Data-driven battery degradation model leveraging average degradation function fitting

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When the batteries of electrical vehicles are used to provide vehicle-to-grid (V2G) ancillary service, battery life is shortened due to additional battery usage. To consider battery degradation, cycle life-based approach with degradation density function (DDF) is popular. However, the previous modelling cannot capture the well-known fact that battery may severely degrade at *both* ends of battery, i.e. when full or empty. A novel method of obtaining DDF using the curve fitting over average degradation function is proposed. The proposed method tightly fits the empirical measurements and thus provides a better way of operating V2G considering battery degradation. The results show that the proposed method reduces battery degradation by up to 28.9% while achieving the same revenue.

Introduction: In the near future, it is expected that traditional combustion engine vehicles will be replaced by electric vehicles (EVs). When a large number of EVs are connected to grid, EVs' batteries can be energy resources that provide ancillary service, called vehicle-to-grid (V2G) [1]. When EVs provide ancillary service such as frequency regulation or spinning reserve, an independent system operator that maintains the stability of power system pays for EVs. However, providing ancillary service may overuse EV's battery and shortens its lifetime. In this regard, to be profitable for both EV's owner and the ancillary service provider, optimal battery scheduling, i.e. charging and discharging discipline should be investigated considering the trade-off between operational benefit and battery degradation.

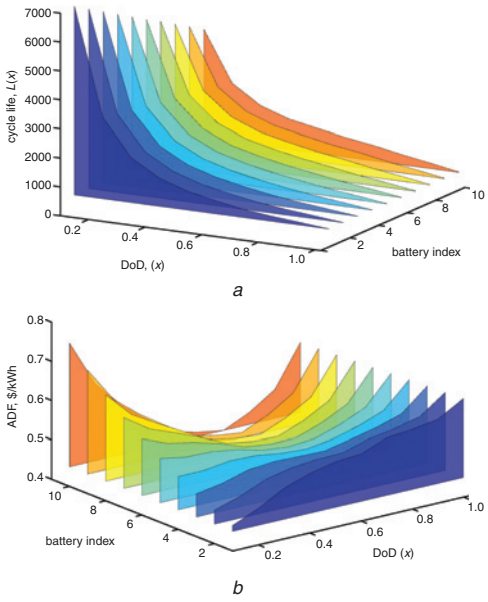

Fig. 1 *Cycle life against DoD and ADF from various sample data*
a Cycle life against DoD
b Average degradation function

Previous work: So far various battery degradation models had been proposed based on the data about *cycle life* against depth of discharge (DoD). Cycle life means how many times battery can be charged and discharged throughout its life, and it depends on how *deeply* the battery is used. Let us denote DoD by $x \in [0, 1]$ and state of charge (SoC) by $y \in [0, 1]$, then simply we have $x + y = 1$. According to various cycle life against DoD curves as shown in Fig. 1*a*, given DoD x, the cycle life denoted by $L(x)$ is inversely proportional to x. For example, the following rule:

$$L(x) = \frac{\alpha}{x^{\beta}} \tag{1}$$

is widely accepted in battery industry where α and β are battery-specific parameters and should be determined by *curve fitting*. Equation (1) is simple and effective to fit empirical data [2, 3]. However, it does not exactly tell how much the battery degrades at each SoC.

To overcome this limitation and quantify battery degradation at *any* SoC, a novel concept of *degradation density function (DDF)* was proposed in [4]. DDF is derived from *average degradation function (ADF)*, which is defined as battery price over *total* transferable energy throughout its cycle life $L(x)$ assuming a fixed DoD x during operation [4]. Let $\psi(x)$ denote ADF

$$\psi(x) = \frac{\text{battery price}}{2 \times \mu^2 \times \text{battery capacity} \times x \times L(x)} \quad (\$/\text{kWh}) \tag{2}$$

where μ is the efficiency of charging or discharging. Then, DDF at SoC y, denoted by $\omega(y)$, is defined by the following integral equation:

$$\psi(x) = \frac{1}{x}\int_{1-x}^{1} \omega(y)\, \mathrm{d}y \tag{3}$$

assuming that charging/discharging rate is within the proper range to keep the battery temperature moderate. Then $\omega(y)$ can be reverse-engineered by differentiating both sides of (3) with respect to x, and we have

$$\omega(y) = \psi'(x)x + \psi(x) \tag{4}$$

In case $L(x)$ is given by (1), ADF is

$$\psi(x) = \frac{\text{battery price} \times x^{\beta-1}}{2 \times \mu^2 \times \text{battery capacity} \times \alpha} \quad (\$/\text{kWh}) \tag{5}$$

and DDF is

$$\omega(y) = \frac{\text{battery price} \times \beta}{2 \times \mu^2 \times \text{battery capacity} \times \alpha} \times (1-y)^{\beta-1} \quad (\$/\text{kWh}) \tag{6}$$

Limitation of the conventional model: One may immediately see that, however, $\omega(y)$ in (6) cannot capture the well-known *fact* that battery may severely degrade at *both* ends of SoC (full or empty), which will be seen in Fig. 2*b*. This limitation comes from that (6) takes a form of monotonic (either increasing or decreasing depending on β) power function. The mismatch is also observable from the ADF in (5). As can be seen from various ADFs in Fig. 1*b*, $\psi(x)$ can be general, i.e. sometimes convex-like but sometimes monotone increasing, unlike the monotonic power function of (5). From these two mismatch observed in (5) and (6), we are motivated to develop a generalised battery degradation model.

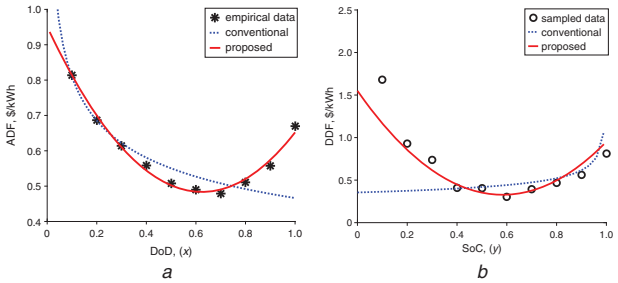

Fig. 2 *ADF and DDF of empirical data, conventional method and proposed method for battery A*
a ADF
b DDF

Average cost-based degradation model: In the previous method, power function-based curve fitting was performed directly in the domain of raw cycle life data, i.e. over $(x, L(x))$. However, as can be seen in (2) and (3), ADF $\psi(x)$ plays an important role in determining DDF $\omega(y)$, so we propose to perform curve fitting in the average degradation domain, i.e. over $(x, \psi(x))$. As can be seen in Fig. 1*b*, ADF can have various shapes, not simply monotonic, so we perform curve fitting with a polynomial function rather than a power function. We will see that the proposed method fits very well with the empirical data in $(x, \psi(x))$ domain as well as the $(x, L(x))$ domain in Fig. 3 and Table 1.

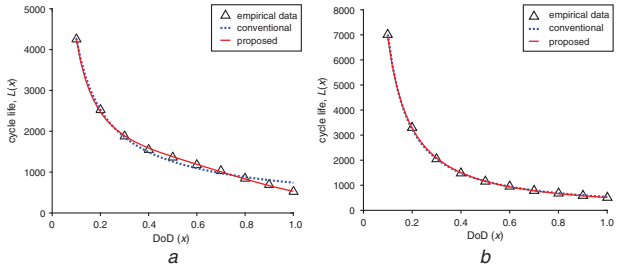

Fig. 3 *Cycle life of empirical data, conventional method and proposed method*

a Battery A
b Battery B

Table 1: Comparison of MAPE

	Battery A			Battery B		
	ADF	DDF	$L(x)$	ADF	DDF	$L(x)$
Conventional (%)	7.63	30.98	9.04	1.66	8.52	1.71
Proposed (%)	1.72	13.07	1.72	1.37	8.00	1.37

In doing curve fitting, choosing a proper order of polynomial is important. Since getting empirical data of $L(x)$ takes long time and is also expensive, the number of available same data is usually limited, e.g. ten samples. Thus, if we use a high-order polynomial for regression, overfitting may occur [5]. In this regard we use the second-order polynomial to capture ADF, i.e.

$$\psi(x) = ax^2 + bx + c \quad (\$/\text{kWh}) \tag{7}$$

where a, b and c are the coefficients determined by curve fitting. Then, using (4), we can obtain the following DDF:

$$\omega(y) = 3a(1-y)^2 + 2b(1-y) + c \quad (\$/\text{kWh}) \tag{8}$$

Verification of the proposed model: To verify the proposed method, we leverage the *discrete* degradation model in [4] as a baseline because the discrete model is independent of continuous curve fitting methods. The discrete model, however, cannot estimate degradation *density* but degradation *mass* at the *measured* DoD only. Nevertheless, as long as the concept of degradation modelling is valid, continuous modelling should be consistent with discrete modelling at the measured DoD. The discrete modelling is similarly given by

$$\frac{\text{battery price}}{2 \times \mu^2 \times \text{battery capacity} \times x \times L(x)} = \frac{1}{x}\sum_{y=1-x}^{1-\Delta x} \bar{\omega}(y) \times \Delta x \tag{9}$$

where $\bar{\omega}(y)$ is a degradation mass function, x and y are discrete, e.g. $x \in \{0.1,\ 0.2,\ \ldots,\ 1\}$, Δx is 0.1.

We then verify the proposed method for two different types of batteries. According to the conventional model with (6), we see that $\beta = 1$ serves as a demarcation point in determining the shapes of DDF. Thus, we test with two different battery types: named as battery A that corresponds to $\beta < 1$ and battery B that corresponds to $\beta > 1$.

Fig. 2*a* shows the ADFs in the case of battery A. We see that the conventional method *severely* underfits the empirical ADF. Furthermore, in Fig. 2*b*, DDF of the conventional method does not match at all with the sampled degradation data from (9). By contrast, the proposed method *tightly* fits the empirical ADF as well as the sampled degradation data.

Fig. 3*a* shows that the proposed method fits the empirical cycle life data closer than the conventional one in the case of battery A. One maybe curious whether our method suffers from overfitting. As can be seen in Fig. 3*b* in the case of battery B, our method also works well without incurring overfitting where the conventional method also works fine.

Table 1 summarises all of the curve fitting results for ADF, DDF and cycle life $L(x)$ in terms of the mean absolute percentage error (MAPE) with respect to empirical/sampled data. In the case of battery A, the proposed method shows the 80% reduced curve fitting error than the conventional method. In the case of battery B, both methods work accurately.

Application to V2G: To show the virtue of the proposed degradation model, we implement the optimal battery scheduling of V2G to minimise the total cost as formulated in [4]. Two different schedulings are made by using dynamic programming based on DDFs from the conventional and proposed methods. In the case of battery A, according to the DDF computed from the proposed method, V2G should *not* operate in low SoC regime where degradation is excessive. However, the conventional method leads to completely opposite operation because DDF is estimated the lowest in the same regime. Thus, V2G scheduling based on the conventional model might be wasteful. To quantify this, in Fig. 4, we calculate the costs and the revenues based on the proposed DDF while V2G scheduling is determined using the conventional DDF. The dot line shows *significant* additional cost of the conventional method, the proposed method reduces battery degradation by 28.9%. In the case of battery B, as expected, since the conventional and proposed DDFs are almost the same, we observe that there is little difference in performance.

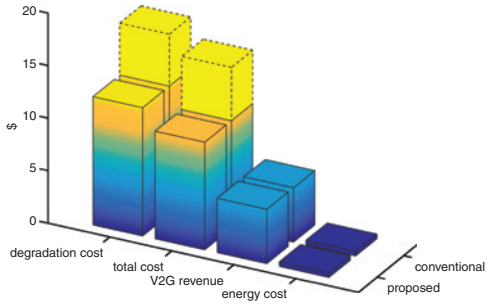

Fig. 4 *Costs and revenue of conventional and proposed methods*

Conclusion: In this Letter, we proposed a novel battery degradation model based on empirical cycle life against DoD data. In doing this, we exploited the second-order polynomial function to capture the ADF, which is used to derive the DDF. By applying the proposed method for two different types of batteries, we verified that the proposed method tightly fits the empirical data without incurring overfitting. The proposed method reduces the MAPE of cycle life data curve fitting by up to 80% compared with the conventional method. Finally, we applied the proposed method for V2G and showed that it can reduce the battery degradation by up to 28.9% while achieving the same ancillary service revenue.

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One or more of the Figures in this Letter are available in colour online.

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