Review on Health-Conscious Energy Management Strategies for Fuel cell Hybrid Electric Vehicles: Degradation Models and Strategies

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Abstract

Considering the overwhelming pressure on worldwide demand of fossil fuels and the climate change caused by air pollution, hybrid electric vehicles have seen a promising future thanks to the development of renewable energy sources. Among various kinds of energy sources that have been used in hybrid electric vehicles, lithium-ion battery and proton exchange membrane (PEM) fuel cell exist to be the most favorable ones owing to their high energy density and power density. However, the degradation issues of the energy sources tend to be neglected when designing the energy management strategies for the hybrid electric vehicles. Concerning existing literature, degradation modelling methods of lithium-ion batteries and PEM fuel cells are reviewed and the possibility of integrating them into health-conscious energy management is discussed. Besides, a variety of energy management strategies that have taken the influence of degradations into consideration are reviewed and classified. The contribution of this paper is to investigate the possibility of developing a health-conscious energy management strategy based on accurate estimation of degradation to improve the durability of the system.

Keywords:
degradation modelling, energy management strategy (EMS), hybrid electric vehicle (HEV), lithium-ion battery, PEM fuel cell

Nomenclature

Abbreviations

HEV	Hybrid electric vehicle
PEM	Proton exchange membrane
EMS	Energy management strategy
SOC	State of charge
DOD	Depth of discharge
RUL	Remaining useful life
SEI	Solid Electrolyte Interface
EIS	Electrochemical impedance spectrometry
ECMS	Equivalent consumption minimization strategy
EDMS	Equivalent degradation minimization strategy
PSO	Particle swarm optimization
PMP	Pontryagin's minimum principle
MPC	Model predictive control
SVM	Support vector machine

Physics symbols

δ_{film}	SEI film thickness	cm
M_p	Average molecular weight of the compounds of SEI	$-$
a_n	SEI surface area	cm^2
ρ_p	Average density of the compounds of SEI	kg/cm^3
F	Faraday constant	$-$
J_S	Side reaction current density	A/s
R_{gas}	Gas constant	$-$
T	Absolute temperature	K
R	Internal resistance	Ω
Q	Battery capacity	$Ampere \cdot hour$
E_a	Activation energy	J/mol
Ah	Charge throughput	$Ampere \cdot hour$
V_{stack}	Fuel cell stack voltage	V

1. Introduction

At the beginning of 21st century, the United States National Academy of Engineering (NAE) has identified the electrification as the greatest engineering achievement of the 20th century [1]. In recent years, the electrification in the automotive field is making a change to the dominant place of internal combustion engines in vehicle's propulsion system. Given the overwhelming pressure on worldwide demand of fossil fuels and the climate change caused by air pollution, various types of new energy vehicles exist to be a promising and practical solution for the upcoming social and environmental problems. Fuel cell hybrid electric vehicles (HEVs), which use fuel cells as the main energy source and battery packs as the energy storage devices, have generated considerable interests recently. Fuel cells and battery packs are proved to be efficient when working together to provide a zero-emission propulsion in electric vehicles. In a battery/fuel cell HEV, the hydrogen fuel is converted into electricity by the on-board fuel cell system and provides most energy needs of the vehicle, while the on-board batteries are used to store regenerated energy and to provide peak power demand. This is because the fuel cell prefers to run in stable conditions and can reach its maximum efficiency at partial load, while the battery can run at high current to make up the weak points of the fuel cell [2, 3]. Different to pure electric vehicles (battery-only electric vehicles), the battery system in fuel cell HEVs could be reduced in size and as a result, it decreases the overall weight and cost of the vehicle [3, 4].

One of the possible configurations of battery/fuel cell HEVs is shown in Figure 1 (a). In this series hybrid configuration, the fuel cell is coupled to the batteries via DC/DC converters and works as a range extender to increase the driving distance and level up the speed. The battery system supplies the power to the traction system directly and it is usually a non plug-in one that is charged by the fuel cell with the continued supply of hydrogen [4, 5, 6]. But if it is needed, the battery system could also be a plug-in one charged by the grid [7, 8, 9, 10]. Another configuration is in parallel, as shown in Figure 1 (b). In this case, the fuel cell system supplies the power to the electric motor directly and the size of the battery system is reduced since it is only in charge of providing the transient power demand and absorb the regenerative braking energy. This kind of topology is commonly found in the literature [11, 12, 13, 14, 15, 16, 17, 18].

Hybrid configuration usually goes with management problems, which should be solved to determine how the energy sources operate with each other. A strategy that controls the energy sources to feed the electric motor in HEVs is called an energy management strategy (EMS). EMSs are usually designed to achieve certain objectives, such as minimizing the consumption and economic cost, optimizing the sizing of energy sources, improving the driving conditions for drivers, etc. In recent years, health management of energy sources has taken significant place when developing EMSs since the degradation of energy sources cannot be neglected [19]. Batteries and fuel cells may suffer from different degrees of degradation during storage and under operation modes. Their current lifetime cannot satisfy the commercial need. For example, fuel cell stacks need roughly a 5000-hour life to enter the market for light-duty electric vehicles while they can currently reach less than 2000 hours [20]. Therefore, health-conscious energy management strategies have generated great interests and numerous studies have proved that it is possible to exercise an active control over the operation and in turn to mitigate the deleterious effects of the degradation [21, 22]. Various EMSs have been applied to vehicle applications and the classification of them can also be found in [21, 23, 24, 25, 26].

However, heath-conscious energy management is still particularly challenging for the following two reasons. First, although the degradation of energy sources are considered in some EMSs, most of the researchers just set boundaries to battery's state of charge based on data-sheets or roughly eliminate the operation dynamics of the fuel cell [9, 16]. This kind of strategy is not accurate and cannot reach the goal of improving the durability due to the lack of the knowledge of the real-time degrading situation. Although researchers have made many efforts to precise the degradation model [27, 28, 29], the conflict between dealing with model dynamics and the complexity of the strategy needs further discussions. To face this challenge, prognostics and health management (PHM) has existed as a promising subject in evaluating the energy source degradation and estimating the remaining useful life (RUL). Various works that perform prognostics on both batteries and fuel cells in order to capture their ageing phenomenon could be found in [30, 31, 32, 33]. However, prognostics only provides a chance to estimate the RUL by quantifying the degradation but the post-decision part hasn't been well investigated yet. Further attention should be paid to the management aspect of PHM, i.e. what could be done after a prognostics prediction is produced. Therefore, a delicately designed EMS based on accurate degradation estimation is demanding.

Second, health-conscious energy management is a non-trivial problem with multiple inputs and various state and control constraints. Numerous researches have been done to solve multi-objective EMSs. For example, in [34], degradation phenomenon is calculated as economic costs and optimized by formulating an equivalent energy cost function. Ref. [35] defines the cycling degradation model of the battery and supercapacitor and optimizes a multi-objective fitness function by generic algorithm. In order to improve on-line operation, Yu et al. merge the parameters of fuzzy logic controller according to the optimization results of non-dominated sorting genetic algorithm-II [36]. However, how one objective should be compromised to the others is hard to determine and the optimality of on-line EMSs can hardly reach the level of off-line calculation.

There have been a number of literature surveys on modelling the degradation of batteries and fuel cells [29, 37]. The existing review papers have focused on classifying various degradation models into different categories and qualifying their effectiveness. They rarely think about the feasibility of integrating them into HEV energy management. In [38], authors have pointed out that the health state estimation of the battery is usually a separately task and there is a lack of numerical relationship between the time behavior of physical parameters and its state of health. Moreover, no one reviews fuel cell degradation models

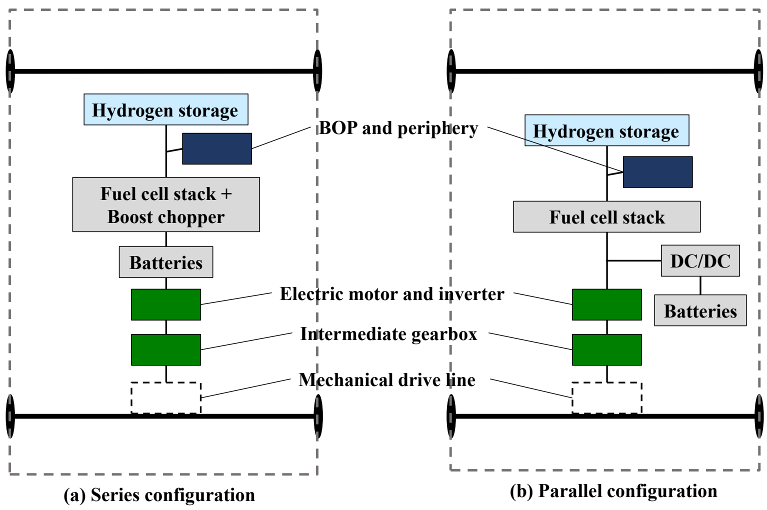

Figure 1: Battery/fuel cell hybrid propulsion: series configuration and parallel configuration

for vehicle application. Therefore, this paper tends to fill this gap, which contributes to review not only the existed degradation modelling methods of both batteries and fuel cells in HEV applications but also the existed health-conscious EMSs that consider the energy source degradation using different approaches. The idea of developing an EMS based on prognostics is proposed and believed to be a meaningful and promising solution to the health management of the hybrid system.

The rest of this paper is arranged as follows: degradation mechanisms and various degradation models of batteries and fuel cells are reviewed in Section 2 and Section 3, respectively, which give a basis for developing health-conscious EMSs for battery/fuel cell HEVs. Taken into consideration the degradation phenomenon, various health-conscious EMSs in the existing literature are classified and discussed in Section 4, together with some open challenges and expected solutions. Finally, conclusions and perspectives are given which clarify the possible study orientations in this field.

2. Lithium-ion battery degradation modelling

Lithium-ion batteries are competitive in vehicle applications thanks to their high energy density and high power density. They have also shown good lifespan attributes without any memory effect. However, the health of lithium-ion batteries can be affected by various affects. The capacity fade and impedance raise of an ageing lithium-ion battery will lead to the reduction of its power output [29]. Figure 2 shows the operation principle of a lithium-ion battery, which consists of a cathode (positive electrode), an anode (negative electrode) and an electrolyte as its conductor. The cathode is of metal oxide while the anode is of porous carbon. During discharge, the ions flow from the anode to the cathode through the electrolyte and separator. The charging process reverses this direction and the ions flow from the cathode to the anode. The change happening at the electrode/electrolyte interface is the most dominant ageing phenomenon of the battery, which is caused by Solid Electrolyte Interface (SEI) formation, shown in the zooming part of Figure 2. The continuous growth of SEI leads to the change of surface porosity, the decrease of active surface and the deposition of metallic lithium, resulting in the loss of capacity and power capability. In order to avoid repetition, other phenomenon regarding to battery's ageing has been summarized in Table 1.

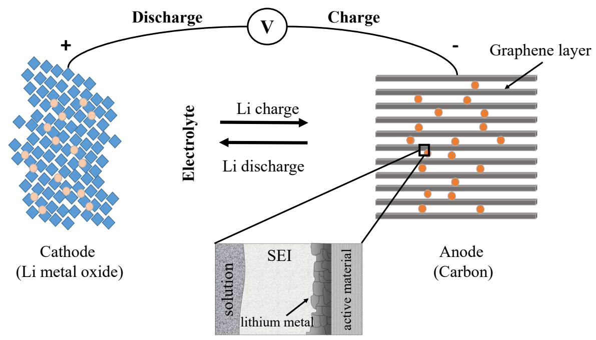

Figure 2: Operation principle of a lithium-ion battery

Since lithium-ion battery is such a complex system that its ageing process is even more complicated, accurately modelling and estimating its degradation is of great significance before developing a health-conscious EMS. Based on the analysis of battery's ageing mechanisms above, different degradation modelling and estimation methods are studied in this section. Some of them are electrochemical models which are closely related to the chemical reactions happening inside the battery. This kind of model is accurate but complicated and difficult to apply in practice. Others are empirical models which can be obtained by fitting experimental data. They are used to estimate the health state of the battery and predict RULs. However, it is in-

Table 1: Summary of ageing phenomenon of lithium-ion battery

Components	Causes	Phenomenon	Results
Anode	Overcharging; very high state of charge (SOC);	Intercalation of solvent/ peeling of graphite/ cracking;	Loss of capacity (loss of active material, loss of lithium);
Anode	High temperature; high SOC;	Dissolution of electrolyte (cathodic oxidation/ anodic reduction); dissolution of binder;	Loss of capacity; loss of power capability;
Anode	High current; high depth of discharge (DOD);	Growth of SEI/ change of surface porosity;	Growth of impedance; loss of power capability;
Anode	High temperature; high SOC;	Decrease of active surface because of continuous growth of SEI;	Growth of impedance; loss of power capability;
Anode	Low temperature; high current; bad design of cells;	Deposition of metallic lithium/ formation of SEI;	Loss of capacity; loss of power capability (loss of lithium);
Anode	High current; high DOD;	Loss of contact active mass particles because of volume change;	Loss of capacity;
Anode	Low SOC; high DOD;	Corrosion of conductor;	Loss of power capability (over-voltage); growth of impedance;
Cathode	Storage condition;	Structural disordering;	Loss of storage places for lithium;
Cathode	High temperature; high SOC;	Migration of soluble species;	Loss of capacity by firm formation on anode;
Cathode	High temperature; high SOC;	Electrolyte decomposition;	Loss of power capability;
Cathode	Low SOC; deep discharge;	Corrosion of conductor;	Loss of power capability (overvoltage); growth of impedance;

evitable that empirical models have the problems of inaccuracy and huge dataset. Therefore, researchers start to place more attention on finding a semi-empirical model, which combines the theoretical aspects with data fitting. This kind of model is more implementable compared to electrochemical ones and at the same time, more accurate than empirical ones [29]. The following part of this section has roughly reviewed these modelling methods according to the output of the models. This work may not be a complete one with an exhaustive survey on all existing battery degradation models but it is committed to finding practical ones that can be used in the energy management of HEVs.

2.1. SEI film thickness model

From an electrochemical point of view, the cell degradation of the battery is, to a large extent, due to the loss of lithium on the SEI. Therefore, researchers have proposed to use the SEI film formation model to symbolize the degradation degree of the battery [19, 36]. The change of the film thickness is written as:

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

where δ_{film} is the film thickness, M_p is the average molecular weight of the SEI layer's compounds, a_n is the specific surface area, ρ_p is the average density of the compounds, F is Faraday's constant and J_S is the side reaction current density calculated by Tafel equation [19]:

$$J_S(x,t) = -i_{0,s} a_n e^{\frac{-0.5F}{R_{gas}T}\eta_S(x,t)} \quad (2)$$

where $i_{0,s}$ denotes the exchange current density for the side reaction, R_{gas} is the universal gas constant and T is the temperature. η_S represents the side reaction over potential, calculated by:

$$\eta_S(x,t) = \phi_1(x,t) - \phi_2(x,t) - U_{ref,s} - \frac{J_{tot}(x,t)}{a_n} R_{film}(x,t) \quad (3)$$

where ϕ_1 and ϕ_2 represent solid and electrolyte potentials, $U_{ref,s}$ denotes the equilibrium potential of the solvent reduction reaction, J_{tot} is the total intercalation current calculated as a sum of intercalation current in anode and R_{film} is the resistance of the film.

However, this model consists of a large number of state variables and a large set of non-linear algebraic constraints, which brings a heavy burden for calculation [39]. To simplify the calculation, Forman et al. have proposed to linearize the constraints by a quasi-linearization method and a family of analytic Padé approximations has been used to reduce the number of state variables [40]. The implementation of this simplification enables real-time operations without a trade-off on the system accuracy.

2.2. Internal resistance model

Rather than using an electrochemical model, the internal resistance of the battery can be estimated by equivalent circuit models. As shown in Figure 3, the model with one ohmic resistance and two RC brunches is commonly used. For example, Remmlinger et al. have proposed to use this equivalent circuit to estimate the internal resistance and derive a temperature-related degradation index calculated from the increase of battery's internal resistance [41]. The index k_d is solved by the equation:

$$R_{i,actual} = k_d R_{i,new}(T) \quad (4)$$

where i is the time step, R denotes the internal resistance and the actual resistance is calculated by identification method using terminal voltage and the measured current. The idea is to calculate the proportion factor between the theoretical resistance of a new battery cell under actual temperature and the actual internal resistance [41]. An exponential expression is used to calculate the theoretical resistance value related to the temperature:

$$R_{i,new}(T) = ae^{-bT} + c \tag{5}$$

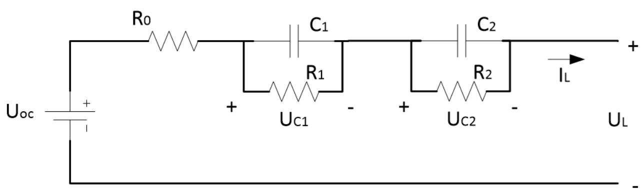

Figure 3: Equivalent circuit of a battery cell

Besides, Stroe et al. have found the dependence of the battery's internal resistance on its storage time, SOC level and temperature [28]. They used a two-step fitting procedure to develop the model for 2.5 Ah LFP/graphite battery cells with all the three aspects:

$$R = (a \cdot e^{\alpha \cdot T}) \cdot (b \cdot SOC^{\beta}) \cdot t \tag{6}$$

where a, b, α and β are the fitting results.

In fact, the internal resistance of the battery can also be estimated through filter algorithm with the help of the equivalent circuit. A broad variety of state estimation methods were proposed and dual extended Kalman filter (EKF) is one of the key scenarios [42, 43, 44]. Instead of observing only the state variables, the internal resistance is regarded as a parameter, which can also be estimated through tracking the system performance [44]. However, the effectiveness and adaptability of this method are highly dependent on the credibility and robustness of the prescribed battery models [45].

2.3. Capacity degradation model

The capacity of a battery refers to how much electrical charge that the battery can hold in its fully charged state. When the capacity fades to the threshold, usually 20%-30% of its original value, batteries are believed to be not able to operate their normal mode and should be replaced [46].

As battery's capacity is the most widely used indicator of battery's state of health (SOH), numerous approaches of capacity estimation and prediction have been proposed in the literature. He et al. have experimentally found that the sum of two exponential functions can well describe the capacity degradation trends of several different batteries, which is frequently used in the studies of battery prognostics [47]. He et al's model is expressed as:

$$Q = a \cdot exp(b \cdot k) + c \cdot exp(d \cdot k) \tag{7}$$

where Q denotes the battery capacity and k denotes the full charge-discharge cycle number.

Xing et al. have compared He et al.'s model with another capacity degradation model in the form of polynomial regression. Particle filter estimation results have shown that the exponential model had better predictive performance [48]. Base on that, the authors have developed another model that have shown an even better regression characteristic over the whole battery life. The model is expressed as [49],

$$Q = \gamma_1 \cdot exp(\gamma_2 \cdot k) + \gamma_3 \cdot k^2 + \gamma_4 \tag{8}$$

However, models in prognostics works are usually verified through the degradation data with regular charge/discharge cycles. When it comes to vehicle applications, randomized charge and discharge process should be considered due to uncertain driving conditions. In order to quantify this kind of capacity fade, semi-empirical models are then proposed in the literature to take more physical parameters into consideration, such as SOC, DOD, Ah throughput, current rate, etc. For example, Wang et al. have carried out the battery ageing tests under different DODs (10%-90%), temperatures (-30°C-60°C) and discharge rates (C/2-10C) [50]. To demonstrate the capacity loss, a power law equation has been adopted with related to time, charge throughput and an Arrhenius correlation of temperature, which is expressed as:

$$Q_{loss} = B \cdot exp(-(\frac{E_a + m \cdot C_{rate}}{RT}))(Ah)^z \tag{9}$$

where B is a pre-exponential factor, E_a is the activation energy, m is the compensation factor for C-rate and Ah is the total charge throughput. This model can also be used to estimate the SOH of the battery [51] and as a battery life indicator to study the degradation issues in vehicle applications [52, 53, 54]. To further improve the accuracy, the parameter B in the above equation has been introduced as a function of SOC in [27], which extends the model to be SOC-related. Similarly, using self-organizing maps, Fernandez et al. have yielded another semi-empirical capacity fade model, in which both temperature and DOD are identified to be the most related aspects of degradation [55]. In order to study its ageing phenomenon under a realistic vehicle driving cycle, Cordoba-Arenas et al. add another parameter into this model, which is the ratio of charge depleting time to total driving time, $\frac{t_{CD}}{t_{CD}+t_{CS}}$ [56].

However, Baghdadi et al. pointed out that Ah-throughput could lead to mistakes in separating calendar ageing and cycle ageing [57]. Therefore, a total ageing expression with only one ageing rate based on Dakin's degradation approach was proposed and tested over three different temperatures (30°C, 45°C and 60°C) with three different SOC levels (30%, 65% and 100%) for calendar ageing and four ageing factors including current, charge throughput, temperature and DOD for cycle ageing. The ageing rate k is express as:

$$k = e^{(a(T) \times I)} \times e^{\frac{cSOC}{a}} \times e^{\frac{d}{a}} \times e^{\frac{-b}{aT}} \tag{10}$$

The capacity is calculated by:

$$Q = Q_0 \cdot exp^{(\pm kt^z)} \tag{11}$$

where the time-dependent parameter z is determined by fitting the logarithm of battery capacity fade according to (11) and it varies with different kinds of batteries. Similarly, Schmalstieg et al. have considered the calendar ageing and cycle ageing separately with different parameters [58]. The normalized capacity is expressed as:

$$Q = 1 - \alpha(T, V) \cdot t^z - \beta(SOC, I, V) \cdot \sqrt{Ah} \tag{12}$$

where α is the calendar ageing coefficient related to the temperature and voltage, while β is the cycle ageing coefficient related to SOC, current, I and voltage, V.

Although semi-empirical models complete the problem by adding physical interpretations of the aging sources, the drawback is that they are highly dependent on the design of ageing experiments [57].

2.4. Residual lifetime model

Estimating the residual lifetime of the battery is another approach to indicate the degradation degree if same conditions were maintained during its lifetime [29]. Some researchers have proposed to use *rainflow counting technique* to estimate the lifespan of the battery [34, 35]. The model is established based on cycle numbers and DOD. The battery degradation is accumulated by counting the swapping SOCs. For example, the effect of cycling is considered in [35] where the rainbow algorithm records the number of charge/discharge cycles with different values of DOD until the end of life. The battery lifetime (L) is calculated by:

$$L(year) = min\Big[L_{nom} \cdot \frac{1}{\sum_{j=1}^{9}(k \cdot 365/L_j)}\Big] \tag{13}$$

where L_{nom} is the nominal value of battery's cycle life with no degradation, k is the counted charge/discharge cycle number according to the rainbow algorithm and L_j is the pre-defined number of life cycles for nine different values of DOD.

Besides, an empirical lifetime prediction model have been proposed in [59] takes into consideration the influence of temperature, SOC as well as DOD, written as:

$$\frac{\Delta L_1}{L} = \int \frac{1}{8760 \cdot L(T + R \cdot \mid P(t) \mid)} dt + \frac{t_{max} - t_{ch}}{8760 \cdot L \cdot T} - \frac{t_{max}}{8760 \cdot L(P_{min} \cdot R + T)} \tag{14}$$

$$\frac{\Delta L_2}{L} = \frac{m \cdot SOC_{avg} - d}{CF_{max} \cdot 15 \cdot 8760} \tag{15}$$

$$\frac{\Delta L_3}{L} = \frac{E_{T,used} - E_{T,base}}{E_{TL}} \tag{16}$$

Equation (14) denotes the temperature-related degradation where P is the charging power. L denotes either the power lifetime or the capacity lifetime which is inversely proportional to the Arrhenius relationship ($r = A \cdot e^{-E/kT}$). The second term and the third term indicate the life expense of no charging plugging in and slow charging, respectively. Equation (15) suggests the SOC-related degradation where CF_{max} is the maximum capacity fade at the end of life and m and d are tuned parameters. Equation (16) is the DOD-related degradation where E_{TL} is defined as the lifetime energy throughput, $E_{T,used}$ is the total change in the remaining energy throughput, and $E_{T,base}$ is the minimum energy throughput required to recharge the battery [59]. This modelling method has also been used in [60] as an analysis tool to demonstrate the effectiveness of the designed EMS.

2.5. Synthesis

Since batteries in HEVs usually have a limited life, health monitoring of battery is of considerable importance in the improvement of the durability of the system. Numerous studies have been done to evaluate the health state of the battery and to quantify the degradation in order to implement health management, as summarized in Table 2. In addition to the above mentioned battery degradation models, some researchers have also transferred the degradation of battery into the economic cost of the system. This kind of method can reduce the number of state variables and make the multi-objective problem into a single-objective one but the accuracy is sacrificed to some extent.

Nevertheless, battery's ageing models on an experimental scale or a simulation scale are insufficient to describe the battery in actual use because the power profiles in automotive applications are completely random. Well-designed ageing tests are helpful in developing models and saving time and costs. However, they can hardly cover all operating conditions. Therefore, in order to develop an effective health-conscious EMS, modelling and estimating battery's ageing performance is one of most crucial problem to solve. Using the same structure of this section, next section gives an introduction to PEM fuel cell as well as its degradation modelling methods.

3. PEM fuel cell degradation modelling

PEM fuel cell is widely used in vehicle applications since it has shown high power density, relatively lower operating temperature (60-80 °C) and low corrosion compared to other types of fuel cells [62]. According to Jouin et al., "PEM fuel cell system" refers to a PEM fuel cell stack and all its auxiliaries (reactant storages, pumps, etc.), while the stack is the part which converts the energy and is referred as the fuel cell [63]. The stack contains several cells and one cell contains different components, namely, electrodes, membrane, gas diffusion layer (GDL) and bipolar plate, as shown in Figure 4. All of these components may suffer from different processes of degradation during usage and the degradation mechanisms on each component are summarized and listed in Table 3. However, degradation happening on each area of the stack cannot reach the same degree, for example, cells near the edges tend to degrade faster [64]. Besides, if we consider degradation on the component level, the degradation between component and auxiliaries cannot be covered and the parameters are hard to obtain. Therefore, fuel cell degradation is generally modelled on the stack level. Various modelling methods have existed in the literature based on its ageing mechanisms.

Similar to the modelling of battery's degradation, various data-driven methods and physical model-based methods are

Table 2: Summary of various battery degradation modelling methods

Model output	Modelling method	Advantages	Disadvantages
SEI film thickness model [19, 36, 40]	Electrochemical model	Accurate with theoretical interpretations;	Complicated; difficult to determine the parameters and their ranges;
Internal resistance model [28, 41]	Electrochemical model/ Equivalent circuit model	Calculated by the instantaneous behaviour of the battery;	Less accurate than the electrochemical models;
Capacity degradation model [27, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 61]	Empirical/ Semi-empirical model	Easy to implement; on-line and close-loop;	Need of large experimental dataset; parameters need to be tuned each time with the changing of operating conditions; heavy computational burden;
Residual life model [34, 35, 59, 60]	Semi-empirical model	Easy to implement; moderate complexity;	Sensitive to operating conditions; least accurate;

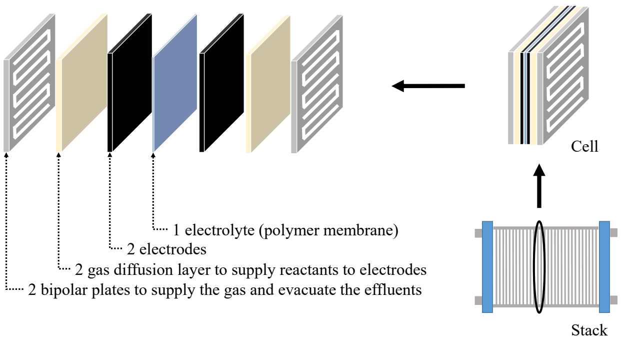

Figure 4: Components in a PEM fuel cell stack

used when estimating the degradation of PEM fuel cell. Data-driven methods depend on the features extracted from the data but once the operating condition changes, the parameters need to be adjusted from time to time [65, 66]. Physical models consider the internal reactions of fuel cell's performance degradation, such as the decline of carbon support, the surface area loss of Pt, etc. However, the degradation process in vehicle applications is much more complex and hard to be expressed by a theoretical model and the identification of the inner parameters is difficult to realize [67, 68]. The rest part of this section has reviewed several modelling methods that have been applied in vehicle applications. The purpose is to find the most effective and implementable methods that could be used to develop an EMS to improve the health management of the fuel cell.

3.1. Stack voltage degradation model

The stack voltage drop of the fuel cell is the most principle change so that the output voltage is widely used to demonstrate the degradation phenomenon [16]. Pei et al. have proposed to use the cycle information to calculate the stack voltage degradation, expressed as [69]:

$$V_{stack} = V_{rate} \cdot D_{fc} \tag{17}$$

$$D_{fc} = k_p(P_1 n_1 + P_2 n_2 + P_3 t_1 + P_4 t_2) \tag{18}$$

where D_{fc} is the degradation rate, k_p is the accelerating coefficient, P_1-P_4 are the degradation rates resulting from load change, start/stop, idling and high power demand, respectively, and n_1, n_2, t_1, t_2 denotes the times of load change, the times of start/stop switches, the time for idling and the time of high power demand, respectively. This model tries to contain the driving conditions in the modelling of fuel cell degradation process. For example, on the electrodes, low current may cause degradation in the catalyst layer while frequent transition of start-up and shut-down and fuel starvation may cause carbon corrosion on the carbon support layer. Chen et al. and Xu et al. have used this model with the real running data of a PEM fuel cell vehicle to analyse the fuel cell's degradation under different driving conditions [70, 71]. However, once tuning of the parameters of this model only works for a specific driving cycle so that it is hardly applicable to general cases.

Fletcher et al. have specified the influence of demanded power on degradation causes and calculated the degradation rate which penalized stack voltage according to the change of power demand [72]. For example, following equations have represented the proportion of fuel cell's performance drop:

$$D_1 = \begin{cases} \frac{1}{n_{max}} & \text{,if } P_{FC,t+1} > 0 \wedge P_{FC,t} < 0 \\ 0 & \text{,otherwise} \end{cases} \tag{19}$$

$$D_2 = \begin{cases} \frac{1}{t_{max}} \times \frac{P_{FC}-0.8P_{max}}{0.2P_{max}} & \text{,if } P_{FC} > 80\% P_{max} \\ 0 & \text{,otherwise} \end{cases} \tag{20}$$

where n_{max} denotes the maximum start/stop switches estimated by the manufacturer, P_{max} denotes the rated power and t_{max} is the maximum lifetime of the fuel cell under P_{max}. D_1 have penalized stack voltage whenever the demanded power drops below $0W$, which represents the degradation causing by non-uniform fuel distribution due to fuel cell's start-up/shut-down cycling. Another penalty D_2 happens when the demanded power is over 80% of the rated value and is assumed to be linear. This degradation rate represents the reactant starvation and thermal degradation of membrane causing by successive high power demand [73].

Besides, Ettihir et al. have proposed to use a semi-empirical model to present the degradation of the stack voltage by measuring both the current and the voltage of the fuel cell [15, 74]. The model is represented as:

$$V_{stack} = V_0 - b\log(i_{fc}) - ri_{fc} + \alpha i_{fc}^{\sigma}\log(1-\beta i_{fc}) \tag{21}$$

Table 3: Major failure modes of different components in PEM fuel cells (Source [37, 63])

Component	Functions	Failure mode	Causes
Membrane	Allow the protons transport from the anode to the cathode; separating the fuel from the air;	Mechanical degradation	Mechanical stress due to non-uniform press pressure; inadequate humidification or penetration of the catalyst and seal material traces;
		Thermal degradation	Thermal stress; thermal cycles;
		Chemical/ electrochemical degradation	Contamination; radical attack;
Electrodes	An electrical conductor used to make contact with the nonmetallic part where electrons leave and enter; the carbon support allows the nanoparticles to have a high dispersion and provides a porous structure electronically conductive;	Loss of activation	Sintering or dealloying of electrocatalyst;
		Conductivity loss	Corrosion of electrocatalyst support;
		Decrease in mass transport rate of reactants	Mechanical stress;
		Loss of reformate tolerance	Contamination;
		Decrease in water management ability	Change in hydrophobicity of materials due to Nafion or PTFE dissolution;
GDL	Allow the reactant to diffuse from the flow fields to the active sites;	Decrease in GDL structure	Degradation of backing material; carbon corrosion;
		Decrease in water management ability	Mechanical stress; change in the hydrophobicity of materials;
		Conductivity loss	Corrosion;
Bipolar plate	Isolate cells and conduct current between cells;	Conductivity loss	Corrosion; appearance of a resistive surface layer;
		Fracture/ deformation	Mechanical stress; thermal cycles;
Sealing gasket	Separate the hydrogen from the air; avoid leaking out of the gas;	Mechanical failure	Corrosion; mechanical stress;

where V_0 denotes the open circuit voltage, b denotes the Tafel slope, r denotes the ohmic resistance and β denotes the inverse of the limiting current. α is a parameter related to diffusion mechanism while σ is related to the water flooding phenomena. Since the identified model is a semi-empirical one, a trade-off is made between its physical meaning and calculation cost.

3.2. Impedance estimation based on EIS

Electrochemical impedance spectrometry (EIS) is a powerful tool to characterize the phenomenon inside the fuel cell and evaluate the fuel cell degradation [75]. EIS is carried out by adding a small sinusoidal perturbation on the nominal current and the impedance is calculated as a ratio between the response and the perturbation. Compared to polarization, the total energy and experimental duration of EIS measurement are significantly reduced, which makes it a promising tool for estimating the performance of the fuel cell without invasion [76]. Different operation conditions or different degrees of system ageing will lead to the change of spectrum shape. To demonstrate that change, Nyquist plots are widely used to indicate the degradation by the derivation of the arcs. Using EIS together with Nyquist plots has made it possible to characterize PEM fuel cell and to study its static and dynamic behaviors regarding performance losses. Figure 5 gives an example of a group of impedance plots, which are recorded during the ageing tests on a fuel cell stack. Using the extracted feature from the EIS plots, one can estimate the operation time of the fuel cell stack, which could be regarded as indicator of its health state [67].

Cadet et al. [76] have proposed the guidelines of using EIS as a diagnostic tool regarding flooding and drying faults of fuel cells and to analyse experimental data with Bayesian networks. Moreover, using EIS with Nyquist evolution plots, Hissel et al. have selected two values (the difference between polarization resistance and internal resistance of the considered fuel cell

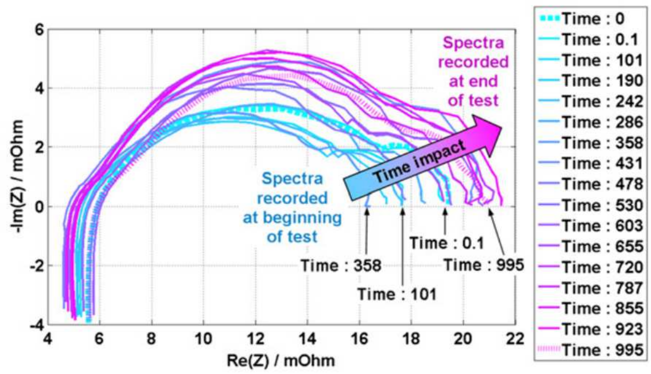

Figure 5: Evolution of the impedance spectra [67]

stack and the maximal absolute phase value of the Nyquist plot) from the Nyquist plots to indicate the fuel cell degradation [77].

3.3. Remaining useful life estimation

Various efforts have been made to estimate the remaining useful lifetime of the fuel cell through state estimation and prognostics approaches. For example, Xian et al. have proposed to use an unscented Kalman filter to estimate the degradation rate of the electro-chemical surface area and the RUL of the stack [78]. Besides, when considering characterization disturbances and voltage recovery, Jouin et al. have used a particle filter framework to estimate the fuel cell's power degradation and the RUL based on a logarithmic expression [79]. Bressel et al. have proposed to use a degradation factor to represent the degradation phenomenon in the fuel cell voltage. Thanks to this degradation factor, fuel cell degradation could be estimated and tracked whatever the operation conditions are [80]. Furthermore, echo-state networks [81] and adaptive neuro fuzzy inference system (ANFIS) [82] are another two data-driven prognostics methods that have been used to estimate the health state of the fuel cell. However, these data-driven methods have not yet been combined to the energy management of hybrid vehicles due to the large calculation cost and low generality for different road conditions.

Another RUL estimation method proposed in [83] have used a surrogate model to present the Pt catalyst diffusion degradation rate. Response surface methodology (RSM) has been used to develop such a surrogate life model in a statistical framework. With the analysis through Pareto plots and scatter plot matrix, the upper potential limit of the fuel cell is found to be the most controllable variable to the Pt catalyst diffusion, following by cycle numbers. This work has indicated that the durability of the fuel cell system can be improved by operating at a relatively low potential with limits number of start/stop cycles.

3.4. Synthesis

The degradation of the PEM fuel cell in HEVs is inevitable which has a significant influence on the durability of the system. The above mentioned methods of degradation modelling, together with their advantages and disadvantages, are compared in Table 4. However, in the literature, when it comes to design a health-conscious EMS, the degradation of the fuel cell is usually considered using a rough model which is not accurate and cannot be generalized to all driving conditions [65, 71, 84]. This is mainly due to the complex structures and reactions of the fuel cell and the difficulties in the modelling. Although some prognostics works have been done to evaluate the health state of the fuel cell but post-prognostics decisions, or in other words, the part of control configuration is lacking. Therefore, it gives us the possibility to design a health-conscious EMS based on state estimation and prognostics, which could not only solve the modelling problems but also realize the automatically corrective control.

4. Health-conscious EMSs

4.1. Multi-objective problem

Developing a health-conscious EMS is generally regarded as a multi-objective problem since the objectives of such an EMS consist of not only minimizing the economic cost of the system but also prolonging its lifetime. Some others may also have the objectives of maximizing the efficiency and minimizing the energy source degradation. Multi-objective optimization problem is also known as Pareto optimization problem, which has more than one objective function to be maximized/minimized simultaneously. Since the objectives are often conflicting with each other, optimal decisions need to be taken with trade-offs between the conflicting objectives. A solution is said to be Pareto optimal or non-dominated if none of the objectives can be improved without degrading some of the other objectives. For example, a multi-objective problem can be stated as follows:

$$\begin{cases} \textit{Objective function:} & F(x) = [f_1(x) f_2(x) f_3(x) ... f_m(x)] \\ \textit{Constraints:} & g_j(x) <= 0, \text{ for } j = 1, 2, ..., k \end{cases} \tag{22}$$

where $x = [x_1 x_2 x_3 ... x_n] \in S$ is an n-dimensional vector of solutions which could be dominated or non-dominated. The set of all non-dominated solutions is called the Pareto front, which is supposed to be the final result of a multi-objective problem [85].

Therefore, how to find a solution that makes at least one objective better off without making others worse off remains discussing in energy management field. The following part of this section have reviewed the existing health-conscious EMSs for fuel cell HEVs in the literature. They are classified into two categories: rule-based health-conscious EMSs and optimization-based health-conscious EMSs.

4.2. Rule-based health-conscious EMSs

Rule-based health-conscious EMS is usually a set of rules that are designed based on human expertise and the aim is to find efficient operation points that mitigate the energy source degradation. This kind of EMS is less sensitive to the real-time driving conditions and easy to implement. However, the rules and the thresholds used to formulate the strategy are hard to define and one cannot declare whether they are the optimal or not. Based on the techniques to formulate the rules, rule-based EMSs are then classified into two categories: the deterministic rule-based strategies and the fuzzy ones, as shown in Figure 6. Some representative works using rule-based EMSs to solve the health management problem are reviewed in the following part of this section.

4.2.1. Deterministic rule-based strategies

Deterministic rule-based strategies are mainly developed through look-up tables and among which, thermostat strategy, frequency split strategy and state machine strategy are mostly used [24]. Thanks to the simple and straightforward way of designing rules, deterministic rule-based strategies are regarded as the most practical way to achieve multiple objectives. For example, in order to reduce system's degradation and fuel consumption at the same time, Marx et al. [86] designed the sizing strategy based on expertise knowledge: reducing degradation by starting as few fuel cells as possible, operating the fuel cell under its open-circuited voltage, limiting the DOD of the battery, and reducing consumption by operating at maximum efficiency as much as possible. State machine method is therefore used to decide how many fuel cells should be turned on and a set of rules are made to decide the power level of the fuel cells. However, the rules are defined based on human expertise and the optimality hasn't been discussed.

To optimize the rules in an intelligent way, researchers have started to combine some optimization techniques with deterministic rules. For example, in [87], the boundaries of SOC and desired torque of the rule-based controller are dynamically calculated by the minimizing the real-time consumption. Also in [88], the optimal parameters for the rule-based EMS are calculated off-line, which allow the vehicle to achieve lower fuel consumption and higher autonomy.

Furthermore, a frequency split EMS has been proposed in [89] which decomposed the power demand into different frequency bands by wavelet transform, and to be health-conscious,

Table 4: Summary of various fuel cell degradation modelling methods

Model output	Modelling method	Advantages	Disadvantages
Stack voltage degradation model [69, 70, 71, 72, 73]	Data-driven method	Easy to implement; disclosure of the influences of related factors the health state	Less accurate; strongly dependent on experiment data (low generality);
EIS impedance estimation [67, 75, 76]	Model-based method	Non-invasive; easy to implement; good performance in diagnostics field;	Incapable of directly solving SOH estimation issues;
RUL estimation [78, 79, 80, 81, 82, 83]	Data-driven/ Hybrid method	Robust to uncertainties and operation conditions;	Large experimental datasets;

the frequencies of the decomposed signals are in the range of acceptable frequencies of the battery and the fuel cell. Therefore, both energy sources are operating in their health modes. However, the Auto-Regressive Integrated Moving Average (ARIMA) model used for the prediction of the time series in this work is highly dependent on the available data and researchers' expertise, which causes generality problem.

4.2.2. *Fuzzy rule-based strategies*

Fuzzy rule-based strategies use fuzzy inference systems to transfer the deterministic inputs and outputs into linguistic ones. The fuzzy outputs are then defuzzyfied into precise control signals for the system. The fuzzy inference system solves the multi-objective problem by adding multiple inputs and designing proper rules. For example, a multi-input fuzzy logic controller has been proposed in [60], in which a set of rules are designed to determine the power split for battery/ultracapacitor storage system. At the same time, some other rules are developed to reduce the battery degradation by sacrificing the operation time of the ultracapacitor. Besides, to manage the fuel cell degradation, Ravey et al. have used the degradation index of the fuel cell as an input of fuzzy logic controller and the reference current of the fuel cell as the output [14]. When degradation or failure happens, the fuel cell can be operated over its efficiency point in order to maintain the battery's SOC. In [53], the C-rate of the battery has been used as an auxiliary input of the fuzzy logic controller in addition to the voltage and the demanded power. C-rate is only functioned in part of the rules which are used to suppress the battery power when the value of C-rate is high. This consideration is responsible for protecting the battery. However, similar to deterministic rule-based strategies, fuzzy rule-based strategies are easy to implement but can hardly reach the optimal if they are applied alone.

A general way to improve the optimality of fuzzy rule-based strategies is to tune the membership functions of the fuzzy logic controller using intelligent methods. For example, Wang et al. have proposed to use the genetic algorithm for fine-tuning the parameters of membership functions [90] and Chrendo et al. have referred that neural network algorithm can also be used to improve the conventional fuzzy logic, which is the so-called adaptive neuro fuzzy inference system [91]. However, these algorithms are developed highly dependent on the driving profiles and the parameters derived for certain driving conditions may not applicable to other conditions. Martinez et al. have proposed to design a survey-based fuzzy logic controller to combine different expertise and use type-2 fuzzy system to handle the uncertainty in the rules [92, 93]. In the application of a fuel cell HEV, the reference fuel cell current has been controlled to satisfy the power demand and maintain the SOC of the battery to avoid further degradation.

4.2.3. *Synthesis*

According to the literature, rule-based strategies are easy to design and implement in real time for HEV applications when designing health-conscious EMSs. However, the optimality of rule-based strategies is hard to achieve. Although some off-line optimization techniques can be combined to the rules to reach better management results, the real-time capability is weakened. On the other hand, above mentioned rule-based strategies in the literature have performed the health management by designing rules on SOC values, degradation models, C-rate, etc. It should be noticed that the rules could only be correctly designed once the degradation models are well defined. However, as we discussed in Section 2 and Section 3, the existing degradation models are rarely satisfied for vehicle applications.

4.3. *Optimization-based health-conscious EMSs*

Optimization-based strategies are often classified into two categories: global optimization strategies and real-time optimization strategies, as shown in Figure 6. The idea of developing a health-conscious global optimization strategy is to get the global optimal solution by solving a health-conscious cost function. However, global optimization strategies are carried out based on the overall driving cycle information, which cannot be applied in real-time applications unless the driving cycle could be predicted. On the contrary, real-time optimization strategies solve the optimization problem by defining an instantaneous cost function, which is updated along with the time. Therefore, real-time strategies are preferred to be as simple as possible due to the heavy computation cost. Various optimization-based EMSs used to solve the health management problem for HEVs are reviewed in the following part of this section.

4.3.1. *Global optimization strategies*

Dynamic programming. Dynamic programming can divide the optimization problem into a series of sub-problems by discretization and the cost function is calculated for each discrete time step. Consequently, a path with the minimum cost at each step is obtained [26]. For example, a cost function for minimizing the overall battery degradation has been formulated in [94] and the power splitting to the battery was determined according to the minimization results. Another optimization problem has been proposed in [8], where the cost function considered the battery degradation, hydrogen consumption, as well as grid recharge expenses. The cost function has been used to evaluate each decision made by the dynamic programming algorithm. Other dynamic programming algorithm applications considering both battery and fuel cell degradation could be found in [7, 95, 96]. However, dynamic programming algorithm is sensitive to driving cycles and the computation load is heavy. To overcome these constraints, stochastic dynamic programming (SDP) method has been proposed that applies a Markov process to represent the power demand and allows real-time application. For example, Fletcher et al. have defined the driving cycle using a Markov decision process, which was subsequently solved by SDP algorithm aiming at minimizing the total cost of hydrogen consumption and fuel cell degradation [73]. Besides, SDP has been proposed in [97] to optimize the energy consumption by integrating the battery lifetime wear model into the cost function and obtaining a single-objective problem. Ref. [19] has formulated a multi-objective problem aiming at finding a trade-off between energy consumption and battery's health. Two battery degradation models, SEI film layer model and Ah processed model, have been evaluated and the problem was solved by a shortest-path SDP.

Moreover, dynamic programming can be used as evaluation, comparison and analysis tools [26]. For example, it can derive the optimal performance condition for a given driving profile and help to formulate rules for real-time management. Carla et al. have used the dynamic programming to produce a dataset which is large enough to train an artificial neural network [98]. The cost function of dynamic programming consisted of both fuel consumption and battery degradation. With the results of dynamic programming, artificial neural network has been implemented with the SOC of the battery and the forecast power demand as two inputs and the fuel cell power as the output and has achieved near-optimal results in real time.

Stochastic search method. Stochastic search methods are commonly used in HEV applications, which are the most effective methods to solve the multi-objective problems. According to [26], frequently used stochastic search methods consist of genetic algorithm, particle swarm optimization (PSO), extreme algorithm, etc. They are able to solve the optimization problem by iterative approach. For example, a multi-objective fitness function including battery cost, capacity cost and total energy cost is formulated in [35]. In each generation of genetic algorithm, the population generates a set of Pareto-optimal solutions and at the end, the most feasible solution with respect to all objective functions is selected. Besides, authors in [22] and [39] have proposed to use a non-dominated sort genetic algorithm (NSGA-II) to solve the optimization problem of two conflicting objectives. With the formation of a Pareto front, the opposite effects of energy minimization and battery health on the cost function are traded off optimally. In [99], three objective functions have been proposed including operation cost, efficiency and system lifetime, which were integrated into a single function through weight aggregation approach. The optimization problem was subsequently solved by PSO algorithm. Furthermore, Chen et al. have proposed a novel EMS which used quadratic equations to find a relationship between fuel rate and battery power and applied simulated annealing method to determine the battery power input when taking into account the SOH of the battery [100]. However, similar to dynamic programming algorithm, stochastic search methods are sensitive to driving cycles and are usually implemented based on specific pre-defined driving conditions. Therefore, unless combining with driving cycle identification, stochastic search methods still lack the generality in HEV applications.

4.3.2. Real-time optimization strategies

ECMS and EDMS. Equivalent cost minimization strategy (ECMS) and equivalent degradation minimization strategy (EDMS) are widely used for real-time optimization in HEV applications. Generally, an equivalent cost function is established to transfer the global optimization problem into local optimization problem by minimizing the cost function in real time [26]. For example, an instantaneous optimization process based on ECMS has been proposed in [36] for a multi-mode power-split HEV. In this work, the battery degradation has been modelled by SEI film growth and integrated into the cost function. Instead of minimizing the total cost, Hissel et al. [101] have proposed to minimize the battery degradation in hybrid energy storage system. The cost function was formed by an equivalent factor which represented the marginal degradation caused by the power demanded from the capacitor. Besides, Pontryagin's minimum principle (PMP) is one of the most commonly used optimal approaches in ECMS and EDMS, which works effectively with constrained optimization problems. For example, in order to prolong battery's lifetime, Liu et al. have minimized the fuel consumption with the constraints of battery's SOC and current, solving by PMP optimal control [102]. To better demonstrate the degradation of battery, a severity factor map has been built based on the battery ageing model and combined into the cost function in [27]. The problem was then solved by PMP to reach a trade-off between battery ageing minimization and fuel consumption minimization. However, Ettihir et al. claimed that some cost function minimization method can only be used to minimize the fuel consumption over a global level and the real performance of fuel cell has been ignored. In order to track the best performance of the fuel cell, they have applied an adaptive recursive least square algorithm to seek the optimal performance of the fuel cell when considering ageing effects and integrated it with PMP to form an adaptive management strategy, A-PMP [15].

Model predictive control (MPC). MPC is another real-time optimization-based approach which assumes that the current state is the initial condition and solves the optimization problem at each sampling instant. It is implemented in three steps: (1) calculate optimal control sequence in a prediction horizon that minimizes the cost function subject to constraints; (2) implement the first part of derived optimal control sequence to physical plant; and (3) move entire prediction horizon one step forward and repeat step (1) [26]. Therefore, it is interesting to use MPC in a multi-objective health conscious EMS since it can involve several constraints into the control actions. For example, Arce et al. have used MPC to track the power demand of a HEV and set constraints to battery's SOC to avoid degradation [103]. On the other hand, the fuel cell degradation is limited by setting the threshold of fuel cell power and the time limit between its start-ups and shut-downs. Due to MPC's receding horizon nature, it is possible to reduce the computation cost when comparing to PMP and dynamic programming results after multiple trials to different driving cycles. However, by dividing the problem into several time steps, the solutions of MPC are usually suboptimal.

Machine learning methods. Machine learning methods are known as intelligent control strategies, which are suitable to solve complex non-linear problems. Therefore, they are widely used in developing EMSs. Various machine learning strategies exist in the literature including neural network, support vector regression (SVR), etc. To be health-conscious, Caihao et al. have used SVR to monitor the SOH of battery in HEV applications, which realized the real-time analysis of battery ageing based on partially charging data [104]. Besides, neural network has been used in [105] to perform power split between two storage system - battery and ultracapacitor. The instantaneous battery current has been considered to have an impact on its degradation and the power delivered by the ultracapacitor could help to handle the peak current demand in the battery, and therefore to reduce the degradation of the battery during operation. These methods have showed some improvements in robustness but the solution is other than an optimal one. To improve the optimality, Chen et al. have proposed to train two neural network modules for known and unknown trips separately based on the optimization results of off-line dynamic programming method and improved the optimality to some extent [106]. However, machine learning methods is not that practical since the computation load of training datasets is considerably heavy.

4.3.3. Synthesis

Optimization-based strategies are widely used in developing health-conscious EMSs and various health-conscious objectives can be achieved through formulating health-conscious cost functions with proper constraints. Global optimization-based strategy is able to find an optimal solution to the cost function and it could also work as an evaluation and analysis tool. However, it cannot be applied directly to a real-time application unless the driving cycle can be identified or predicted by other identification or prediction approaches. When it comes to instantaneous applications, real-time optimization-based strategies are used but they are not supposed to be designed in a complicated way due to the computational burden and memory limits. Therefore, one has to reduce the complexity of the problem in order to make it implementable. Another weak point of real-time EMSs is low optimality since they lack the global understanding of the problem.

4.4. Open issues and remaining challenges

In light of quantitative and qualitative literature survey on developing a health-conscious energy management strategy for HEVs, there are still some challenging problems to be solved. The two main aspects are discussed as follows and challenges are pointed out to find possible solutions.

4.4.1. Open issue 1: degradation modelling

As discussed in Section 2 and Section 3, considerable efforts have been made to model the degradation of lithium-ion batteries and PEM fuel cells. However, most of the existing health-conscious EMSs just set boundaries to battery's SOC or limit the upper or lower voltage to protect the fuel cell, which can hardly quantify the degradation or the lifetime of the energy sources. Other studies quantify the ageing phenomenon by degradation rate, which are highly dependent on the driving conditions (acceleration, idling, etc.). With different driving cycles and different vehicle configurations, the accuracy cannot be guaranteed. Although some prognostics and health management works have been done to predict the RULs of the battery and the fuel cell, they have neither been well combined to the EMSs, nor applied in the vehicle application yet. Besides, whether the degradation of different energy sources in hybrid systems will have an influence on each other hasn't been investigated yet. It is hard to say the degradation of the fuel cell will not accelerate the degradation of the battery in the same system or vice versa. More studies are expected to be launched in this field.

4.4.2. Open issue 2: optimality

Optimality of multi-objective health-conscious EMSs is always regarded as a tough issue and generates many discussions. As discussed above, the optimality of rule-based strategy can hardly be assured if the rules are designed based on human expertise. One possibility is to use other optimization techniques to tune the rules or the membership functions of the fuzzy logic controller off-line. However, the control effects of all existing off-line optimizations are affected by different driving cycles and in vehicle applications, the operation conditions of the vehicle is changing all the time so that the off-line tuning is rarely convinced. Although real-time optimization strategies can adjust the control strategies according to the current state of the vehicle, the computation burden is too high and the calculation speed is limited. The existing approaches usually choose to reduce computation load at the expense of optimization performance. Moreover, without a global understanding of the driving condition, their optimality can be also weakened.

4.4.3. Facing the challenges

To face the afore-mentioned issues, finding a good modelling method of degradation and improving the optimality of the EMSs are demanding. Works have been done to exhaustively search for the accurate degradation models but due to the variable operation conditions, the existing degradation models are far from satisfaction. In this case, state estimation and prognostics technique could be one of the possible solutions to

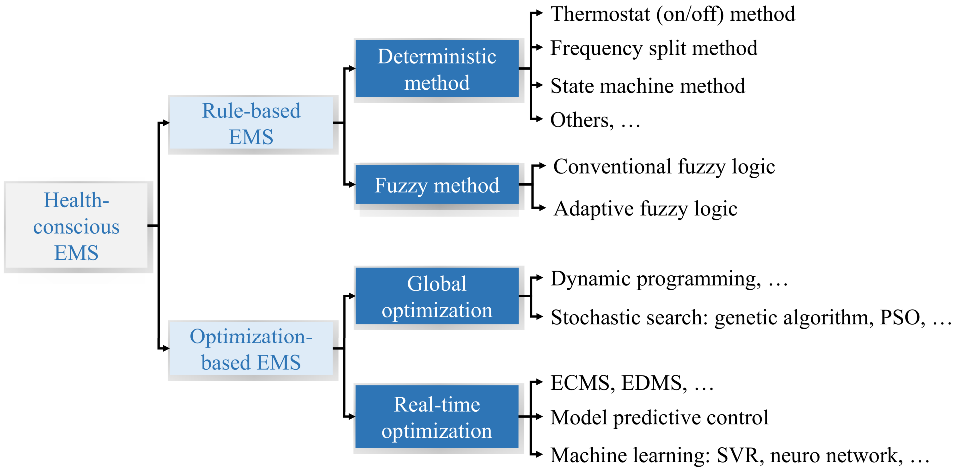

Figure 6: Category of health-conscious EMSs used for battery/fuel cell HEV applications

take automatic corrective actions along with the vehicle's operation. Prognostics-enabled Decision Making (PDM) is a newly emerging research area that aims to integrate prognostic health information and knowledge about the future operating conditions into the process of selecting subsequent actions for the system. It is of great interest in health assessment and life prediction of the energy sources, with which one can incorporate the current state of health into the health management. Since the prognostics of battery and fuel cell has remained on component level and has not yet been combined in the control part of the system, a proposition of health-conscious EMS based on prognostics aiming at preserving the system and improving its durability should be highlighted in the near future.

Furthermore, the optimality of this kind of health-conscious EMS remains discussing. The difficulty comes from not only its multiple objectives but also the various operation conditions in real time. Solutions depend on which kind of strategy is going to be used. The optimality of rule-based EMSs can be achieved by designing the rules delicately and combining intelligent algorithm, while for optimization-based EMSs, possible perspectives could be placed on the prediction of driving cycles to improve global strategies or reducing computation burden of real-time strategies and improving its optimality.

5. Conclusion

This paper has thoroughly analyzed the development status of health-conscious energy management strategies for fuel cell HEVs. The degradation mechanisms of lithium-ion batteries and PEM fuel cells are described at first, which give evidence to a wide choice of degradation modelling and estimation methods. Pros and cons are analyzed in details. Based on quantitative analysis, qualitative analysis of the existing health-conscious EMSs for HEVs is given. The authors have pointed out that the degradation modelling and optimality are two main concerns in developing health-conscious EMSs for hybrid systems. Proposing practical degradation modelling and estimation methods, formulating a multi-objective problem to consider degradation and realizing a good balance to solve the conflict between complexity and optimality are the three future trends derived from the analysis. The objectivity of this work is not only a literature survey but also to facilitate the development of an effective and practical health-conscious EMS and help to solve the durability problem of HEVs.

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