



HAL
open science

A load allocation strategy for stochastically deteriorating multi-stack PEM fuel cells

Jian Zuo, Catherine Cadet, Zhongliang Li, Christophe Bérenguer, Rachid Outbib

► To cite this version:

Jian Zuo, Catherine Cadet, Zhongliang Li, Christophe Bérenguer, Rachid Outbib. A load allocation strategy for stochastically deteriorating multi-stack PEM fuel cells. ESREL 2022 - 32nd European Safety and Reliability Conference (ESREL 2022), Aug 2022, Dublin, Ireland. pp.R22-01-051, 10.3850/978-981-18-5183-4_R22-01-051-cd . hal-03843418

HAL Id: hal-03843418

<https://hal.science/hal-03843418v1>

Submitted on 18 Nov 2022

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons Attribution - NonCommercial - NoDerivatives 4.0 International License

A load allocation strategy for stochastically deteriorating multi-stack PEM fuel cells

Jian Zuo

*Univ. Grenoble Alpes, CNRS, Grenoble INP¹, GIPSA-lab, 38000 Grenoble, France.
LIS Laboratory, Aix-Marseille University, 13397 Marseille, France. E-mail: jian.zuo@grenoble-inp.fr*

Catherine Cadet

*Univ. Grenoble Alpes, CNRS, Grenoble INP¹, GIPSA-lab, 38000 Grenoble, France.
E-mail: catherine.cadet@grenoble-inp.fr*

Zhongliang Li

LIS Laboratory, Aix-Marseille University, 13397 Marseille, France. E-mail: zhongliang.li@lis-lab.fr

Christophe Bérenguer

*Univ. Grenoble Alpes, CNRS, Grenoble INP¹, GIPSA-lab, 38000 Grenoble, France.
E-mail: Christophe.berenguer@grenoble-inp.fr*

Rachid Outbib

LIS Laboratory, Aix-Marseille University, 13397 Marseille, France. E-mail: rachid.outbib@lis-lab.fr

Multi-stack Proton Exchange Membrane (PEM) fuel cell systems have received growing interest owing to their high operation efficiency, larger capacity, and flexible operation mode. One of the biggest hurdles for the application of a multi-stack PEM fuel cell system is its limited durability. A load allocation strategy is proposed based on the deterioration information of a fuel cell system. This allocation strategy aims at extending the system's lifetime through better management of its deterioration. A dynamic type of load demand is considered as the system production requirement. The decision-making process takes the fuel cell resistance of the different stacks as inputs and decides the optimal load allocation for the PEM fuel cell system. In the proposed setting, the load allocation is updated whenever there is a demand change event until system failure. The behavior and performance of the proposed allocation strategy are assessed by Monte Carlo simulations. The lifetime distribution results of the proposed load allocation strategy are compared with the classical average load split method. It is confirmed that the proposed strategy can efficiently balance overall system deterioration, thus achieving an improved lifetime for the studied fuel cell system.

Keywords: PEM fuel cell, Multi-stack, Load allocation, Stochastic deterioration model, Dynamic load demand, Decision-making, Monte Carlo simulations.

1. Introduction

Proton exchange membrane (PEM) fuel cell shares the advantage of low operating temperature, high power density, and easy scale-up, making it one of the most suitable clean energy devices Ogungbemi et al. (2021). Though promising for various industrial applications, e.g., fuel cell electric vehicles (FCEV), current PEM fuel cells still suffer from limited durability Dhimish et al. (2021). A promising solution is to use a multi-stack fuel cell system (MFCS), i.e. to put several stacks in parallel, to provide the power. First, the

growing power demand requires a fuel cell system with a higher capacity which can be satisfied by using MFCS. Additionally, multi-stack PEM fuel cell systems enable flexible operating mode among the stacks, and the parallel structure greatly improves the system reliability compared with a single stack configuration. Finally, the possibility of power-sharing among stacks can improve both the overall system efficiency and durability.

Prognostics and Health Management (PHM) techniques including a multi-layer based Energy Management Strategy (EMS) can address the

durability challenge of fuel cells. In addition, the hierarchical architecture of PHM enables to handle fuel cell system management from the observation stage to diagnosis analysis, deterioration modeling, lifetime prediction, and finally to decision making Yue et al. (2021).

One of the challenges of developing EMSs for a PEM fuel cell system lies in the integration of its deterioration aspects into the decision-making procedure, thus forming a health-aware EMS. Fuel cell deterioration can be estimated thanks to online measurements. Then, the remaining lifetime of the stack can be predicted based on a deterioration model. However, fuel cell deterioration or aging is due to complex electrochemical, mechanical, and thermal mechanisms, which are difficult to model. Current studies on fuel cell deterioration mainly focus on either deterioration mechanism understanding or empirical model developing Pei et al. (2008), so there is no standard formula for modeling fuel cell aging. For instance, an online system parameters identification power distribution-based method is proposed to reduce fuel cell system hydrogen consumption Wang et al. (2019). In Wu *et al.* Wu et al. (2019), the energy distribution is performed by solving a convex optimization problem minimizing the overall energy costs of a hydrogen vehicle. A typical empirical fuel cell load-dependent aging model is proposed by Pei et al Pei et al. (2008). The load varying, start-stop, high power load are identified as the main aging factors for the fuel cell.

However, a few works in the literature take into account stack aging and deterioration. In Herr et al. (2017), the authors proposed a post-prognostics decision process to manage the energy distribution of an MFCS. In this paper, the fuel cell deterioration is linked with the load. Thus, a change in the load distribution will also change the predicted stack life. Zhou et al. (2022) further studied a scenario-oriented EMS for MFCS. An optimal stacks allocation scheme is analyzed with respect to different stacks numbers, application scenarios, and system efficiency. However, the estimation of the system lifetime is based on a deterministic deterioration model which limits the

interests of the proposed method. Indeed, one of the specificities of fuel cells is their individual variability, both in terms of dynamic behavior and deterioration. These individual variabilities affect the reliability of the prediction of the behavior of the multi-stack system and therefore require the use of stochastic modeling to account for this source of uncertainties.

This work proposes a load allocation strategy based on the deterioration information of an MFCS to extend the system's lifetime. Firstly, the overall resistance is chosen as the fuel cell deterioration index. Then, a load-dependent stochastic deterioration model based on the Gamma process is built. The decision-making process takes the fuel cell resistance of the different stacks as inputs and decides the optimal load allocation for the PEM fuel cell system. The behavior and performance of the proposed allocation strategy are assessed by Monte Carlo simulation for dynamic load demands. To be as close as possible to the actual behavior of MFCS, different variances of the internal resistance deterioration behavior, as well as heterogeneity between the stacks deterioration behaviors, are considered. Finally, the lifetime distribution results obtained with the proposed load allocation strategy are compared with those of the classical average load split method.

2. Problem Statement

The MFCS consists of n parallel connected stacks (Figure 1). All the stacks are identical but are providing different load power, denoted $\{L_i\}_{i=1,\dots,n}$. The global load demand is noted L_d . As the system provides exactly the total amount of power, the contribution of each stack can be written as a part of the global load demand, and be written as:

$$L_i = \gamma_i L_d, \text{ where } \sum_{i=1}^n \gamma_i = 1 \quad (1)$$

The external load demand dynamics are considered as a sequence of piecewise constant values, each value representing an event for which the optimal load distribution will be calculated, Figure 1.

The problem addressed in this paper can be

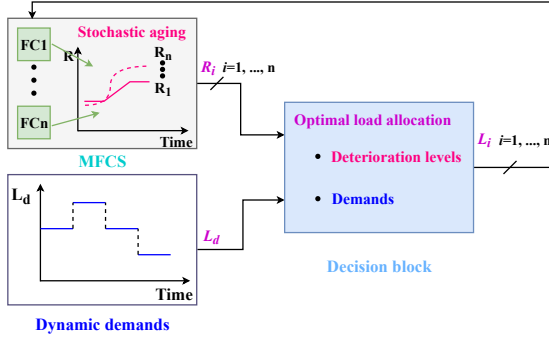


Fig. 1. Proposed EMS principle.

split into two parts. The first part of the problem is to build a load-dependent model of fuel cell deterioration. Then, the second part is to build an optimal EMS for MFCS based on this model.

2.1. Fuel cell deterioration indicator

The deterioration indicator is taken from the empirical equation proposed in Kim et al. (1995):

$$V_s = n \left(E_0 - RI - A \ln(I) - m_1 e^{(m_2 I)} \right) \quad (2)$$

where V_s is the stack voltage, n is the number of cells, I is fuel cell current density. E_0 is open circuit voltage, A is the Tafel parameter for oxygen reduction, R is the overall resistance, m_1 and m_2 are transfer coefficient related parameters.

The output power of a fuel cell stack (L) is then expressed as $L = V_s I$. It has been shown in Zuo et al. (2021) that the overall resistance R is representative of the stack degradation level. Thus, the overall resistance R is chosen as the health indicator.

2.2. System lifetime and failure definition

A fuel cell stack is assumed to fail when its deterioration level R exceeds a fixed threshold, which is called the failure threshold FT . The failure time corresponds to the first hitting-time of level FT by $R(t)$. Then, the fuel cell stack lifetime denoted T_R , is defined as the time duration from the time the stack is put into use to the time of stack failure, and is written :

$$T_R = \min_t (R(t) > FT) \quad (3)$$

For a multi-stack system, the system failure is defined as the end of the system's ability to supply the external global load demands. Thus, the failure of one stack does not necessarily correspond to the MFCS failure, as long as the external power load demand can be provided by the other stacks.

3. Fuel cell load-dependent deterioration model

The load and the load variations are considered to build the load-dependent deterioration model. The fuel cell resistance aging model is expressed as:

$$\Delta R = \Delta R_L + \Delta R_{\Delta L} \quad (4)$$

where ΔR is the overall resistance increment. ΔR_L is the load level contribution and $\Delta R_{\Delta L}$ is the load variation contribution to the resistance increment.

The deterioration due to the load is modeled as a Gamma process, which means that the increment of the deterioration level due to the load level between time t_1 and t_2 writes:

$$\Delta R_L(t_1, t_2) = R_L(t_2) - R_L(t_1) \sim \text{Ga}(\Delta\alpha, \beta) \quad (5)$$

where $\text{Ga}(\cdot)$ represents the probability density function of the Gamma law; α is the shape parameter of the Gamma process ($\Delta\alpha = \alpha(t_2) - \alpha(t_1)$) and β is the scale parameter.

The nominal conditions offer a relatively better reaction environment (water content, heat condition, etc) for fuel cells, thus they are associated to the lowest deterioration rate. On the contrary, deviating the load with respect to the nominal conditions will gradually increase the deterioration rate due to the less favourable operating conditions. The deterioration parameters under nominal conditions, i.e. α_0, β_0 are estimated from fuel cell aging test data Gouriveau et al. (2014). The empirical average resistance deterioration rate function $D(L)$ with respect to the load is thus formulated as:

$$D(L) = A(L - L_{nom})^2 + B \quad (6)$$

where A is expressed by two parts with respect to the load range, i.e. $A = A_1, L_{min} \leq L < L_{nom}$ and $A = A_2, L_{nom} \leq L \leq L_{max}$. The values

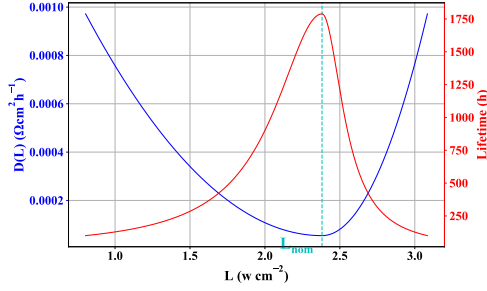
4 *J.Zuo et al.*

Fig. 2. Deterioration rate of ΔR_L and expected lifetime functions of load.

of A_1 , A_2 , B are estimated from the expected lifetime data, see Figure 2. Thus, the shape parameter $\alpha(L)$ can be estimated from the relation:

$$D(L) = \alpha(L)\beta \quad (7)$$

as the scale parameter β is not varying. More details can be found in Zuo et al. (0).

The resistance deterioration increment due to the load variation (ΔL) is:

$$\Delta R_{\Delta L} = K\Delta L \quad (8)$$

where $K = 7.58 \times 10^{-6}$ ($\Omega\text{cm}^2/\text{Wcm}^{-2}$) Pei et al. (2008).

4. Energy Management Strategy

4.1. Decision-making principle

The external load demand dynamics are considered as a sequence of piecewise constant values, each value corresponding to what will be called hereinafter as an ‘‘event’’. The decision-making process is event-based, i.e. the load repartition is estimated at each new event. We assume here that several future events are known.

Figure 3 depicts the diagram of the event-based decision-making process with m future known events. The current event E_{ind}^0 is the beginning of current decision. The decision horizon ranges from E_{ind}^0 to E_{ind}^m . T^j is the time length of event j ($j = 0, \dots, m$). The system is required to produce exactly the amount of external load demands, and the output power of each stack is constrained within the fuel cell production range, i.e. from L_{min} to L_{max} .

$\{R_{fci}^0\}_{i=1, \dots, n}$ are the resistance levels of all stacks at initial event E_{ind}^0 which is assumed to

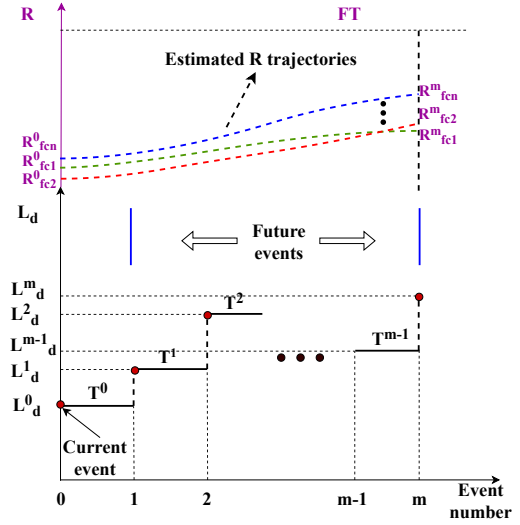


Fig. 3. Principle of the proposed decision procedure.

be measured. The deterioration levels at decision m are estimated by Eq. (4). The future global deterioration weighted by the distance of current deterioration to the failure threshold FT is defined as the optimization index J . With all combinations of load allocations $\gamma_i L_d^j$, the optimal decision is decided by minimizing J . The calculation of J will be derived in the following Section 4.2. In this way, the global system aging is being balanced which helps to improve system lifetime.

4.2. Objective function formulation

The objective function is formulated so as to minimize the resistance increments along the decision-making horizon. Then the proposed dynamic optimization problem is formulated as:

$$\begin{aligned} & \text{Minimize} \\ & J = \sum_{i=1}^n \omega_i^0 \sum_{j=0}^{m-1} (\Delta R_{L,i}^j + (\Delta R_{\Delta L,i}^j)^2) \\ & \text{subject to} \\ & L_{min} \leq \gamma_i^0 L_i \leq L_{max}, \sum_{i=1}^n \gamma_i^0 = 1 \\ & \Delta R_{L,i}^j = D(\gamma_i^0 L_d^j) \cdot T^j \\ & \Delta R_{\Delta L,i}^j = K(\gamma_i^0 L_d^{j+1} - \gamma_i^0 L_d^j) \end{aligned} \quad (9)$$

where T^j is the time length of event j ; L_d^j defines the external dynamic load demands; γ_i^0 is the load allocation ratio for FC i (assuming same allocation

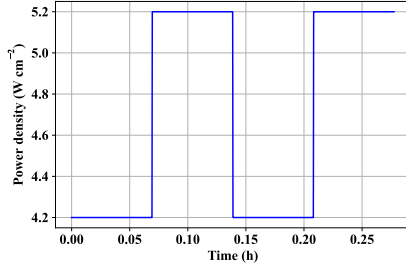


Fig. 4. Dynamic load demand cycle.

ratio for all events); and ω_i^0 is the corresponding weight of the overall FC*i* aging (R_{fci}^0). Note that the deterioration term due to load variation $\Delta R_{\Delta L,i}^j$ is expressed with a quadratic form for the optimization convenience. K is given in Eq. (8).

The distance of the deterioration level to the preset failure threshold FT is leveraged to formulate the weight factor ω_i^0 :

$$\omega_i^0 = \frac{1/(FT - R_{fci}^0)}{\sum_{i=1}^n 1/(FT - R_{fci}^0)} \quad (10)$$

The defined weight terms (ω_i^0) aims to balance the aging of all stacks, i.e., by adjusting the value of weights to force the less deteriorated stacks to operate under less desirable conditions so as to allow the more deteriorated stacks to work at relatively more desirable conditions. More details on the system lifetime control effects will be further discussed in Section 5.

5. Results and Discussions

5.1. Simulation settings

As a first attempt, the studied MFCS is assumed to consist of two identical stacks ($n = 2$). Table 1 summarizes the key parameters of the stacks. The other chosen parameters are $\beta_0 = 4.4 \times 10^{-4}$, $FT = 0.2775 \Omega \text{ cm}^2$, and $R_0 = 0.1803 \Omega \text{ cm}^2$.

Figure 4 depicts the dynamic demand cycle used in the simulation. It consists of two levels of load demand, chosen to frame the nominal value. The whole simulation cycle is a repetition of these two levels with a load duration of 250 s. To study the performances of the EMS, deterioration trajectories with different variances but the same average trend are simulated. Hence, the initial shape

Table 1. Fuel cell stack parameters.

Conditions	L (Wcm^{-2})	Lifetime (h)	α_0
Minimal	0.8035	100	2.227
Nominal	2.3811	1788	0.125
Maximal	3.084	100	2.227

and scale parameters (α_{ini} , β_{ini}) of the studied Gamma process are modified by introducing a constant ℓ :

$$\alpha_{ini} = \alpha_0/\ell, \beta_{ini} = \beta_0 \cdot \ell \quad (11)$$

where $\ell = 5, 10, 20, 30$ so as to gradually increases the deterioration trajectory variance.

In addition, this work also investigates the influence of deterioration imbalance between the stacks. This is done by assigning different initial resistance values (R_{fc1}^{ini} and R_{fc2}^{ini}):

$$R_{fc1}^{ini} = R_0 + \Delta R_0, R_{fc2}^{ini} = R_0 \quad (12)$$

The modified increment terms of $\Delta R_0 = 0.0, 0.01, 0.02, 0.03 \Omega \text{ cm}^2$ are studied.

Using the previous setting, simulations on a 2-stack system are performed. One future event is being considered (i.e. $m = 1$) in the objective function. The Sequential Least-Squares Programming (SLSQP) algorithm is used to solve the optimization problem. Due to the stochastic behavior of the stack aging, modeled by a Gamma process, the system lifetime is estimated with Monte Carlo simulations. The simulation of the system from the beginning of use till system failure (denoted as one-run) is repeated N times, obtaining N system lifetime samples. Then the average system lifetime ($T_{R,dec}$) is estimated by the average of those lifetime samples. According to the simulations, $N = 300$ ensures the convergence of $T_{R,dec}$.

The results are compared with the classic average load split method, which distributes the overall load demand evenly among stacks.

5.2. Simulation performance indicators

Two lifetime-related indicators are established to assess the performance of the proposed strategy. The first indicator gives the relative improvement in lifetime compared to the average load split

6 *J.Zuo et al.*

strategy which is computed by:

$$\Delta T_{R,pct} = \frac{T_{R,dec} - T_{R,ave}}{T_{R,ave}} \times 100\% \quad (13)$$

where $T_{R,dec}$ stands for the average lifetime of the proposed load allocation decisions. $T_{R,ave}$ is the average lifetime of the average split method.

The second indicator $T_{R,pct}^+$ represents, in percentage terms, the number of the simulated lifetimes that are higher than those of the average split method. Let N^+ denote the number of lifetimes where the lifetime obtained by the load allocation decision ($T_{R,dec}$) is larger than the results of average split ($T_{R,ave}$). Then the proposed indicator is written as:

$$T_{R,pct}^+ = N^+/N \times 100\% \quad (14)$$

5.3. Simulation results

5.3.1. Analysis of the proposed strategy behavior on a single realization

Firstly, the decision strategy behavior is examined on a single simulated deterioration path, according to the predefined parameter settings (Section 5.1), $\ell = 5$, $\Delta R_0 = 0.01 \Omega \text{ cm}^2$ are chosen, denoted as case 1.

Figure 5 presents the overall resistance values and the optimal allocation decisions of studied four events in case 1. It is noticed that for the previous two decisions, the FC1 is more deteriorated. And the aging trend is reversed for the last two decisions (Figure 5 (a)). Combing with the optimal allocations (Figure 5 (b)), it is confirmed that our strategy lets the more deteriorated stacks operate at relatively more desirable conditions than the ones that are less deteriorated. According to the recorded deteriorations, the sudden increment of R_{fc2} is due to the load effect, i.e. $\Delta R_{fc2,L}$ (increased $4.185 \times 10^{-3} \Omega \text{ cm}^2$ from event 2 to event 3 while the other increments are nearly zero) which confirms the stochasticity in ΔR_L . This stochasticity is investigated by a stochastic gamma process with different initial resistance and increment variance to account for individual variabilities in an MFCS (see section 5.3.2).

Figure 6 shows the overall load decisions distribution of our strategy. It can be seen that most of the allocation decisions are distributed between

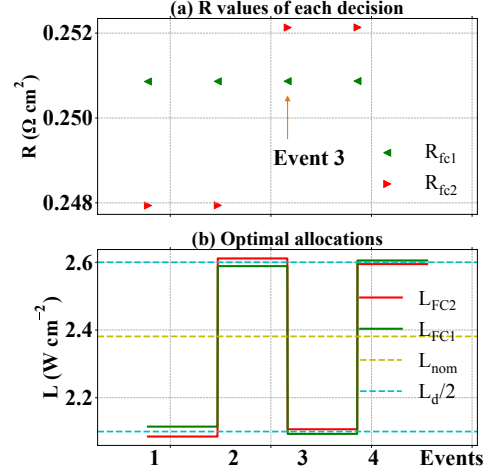


Fig. 5. Case 1: four events.

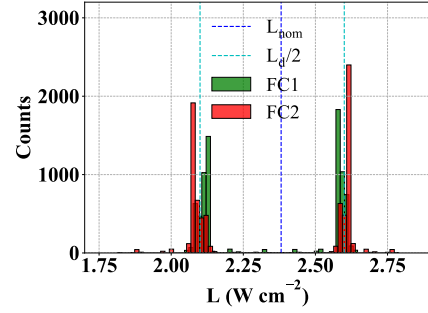


Fig. 6. Overall load allocation histogram of case 1.

2 to 2.25 W cm^{-2} on the left side and between 2.5 to 2.75 W cm^{-2} on the right side. Instead of assigning demands with a fixed average split, our strategy optimally decides the load allocations conditionally to the estimated system resistance at the decision stage.

5.3.2. Overall performance analysis

Let now examine the results of the $N = 300$ simulation histories. Figure 7 presents the lifetime histograms and corresponding fitted Gaussian probability distribution functions (pdf) for $\Delta R_0 = 0.01 \Omega \text{ cm}^2$ and different deterioration variances. In all these figures, the pdf of our strategy presents a higher mean value than the average split strategy, proving thus that an extended lifetime is achieved. Additionally, the pdfs curves widen as the value

of ℓ increases, i.e., as the variance of stack aging becomes larger. According to the definition of system lifetime (Eq. 3), a greater variance in the R trajectories will widen the interval of the first-hitting-time of FT and thus that of the simulated lifetimes as well. In Figures 7 (a), (b), and (c), it is seen that the pdf curve of our strategy is more centered on the mean than the one of the average split method. However, in Figure 7 (d), the two pdf curves are similar in terms of the pdf curve width. This is caused by the growing variance in R trajectories. The calculated standard deviation results further justify the observations. In Figure 7 (a), the standard deviation of our strategy is 47.52, whereas that of the average split is 66.37. The standard deviation of our method (137.61) is slightly bigger than the average split (133.67) in Figure 7 (d). In the obtained results, the histograms results of $\Delta R_0 = 0.0, 0.02, 0.03 (\Omega \text{ cm}^2)$ show similar trends.

The two proposed lifetime-related performance indicators are computed and listed in Tables 2 and 3. In general, the $\Delta T_{R,pct}$ results of the groups with initial increment (i.e. $\Delta R_0 > 0$) are higher than the group with identical initial resistance. This proves the efficiency of the proposed strategy in dealing with imbalanced deterioration in MFCS. Moreover, in Table 2, the $\Delta T_{R,pct}$ values are monotonically increasing as ℓ increases. In comparison, the value of $\Delta T_{R,pct}$ shows a fluctuation trend. These results show that the R trajectory variance and deterioration level of all stacks have a mutual influence on the lifetime control effects. Setting a bigger variance will vary the resistance values of all stacks. The proposed strategy tries to reverse this imbalanced aging through optimized load allocations, which helps to decrease the overall system deterioration, thus improving the lifetime. But in the cases where ΔR_0 is much bigger or variance is too high, it will limit the control effects of the proposed strategy. These findings encourage us to study the behavior of the proposed strategy under different variance levels (e.g. consider the random effects in the Gamma process). The results of $T_{R,pct}^+$ in Table 3 confirm that generally over 60% lifetimes simulated with allocation decision are better than the average split

method. In some cases, $T_{R,pct}^+$ even reaches 85%.

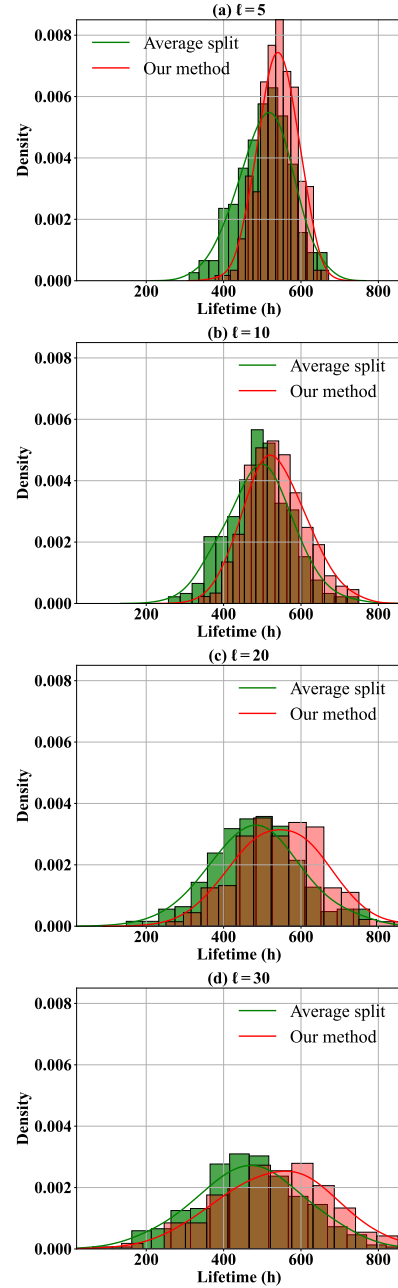


Fig. 7. Lifetime histograms (and fitted Gaussian pdf) for $\Delta R_0 = 0.01 \Omega \text{ cm}^2$.

6. Conclusion

This work proposed a load allocation strategy for an MFCS. The dynamic load demands are

Table 2. Simulation results for $\Delta T_{R,pct}$.

ΔR_0 (Ωcm^2)	$\Delta T_{R,pct}$ (%)			
	$\ell = 5$	$\ell = 10$	$\ell = 20$	$\ell = 30$
0.0	5.8	6.3	6.7	15.1
0.01	6.5	8.9	12.8	13.9
0.02	9.6	12.4	10.3	13.7
0.03	17.6	18.7	10.7	14.8

Table 3. Simulation results for $T_{R,pct}^+$.

ΔR_0 (Ωcm^2)	$T_{R,pct}^+$ (%)			
	$\ell = 5$	$\ell = 10$	$\ell = 20$	$\ell = 30$
0.0	66.7	63.5	59.3	67.3
0.01	66.0	66.7	62.3	66.7
0.02	74.0	69.0	61.7	64.3
0.03	85.7	75.7	61.0	61.3

considered as the application scenario. Fuel cell overall resistance is chosen as a health indicator, and the load and the variation of load are considered as two major deterioration drivers. The main contribution is to propose a stochastic Gamma process-based deterioration model for handling multi-stack fuel cell system individual variability in terms of their deterioration. The load allocations are then decided by solving a sequential optimization problem. Our strategy can help improve system lifetime by 18.7% ($\ell = 10$, $\Delta R_0 = 0.03 \Omega cm^2$) compared with average split method.

References

- Dhimish, M., R. G. Vieira, and G. Badran (2021). Investigating the stability and degradation of hydrogen pem fuel cell. *International Journal of Hydrogen Energy* 46(74), 37017–37028.
- Gouriveau, R., M. Hilairet, D. Hissel, S. Jemei, M. Jouin, E. Lechartier, S. Morando, E. Pahun, M. Pera, and N. Zerhouni (2014). Ieee phm 2014 data challenge: Outline, experiments, scoring of results, winners. In *Proc. IEEE Conf. Prognostics Health Manage.*, pp. 1–6.
- Herr, N., J.-M. Nicod, C. Varnier, L. Jardin, A. Sorrentino, D. Hissel, and M.-C. Péra (2017). Decision process to manage useful life of multi-stacks fuel cell systems under service constraint. *Renewable energy* 105, 590–600.
- Kim, J., S.-M. Lee, S. Srinivasan, and C. E. Chamberlin (1995). Modeling of proton exchange membrane fuel cell performance with an empirical equation. *Journal of the electrochemical society* 142(8), 2670.
- Ogungbemi, E., T. Wilberforce, O. Ijaodola, J. Thompson, and A. Olabi (2021). Selection of proton exchange membrane fuel cell for transportation. *International Journal of Hydrogen Energy* 46(59), 30625–30640.
- Pei, P., Q. Chang, and T. Tang (2008). A quick evaluating method for automotive fuel cell lifetime. *International Journal of Hydrogen Energy* 33(14), 3829–3836.
- Wang, T., Q. Li, L. Yin, and W. Chen (2019). Hydrogen consumption minimization method based on the online identification for multi-stack pemfcs system. *International Journal of Hydrogen Energy* 44(11), 5074–5081.
- Wu, X., X. Hu, X. Yin, L. Li, Z. Zeng, and V. Pickert (2019). Convex programming energy management and components sizing of a plug-in fuel cell urban logistics vehicle. *Journal of Power Sources* 423, 358–366.
- Yue, M., Z. Al Masry, S. Jemei, and N. Zerhouni (2021). An online prognostics-based health management strategy for fuel cell hybrid electric vehicles. *International Journal of Hydrogen Energy* 46(24), 13206–13218.
- Zhou, S., G. Zhang, L. Fan, J. Gao, and F. Pei (2022). Scenario-oriented stacks allocation optimization for multi-stack fuel cell systems. *Applied Energy* 308, 118328.
- Zuo, J., C. Cadet, Z. Li, C. Berenguer, and R. Outbib (0). Post-prognostics decision-making strategy for load allocation on a stochastically deteriorating multi-stack fuel cell system. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability* 0(0), 1748006X221086381.
- Zuo, J., C. Cadet, Z. Li, C. Bérenguer, and R. Outbib (2021). Post-prognostics decision making strategy to manage the economic lifetime of a two-stack pemfc system. In *2021 Annual Reliability and Maintainability Symposium (RAMS)*, pp. 1–7. IEEE.