

Post-prognostics decision making for a two-stacks fuel cell system based on a load-dependent deterioration model

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ABSTRACT

Multi-stacks proton exchange membrane fuel cell (PEMFC) system has been applied to combined heat and power system (CHP), and serves as an alternative energy device due to its high efficiency and zero emission. Owing to the limited durability and larger power supply demand, the management of multi-stacks PEMFC system to obtain a longer service time has received recently growing attention. From the prognostics and health management (PHM) point of view, a post-prognostics decision making for multi-stacks PEMFC system is addressed in this work. Firstly, a load-dependent stochastic deterioration model is proposed for PEMFC. The overall ohmic resistance is chosen as the health indicator of PEMFC. Then the resistance is modeled using a Gamma process whose shape parameter is taken as a function of the current load applied to the stack. Finally, for the post-prognostics decision making phase, a decision probability based load repartition criterion is built to identify the optimal load split between the two stacks. The decision probability is calculated based on the system lifetime results (EoL) in each decision step. The EoL results of the decision phase are further compared with the system EoL that calculated without decision making strategy. The comparison result shows that extended service time can be achieved using the proposed post-prognostics decision making method.

1. INTRODUCTION

Facing with a growing challenge of environmental pollution and the threat of a fossil energy shortage, fuel cell technology emerged as an alternative energy device that is able to apply renewable and clean hydrogen to produce electricity, which has received intense attention for the last two decades (Pandey, 2019) (Dekel, 2018). Among all different types of fuel cells, one of the most widely used fuel cell technologies is proton exchange membrane fuel cell (PEMFC). Recently, with the rapid progress in fuel cell technology, multi-stacks PEMFC system has drawn an increasing attention of researchers due to the high power demands in the application fields like combined heat and power system (CHP) (Marx, Boulon, Gustin, Hissel, & Agbossou, 2014). However, despite the promising research interest, challenges like reliability and durability of PEMFC technology remains to hinder its larger-scale commercialization.

Among the proposed approaches in the published literature, research works on PHM appears to be of great interest towards the health state assessment and lifetime prediction of PEMFC. PHM approaches mainly focus on the early detection of system deterioration to avoid early failure and decide for mitigation actions, and therefore increase the reliability and durability of PEMFC (Jouin, Gouriveau, Hissel, Péra, & Zerhouni, 2016) (Jouin, Gouriveau, Hissel, Péra, & Zerhouni, 2013). Generally, the implementation of a PHM approach consists of seven layers: data acquisition, data processing, condition assessment, diagnostic, prognostics, decision support and human-machine interface. Several research works have been addressed explicitly and specifically the issue of resorting to a PHM framework to solve the reliability and

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durability challenges of PEMFC (Herr et al., 2017) (Rama, Chen, & Andrews, 2008) (Jouin et al., 2013).

An increasing number of works are being focused on RUL prognostics considered as a key component of PHM chain. Zhang et al. (D. Zhang, Cadet, Yousfi-Steiner, & Bérenguer, 2018) developed a particle filtering based prognostics approach which considering degradation recovery phenomena. Zhou et al. (Zhou, Al-Durra, Zhang, Ravey, & Gao, 2018) proposed a novel robust prognostic approach that contains three phases for PEMFC degradation prediction and RUL estimation. An adaptive data-driven prognostic strategy is proposed for PEMFC by Li et al. (Li, Zheng, & Outbib, 2019). As can be seen in these works, various approaches have been developed to achieve a high RUL prediction accuracy. However, the RUL prediction remains of limited interest if it is not used to make a decision, and its performance can be sensibly assessed only at the level of the whole processing chain, i.e. from prediction to decision-making.

In order to forge a more comprehensive implementation of PHM framework for PEMFC to extend its useful lifetime, this work proposes a post-prognostics decision making strategy for a multi-stacks fuel cell system. Whenever a prognostics method has been developed to predict the RUL of PEMFC, decisions have to be made for the system to achieve a useful lifetime extension. Firstly, the problem formulation, including fuel cell deterioration model and decision making problem are presented. The methodology is then detailed, given the RUL determination and the decision strategy. Finally, simulations are carried out and the results are compared with deterioration calculated without decision making procedure.

2. PROBLEM FORMULATION

2.1. Fuel cell deterioration model

Until now, the deterioration mechanisms of PEMFC are not fully known yet, because of the complex electrochemical mechanical, and thermal degradations are involved in different components of a PEMFC stack (Jouin et al., 2016) (Rama et al., 2008) (Ous & Arcoumanis, 2013) (X. Yu & Ye, 2007). These degradations tend to be highly dependent on the PEMFC operating conditions. For example, when a PEMFC is operated through an automotive cycle, it may suffer from more serious degradation. Thus, in this work, the degradation of fuel cells is modeled as a function of the load.

A usual tool used to characterize fuel cells is the polarisation curve, which illustrates the cell voltage with respect to the current density. As depicted in Fig.1, there are mainly four types of voltage losses in PEMFC, fuel crossover loss, activation loss, ohmic loss and concentration loss. In this work, the output voltage of PEMFC is calculated using an empirical model (Kim, Lee, Srinivasan, & Chamberlin, 1995) as:

$$V_{st} = n(E_0 - RJ - A \ln(J) - m_1 \exp(m_2 J)) \quad (1)$$

where n is the number of cells in one PEMFC stack, J represents the current density, R is the overall resistance of PEMFC, A is the Tafel parameter for oxygen reduction, m_1, m_2 represent the constant related to the mass transport overpotential. E_0 is the voltage term related to reversible potential of PEMFC.

Eq.(1) involves the parameter set $Q = \{E_0, R, A, m_1, m_2\}$. The parameter values vary with the degradation of the fuel cell. As indicated by recently published investigations, (D. Zhang et al., 2018) (D. Zhang, Cadet, Yousfi-Steiner, Druart, & Bérenguer, 2017) (Jouin et al., 2016), the resistance R is representative of the global state of health of the fuel cell. It is therefore chosen as the degradation indicator of the fuel cell in this work. The deterioration model of R will be explained in next section.

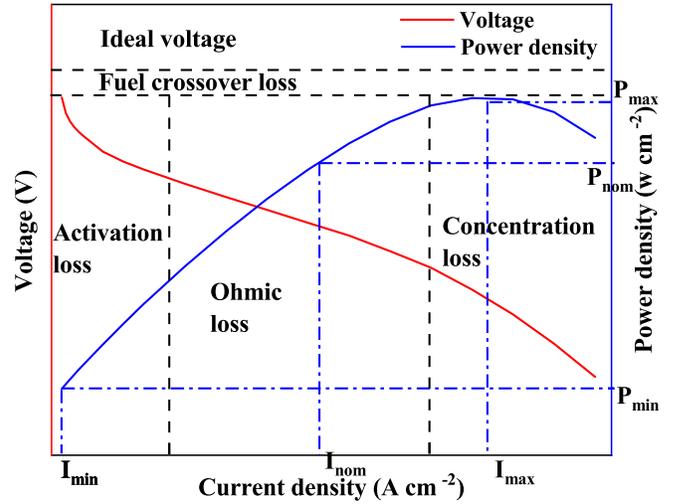


Figure 1. Polarization curve and corresponding power curve of PEMFC.

2.2. Decision making problem

The objective of the decision making phase is to decide the optimal load repartition for two-stacks system at each decision step in order to obtain the maximum system service time. The idea of the management of the system lifetime through the post-prognostics decision making process is due to the deterioration of the PEMFC is directly affected by its operation load level (Herr et al., 2017) (X. Zhang, Yang, Luo, & Dong, 2017).

The following assumptions are made on the proposed two-stacks fuel cell system:

- Constant load demand is defined for the two-stacks PEMFC system, denoted as I_{load} .
- The two PEMFC stacks in the system are identical. The output power of each PEMFC stack ranges from the

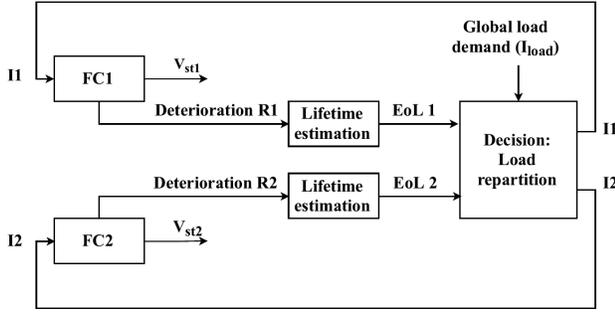


Figure 2. Schematic of the post-prognostics decision making strategy.

minimal output power P_{min} to maximum output power P_{max} , as shown in Fig. 1.

- This work only focused on the management of fuel cell, the management of the auxiliary systems is not concerned here.
- The two PEMFC stacks in the system are connected in parallel.
- The value of the fuel cell resistance is considered to be measured in this work. The resistance value can be further estimated thanks to an observer.

The block function scheme of the problem studied in this work is shown in Fig.2. The variables (current density, voltage, lifetime and so on) are represented by arrows, and the block in the figure represents the fuel cell or the calculation to be done in the work. The problem is to estimate the PEMFC degradation, then to estimate the EoLs and at last to define a way to decide the load repartition to satisfy the global load demand.

3. POST-PROGNOSTICS DECISION MAKING

3.1. Gamma process deterioration modeling

In order to simulate the deterioration path of R , a Gamma process was adapted to calculate the deterioration value which increases with time. In the previous section 2.1, the basic knowledge about fuel cell deterioration and the influence of the operating load have already been introduced. Furthermore, the global resistance R has been chosen as a deterioration indicator that is supposed to be measured. In this subsection, the deterioration level is modeled as a stochastic Gamma process, and the dependency on time and load demand is explicitly expressed.

A Gamma process is a stochastic process with independent, positive increments that obey a Gamma distribution $\Gamma(\alpha, \beta)$ characterized by two key parameters: its shape parameter α and scale parameter β . Gamma processes are suitable for continuous and monotonous deterioration modelling, (van

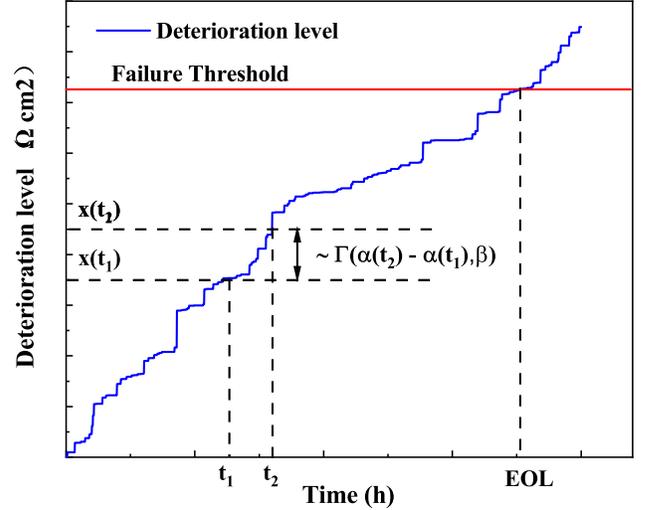


Figure 3. Deterioration path of a Gamma process.

Noortwijk, 2009). By definition, for a Gamma process $x(t)$ with shape parameter $\alpha(t)$ and β , we have the following properties, see Fig.3:

- $x(0) = 0$, with probability equal to 1 ;
- the deterioration increment $\Delta x(t_1, t_2) = x(t_2) - x(t_1)$ between t_1 and t_2 is characterized by

$$\Delta x(t_1, t_2) \sim \Gamma(\alpha(t_2) - \alpha(t_1), \beta) \quad (2)$$

On a unit time interval $\Delta t = 1$, the mean and variance of the degradation increment Δx are given by:

$$\text{Mean}(\Delta x) = \alpha \cdot \beta \cdot \Delta t = \alpha \cdot \beta \quad (3)$$

$$\text{Var}(\Delta x) = \alpha \cdot \beta^2 \cdot \Delta t = \alpha \cdot \beta^2 \quad (4)$$

Using Gamma processes, various deterioration behaviors can be simulated by resorting to different α and β values. In this work, one of the key process is to properly choose the parameters for the Gamma process so that a deterioration path with sufficient variance can be achieved. This specific setting obeys the intrinsic aspect of PEMFC deterioration, for it is a stochastic process with uncertainty involved in it. Moreover, for a Gamma process given with a known parameters, when a failure threshold (FT) of the deterioration is defined, the average end of life (\overline{EoL}) can be calculated by:

$$\overline{EoL} = \frac{FT}{\alpha \cdot \beta} \quad (5)$$

Finally, in order to introduce the dependence of the deterioration process to the load applied to the system, the shape parameter of the Gamma law is assumed to be a function of the current load I , i.e. $\alpha(I)$. The form of this function is detailed in the next section. The parameter β is taken as a constant. The proposed Gamma process-based deterioration

model is stochastic and not deterministic, this makes the modeling work and following decision making approach more challenging and suitable for real fuel cell lifetime management.

3.2. PEMFC load dependent deterioration modeling

As already mentioned, we have to consider that the deterioration rate changes with the current load. The shape parameter α in Gamma process Eq.(2) is set by referring to a real fuel cell deterioration rate, whereas the scaling parameter β is defined as a constant value. An asymmetric quadratic function is defined to describe the relationship between the deterioration rate and the current density (load level), as shown in Fig.4. The current density represents the operating load demand level of a PEMFC.

The deterioration rates are defined based on the deterioration mechanism of PEMFC. When PEMFC is operated at lower current density load, the output voltage of the fuel cell is relatively high, this will causing great damage to the PEMFC membrane (Endoh, Terazono, Widjaja, & Takimoto, 2004). Besides, high voltage may also cause deterioration to other key components of PEMFC, like catalyst layer (CL), gas diffusion layer (GDL), further causing a performance decreasing (Chung, Kim, Sung, Lee, & Chung, 2009) (Y. Yu et al., 2012). As the deterioration of PEMFC is dependent on its operating load level, different deterioration rate can be set with respect to the current load level.

In this work, it is assumed that the average EoL of PEMFC operating at the minimal current density I_{min} is \overline{EoL}_1 . Similarly, for the nominal current density I_{nom} and maximum current density I_{max} , the average EoL are \overline{EoL}_2 and \overline{EoL}_3 respectively, with $\overline{EoL}_1 < \overline{EoL}_3 < \overline{EoL}_2$. The average deterioration rate \bar{r}_i can then be calculated for these three different cases as:

$$\bar{r}_i = \alpha_i \cdot \beta = \frac{FT - R0}{\overline{EoL}_i} \quad (6)$$

where $i = 1, 2$ and 3 corresponding to the minimal, nominal and maximum current density respectively. $R0$ represents the initial deterioration level. The calculated deterioration rate is further used to define the parabola function as shown in Fig.4.

The deterioration path can be simulated with an identified model. For a given realization of the deterioration path, the failure time of the PEMFC is defined as the first time when the deterioration level exceeds the failure threshold FT . The specific application and simulation results will be further described in the results and discussion section.

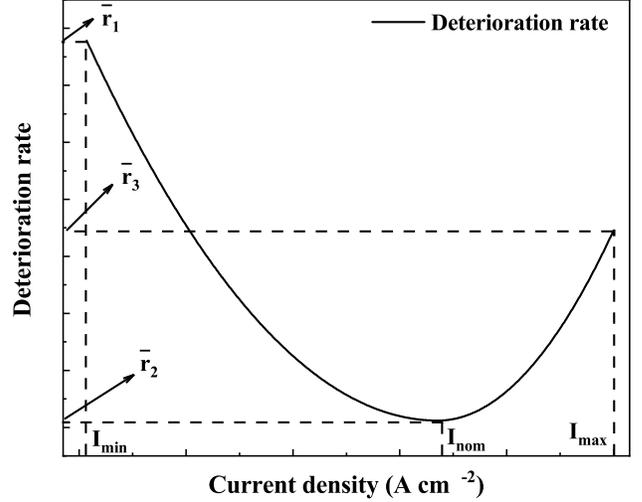


Figure 4. Deterioration rate vs current density.

3.3. Decision making for the load repartition for a two-stacksystem

The developed model is then used for the post-prognostics decision making phase to decide the optimal load split between two PEMFC stacks so that the maximum system service life can be achieved. This decision making procedure is made periodically, at fixed decision time interval ν .

For each decision period, the decision probability is noted as P_d and the decision threshold FT_d . As shown in Fig.5, A system with two PEMFCs has been running for t_0 . FC1 and FC2 are two PEMFC stacks in the system. For these two PEMFCs, the failure occurs due to an excess of deterioration threshold, and the distribution law of the failure time T can be calculated analytically as (Wenjia Xu & Wenbin Wang, 2012):

$$F(t) = P(T \leq t) = \frac{\Gamma(\alpha t, FT_d \cdot \beta)}{\Gamma(\alpha t)} \quad (7)$$

where T is the first hitting time of the level FT_d by the stochastic process $x(t)$.

According to the previous discussion, the threshold used for the decision making at each decision step can be set as:

$$FT_d = \alpha \cdot \beta \cdot \nu + D_{init} \quad (8)$$

where the parameter ν plays a role similar to \overline{EoL} in Eq.(5). D_{init} represents the initial deterioration level at the beginning of each decision interval ; for decision step 1, its value equals to $R0$.

Eq.(7) defined an analytical approach to calculate the decision probability P_d . Considering the decision time interval ν , P_d is decided by:

$$P_d = F(\nu) \quad (9)$$

This approach is sketched in Fig.5: the red and black solid curves above the decision threshold represent the predicted lifetime distribution for FC1 and FC2 that are calculated at time t_0 . P_1 is the probability that the deterioration level of FC1 exceeds the decision threshold before $(t_0 + \nu)$ hours ; similarly, the decision probability of FC2 is P_2 . In this work, the decision criterion is then defined as $(1 - P_1) \cdot (1 - P_2)$, and we seek to maximize the criterion to obtain the longest system lifetime. This is realized by searching the optimal load split between the two stacks. The solid line below FT_d is the corresponding deterioration trajectories simulated for FC1 and FC2 after the decision.

A Gamma process based simulation was performed. Two types of deterioration trajectories are simulated :

- Trajectories developed with decision making, for FC1 and FC2, denoted as R1 and R2 respectively
- Trajectories developed without decision making, used as comparison group, the corresponding trajectories are denoted as R1c and R2c for FC1 and FC2 respectively.

In order to justify the efficiency of the proposed decision making strategy, the lifetime of two stacks system are calculated based on the simulated trajectories. For system lifetime calculated based one single deterioration trajectory, the simulation was denoted as one time running simulation; for system lifetime calculated based on N deterioration trajectories (average system lifetime), the simulation was denoted as N times running simulation. The lifetime for one time simulation (EoL_1) was calculated by:

$$EoL_1 = \min\{EoL_{R1}, EoL_{R2}\} \quad (10)$$

where EoL_{R1} represents the lifetime of FC1, EoL_{R2} represents the lifetime of FC2.

The lifetime of the system can then be estimated by averaging the results over the N simulations (\widehat{EoL}_N):

$$\widehat{EoL}_N = \frac{1}{N} \sum_{i=1}^N (\min\{EoL_{R1i}, EoL_{R2i}\}) \quad (11)$$

where EoL_{R1i} represents the lifetime results of FC1 calculated by the i th deterioration trajectory, EoL_{R2i} represents the lifetime results of FC2 calculated by the i th deterioration trajectory.

In this work, the EoL calculated from R1 and R2 (with the decision making algorithm implemented) are denoted as EoL_{1d} and EoL_{2d} , the results that are calculated from R1c and R2c are denoted as EoL_{1c} and EoL_{2c} . Similarly, at the system level, for EoL_N , we have EoL_{Nd} and EoL_{Nc} .

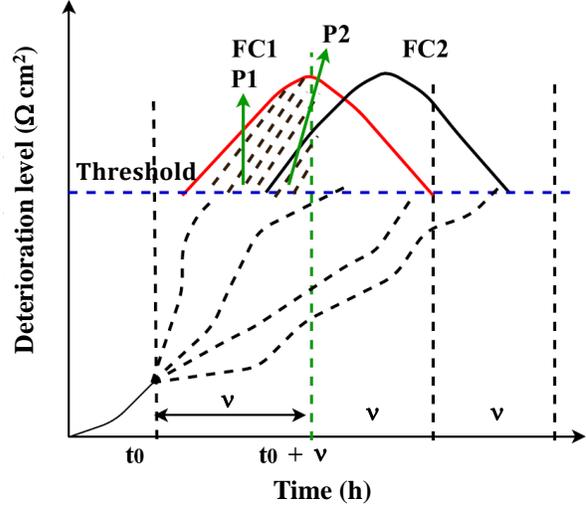


Figure 5. Principle of decision making strategy

4. RESULTS AND DISCUSSION

4.1. load-dependent deterioration simulation

As described in Section 2, R_0 is identified by fitting the polarization curve model to the measured data of an actual PEMFC stack. The fitting results were summarized in Table 1. The load-dependent modeling results were presented in Fig.6. For the Gamma process, the scaling parameter β is defined as constant value 0.32. R_0 represents the initial overall resistance of the PEMFC stack, and is further used in the deterioration simulation part.

The shape parameter was modeled as a function of the current load, and was calculated based on Eq.(6) and Fig.4, as introduced in section 3.2. In this work, the FT for one PEMFC stack is defined as 1.9. The desired average EoL and the corresponding values for the average deterioration rates under the different possible load conditions based on Eq.(6) are summarised in Table 2 . The values for I_{min} , I_{nom} and I_{max} are calculated as 0.214, 0.7 and 1.6 Acm^{-2} respectively, based on the knowledge of the concerned PEMFC. In Fig.6,

Table 1. Parameters fitting results for Polarization equation

E_0	R_0	A	m_1	m_2
0.8034	0.1797	0.0236	$2.692e^{-5}$	0.0092

it is clearly seen that the resistance deterioration path is directly influenced by the current load. At the beginning, from 0 to 200h, the current density J equals to I_{nom} , according to the function defined in Fig.4, the deterioration rate is the lowest; then J increase to I_{max} , deterioration rate increased accordingly; next J decrease to the nominal value, deterioration rate decreased; and next period, the deterioration rate reaches the maximum level for the current density decreased

to I_{min} ; and finally when the current density level recovers to I_{nom} , then deterioration rate decreases. These results prove that the PEMFC deterioration is dependent on the operating current load and the proposed load-dependent deterioration model works.

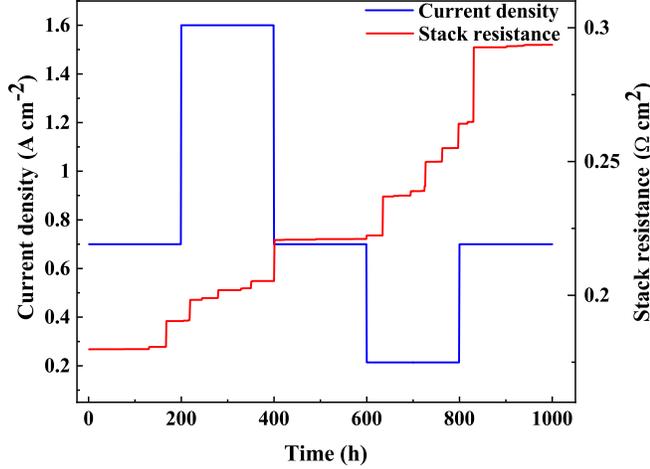


Figure 6. Load-dependent deterioration model results for one stack.

Table 2. Parameter calculation results for Gamma process simulation

	I_{min}	I_{nom}	I_{max}
$EoL (h)$	200	2800	300
$\bar{r} (e^{-4})$	128	9.15	85

4.2. Results for post-prognostics decision making

This subsection presents the main results of the proposed post-prognostics decision making strategies for the two-stacks system. As introduced in Section 3.3, a load repartition decision is performed every ν (decision time interval), formulating a multi-step decision making strategy. In this work, the decision time interval ν is defined as 150 h. The first step is based on the PEMFC deterioration model combine with the Gamma process to simulate the deterioration path for each PEMFC. The current load demand in this work is defined as a constant value, $I_{load} = 1.8 A cm^{-2}$.

Based on Eq.(8), the FT_d corresponding to the maximum deterioration rate \bar{r}_1 which used in this work is calculated for each decision step. The scheduled simulation horizon in this work is 3900 h, Therefore, the decision steps equals to 26. The FT_d for the first decision step was calculated by Eq.(8), its value is 0.5899. Due to the limits in Eq.(7), the FT_d in each step should no less than the initial deterioration level, therefore, an adaptive decision threshold were calculated for the follow step, with 35% increment of the initial deterioration level. Then based on the analytical method proposed in

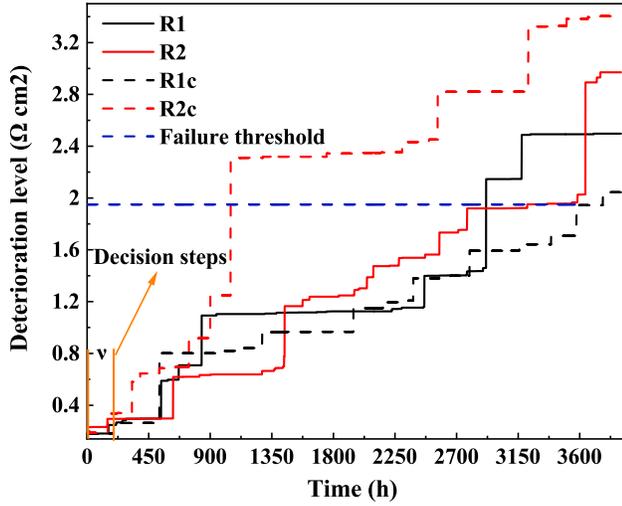
section 3.3, the decision probability for current density ranging from I_{min} to $1.5 A cm^{-2}$ with 1287 groups was investigated. The load repartition results were summarized in Fig.7, 8, 9, 10, and Table 3.

Fig.7 shows the post-prognostics decision making results of one time running the simulated deterioration trajectories were compared with the curves obtained without decision making strategy. Besides, for the comparison group, the current density of both stack was set as $0.9 A cm^{-2}$. From Fig.7(a), it is clear seen that for the deterioration trajectories with decision making strategy, its deterioration is much smaller. Besides, the deterioration level of R1 and R2 changes during the operating time, this is due to the mitigating effects of the proposed decision making strategy. Combining with the load repartition results in Fig.7(b), FC1 and FC2 both begins at $0.9 A cm^{-2}$, but in the following periods, their current load changes at each decision step, this helps to investigate the health state of each fuel cell stack and thus extend the system lifetime. Finally, the system lifetime results were calculated based on Fig.7, summarized in Table 3. For one time running simulation, EoL_{1d} is 2916 h, much high than EoL_{1c} (1049 h).

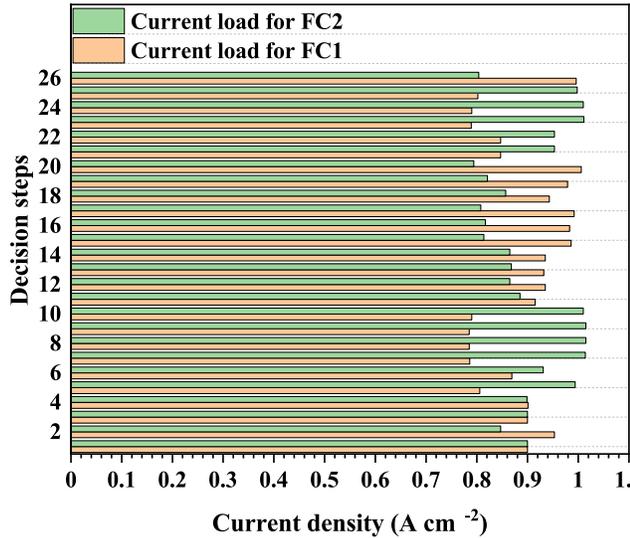
However, because of the stochastic nature of the system evolution, the EoL results on a single simulation run are not enough to prove the efficiency of the proposed decision strategy. Therefore, the average deterioration trajectories and median EoLs are further discussed, see Fig.8. Fig.8 shows that the trajectories of R1, R2 and R1c, R2c are very close and the load repartition strategy does not show obvious effects on the mean deterioration path compared with Fig.7(a). However, the active load repartition reduces the variance between the deterioration trajectories of both stacks within the same fuel cell stack : they are synchronized which increases the system lifetime and a fast deterioration behavior of one stack is compensated and balanced with the deterioration of the other stack. Without the decision making strategy, the deterioration paths remain desynchronized and there is high risk that one of the two FC stacks fails early, hence reducing the lifetime of the system.

Moreover, for a set of 100 simulations, histograms of the system lifetimes with and without decision are shown in Fig.9. By comparing Fig.9(a) and Fig.9(b), the system lifetime results with decision are mostly distributed in the range (2500, 4000) h, with a median lifetime of 3018.5 h. The lifetimes without decision are mainly distributed in (1500, 3000) h with a median lifetime value equal to only 2662 h. The specific deterioration trajectories from a set of 10 simulations are presented in Fig.10. The overall results in Fig.10 show that the trajectories that developed with decision are more grouped together with a low variance and that the deterioration tends to be lower than that without decision, which proves that the proposed decision making strategy can help

to mitigate the system deterioration, improving its lifetime.



(a) One time running simulation



(b) Load repartition for two-stacks system

Figure 7. PEMFC Deterioration trajectories build for two-stacks (R1 and R2 with load repartition, R1c and R2c without decision)

5. CONCLUSION

A post-prognostics decision making strategy was proposed to decide the optimal load split between the two stacks in order to maximize the system lifetime. In this work, two PEMFC stacks need working simultaneously to provide the desired system load demand, the decision criterion is then constructed to further calculate the optimal load repartition for two stacks. To well demonstrate the efficiency of the proposed decision making strategy, results based on one time running simulation and multi-times running simulation (100 times) were both discussed in this work. For one time running simulation,

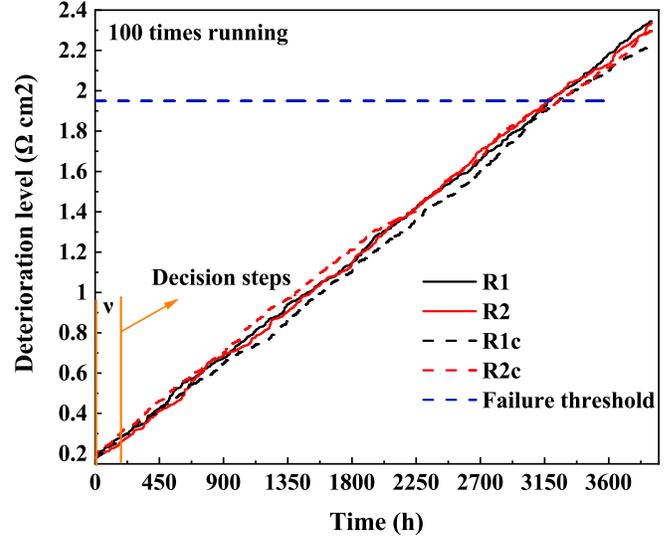


Figure 8. Average deterioration results (100 times running)

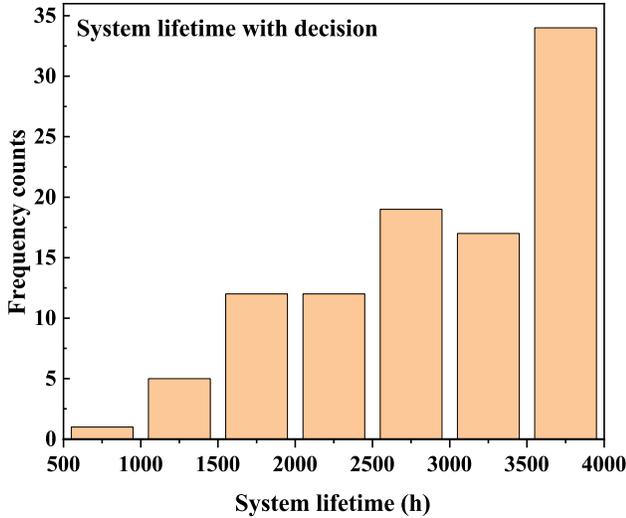
Table 3. Examples of EoL results for a single simulation and for 100 simulations (median and average values).

	EoL_1 (h)	EoL_{100} (h)	EoL_{100} (h)
	EoL_1 (h)	Median	Mean
with decision	2916	3018.5	2908.8
without decision	1049	2662	2615.1

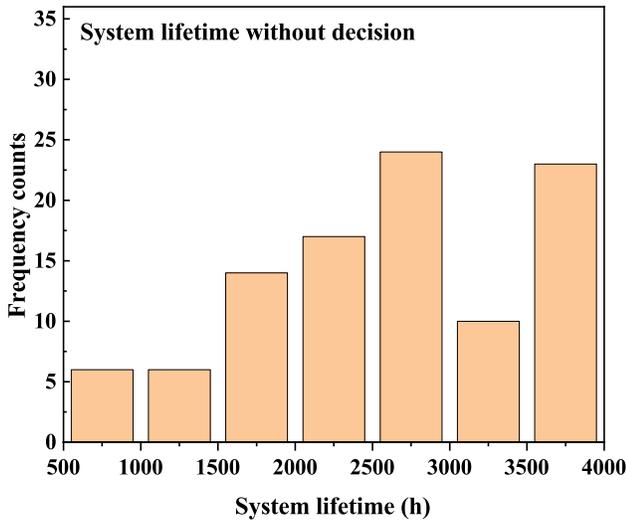
the system lifetime results after decision making strategy is 2234 h, much higher than the results calculated without a decision (1029 h). For average simulation results EoL_{100d} is 2908.8 h, higher than EoL_{100c} (2615.1 h), besides, the trajectories and system lifetime statistic results prove that the proposed post-prognostics decision making strategy can help to mitigate the deterioration and to improve the system lifetime. Based on the proposed post-prognostic decision making framework, future work will be focused on the combination with real fuel cell test data to further study its application on multi-stacks fuel cell system.

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(a) System lifetimes histogram (with decision)



(b) System lifetimes histogram (without decision)

Figure 9. Histograms of the observed system lifetimes for 100 simulations

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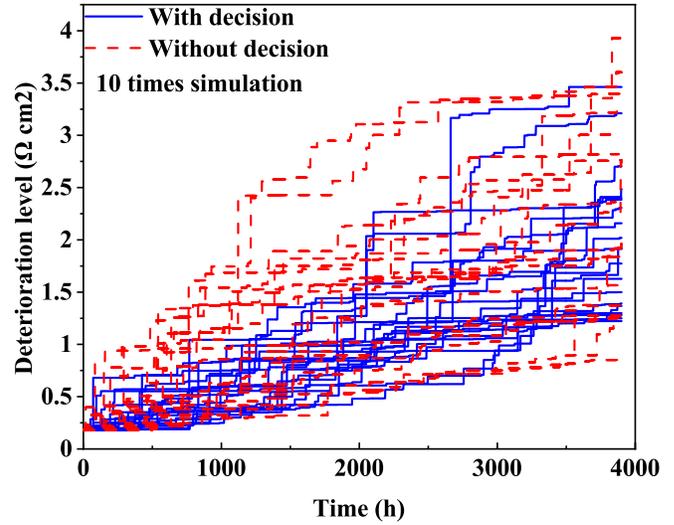


Figure 10. 10 times simulation deterioration trajectories results

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