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Fuel Cell Stochastic Deterioration Modeling for Energy Management in a Multi-stack System

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Abstract - Fuel cells are promising clean power sources which use hydrogen and oxygen to generate electricity. However, the limited durability that is decided by various degradation phenomena remains one of the main barriers hindering their commercialization. Fuel cell deterioration modeling contributes to model and reproducing fuel cell deterioration behaviors, thus serving as a key step to decreasing fuel cell system deterioration. Fuel cell deterioration behavior is characterized by two main features, namely, load-dependent and stack-to-stack deterioration heterogeneity. A Gamma process with random effect-based deterioration model is used to account for the above deterioration features of fuel cells. Different types of random effects are introduced to the studied Gamma process on its scale parameter, taken as a random variable following a gamma law. Fuel cell degradation trajectories are studied by the developed deterioration models using the Monte Carlo simulation method. The lifetime distributions of the proposed models are analyzed for investigating their deterioration behavior.

Keywords - Fuel cell, load-dependent deterioration modeling, gamma process, random effects.

I. INTRODUCTION

Proton exchange membrane (PEM) fuel cell is recognized as one of the most promising clean power sources due to the high operation efficiency, suitable operation temperature and zero-emission. PEM fuel cell has been applied to transportation and stationary fields which serves as the primary power device. However, the high cost and limited durability remain as the two main challenges that hinder its commercialization. To use multi-stack fuel cells (MFC) instead of single stack fuel cell is considered as a promising solution. Indeed, these systems can extend the functionality of a single stack and offer more redundancy, enhanced durability, and flexible modular architecture compared with a single stack fuel cell system [1]. To operate, integrate and interconnect several devices in a generation system, a control system to manage the energy is necessary. A proper energy management strategy enables the system to supply the demand, increase the lifetime of the elements, reduce operating costs and therefore maximize system performance, providing a technically and economically feasible option. To build such a deterioration-aware EMS, it is necessary to develop a deterioration that reproduces the dynamic degradation behavior of MFC systems according to the operating parameters. On the other hand, fuel cell deterioration is

linked to electrochemical, mechanical, and thermal related mechanisms. Those deterioration mechanisms are difficult to directly model with a “white-box” method that relying on the exact laws of physics. The problem of this work is thus focuses on build a deterioration model adapted for the energy management of MFC systems.

The deterioration of an MFC highly depends on the external demand profile. Different operation modes imposes different levels of deterioration on fuel cells. Consequently, the deterioration of a fuel cell is modeled as a function of its operation load. This deterioration characteristic is summarized as load-dependency. Another characteristic is the stochasticity. Stack-to-stack deterioration heterogeneity may exist due to the stochasticity in the intrinsic fuel cell deterioration phenomena.

To overcome above fuel cell deterioration modeling challenge, this work proposed a load-dependent stochastic degradation model for MFC system. Firstly, the fuel cell resistance is chosen as a deterioration health indicator, as it contains the key deterioration of a fuel cell. Next, The deterioration of a fuel cell is represented by the increment of fuel cell stack resistance. Stochastic Gamma processes are used to build the stochastic deterioration models. The shape parameter of the considered Gamma process is further perturbed as an empirical function of fuel cell operation power load which makes fuel cell deterioration load-dependent. Lastly, a random effect is introduced to the Gamma process on its scale parameter, taken as a random variable following a Gamma law.

Monte Carlo simulations are performed to investigate the deterioration behavior of the proposed models. The first-hitting time of a failure threshold is presented and analyzed.

II. PROBLEM STATEMENT

The problem of this work is focused on the deterioration modeling of an MFC system. The deterioration modeling problem requires modeling fuel cell stack deterioration under a dynamic load profile. The deterioration of different operation modes need to be considered in the proposed model. Another part of the modeling problem is how to handle the load-dependent, stochasticity, and stack-to-stack variability characteristics.

A. Fuel cell deterioration indicator

Fuel cell polarization curve is a typically characterization approach for measuring fuel cell output voltage. The deterioration indicator is taken from the empirical polarization equation proposed in Kim *et al.* [2]:

$$V_s = n(E_0 - RI - A \ln(I) - m_1 e^{(m_2 I)}) \quad (1)$$

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 reaction. R is fuel cell overall resistance. m_1 and m_2 are transfer coefficient related parameters.

It has been shown by Zuo *et al.* [3] that the overall resistance R is representative of the stack degradation level. Thus it is chosen as the health indicator.

B. First hitting-time of a fuel cell

A fuel cell is said to fail when the defined HI $R(t)$ 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 lifetime (T_R) is expressed as:

$$T_R = \min(R(t) > FT) \quad (2)$$

C. Dynamic load profile

A dynamic type load profile that is usually used by automotive fuel cells is proposed to simulate the fuel cell deterioration path (Figure 1) [4].

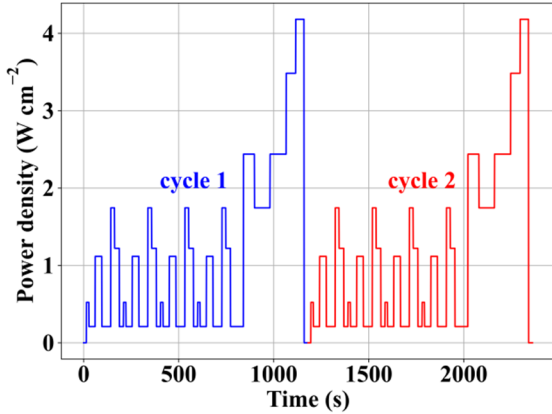


Fig. 1. FC-DLC dynamic load profile.

The deterioration modeling problem requires modeling fuel cell stack deterioration under a dynamic load profile. As can be seen in the load profile, various operation modes exist which are needed to be considered in the deterioration model.

III. METHODOLOGY

A. Gamma process

Gamma process (GP) is a stochastic process with independent, positive increments that obeys a gamma distribution [5]. By definition, for a gamma process $X(t)$ with shape parameter $\alpha(t)$ and scale parameter β , the increment $\Delta X(t_1, t_2) = X(t_2) - X(t_1)$ between time t_1 and t_2 ($t_2 > t_1 \geq 0$) has a gamma density:

$$f_{\alpha(t_2-t_1), \beta}(x) = \frac{\beta^{\alpha(t_2-t_1)} x^{\alpha(t_2-t_1)-1}}{\Gamma[\alpha(t_2-t_1)]} e^{-\beta x} \text{ for } x \geq 0. \quad (3)$$

where $\Gamma(\alpha(t_2 - t_1)) = \int_0^{+\infty} x^{\alpha(t_2-t_1)-1} e^{-x} dx$. This gamma distribution is denoted as $\text{Ga}(\alpha(t_2 - t_1), \beta)$.

The mean deterioration in the time interval (t_1, t_2) is

$$E[\Delta X(t_1, t_2)] = \alpha(t_2 - t_1)\beta \quad (4),$$

and the variance is

$$\text{Var}[\Delta X(t_1, t_2)] = \alpha(t_2 - t_1)\beta^2 \quad (5).$$

Gamma process is considered as a relevant tool for modeling fuel cell resistance deterioration for following reasons:

- 1) It is suitable to model monotonic continuous increasing deterioration that accumulates over time through many tiny increments. Fuel cell resistance deterioration follows a similar trend. It is gradually increasing during fuel cell operation.
- 2) A gamma distributed increments of different time duration still obeys a gamma law which makes gamma process suitable for modeling various deterioration processes.

Therefore, the gamma process is used to build the stochastic load-dependent model of a fuel cell.

B. Fuel cell load-dependent deterioration model

The load amplitude, load varying, and start-stop are considered to build the load-dependent deterioration model. The fuel cell resistance deterioration model is expressed as:

$$\Delta R = \Delta R_L + \Delta R_{\Delta L} + \Delta R_{ss} \quad (6)$$

where ΔR is the overall resistance increments (i.e. the deterioration). ΔR_L , $\Delta R_{\Delta L}$, and ΔR_{ss} are the deterioration caused by load, load varying, and start-stop effects, respectively.

ΔR_L is modeled through a gamma process with shape parameter α and scale parameter β , i.e., $\text{Ga}(\alpha, \beta)$. To make ΔR_L load-dependent, the shape parameter α is modeled as a function of the load L . For a stationary gamma process, the mean of the resistance increment over a unit time interval $\Delta t = 1$ is expressed as:

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

To build this deterioration rate function, the nominal load (L_{nom}) condition offers a relatively better reaction environment, e.g., water content, heat condition, etc. for fuel cells, thus it is linked with the lowest deterioration rate. On the contrary, deviating the load with respect to the nominal conditions will gradually increasing the deterioration rate due to the less favorable operating conditions. The empirical deterioration rate function $D(L)$ is thus formulated as:

$$D(L) = A(L - L_{nom})^2 + B \quad (8)$$

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 $A = A_2, L_{nom} \leq L \leq L_{max}$. Figure 2 presents the curves of the proposed deterioration function. More details can be found in our previous work [3].

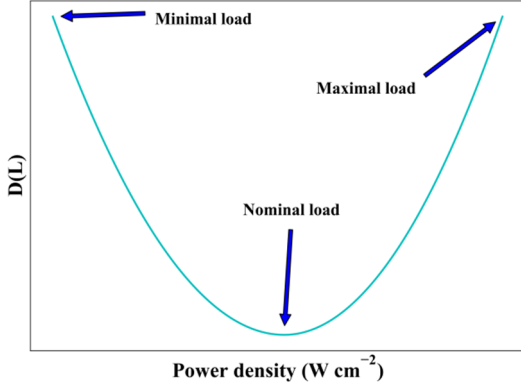


Fig. 2. Dependence of fuel cell resistance deterioration rate on loads.

The resistance deterioration due to load variation (ΔL) is computed by:

$$\Delta R_{\Delta L} = K\Delta L \quad (9)$$

where K is the constant terms with values taken from Pei *et al.* [6].

The resistance increment of each start-stop cycle is defined as a constant:

$$\Delta R_{ss} = R_0 r_{ss} \text{ per cycle} \quad (10)$$

where R_0 is the initial resistance of a fuel cell. The value of r_{ss} is set to 3.92×10^{-5} [6].

C. Gamma process with random effects

The deterioration of a fuel cell can be affected by different source of variations. These can be described as the intrinsic variation in the deterioration of a specific fuel cell and the different behaviors of the deterioration path for every product. For example, in an MFC system, those variation exists in a single fuel cell stack as well as between different stacks. This implies that the deterioration in different fuel cell stacks (which also exists in other products) has a large variation due to some hidden effects. And the standard GP model is unable to capture such variations, i.e., individual deterioration heterogeneity. This can be translated through the introduction of a random parameter (also known as the frailty variable) in the GP model where each individual corresponds to one realization of the random parameter.

On this basis, we proposed a GP model with random effects for modeling MFC system deterioration. A random effect is imposed on the GP on its scale parameter, taken as a random variable following a gamma distribution. More precisely, three different types of random effects-based models are investigated.

Recall the GP ($\text{Ga}(\alpha, \beta)$) as proposed for modeling ΔR_L . The first random effects model is expressed as:

$$\begin{aligned} \Delta R_L(t_1, t_2) &\sim \text{Ga}(\Delta\alpha, \beta_s) \\ \beta_s &\sim \text{Ga}(\delta, \phi) \end{aligned} \quad (11)$$

where δ, ϕ are the shape and scale parameters which formulates the gamma distribution for sampling β_s .

This model is called Gamma process random effect (GP-RE) model. Note that this GP-RE model is defined by only perturbing the scale parameter in GP which modifies both the mean and variance of the original GP model. However, in practice, other possibilities of modeling

random effects exist. For instance, the studied MFC system deterioration presents only a large dispersion of the deterioration rates or only a large variation of the variance of the deterioration observations within each stack. In this regard, the random effect only affects the mean or the variance of the deterioration process (GP model) which introduces Gamma process random mean (GP-RM) and Gamma process random variance (GP-RV) models.

GP-RM model is formulated by parameterizing the shape parameter of the GP model into ν to keep a constant variance, which writes:

$$\begin{aligned} \Delta R_L(t_1, t_2) &\sim \text{Ga}(\nu, \beta_s) \\ \nu &= \Delta\alpha \left(\frac{\beta}{\beta_s}\right)^2, \beta_s \sim \text{Ga}(\delta, \phi) \end{aligned} \quad (12)$$

For GP-RV model, the shape parameter is parameterized to keep a constant mean (independent of the random effect), which is expressed as:

$$\begin{aligned} \Delta R_L(t_1, t_2) &\sim \text{Ga}(\nu, \beta_s) \\ \nu &= \Delta\alpha \frac{\beta}{\beta_s}, \beta_s \sim \text{Ga}(\delta, \phi) \end{aligned} \quad (13)$$

Since the random-effects for all models are added through gamma law, one basic principle here is to keep the mean value ($\delta\phi$) equal to the original β (denoted as β_0). In the above three random effects models, the scale parameter of standard GP follows a gamma distribution and it is unit-specific, such that it can capture the individual deterioration variability. The deterioration behaviors of proposed models, i.e., GP, GP-RE, GP-RM, and GP-RV models will be checked for fuel cells in the results section.

IV. RESULTS & DISCUSSION

A. Gamma process parameters estimation

The identification of the scale and shape parameters of the gamma process, representing the deterioration modeling is based on the IEEE PHM 2014 data challenge, which provides two typical durability test datasets on two fuel cell stacks [7]. These fuel cell stacks consist of 5 single cells with an active area of 100 cm^2 .

The resistance values were fitted based on the measured polarization curves with the aging data, as shown in Figure. The parameters are estimated by using the non-linear least square approach to fit the polarization equation to all measured polarization curves.

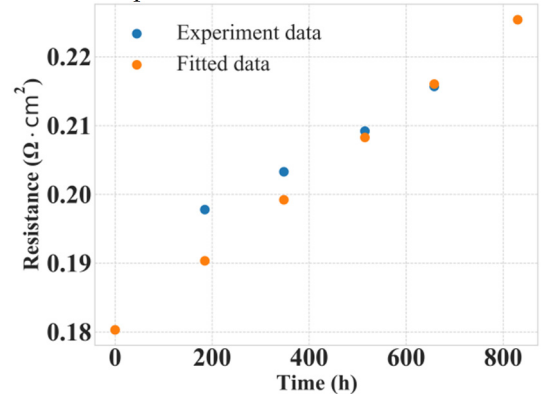


Fig. 3. Fuel cell resistance original experimental data and MoM fitted data (under nominal condition).

The resistance estimations as shown in Figure 3 (labeled as experimental data) are used to estimate the shape and the scale parameters of proposed GP model. To this aim, the method of moments (MoM) is applied [8]. From the data, the resistance and time increments are defined as:

$$\begin{aligned}\Delta t_i &= t_i - t_{i-1} \\ \Delta R_i &= R_i - R_{i-1}\end{aligned}\quad (14)$$

where $i = 1, 2, \dots, n$ are the number of data.

According to Cinlar *et al.* [8], the estimated values of α and β , written α_0 and β_0 , can be estimated from the solution of the equations:

$$\begin{aligned}\alpha_0 \beta_0 &= \frac{\sum_{i=1}^n \Delta R_i}{\sum_{i=1}^n \Delta t_i} = \frac{R_n - R_1}{t_n - t_1} \\ R_n \beta_0 \left\{ 1 - \frac{\sum_{i=1}^n \Delta t_i^2}{(\sum_{i=1}^n \Delta t_i)^2} \right\} &= \sum_{i=1}^n \left[\Delta R_i - \frac{\Delta t_i (R_n - R_1)}{t_n - t_1} \right]^2\end{aligned}\quad (15)$$

The estimated parameter values are $\alpha_0 = 0.1245$, $\beta_0 = 4.34 \times 10^{-4}$. The resistance values of fitted parameters and the original experimental data are plotted in Figure 3 for comparison. It can be observed that the GP model can capture the deterioration trend and keeps a high fitting accuracy for most of the points.

It should be noted that currently one of the big challenges for fuel cell deterioration modeling studies is the lacking of experimental datasets. Fuel cell is a relatively new technology, besides, the experimental work on fuel cell is both a time-consuming and costly task. More works need to be done in this respect to promoting fuel cell application. For our case, only the nominal experimental data is available and can be used to estimate parameters for the GP model.

C. Main simulation parameters

The main simulation parameters are summarized in Table 1. The Min, Nom, and Max stands for three typical operation load condition for fuel cells, i.e. the minimal, nominal, and maximal loads.

TABLE 1
Main parameters of the fuel cell stack.

| Conditions | L (W cm ⁻²) | Average Lifetime (h) | α_0 | β_0 | FT (Ω cm ²) |
|------------|----------------------------|----------------------------|------------|-----------------------|------------------------------------|
| Min | 0.175 | 500 | 0.4454 | | |
| Nom | 2.381 | 1788 | 0.1245 | 4.34×10^{-4} | 0.2775 |
| Max | 4.181 | 500 | 0.4454 | | |

There are three extra parameters defined for the proposed GP-based models, i.e., ι , δ , and ϕ . The ι is defined to tune the deterioration variance of the GP model through:

$$\alpha = \alpha_0 / \iota, \beta = \beta_0 \iota \quad (16)$$

ι is set to 20 for all simulations.

δ and ϕ define the gamma distribution used in the proposed random effects models, which are computed by:

$$\delta = 1/h, \phi = \beta_0 \iota \cdot h \quad (17)$$

where h is equal to 1.5.

The initial resistance is set as $0.1803 \Omega \text{ cm}^2$ for all simulations.

D. Fuel cell deterioration trajectory result

Figure 4 presents resistance deterioration trajectories during one dynamic cycle. The accumulated resistance values include the deterioration of load, load varying, and start-stop effects. Figure 5 shows the simulated deterioration trajectories of the MP, MP-RE, MP-RM, and MP-RV models. By comparing the RE models with GP model, it is observed that the deterioration behavior is affected by different random effects.

For instance, in the GP-RM model, the resistance deterioration rates are modified for different trajectories, obtaining relatively lower lifetimes compared with the GP model. In GP-RE model, both the deterioration rate and variance of the trajectories are influenced by RE. A relatively wide range of lifetimes is obtained. For GP-RV model, the deterioration rate is not influenced by the RE, only the variance is altered. Thus the simulated lifetimes generally lie in a similar range as GP.

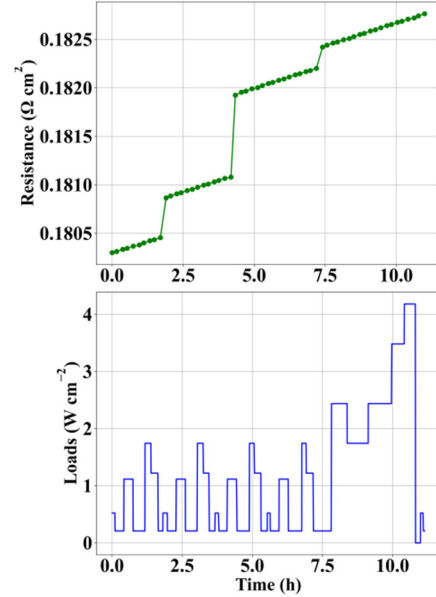


Fig. 4. Example resistance trajectory of GP model.

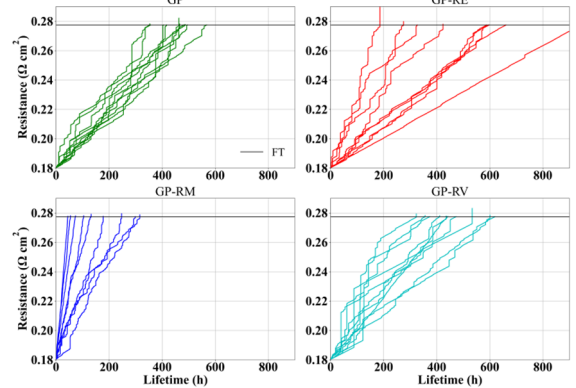


Fig. 5. Example resistance trajectories of proposed models.

Figure 6 plotted the lifetime histograms of 300 runs (Monte Carlo simulations) for all models. It is observed

that the lifetimes of GP-RE and GP-RM models are lied in a wide range compared to the GP model. But in GP-RV model, the distribution is similar to GP. These results are further confirmed in the cumulative distribution function (CDF) results as shown in Figure 7. The CDF curves of GP, GP-RV models are nearly overlapped, whereas the GP-RE and GP-RM models extend the CDF curve to a wide range.

Table 2 summarized the statistical results of simulated lifetimes. The GP-RE model produced the longest lifetime. The GP-RE model modified the system lifetime to a lower value. However, in GP-RV, the lifetime is similar to GP. In terms of standard deviation (Std) results, the RE-based models are relatively larger than the GP model.

This work mainly focused on the random effect-based stochastic deterioration modeling of fuel cells. The next step of work will be focused on the statistical inference studies of the proposed deterioration models.

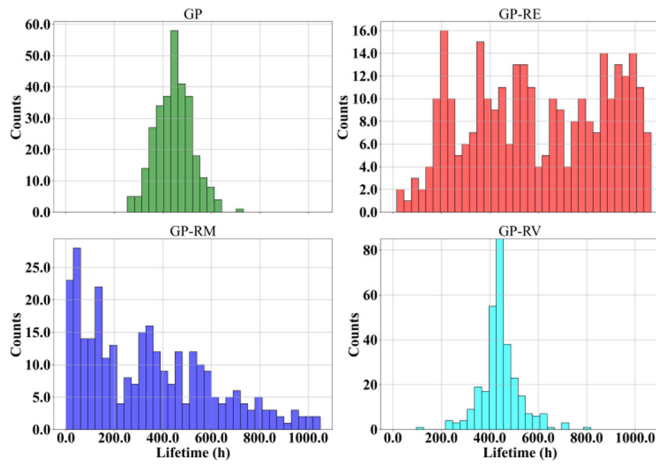


Fig. 6. Lifetime histograms of GP, GP-RE, GP-RM, and GP-RV models.

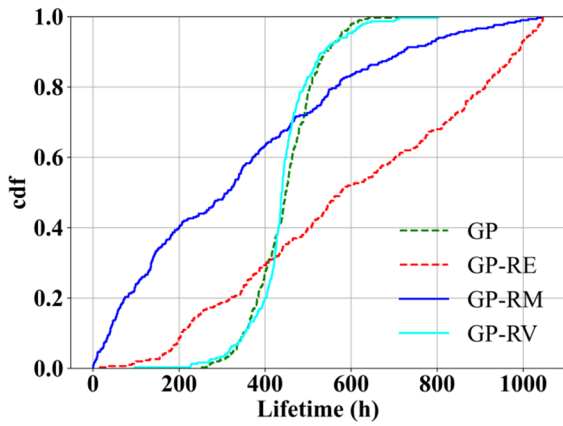


Fig. 7. CDF curves of four models.

TABLE 2
Lifetime statistic results.

| Models | Mean lifetime (h) | Median lifetime (h) | Std |
|--------|-------------------|---------------------|-----|
| GP | 447.4 | 447.6 | 75 |
| GP-RE | 600.9 | 575.8 | 284 |
| GP-RM | 337.5 | 312.1 | 262 |
| GP-RV | 444.1 | 438.9 | 80 |

V. CONCLUSION

This work explores fuel cell stochastic deterioration modeling for energy management in a multi-stack system. The main contributions of this work are three-fold: 1) We highlighted the need for stochastic deterioration modeling in fuel cells considering the existing research gaps in fuel cell studies; 2) We explored the possibilities of applying the Gamma process to modeling fuel cell deterioration. The GP-RE, GP-RM, and GP-RV models are proposed to account for individual stack deterioration heterogeneity. 3) We simulated fuel cell deterioration trajectories with a typical automotive load profile with load, load varying, and start-stop operating modes which are the main causes of fuel cell deterioration. The first-hitting time histograms and cumulative density functions are discussed.

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