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An Online Prognostics-Based Health Management Strategy for Fuel Cell Hybrid Electric Vehicles

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Abstract

As the energy transformation in the transportation sector is taking place driven by the development of fuel cell technologies, fuel cell hybrid electric vehicles become available solutions owing to their long driving duration and zero emissions. However, the unsatisfied lifespan of fuel cells is an inevitable obstacle for their massive commercialization. This paper aims to propose an online adaptive prognostics-based health management strategy for fuel cell hybrid electric vehicles, which can improve the durability of the fuel cell thanks to online health monitoring. Here, particle filtering method is adapted for online fuel cell prognostics and the uncertainty of the predicted results is calculated based on the distribution of particles. A health management strategy is developed based on prognostics and a decision-making process is designed by considering the prognostics uncertainty through a decision fusion method. The obtained results show that the developed strategy has effectively improved the durability of the on-board fuel cell by up to 95%. Moreover, a sensitivity analysis of the prognostics occurrence frequency and probability calculation has also been conducted in this paper.

Keywords:

decision fusion, health management, fuel cell, hybrid electric vehicle, prognostics

Nomenclature

Abbreviations

<i>EMS</i>	energy management strategy
<i>FLC</i>	fuzzy logic controller
<i>GA</i>	genetic algorithm
<i>HEV</i>	hybrid electric vehicle
<i>MF</i>	membership function
<i>PDM</i>	prognostics-enabled decision-making
<i>PEM</i>	proton exchange membrane
<i>PHM</i>	prognostics and health management
<i>SOC</i>	state of charge
<i>SOH</i>	state of health
<i>WOB</i>	width of bin

Symbols

i_{bat}	battery current
-----------	-----------------

i_{fc}	fuel cell current
m_{H_2}	hydrogen consumption
P_{fc}	fuel cell power
Q_{max}	maximum available battery capacity
V_{bat}	battery voltage
$V_{fc-degrade}$	fuel cell degraded voltage
V_{fc}	fuel cell voltage
V_{ini}	initial voltage

1. Introduction

Hydrogen, as a clean energy carrier, is leading the energy transformation in today's transportation sector and the development of fuel cell technology has accelerated this momentum. Fuel cell hybrid electric vehicles (HEVs), which offer a similar recharge time to that of the current gasoline solution and a comparable autonomy, have seen widespread use in replacing the traditional fossil fuel combustion vehicles [1]. However, on-board fuel cells are subject to unsatisfying durability [2]. According to the U.S. Department of Energy, the technical durability of integrated hydrogen-fueled polymer electrolyte

membrane (PEM) fuel cell power systems and fuel cell stacks operating on direct hydrogen should attain 8000 hours for transportation applications, however, only 4000 to 5000 hours have been reached nowadays [3].

Prognostics and health management (PHM) technologies have been applied to improve the durability of fuel cells, which relies on the predictive nature of prognostics to anticipate and predict the remaining useful life (RUL) of the fuel cell and uses a post-prognostics decision support layer to design maintenance, control and management actions [4]. Prognostics approaches exist in three manners: data-driven approach, model-based approach, and hybrid approach [5]. Methods like filtering algorithms [6, 7], neural networks [8, 9, 10], and other predictive algorithms have been developed in the literature. However, most fuel cell prognostics methods are developed based on finished experimental degradation data, some of which are obtained under constant operating conditions. Although they are devoted to estimating the health state of the fuel cell, the real driving conditions have not been considered. Moreover, prognostics itself cannot reach the goal of improving durability, i.e., post-prognostics decisions and mitigation actions are lacking [11].

To improve the durability of fuel cells in HEV applications, efforts have been made to develop health-conscious energy management strategies (EMSs) [11]. A deterministic dynamic programming strategy and a rule-based strategy have been developed in [12] to minimize the cost and at the same time, respect the operation limits to avoid degradation. Liu et al. have developed a multi-objective EMS to achieve optimal cost and fuel cell lifetime based on predicted vehicle speed and battery state of charge [13]. Moreover, an equivalent consumption minimization strategy has been developed in [14], which considers the fuel cell degradation in the objective function. However, existing researches usually consider the fuel cell degradation by setting constraints or using fitting degradation models in the strategies, which are less accurate and cannot signify the real health state of the system. The developed fuel cell prognostics technologies are less applied to the energy management of HEV applications. Without an exact understanding of the current health state, the actions taken by the controller may be not appropriate and may even cause more damages to the system's health, shortening its lifetime [15].

To go further from prognostics to health management for fuel cell HEV applications, a prognostics-enabled decision-making (PDM) process has been proposed in [16], which uses the data provided by the prognostics step to reconfigure the mission of a fuel cell HEV depending on its health state. The decision is made by allocating confidence factors to different degradation states and fusing the parameters of fuzzy logic controllers based on the confidence factors to find the optimal power distribution between the fuel cell and the energy storage system in real time. However, the confidence factors in [16] are obtained through a classification method based on a Gaussian-shaped fuzzy inference system, while only the median value of RUL predictions is used. Therefore, the classification results are less convinced if RUL uncertainties are not considered. To improve this deficiency, the uncertainties of the prognostic results are examined

based on the particle filtering prognostics method in this paper. To develop the prognostics-based health management strategy, a probability calculation method is then introduced to obtain the probability values allocated to different degradation states, and a decision fusion approach is applied to calculate the confidence factors to the offline-optimized fuzzy logic controllers and to determine the parameters of the online operating controller.

The reminder of the rest of this paper is as follows: Section 2 introduces an online prognostics method for the fuel cell based on particle filtering with an analysis of the sources of uncertainties. Section 3 presents the development of the proposed prognostics-based EMS for a fuel cell HEV, while the simulation results are compared and discussed in Section 4 before concluding.

2. Online prognostics based on particle filtering

The online particle filtering prognostics method has been proposed in this section to be combined with the health management strategy of the studied fuel cell HEV. It allows one to track and to continuously estimate the state of health of the fuel cell, and furthermore, to predict the RUL.

2.1. Particle filtering prognostics

2.1.1. Particle filtering

Particle filtering is essentially a nonlinear Bayesian tracking approach that the unknown states from noisy observations can be estimated with available prior knowledge. In a typical Bayesian tracking problem, two models are required to describe the system: state model and measurement model.

State model:

$$\mathbf{x}_k = f(\mathbf{x}_{k-1}, \mathbf{u}_k, \mathbf{w}_k) \leftrightarrow p(\mathbf{x}_k | \mathbf{x}_{k-1}) \quad (1)$$

where the initial distribution of the states \mathbf{x}_k is modelled as $p(\mathbf{x}_0)$ and the state transition is based on a probabilistic model $p(\mathbf{x}_k | \mathbf{x}_{k-1})$. \mathbf{u}_k is the command input and \mathbf{w}_k is process white noise, non-necessarily Gaussian [17].

Measurement model:

$$\mathbf{z}_k = h(\mathbf{x}_{k-1}, \mathbf{v}_k) \leftrightarrow p(\mathbf{z}_k | \mathbf{x}_k) \quad (2)$$

where the measurement \mathbf{z}_k is of a marginal distribution $p(\mathbf{z}_k | \mathbf{x}_k)$ and \mathbf{v}_k is the measurement white noise, non-necessarily Gaussian [17].

The state estimation is realized by recursively estimating the state probability distribution function $p(\mathbf{x}_k | \mathbf{z}_{1:k})$ using a prediction step and an update step:

Prediction step:

$$p(\mathbf{x}_k | \mathbf{z}_{1:k-1}) = \int p(\mathbf{x}_k | \mathbf{x}_{k-1}) p(\mathbf{x}_{k-1} | \mathbf{z}_{1:k-1}) d\mathbf{x}_{k-1} \quad (3)$$

Update step:

$$p(\mathbf{x}_k | \mathbf{z}_{1:k}) = \frac{p(\mathbf{z}_k | \mathbf{x}_k)p(\mathbf{x}_k | \mathbf{z}_{1:k-1})}{p(\mathbf{z}_k | \mathbf{z}_{1:k-1})} \quad (4)$$

where

$$p(\mathbf{z}_k | \mathbf{z}_{1:k-1}) = \int p(\mathbf{z}_k | \mathbf{x}_k)p(\mathbf{x}_k | \mathbf{z}_{1:k-1})d\mathbf{x}_k \quad (5)$$

In fact, the above Bayesian tracking equations are conceptual. To analytically solve this problem, particle filtering is widely applied to give approximate solutions owing to its ability to solve nonlinear and non-Gaussian problems. Particle filtering is implemented based on sequential importance sampling (SIS) technique, which is a Monte-Carlo method to calculate $p(\mathbf{x}_k | \mathbf{z}_{1:k})$ by sampling the states into particles and allocating weights to the particles. Details could be found in [18]. The steps for implementing SIS-type particle filtering are described as follows:

1. In the first step ($k = 1$), n particles with an initial distribution $p(x_0)$ are generated;
2. Propagate the n particles from x_{k-1} to the next state x_k using (1) to calculate the probability density function;
3. The weights associated to the particles are calculated by the likelihood of the state to the latest measurement \mathbf{z}_k :

$$\mathcal{L}(\mathbf{z}_k | \mathbf{x}_k, \sigma_{v_k}) = \frac{1}{\sqrt{2\pi}\sigma_{v_k}} \exp\left(-\frac{(\mathbf{z}_k - \mathbf{x}_k)^2}{2\sigma_{v_k}^2}\right) \quad (6)$$

4. In order to avoid the dying away of the particles, a resampling process is performed to exclude small-weighted particles by setting a given weight limit and replicate those large-weighted particles;
5. The rebuilt posterior probability density function by resampling is, therefore, recursively transferred to the following iteration as its prior probability density function;
6. Step 2 to 5 are repeated until there is no more measurement.

Prognostics require the state model to output new state estimates when the measurement is no longer available, and then to predict the future health state and the RULs. To adapt particle filtering for prognostics purpose, it needs a prediction phase in addition to the above-described state estimation process. When there is no measurement available, i.e., the prediction is started, the state \mathbf{x}_k is propagated to \mathbf{x}_{k+1} without calculating the likelihood of (6) and the parameters of the model are propagated with the noises.

2.1.2. RUL estimation

RUL is a term that indicates how long the system could remain in use, it is calculated based on a pre-defined end-of-life (EOL) threshold λ . The estimated probability density function of the RUL at time k is:

$$\hat{p}(RUL \leq l | \mathbf{z}_{0:k}) = \hat{p}(\mathbf{x}_{k+l} \geq \lambda | \mathbf{z}_{0:k}) \quad (7)$$

It is updated based on new $\mathbf{z}_k, k = k_p + 1, \dots, k_p + l$. The RUL uncertainty can be represented by the final distribution of the particles obtained when the failure threshold is reached [19].

The pseudo-code of implementing the particle filtering prognostics method is presented in Algorithm 1.

Algorithm 1 Particle filtering prognostics

Initialize $x_0^i, w_0^i, v_0^i, u_0^i$ with uniform distribution

Time step $k = 1$

while $x_k^i > \lambda$ and $k \leq k_p$, **do**

for $i = 1, \dots, n$, **do**

 Generate particles $x_k^i \sim p(x_k^i | x_{k-1}^i, w_{k-1}^i, u_{k-1}^i)$

 Allocate weight $\omega_k^i = \mathcal{L}(z_k^i | x_k^i, v_k^i)$

end for

 Normalize weight $\omega_k^i = \omega_k^i / \sum_{i=1}^n \omega_k^i$

 Calculate the cumulative sum of the normalized weights

$Q_k^i = \text{Cumsum}(\omega_k^i)_{i=1}^n$

for $i = 1, \dots, n$, **do**

$j = 1$

 Draw a random value $u^i \sim U[0, 1]$

while $Q_k^i < u^i$, **do**

$j = j + 1$

end while

 Update state $x_k^j = x_{k-1}^j$

 Update noises $w_{k-1}^j = w_{k-1}^j, v_{k-1}^j = v_{k-1}^j$

 Update parameters $u_k^j = u_{k-1}^j$

end for

$k = k + 1$

end while

for $i = 1, \dots, n$, **do**

Start prognostics from k_p

while $x_k^i > \lambda$, **do**

 Propagate particles to the next time step $x_k^i =$

$f(x_{k-1}^i, w_{k-1}^i, u_{k-1}^i)$

$k = k + 1$

end while

 Estimate $\hat{RUL}_k^i = (k - k_p) \cdot \Delta t$

end for

2.2. Online prognostics implementation

2.2.1. Model selection

The degradation trend of the fuel cell degradation dataset could be caught by various empirical models [19, 20, 21]. In order to include more possibilities of variation, the 2nd order exponential degradation model is chosen to track the fuel cell's performance and perform prognostics:

$$V(t) = b_1 \cdot \exp(b_2 \cdot t) + b_3 \cdot \exp(b_4 \cdot t) \quad (8)$$

where b_1, b_2, b_3 and b_4 are the model parameters, b_1 and b_3 determine the initial state and b_2 and b_4 define the degradation rate. Then, the state space model could be written as (9):

$$\begin{aligned} x_{1,k} &= x_{1,k-1} \cdot \exp(b_2) + w_{1,k}, & w_{1,k} &\sim \mathcal{N}(0, \sigma_{w1}^2) \\ x_{2,k} &= x_{2,k-1} \cdot \exp(b_4) + w_{2,k}, & w_{2,k} &\sim \mathcal{N}(0, \sigma_{w2}^2) \end{aligned} \quad (9)$$

where $x_{1,k}$ and $x_{2,k}$ are two first-order independent Markov processes and the present voltage state can be obtained from $x_{1,k}$ and $x_{2,k}$:

$$x_k = b_1 \cdot x_{1,k} + b_3 \cdot x_{2,k} \quad (10)$$

1 where b_1, b_2, b_3 and b_4 are also states to be transited. The
 2 measurement model is then written as:

$$z_k = x_k + v_k, \quad v_k \sim \mathcal{N}(0, \sigma_v^2) \quad (11)$$

3 where v_k are supposed to be included in the measurement signal
 4 as the measurement noise. As the initial distributions of the
 5 parameters are unknown, uniform distributions is applied [22].
 6 The process noise variance is refined as $\sigma_w^2 = 10^{-4}$ and same
 7 process noise is assigned to the unknown parameters ($b_1, b_2,$
 8 b_3 and b_4). The measurement noise v_k is not considered as it
 9 is supposed to be contained in the input signals. Moreover, the
 10 number of particles is fixed as $n = 2000$.

11 2.2.2. Data preprocessing

12 During the system's online operation, voltage disturbances
 13 are inevitable. The original signal is too noisy to implement
 14 prognostics. Thus, the data should be preprocessed to remove
 15 the peaks and filter the noises. To this end, a kernel smoother
 16 is applied. The estimated point $f(t_j)$ is calculated based on the
 17 weighted moving average:

$$f(t_j) = \frac{\sum_{i=1}^n s_i \cdot u(t_j)}{\sum_{i=1}^n s_i} \quad (12)$$

where

$$s = K\left(\frac{t_j - t}{h}\right) \quad (13)$$

h is the bandwidth and K is a Gaussian Kernel function written
 as:

$$K(t) = \frac{e^{-\frac{t^2}{2}}}{\sqrt{2\pi}} \quad (14)$$

18 Besides, during online operation, the signal measured at each
 19 time step is too voluminous, and using these data points to esti-
 20 mate the states requires huge storage memory, up to gigabytes
 21 to store the states, estimated parameters, and particle weights.
 22 This would not be actually allowed in industrial applications.
 23 Besides, too many points for state estimation will lead to over-
 24 fitting problems, resulting in the divergence of the model [23].
 25 Therefore, the measured signal should be reduced. Moreover,
 26 based on the hypotheses that the degradation of the fuel cell is
 27 only due to the ageing effects and no sudden damage happens
 28 during its operation, the degradation will not progress largely
 29 on short time scales, time scales longer than an hour should be
 30 suitable for industrial application [24, 25]. Therefore, in this
 31 study, to track the state of the system and to perform prognos-
 32 tics, the data is reduced at one point per hour.

33 2.2.3. Prognostics result demonstration

34 Figure 1 shows an example of the online estimation and prog-
 35 nostics result of the fuel cell degradation at prediction time
 36 $t_\lambda = 500th$ hour. The fuel cell is assumed to reach its EOL
 37 at a predefined threshold ($D_{fc-degrade} = 10\%$). The predicted
 38 RUL is [84 143 284] hours with a confidence interval (CI) of
 39 [5% 50% 95%] whereas the true RUL is 159 hours.

40 The estimated voltage drawn in Figure 1 is the successive
 41 positions of the top of the particles distribution [19]. According

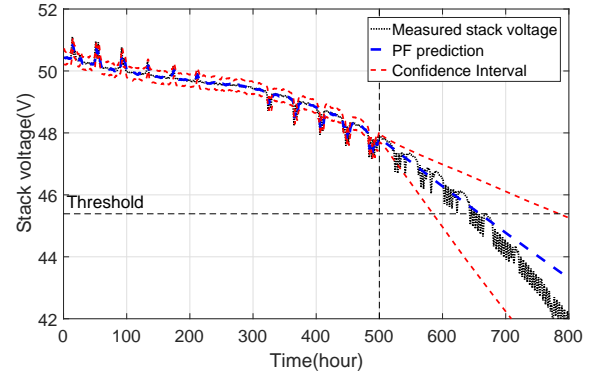


Figure 1: Fuel cell prognostics result

to (7), the distribution of the predicted RULs is represented by
 the distribution of the particles when reaching failure voltage,
 as shown in Figure 2.

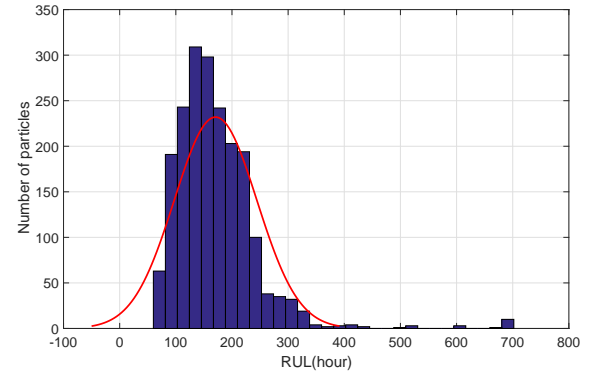


Figure 2: Predicted RUL distribution

2.3. Prognostics uncertainties

In fact, implementing online prognostics needs to contend
 with multiple sources of uncertainties. Generally, it is impos-
 sible to eliminate all the uncertainties no matter what kind of
 prognostics method is used. The sources of prognostics uncer-
 tainties are discussed in details:

- **Model uncertainties:** It is due to the lack of an accurate analytical model for the degrading fuel cell system. As the system is dynamic and sensible to the operation conditions, it is nonviable to find a model that covers all possible variables.
- **Input uncertainties:** It refers to the sensors that are used to monitor the system. The measurements of sensors come with a variety of noises due to electrical interference, digitization error, sensor bias, dead-band, backlash and response non-linearity, etc [26].
- **Measurement uncertainties:** All measurements are subject to uncertainties, which is a quantification of the doubt about the measurement results. Noisy measurements may

due to electrical, mechanical, or even thermal condition variations.

- **External uncertainties:** It contains the uncertainties coming from the operation conditions and environment. During online operation, the operation conditions are dynamic and random and the future loading conditions and environment always remain unknown. It is another inevitable source of uncertainties.

When it comes to the particle filtering prognostics, the uncertainties of the learning phase is provided by all the above-mentioned uncertainties and can be indicated by the distribution of the particles. Then, the uncertainties of the prediction phase account for all the previously quantified uncertainties, which are used to predict the future states and their uncertainties, as well as the RULs and their uncertainties. The future states and their uncertainties are calculated by propagation using the prediction model, while the calculation of the RULs and their uncertainties depend also on the threshold function, which is used to indicate the EOL.

3. Prognostics-based health management strategy

A health management strategy is proposed in this section, in which the power distribution between the fuel cell and the battery is performed using fuzzy logic control (FLC), which is optimized by genetic algorithm (GA), and a PDM process considering RUL uncertainty is designed to redistribute the power between different power sources in the studied fuel cell HEV.

3.1. System description

The studied fuel cell HEV is build in MATLAB®/Simulink® environment and the structure is shown in Figure 3. A proportional-integral (PI) speed controller is used to track the reference speed in the propulsion system, which is modelled based on the literature [27]. The power train consists of a 16kW PEM fuel cell stack and a 80V, 40Ah lithium-ion battery pack, which are used to provide the demanded power profile. All components are connected by current and voltage signals using a feedback loop. An EMS is then designed to split the power between the fuel cell and the battery based on the speed of the vehicle and the battery's state of charge (SOC). In order to be health-conscious, it is designed also depending on the fuel cell health state. The models of the fuel cell and the battery are detailed as follows.

3.1.1. Fuel cell modelling

The fuel cell in the studied vehicle is regarded as a voltage source based on the following current-controlled model, which is deduced from its polarization curve given in [27]. The fitting result is written as:

$$V_{fc} = f(i_{fc}) = \alpha_1 \cdot i_{fc}^3 + \alpha_2 \cdot i_{fc}^2 + \alpha_3 \cdot i_{fc} + \alpha_4 \quad (15)$$

The fitting factors are $\alpha_1 = -6.7791e - 07$, $\alpha_2 = 0.00044927$, $\alpha_3 = -0.11913$ and $\alpha_4 = 59.124$.

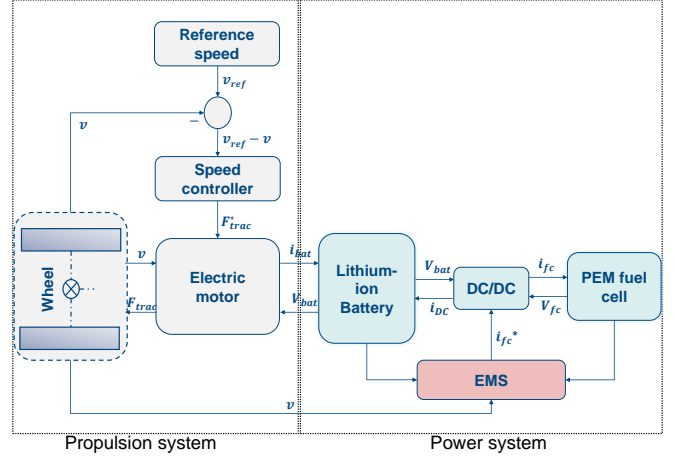


Figure 3: Structure of the studied fuel cell HEV

The performance degradation of the fuel cell is considered on the stack level, which can be indicated by the loss of its stack voltage no matter what degradation is happening on the cell or the component level. Here, the degraded voltage of the fuel cell is modelled based on its operation points and on/off switches [28, 29], written as:

$$V_{fc-degrade} = V_{ini} \cdot D_{fc-degrade} = V_{ini} \cdot (D_{fc} + D_{on/off}) \quad (16)$$

where

$$D_{fc} = \delta_0 \int \left(1 + \frac{\alpha(P_{fc} - P_{nom})^2}{P_{nom}^2}\right) dt \quad (17)$$

$$D_{on/off} = \begin{cases} \sum \Delta_{switch}, & \text{if } P_{fc,t} \geq 0 \wedge P_{fc,t-1} < 0 \\ 0, & \text{otherwise} \end{cases} \quad (18)$$

In (17) and (18), V_{ini} is the initial available fuel cell supplied voltage, P_{nom} is the nominal fuel cell power and $P_{nom} = 6000W$, which is regarded as the maximum efficiency operation point, α and δ_0 are the load coefficients and Δ_{switch} is the voltage loss coefficient for fuel cell's once switch. The coefficients are fitted based on the historical datasets presented in [30].

3.1.2. Battery modelling

An electrical equivalent circuit model is used to represent the battery's behaviour, which describes the battery operating characteristics using a RC circuit network. The output battery voltage is calculated by:

$$\begin{cases} \dot{u}_{C_c} = -\frac{u_{C_c}}{R_c C_c} + \frac{i_{bat}}{C_c} \\ V_{bat} = u_0 - u_{C_c} - i_{bat} R_s \end{cases} \quad (19)$$

where u_0 , R_s , R_c and C_c are estimated based on experimental data [27]. As there is no sensor that could read SOC directly, SOC is estimated here by ampere-hour counting (Coulomb counting) method, expressed as:

$$SOC_t = SOC_{t_0} + \eta \int_{t_0}^t \frac{i_\tau}{Q_{max}} d\tau \quad (20)$$

where η denotes the coulombic efficiency ($\eta = 0.95$ when charging and $\eta = 1$ when discharging), i_τ is the battery current at time instant τ ($i_\tau > 0$ when charging and $i_\tau < 0$ when discharging), and Q_{max} is the maximum available capacity of the battery.

In this study, the battery used in the fuel cell HEV is assumed to have a much longer lifetime than the fuel cell so that the battery degradation cost and the interaction between the battery and the fuel cell are not considered.

3.2. Energy management based on GA-optimized FLC

EMS is a strategy to be designed in hybrid vehicles, which defines the amount of power that must be produced by different power sources. The objectives of EMS could be consumption minimization, power source degradation mitigation, driving performance improvement, etc. Sometimes, these objectives may be conflicted with each other. In this study, the objective of the proposed EMS controller is to find a trade-off between increasing the system lifetime and saving the hydrogen consumption.

3.2.1. FLC design

The baseline strategy is a fuzzy rule-based strategy as it can easily be implemented in real time without huge computation burdens. The input of the FLC is the SOC of the battery and the output is the reference current of the fuel cell. The FLC is designed by considering the following objectives:

1. The range of SOC of the battery should be limited to ensure that the battery pack can provide enough power for transient power demand and at the same time, remain enough capability for regenerative braking;
2. The fuel cell is preferred to work around its highest efficiency point, P_{nom} , to save hydrogen consumption;

In this respect, the SOC of the battery is controlled to 75% as its optimal operation point and the corresponding output is the optimal i_{fc} . The control rules are written as:

1. If the SOC is *low*, then the fuel cell runs at $i_{fc-high}$;
2. If the SOC is *medium*, then the fuel cell runs at i_{fc-med} ;
3. If the SOC is *high*, then the fuel cell runs at i_{fc-low} .

Details of the FLC implementation could be found in the authors' previous work [16].

3.2.2. Offline GA optimization

Although the FLC is easy to implement in real time, it can hardly reach the optimal solution if the MFs are designed without combining any optimization procedure [11]. To encounter with this problem, in this study, the parameters of the MFs of the output i_{fc} are tuned by offline GA optimization method. GA is well adaptive to the optimization of FLCs, in which all the parameters of MFs are coded in one chromosome and they

are selected, crossed and mutated to find an optimal solution to a defined objective function. Here, the objective function is a weighted polynomial function including fuel cell degraded voltage $D_{fc-degrade}$, SOC range ΔSOC and hydrogen fuel consumption m_{H_2} :

$$ObjFun = -w_1 \cdot D_{fc-degrade} - w_2 \cdot \Delta SOC - w_3 \cdot m_{H_2} \quad (21)$$

with

$$\Delta SOC = \int f(1 + \frac{(SOC_{bat} - SOC_{init})^2}{SOC_{init}^2}) dt \quad (22)$$

where w_1 , w_2 and w_3 are the weighting factors. The optimization is implemented on a repeated WLTC Class 2 driving cycle and the optimized MFs under different degradation states ($D_{fc-degrade}$ is 0%, 3%, 6% and 9% of the initial stack voltage value) have been plotted in Figure 4. The first line is the MFs of the input SOC, the second line is MFs of the optimised fuel cell reference current and the last line is the evolution of the values of the objective function (calculated by (21) and (22)).

3.3. Prognostics-based health management based on PDM

A PDM process is proposed in this section to fulfill the health management for the long term operation of the studied fuel cell HEV. A decision fusion algorithm is applied to consider the prognostics uncertainty when determining the parameters of the online FLC.

3.3.1. Proposed PDM process

A PDM process is to select system actions based on the predictions of future system health states [31]. Speaking about PDM in HEV applications, PDM process turns out to be a part of EMS. The proposed prognostics-based health management strategy uses the predictive nature of the prognostics process to obtain the current health state of the fuel cell and conducts energy management though FLC, which is automatically adapted to the current health state.

According to Section 2, the prognostics algorithm is able to estimate the future states based on the previous degradation trend at each desired time instant. However, the degradation of power sources is a long-term procedure and it is redundant to predict their RULs on short time scales, which will lead to huge computation burdens and insufficient memory. Some researchers propose to define the time instants in order to indicate when to start performing the prognostics. According to [24], prognostics can be triggered by monitoring the health indicator. When it comes to implementing EMS, the key point is to select control actions that are suitable for the current health state. The above described health-conscious fuzzy logic control strategy tuned by offline GA optimization may be not feasible and impossible to execute in real time as the FLC cannot be tuned at each time instant and at each degradation state. Therefore, a solution is proposed in this paper, as shown in Figure 5. The idea is to optimize a limited number of FLCs under different degradation states and when RULs are obtained through the online prognostics server, corresponding probabilities to these

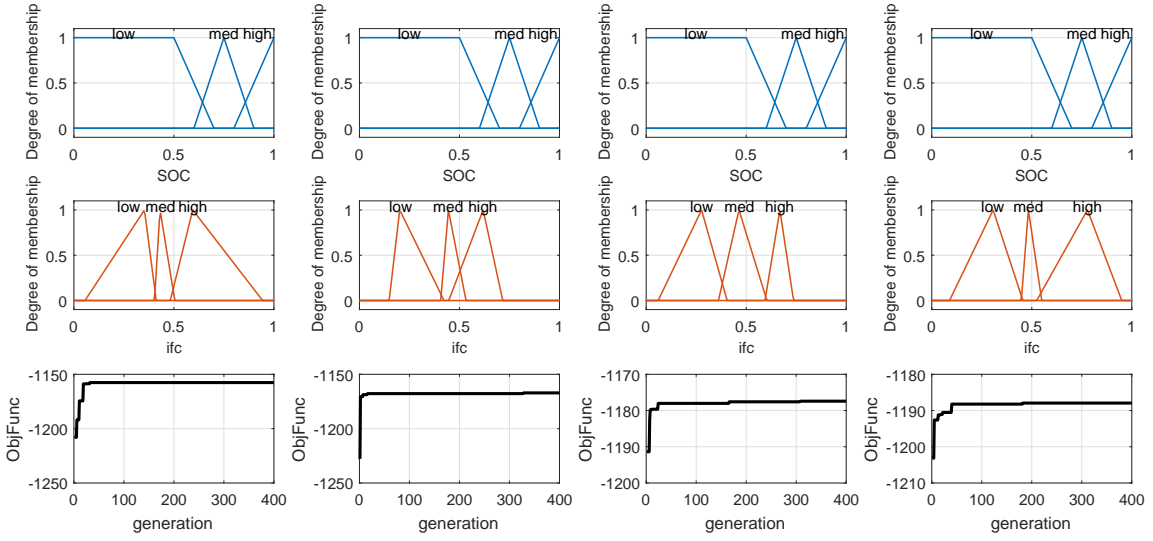


Figure 4: Optimization results under different degradation states ($V_{fc-degrade} = 0\%/3\%/6\%/9\% \cdot V_{init}$ from left to right)

1 degradation states are calculated based on the results of prognostics.
 2 Then, a decision fusion method is applied to calculate
 3 the confidence factors to the offline optimized FLCs and refine
 4 the parameters of the online used FLC.

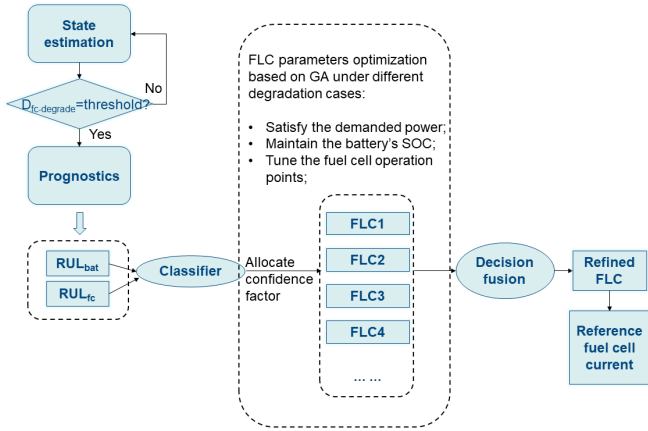


Figure 5: Proposed structure of PDM for developing a health-conscious EMS

3.3.2. Probability calculation

6 In this study, all the pre-mentioned uncertainty factors in Section 2.3 are assumed to follow a Gaussian distribution (that is, additive Gaussian white noise) so that the prognostics uncertainty is additive and the output RUL also follows a Gaussian distribution. It can be expressed by the distribution of particles.

7 The idea of considering prognostics uncertainty during the PDM process is to partition the possible solutions into bins. For example, the RUL distribution plot in Figure 2 has been partitioned into bins with a width of approximately 20 hours. Suppose that the decision to be made is to determine the probabilities of the prognostics results to a limited number of degrada-

tion cases, therefore, the number of particles indicating different RUL values can be recorded in different cases, represented by bins. By normalizing the bin counts with a sum of 1, each bin count represents the probability that an observed RUL falls within that bin, as shown in Figure 6.

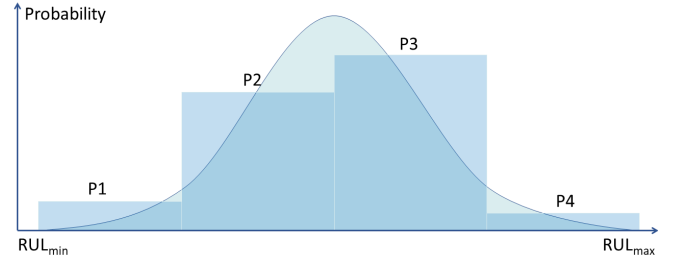


Figure 6: Probability calculation based on RUL uncertainty

22 Suppose that during the online prognostics process, $RUL_{min} = 0$ hour and $RUL_{max} = RUL_{CI=50\%} + t_\lambda$ hours, different widths of bins (WOB) are defined and the corresponding probability values of the RUL prediction results in Figure 2 are calculated and listed in Table 1.

27 The calculation of probability is a necessary step for decision making. Online prognostics at the module level is used to assess in real time the fuel cell's health state and estimate its RUL, while during the decision-making process, the system must be auto-reconfigured depending on the health state to operate with the expected performance. The probability indicates the possibility of the fuel cell falling in a certain degradation state, which should be considered when determining the confidence factors of FLCs that have been optimized offline under certain degradation states, described in the next part of this section.

Table 1: Probability calculation under different widths of bins (WOB)

$WOB = 0.5 \cdot RUL_{max}$	P1					P2				
	0.9879					0.0121				
$WOB = 0.4 \cdot RUL_{max}$	P1				P2			P3		
	0.3208				0.6727			0.0065		
$WOB = 0.3 \cdot RUL_{max}$	P1			P2			P3			P4
	0			0.9407			0.0558			0.0035
$WOB = 0.2 \cdot RUL_{max}$	P1		P2		P3		P4		P5	
	0.3208		0.6199		0.0528		0.0050		0.0015	
$WOB = 0.1 \cdot RUL_{max}$	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
	0	0.3208	0.4158	0.2041	0.0473	0.0055	0.0030	0.0020	0.0010	0.0005

3.3.3. Decision fusion based on probability

The parameters of the online used FLC could be obtained through a decision fusion method based on probability calculation. The implementation of decision fusion is in light of the Dempster-Shafer theory. The Dempster-Shafer theory is a commonly used mathematical decision fusion method introduced by Dempster and Shafer [32, 33]. Different from the Bayesian method, Dempster-Shafer theory justifies the use of combined evidence from different measures.

To combine Dempster-Shafer theory to our problem, the use of Dempster-Shafer theory to fuse offline optimization results is firstly justified. Numbering the four optimized FLCs in Figure 4 as FLC1, FLC2, FLC3, and FLC4, one may know that FLC1 is optimized as the optimal solution when $D_{fc-degrade} = 0$, however, we don't know if it can also generate good results when $D_{fc-degrade} = 3\%$. If the range of the MFs of FLC1 contains the range of the MFs of FLC2, it means that FLC1 can work well even when $D_{fc-degrade} = 3\%$. To include this situation, when generating the online used FLC, we need to consider not only the FLC parameters for each degradation state but also the relationship between the different FLCs.

Using the basic probability assignments calculated from the online prognostics process, one can combine the evidence from different degradation states and calculate the belief measure value that takes into account all possible states according to Dempster-Shafer theory:

$$Bel(A) = \sum_{B \subseteq A} m(B) \quad (23)$$

To understand this equation, it is done in a geometrical way. As seen in Figure 7, they are the MFs of "ifc=high" extracted from Figure 4.

To calculate the belief measure value of each side, one should longitudinally compare the range of the four S1 and four S2 of the MFs. As indicated by (23), a combined belief measure value is obtained if the range of one side is the subset of the range of another side. For example, S2 of the MF of "ifc=high" in FLC1 has a larger range "a" that contains the range of S2 in FLC2 and FLC3, "b" and "c", respectively, so that the belief measure value of it is determined as P1+P2+P3. To be noted, as $x_{43} > x_{13}$, the range "a" does not contain range "d", therefore, the probability P4 is not taken into account. Other belief measure values for each side of each MFs are obtained using the same method.

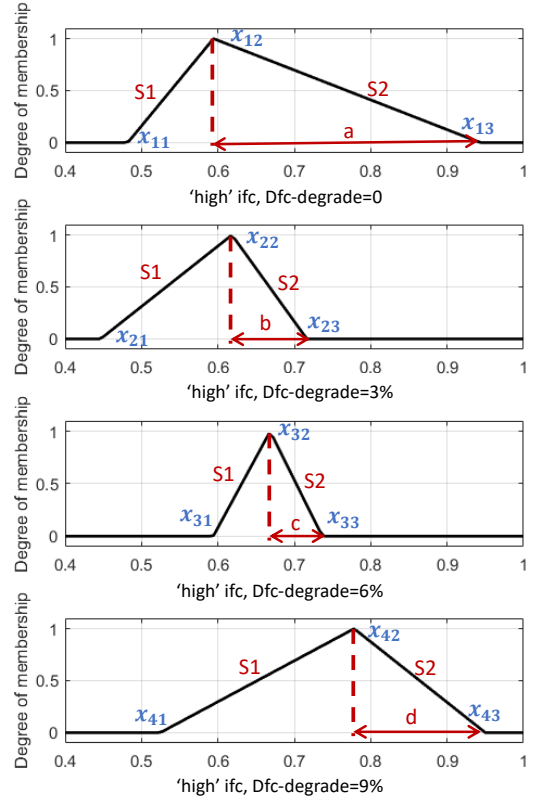


Figure 7: Optimized 'high' Ifc MFs under different degradation cases

Then, to obtain the basic belief assignment $m(A)$ for the MF of one case, a Möbius transformation is used given the belief measure value of each side [34]:

$$m(A) = \sum_{B \subseteq A} (-1)^{|A-B|} Bel(B) \quad (24)$$

This equation is simplified as (25) by neglecting the term $(-1)^{|A-B|}$. This is because the cardinality of $A-B$ is uncountable and insignificant [35].

$$m(A) = \sum_{B \subseteq A} Bel(B) \quad (25)$$

As an MF consists of two sides, the assigned probability to the MF is calculated by the weighted arithmetic mean of the side belief measure values [16]. Then, the parameters of the

1 online used FLC could be determined and adapted to the current
 2 health state.

3 4. Result discussion

4 4.1. Comparison analysis

5 The health management strategy is coded in the EMS module of the simulated fuel cell HEV model (Figure 3). The simulation is run on a repeated WLTC class 2 driving cycle up to thousands of hours. At first, two scenarios have been proposed to justify the effectiveness of the proposed strategy. In the first test, the FLC optimized under no degradation state ($D_{fc-degrade} = 0\%$) is used all along with the simulation until the fuel cell reaches its EOL. Then in the second test, the parameters of the online used FLC are refined according to the prognostics results considering uncertainty. The WOB is defined as $0.3 \cdot RUL_{max}$ and the prognostics is triggered once $D_{fc-degrade}$ falls by 1%. The simulation stops when the fuel cell reaches the same EOL value. The evolution of the power distribution is plotted in Figure 8, in which the fuel cell operates smoothly and the battery provides all the dynamics in the demanded power.

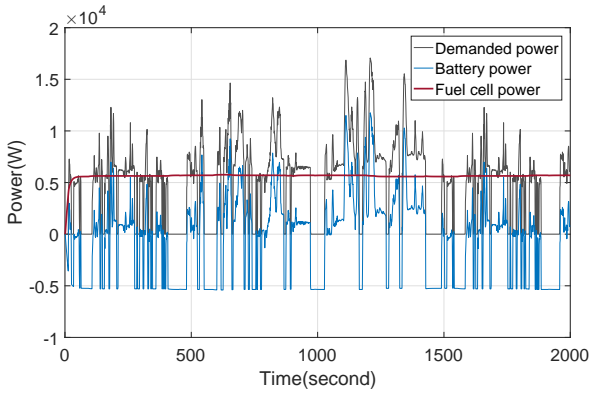


Figure 8: Power distribution between fuel cell and battery

20 However, as the fuel cell degrades, the developed EMS based
 21 on optimized FLC without considering degradation will lose its
 22 optimality. The fuel cell can no longer operate with the least
 23 dynamics, as shown in Figure 9. Large variations could be observed
 24 in the fuel cell power from the 200th hour, which contributes to its
 25 further degradation.

26 The proposed prognostics-based health management strategy
 27 in this paper has conducted to encounter this problem. The
 28 health state of the fuel cell is considered in the EMS through
 29 online prognostics and the FLC parameters are adapted online.
 30 The demanded power can, therefore, be redistributed between
 31 the fuel cell and the battery to avoid large variations in the fuel
 32 cell provided power, as shown in Figure 10.

33 To compare the durability, the evolution of the fuel cell stack
 34 voltage and the battery SOC are compared in Figure 11 and Figure
 35 12. The fuel cell has reached its EOL at 763 hours using the
 36 EMS without prognostics, while the prognostics-based EMS
 37 has prolonged the fuel cell lifetime to 957 hours, by 25.5% approximately.
 38 Besides, compared to prognostics-based EMS, the

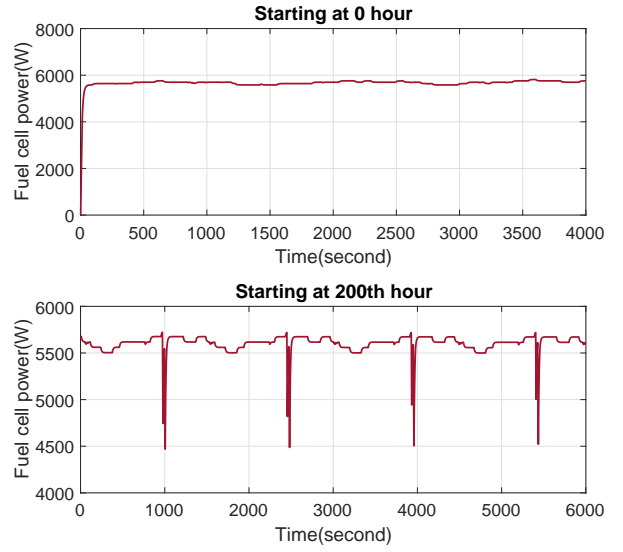


Figure 9: Fuel cell power at 0 hour and 200th hour using EMS without prognostics

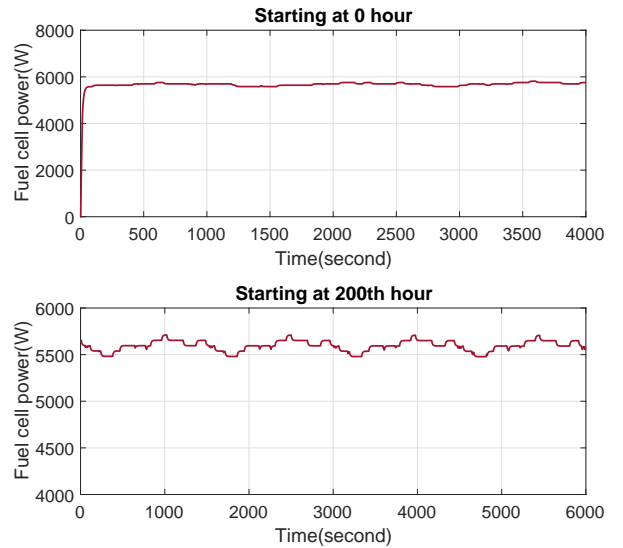


Figure 10: Fuel cell power at 0 hour and 200th hour using prognostics-based health management strategy

39 EMS without tuning the FLC parameters cannot maintain the
 40 SOC of the battery. Battery SOC has dropped to a lower value
 41 along with the time, which also contributes to battery degradation,
 42 as shown in Figure 12.

43 4.2. Discussion on prognostics occurrence frequency

44 To further investigate the influence of prognostics occurrence,
 45 more scenarios with prognostics happening at different
 46 frequencies are designed, while the WOB remains at the same.
 47 The prognostics process is triggered by monitoring the fuel cell
 48 degradation with the degradation interval $\Delta D_{fc-degrade}$ equal

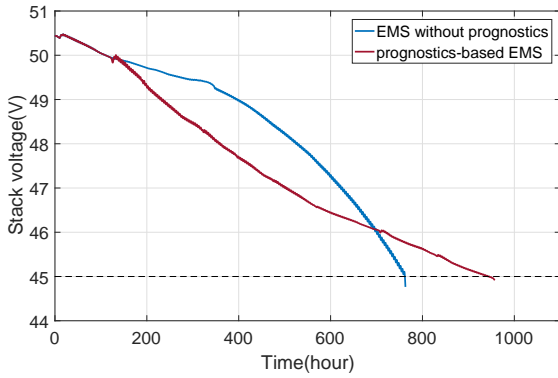


Figure 11: Evolution of the measured fuel cell stack voltage

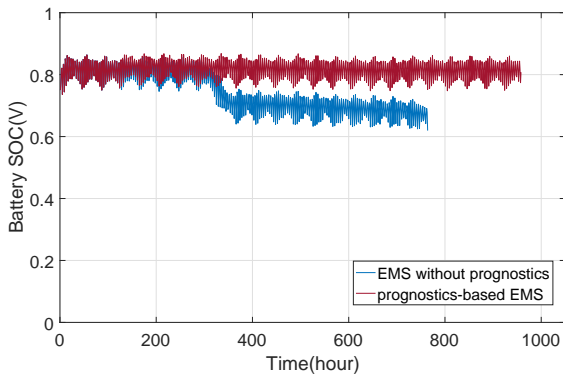


Figure 12: Evolution of the measured battery SOC

1 to 1%, 2%, 3%, 4% and 5%, while the WOB remaining as
2 $0.3 \cdot RUL_{max}$.

3 The comparison of life improvement is listed in Table 2.
4 Compared to the EMS without prognostics, the proposed
5 prognostics-based health management strategy improves the
6 lifetime of the fuel cell with a minimum value of 42.6% and
7 the strategy with $\Delta D_{fc} = 3\%$ has reached the longest lifetime,
8 84.6% longer than the EMS without prognostics. Obviously,
9 it doesn't mean that frequent prognostics can lead to better
10 performance of the fuel cell durability. Frequent prognostics
11 ($\Delta D_{fc} = 1\%, 2\%$) have even worse performance than less fre-
12 quent prognostics ($\Delta D_{fc} = 3\%, 4\%, 5\%$). This is because when
13 the prognostics horizon is large, the prognostics accuracy can-
14 not be guaranteed due to the lack of learning data. When the
15 uncertainty accumulates, the probability calculation will also
16 be influenced so that one cannot reach the optimal parameters
17 of the online used FLC. However, when the frequency becomes
18 lower, i.e., fewer prognostics are implemented, the performance
19 becomes worse, as well. This is due to the reason that the degra-
20 dation of the fuel cell hasn't been fully considered in the strat-
21 egy. If we compare the hourly hydrogen consumption, the result
22 does not vary a lot as our objective function is defined to find a
23 trade-off between degradation mitigation and saving consump-
24 tion. The EMS without prognostics consumes less because the
25 SOC of the battery drops to a lower value.

Table 2: Lifetime improvement comparison with different prognostics occurrence frequency

Prognostics frequency ($WOB = 0.3 \cdot RUL_{max}$)	Lifetime im- provement	m_{H_2} (g/hour)
EMS without prognostics	-	41.2
$\Delta D_{fc} = 1\%$	25.5%	42.0
$\Delta D_{fc} = 2\%$	58.2%	41.9
$\Delta D_{fc} = 3\%$	84.6%	41.9
$\Delta D_{fc} = 4\%$	80.0%	41.9
$\Delta D_{fc} = 5\%$	54.7%	41.7

4.3. Discussion on WOB of probability calculation

27 Further analysis of how the WOB s of probability calculation
28 will have an influence on the system performance is discussed
29 by defining different WOB s. More simulations are executed
30 with $WOB = 0.5 \cdot RUL_{max}$, $0.4 \cdot RUL_{max}$, $0.3 \cdot RUL_{max}$, $0.2 \cdot$
31 RUL_{max} and $0.1 \cdot RUL_{max}$, respectively. The prognostics process
32 is triggered with the fuel cell degradation interval $\Delta D_{fc-degrade}$
33 equal to 3%, as it has been proved to have the best performance,
34 presented in Section 4.2.

35 The comparison of life improvement is listed in Table 3. It
36 shows that the strategy with WOB of probability calculation
37 that equals $0.4 \cdot RUL_{max}$ has reached the best performance. The
38 durability of the fuel cell has been improved by 95.4%. How-
39 ever, the EMS with WOB of 0.5 can only improve the lifetime
40 by 19.5%. This is because the FLC formulated based on the
41 probability calculation with $WOB = 0.5 \cdot RUL_{max}$ cannot take
42 into account the high degradation state. Besides, the EMS with
43 smaller WOB s ($WOB = 0.1 \cdot RUL_{max}$, $WOB = 0.2 \cdot RUL_{max}$)
44 are less satisfied due to the uncertainty in the prognostics re-
45 sults. Once the uncertainty is accumulated to a high level, the
46 refined FLC cannot generate the best results. Once again, the
47 hourly consumed hydrogen are compared. The strategy that
48 reached the best lifetime improvement can also avoid high hy-
49 drogen consumption.

Table 3: Lifetime improvement comparison with different WOB s

WOB ($\Delta D_{fc} = 3\%$)	Lifetime im- provement	m_{H_2} (g/hour)
EMS without prognostics	-	41.2
$WOB = 0.1 \cdot RUL_{max}$	61.7%	41.8
$WOB = 0.2 \cdot RUL_{max}$	60.8%	41.8
$WOB = 0.3 \cdot RUL_{max}$	87.3%	41.9
$WOB = 0.4 \cdot RUL_{max}$	95.4%	41.9
$WOB = 0.5 \cdot RUL_{max}$	19.5%	41.6

50 According to the above analysis, when selecting the parame-
51 ters, i.e. the prognostics occurrence frequency and the WOB of
52 probability calculation, to define the online prognostics-based
53 health management strategy, it is important to improve the pre-
54 diction performance of the prognostics method and to define the
55 necessary points for reconfiguration according to the character-
56 istics of the system.

5. Conclusion

This paper has contributed to developing an enhanced on-line prognostics-based health management strategy considering prognostics uncertainty for fuel cell HEVs. The strategy is realised based on a GA-optimized FLC. A PDM process has been proposed, which refines the parameters of the FLC using a decision fusion method based on RUL probability calculation. Results showed that by taking into consideration the health states, the proposed prognostics-based health management strategy has effectively stabilized the fuel cell operation and maintained the battery SOC, which helped to mitigate the degradation of the power sources by up to 95% without sacrificing the hydrogen consumption. Moreover, variations on the prognostics occurrence frequency and the calculation of probability have also been examined and results showed that proper parameters of the strategy could help to improve the EMS performance. For the perspectives, further researches on hybrid system dynamic degradation monitoring and experimental validation are expected in the future.

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