of these operating points and how to select the suitable combination for having an efficient performance is the duty of a systemic EMS. Fig. 12 presents the general structure of a systemic EMS which has a management level and a control level. Normally, in the management level, the reference signals are determined, and the control level is responsible for reaching these references by tuning the control variables. For instance, the required reference power from the FC system in a specific stack temperature can be supplied by controlling the current of the FC and the cooling fan duty cycle as the control variables. There are quite a few studies in the literature which have attempted to design a systemic EMS for a FCHEV. In [23], an EMS based on QP determines the required power from a FC stack (H-500 Horizon) and a concurrent current and cooling fan control is carried out to provide the power with the highest efficiency. This paper shows that systemic management enhances the efficiency by almost 4%. In [24], the influence of supplying the FC power by concurrent control of current and temperature over the performance of a rule-based EMS and an optimal EMS is investigated. It is concluded that compared to a conventional strategy which only tunes the FC current, the inclusion of temperature dimension has decreased the hydrogen consumption up to 5.3% and 4.1% in the rule-based and DP, respectively. In [172], an approach based on sliding mode variable structure control is proposed to supply the requested power from a H-300 Horizon FC considering the current and temperature operating parameters. In [173], a state machine based EMS in a FCHEV, composed of FC, battery, and SC, is combined with an optimal oxygen excess ratio control of the FC stack. This local control (oxygen excess ratio) maximizes the FC output net power. In [174, 175], a load-following based EMS is proposed in which the FC output power is controlled considering the fuel flow rate and the air flow rate. In [176], a multi-stack FC system is proposed for a FCHEV. In this work, the activation of each FC is based on the requested power from the vehicle and a thermal management technique. In [177], a systemic analysis of a PEMFC stack is performed considering the inlet temperature, pressure, air stoichiometry ratio, and coolant flow rate for a vehicular application. This analysis shows that air stoichiometry ratio and cooling fan operation are more essential for power consumption than cooling pump. In [178], the effect of external and internal humidification is studied on three different FCs of a road vehicle. The self-humidification method is declared as the most practical one for FCHEVs even though it needs precise control of the stack temperature. In [179], the effect of the operating parameters (temperature, fuel pressure, fuel flow rate, air pressure, and air flow rate) on the output voltage of a FC stack is scrutinized for electric vehicle applications. It is concluded that the temperature has a great impact on the FC performance followed by fuel pressure and fuel flow rate which have lower degrees of influence. In [180], an EMS based on PMP is developed for a FC-battery range extender vehicle. In this study, to enhance the overall performance of the system, FC balance-of-plant operating conditions optimization is performed to find an optimum path for the cathode inlet pressure and stoichiometry at different current densities and create a parametrized compressor map with optimum operating conditions. In [181], an EMS based on reinforcement learning is developed for a plug-in FCHEV where the efficiency of the FC system in terms of power and temperature and the efficiency of the battery pack in terms of power and SOC are considered for designing the strategy.

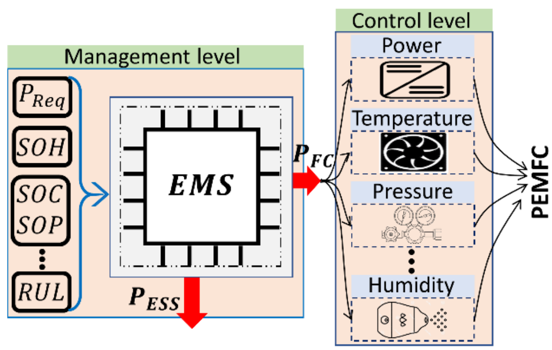

Fig. 12. The general structure of systemic EMSs.

5. Future perspectives:

Having discussed the existing methods regarding the online estimation of power sources (FC, SC, and battery) in a FCHEV and their integration into health-aware EMSs, it has become crystal clear that more efforts are required in this line of research and development. In fact, there is rich literature on designing conventional EMSs. However, the integration of health awareness factors into the EMS design has still a long way to go. Looking forward, some of the future research directions are shown in Fig. 13 and discussed hereinafter.

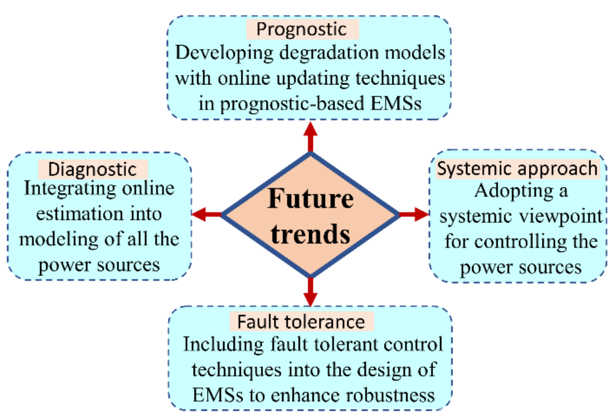

Fig. 13. The illustration of future trends for designing health-aware EMSs.

5.1. Promoting online estimation in prognostic-based energy management strategies:

As discussed in the prognostic-based EMSs section, most of the existing strategies in this category are based on offline degradation models of the power sources. In fact, developing a precise degradation model for the electrochemical devices is very demanding. Abundant research has been conducted on developing degradation models for FCs and batteries. However, due to variable operating conditions specifically in vehicular applications, a cohesive model considering different aspects and suitable for energy management applications has not been established yet. The utilized degradation models in the design of prognostic-based EMSs are mostly based on degradation rates. These rates are highly dependent on the variation of the driving cycle, technology of the tested FC stack, the set ambient conditions, and so forth. Therefore, the accuracy of the model cannot be assured in different conditions. One of the viable options in this respect is to integrate the online state estimation based prognostic techniques into the design of an EMS. In fact, these methods can provide some corrective feedbacks to adjust the parameters of the degradation models while the vehicle is under operation. Acquiring information about the actual degradation state of the FC system, as the main power source, and battery pack, as the secondary one, can make the successive decisions and actions more practical and relevant. In short, it will be of great interest to incorporate the up-to-second SOH prediction of the power sources into the decision-making process of an EMS in future studies. This can be done in the introduced framework in Fig. 10 of this paper utilizing online health estimators.

5.2. Promoting online estimation in diagnostic-based energy management strategies:

As discussed throughout the paper, another approach for developing health-aware EMSs is to diagnose the actual energetic characteristics of the power sources using some semi-empirical models without getting involved with developing a degradation model which is a complicated and time-consuming task. The existing diagnostic-based papers mainly discussed the employment of online estimation strategies for tracking the performance of the FC system. However, a FCHEV is an arrangement of different subsystems, such as PEMFC, battery pack, and SC. Each subsystem assumes significant responsibilities and their performance can be improved by precisely estimating their parameters. Considering the discussed points, it is clear that the PEMFC is not the only subsystem in a FCHEV that is in need of online estimation. As the FCHEVs come in different architectures with two or all the mentioned power/energy sources, it stands to reason to link the online estimation strategies of these sub-systems to the development of a health-aware and energy-aware EMS to obtain results which are closer to the real state of the components during their lifetime. While designing a diagnostic-based EMS, the online modeling of the PEMFC is required since it is the main power source and its ME and MP point of operation change by the time. Regarding the battery, output voltage decreases through time (capacity fade and resistance increase), and accordingly the battery SOC requires to be estimated online as it is an integral part of any EMS and is afflicted by the variation of the SOH. Concerning the SCs, it is reasonable to exclude the ageing of a SC from the online SOH estimation process as its lifetime is much longer than that of the vehicle and the other power sources (FC and battery). However, the online estimation of the SC SOC is still a missing factor while designing an EMS. Direct SOC calculation based on voltage measurement could have noticeable error owing to the occurrence of leakage currents, self-discharge, and side-effect reactions. To summarize, in future, the online state estimation of the all the on-board power sources should be considered and incorporated into the EMS design procedure with respect to the introduced framework in Fig. 11 of this manuscript.

5.3. Promoting the design of systemic energy management strategies:

The notion of adopting a systemic approach for developing multi-dimensional EMSs is an effective technique which has escaped the attention of many researchers. Only few attempts have been made in this line of work in the literature as previously discussed. This type of EMS requires a system-level perspective to develop a unified strategy including several local controllers. As discussed in this manuscript, the performance of a PEMFC stack, in terms of power delivery and efficiency, depends on several aspects, such as current, temperature, pressure, and so forth. Regarding the PEMFC as a system provides this opportunity to develop several local management strategies for controlling each of these aspects to enhance the energetic performance of the system to the utmost. Considering this point, future studies should develop EMSs that in addition to power distribution between the components can handle the required local control of the multi-physic components. That implies that not only the amount of required power but also how to reach this level of power from the FC stack is significant. Water management, pressure control, and thermal control are example of the local controllers that can be defined for a FC system while designing an EMS.

This idea can be also extended to the battery pack. Batteries are produced to work within particular temperature extremes, and they will stop working if there is no cooling system to keep it in a working range. Both high and low temperatures can deteriorate the overall performance of the battery and lead to a reduced lifespan. In case of vehicular applications, since the capacity and charge/discharge rate rise, the concerns related to the battery security become more important. Therefore, the use of a battery thermal management system seems to be necessary in a FCHEV to satisfy the request in higher power and improve the driving performance. The main point here is that the charge/discharge capacity of the battery is highly affected by temperature. This will further influence the performance of the vehicle as the discharge rate ascertain the acceleration performance of a FCHEV. Future EMSs should attempt to manage the use of FC and battery in a way to reach a compromise in the thermal performance of these components. Moreover, the addition of SCs to absorb the high dynamic peaks could be fruitful in this direction.

Another worth noting aspect is about the role of OETs in the development of local controllers for systemic EMSs. In fact, the complex structure of the electrochemical power sources makes the measurement of some internal parameters/states challenging and sometimes impossible. Accessibility to these states is necessary for designing precise controllers. Therefore, online observers that act like virtual sensors can be used for monitoring these states and performing the required control actions. To give some examples about the internal states which can be quantified by observers, water content in membrane, liquid saturation, oxygen, and hydrogen partial pressures can be mentioned.

5.4. Integrating fault tolerant control techniques into energy management design:

Fault tolerant control (FTC) is defined as the capability of a system's control to embrace any unanticipated malfunction while maintaining to provide the desired performance. In electrochemical power sources specifically FC and battery, fault occurrence is highly plausible due to the strong parameter coupling. Typically, FTC methods involve a diagnosis component that allows the detection and the separation of a fault, and a control part that is responsible for an optimal control strategy to find the best operating point to recover/mitigate the fault. In this regard, it can be stated that equipping an EMS with a FTC technique can undoubtedly enhance the robustness of the strategy in faulty operational conditions. Since the basis for including the diagnosis techniques into the design of an EMS was discussed under the diagnostic-based health-aware EMSs in this manuscript, a further step could be combining FTC techniques with the conventional strategies. Since few papers, if any, have considered this point while designing an EMS, it can be a great topic for future endeavors in this line of work.

6. Conclusion

The powertrain of a FCHEV is composed of two or more power/energy sources with different energetic characteristics. Hence, the design of an EMS is vital to enhance the performance of the vehicle in terms of fuel economy, lifetime, and reliability. Thus far, several EMSs, mainly based on invariable models, have been developed for FCHEVs. However, the performance of the powertrain subsystems (FC, battery, and SC) is impacted by the varying operating conditions, aging, degradation phenomenon, and so forth. From the reported results in the literature, ignorance of health adaptation can raise the hydrogen consumption from nearly 6.5% to 24% depending on the EMS. To this end, this paper aims at reviewing the use of heath monitoring techniques, which are good candidates to deal with the mentioned uncertainties, in the design of EMSs. In the first place, the existing modeling techniques for the electrochemical power sources are concisely studied as they have a crucial role in developing the health monitoring techniques and EMSs. Subsequently, a quick review of prognostic, diagnostic, and state estimation in each of the FC, battery, and SC is performed. Different ways for synthesizing the use of these algorithms in designing a health-aware EMS are then explored which have led to the introduction of prognostic-based, diagnostic-based, and systemic strategies. This is a new taxonomy for classifying the EMSs in FCHEVs. The fundamental principles, strengths, and weaknesses of each category are discussed. Finally, forthcoming trends in this line of work are presented for promoting future research endeavors.

Acknowledgements

This research was funded by Fonds de Recherche du Québec-Nature et technologies (FRQNT) [Bourses de recherche postdoctorale B3X, file number: 284914], Natural Sciences and Engineering Research Council of Canada (NSERC) [RGPIN-2018-06527 and RGPIN-2017-05924], and Canada Research Chairs program [950-230863 and 950-230672].

CRediT author statement

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