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The explainable uncertainty in degradation process: a discovery from non-accelerated batteries degradation experiment

1st Dongzhen Lyu*
School of energy and power engineering,
Huazhong University of Science and Technology,
WuHan, China
Energy Department, Politecnico di Milano,
Milano, Italy
lvdongzhen@yeah.net

2nd Bin Zhang
Department of Electrical Engineering,
University of South Carolina,
Columbia, USA
zhangbin@cec.sc.edu

3rd Enrico Zio
MINES ParisTech, PSL Research University,
Antipolis, France
Energy Department, Politecnico di Milano,
Milano, Italy
enrico.zio@polimi.it

4th Tao Yang
School of energy and power engineering,
Huazhong University of Science and Technology,
WuHan, China
hust_yt@hust.edu.cn

***Abstract*—The uncertainties in the degradation process have always been regarded as a major challenge in the practical applications of Prognostics and Health Management. This article discusses the uncertainties in the degradation process of Lithium-ion batteries, points out their potential consequences in practical applications, and then we summarizes some commonly adopted aftertreatment solutions for them. To proceed realistic analysis, we present a non-accelerated degradation experiment with several Lithium-ion batteries. The experiment lasted for more than ten months and the data highlighted the uncertain fluctuations and periodic waves in SOH degradation process. Furthermore, this article reveals the delayed correlation between SOH degradation and changing environmental temperature. Finally, we provide some possible solutions for guiding practical applications of our finding.**

***Index Terms*—Prognostics and Health Management, explainable mechanism, non-accelerated degradation, delayed correlation**

I. Introduction

Lithium-ion batteries have features of low self-discharge rate (maintain charged power at suspension), low weight (lightweight lithium and carbon-made electrodes), high energy efficiency (high chemical reactivity of lithium), no memory effect, stable electro-chemistry characteristics, and long lifetime [1], [2]. These advantages have played a major role in their widely used in many important applications, including consumer electronics, electric vehicles, aerospace equipment, and large-scale energy storage. However, its performance will experience inevitable degradation after a long time of operation [3]. This phenomenon seriously affects the reliability of Li-ion batteries and can result in many challenges for its practical applications [4].

For Lithium-ion batteries, the accurate acquisition of its degradation information is necessary to ensure the safety of electronic equipment, and then meaningful to minimise maintenance costs [5]. The prognostics and health management (PHM) is an engineering discipline concerned with the reliability and safety assessment of the degradation process. At present, lots of techniques have been developed to devise proper methods for the prediction of future capacity dynamics and remaining useful life [1].

Specifically, according to the type of adopted prognostic model, such as originated from empirical expert knowledge or historical operation data [6], existing approaches can be generally divided into model (or physics)-based method, data-driven method, and hybrid method, the detailed discussion and classification can be found in [2], [6], [7]. In conclusion, the directly or indirectly degradation dynamics modelling plays an extremely important role in the engineering PHM applications of Lithium-ion batteries. However, uncertainty is a major consideration for practical applications in the real world, and due to the inherently stochastic nature of battery degradation and changing operation environment, the degradation process of Lithium-ion batteries contains a lot of uncertainties [8].

Generally, these uncertainties can be categorized into two categories of epistemic uncertainty and aleatory uncertainty [6]. The aleatory uncertainty describes the natural variation and intrinsic randomness of degradation process, it is typically unpredictable and irreducible [5]. The epistemic uncertainty mainly refers to the incomplete information about the practical degradation process, such as insufficient or incomplete modelling. These uncertainties bring many challenges and difficulties to the practical modelling process, and the proper management of uncertainty is very critical to achieving reliable prognostic [6].

The remaining paper is organized as follows. Section II summarizes some commonly adopted datasets and provides a thorough discussion about uncertainty management. Section III introduces the technical details of our non-accelerated degradation experiment and then points out its potential meaning in theoretical analysis and practical application. Section IV provides a comprehensive discussion about the delayed correlation between SOH degradation and changing environmental temperature, and then outlines its possible application scenarios and future development route.

II. Theoretical and Practical Background

PHM is an experimental oriented research, and the acquisition of practical degradation data is the common foundation of all the related research. However, there face many difficulties in obtaining reliable degradation data. First, the degradation experiments need to be implemented on the professional equipment, that able to provide stable output current and voltage, and monitor the electrical signals from batteries. Besides, due to the long lifetime of Lithium-ion batteries, the degradation process is time-consuming and can typically take several months. Further, the stability of the battery will gradually decrease during the degradation experiments and might introduce extra fire hidden trouble, thus the experiments needs to be monitored for 7×24 hours.

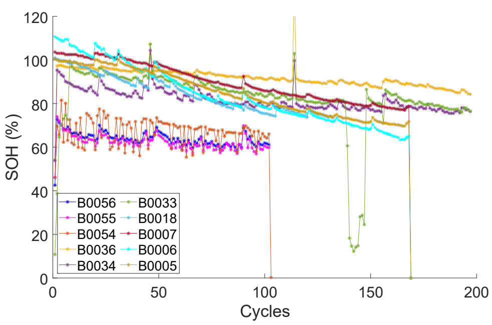

Fig. 1. Nasa batteries degradation data published in 2007

In view of above mentioned common difficulties, many researchers have adopted public datasets for the development and verification of their investigations. The Prognostics Center of Excellence (PCoE) at NASA provides a series of degradation data in 2007 [9], [10]. Fig. 1 shows degradation trajectory of some batteries (with over 100 cycles). This dataset spurred many more related investigations for the degradation of Lithium-ion batteries. However, the experiment procedure lasts a short period and the degradation depth is not obvious.

Then the Center for Advanced Life Cycle Engineering (CALCE) at the University of Maryland provided another dataset since 2011 [2], [11], [12]. Fig. 2 and Fig. 3 show the degradation trajectory of CS2 and CX2 dataset. The main characteristic of this dataset is the existence of massive upward and downward fluctuations.

Recently, Toyota Research Institute provides a large dataset [13] as shown in Fig. 4. This dataset recorded the degradation process for hundreds of batteries and adopted the fast charge technique to speed up the degradation progress. The degradation process in this dataset varies from 20 days to 50 days, and their SOH degradation trajectories have significant difference with each other.

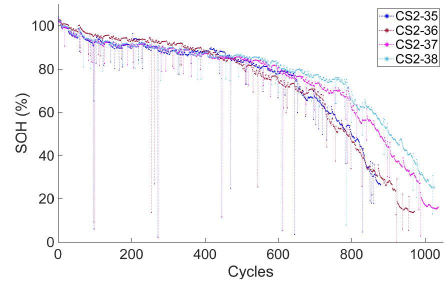

Fig. 2. CS2 Batteries degradation data published in 2011

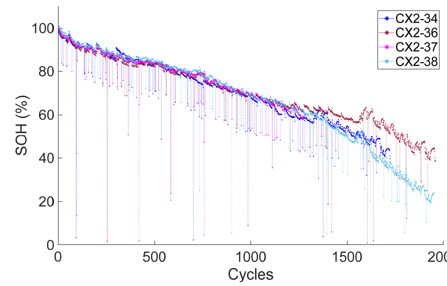

Fig. 3. CX2 Batteries degradation trajectory published in 2011

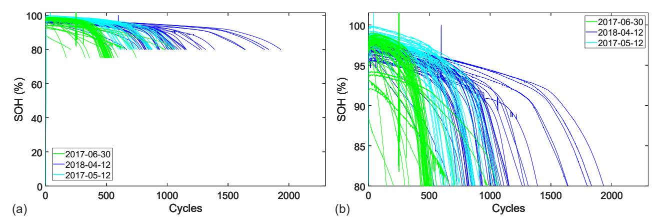

Fig. 4. Toyato batteries degradation data published in 2019

There show significant difference between different datasets, and the difference within the same dataset is also obvious. We have provided a thorough discussion of the uncertainties in the degradation process of Lithium-ion batteries in one of our previous works [8], but a reasonable and convincing mechanism of uncertainty has remained a deep mystery in the PHM applications of Lithium-ion batteries. Specifically, there could exist intricate momentary performance fluctuations during the operation process of Lithium-ion batteries. A typical (not exclusive) example of this phenomenon is the regeneration of Lithium-ion batteries, which refers specifically to these upward SOH fluctuations after a longtime rest [7], [14]. As concluded in literature [15]–[18], there exist extensive successful PHM applications for Lithium-ion battery, while most of them omitted their practical influence.

So far, some researchers have focused on these issues, but the related improvements are still very limited due to limited volume of experiment data. First, this phenomenon is inevitable and hard to explain, and it is a natural thought to treat it as uncertainty, thus many approaches tended to directly remove or eliminate related data [19]. Second, this phenomenon is commonly no-predictable, thus the possible treatment would be to make “timely detection” or “timely management”. Those solutions all can be classified as aftertreatment, which can only be implemented after the actual happens of regeneration phenomenon. Besides, it has been widely accepted that the regeneration phenomenon is related to rest time, and some approaches tired to predict the occurrence of regeneration based on rest time. However, a reliable mechanism between rest time and regeneration is still controversial in academia [20]. Besides, the rest time itself, may depends on the preferences of the user, thus its occurrence and duration are usually random and unpredictable. These paradoxes limit the further development of related investigations.

The following summarizes some efforts and attempts to deal with these regeneration phenomenon in the SOH degradation process. Reference [17] treated regeneration as randomness and eliminated it from data. Reference [21] selected to remove regeneration related data in their approach. Reference [19] attempted to make automatic detection of the occurrence of regeneration. Reference [22] regarded regeneration as anomaly point and pursued its timely detection. Reference [23] addressed the detection of regeneration phenomena in their approach. Reference [24] detected the occurrence of regeneration in their approach. Reference [25] monitored and made automatically detection of regeneration in their approach. Reference [26] improved the reliability and robustness of their model to deal with the occurrence of regeneration. Reference [15] tried to timely capture the regeneration and then made model adaptation accordingly. Reference [27] captured the fluctuations of the degradation process and reduced its affections in their proposed approach. Reference [14], [28]–[31] all attempted to predict regeneration based on rest time.

However, even though the regeneration (upward SOH fluctuation) can be partially and roughly explained by the rest time [8], there still exist many downward fluctuations in the SOH degradation process of Lithium-ion batteries. Further, different from the upward SOH fluctuations that bring out no negative effects, the instantaneous downward SOH fluctuations can cause inconvenience to users and directly affect their experience.

For example, if Lithium-ion batteries are adopted as the main power for electric vehicles and smartphones, then when the temperature drops sharply, the broke down of electric vehicles occurs frequently, and the “sudden death” of the smartphone also occurs frequently. Besides, if Lithium-ion batteries are adopted to provide power to the controlling system, some catastrophic consequences can also happen when the power supply is unreliable.

Clearly, for those downward SOH fluctuations, existing solutions about “timely detection”, “timely management” or “make model adaptation to uncertainty” are far from reducing or preventing their consequences.

III. Uncertainties in Non-accelerated Degradation Experiments

As mentioned above, the degradation process of Lithium-ion batteries is very time-consuming, thus almost all the existing public datasets adopted accelerated working settings to speed up the implementation of their degradation experiment. However, batteries under daily utilization are difficult to encounter these accelerated working conditions, and there may exist some differences between the accelerated degradation and non-accelerated degradation.

We think that the degradation process under accelerated working conditions is different from that under non-accelerated working conditions, but we expect there exists a transfer relationship, so that the data from accelerated experiments can be used to guide the PHM applications in the practical.

To the best of the authors’ knowledge, the current setting in existing degradation experiments is no less than 1 C. We, therefore, conduct some experiments and generate some battery degradation data with non-accelerated working conditions. C is the current unit corresponding to the nominal capacity of the battery, 1 C is able to discharge the battery with a nominal capacity in 1 hour, and 1/3 C is in 3 hours.

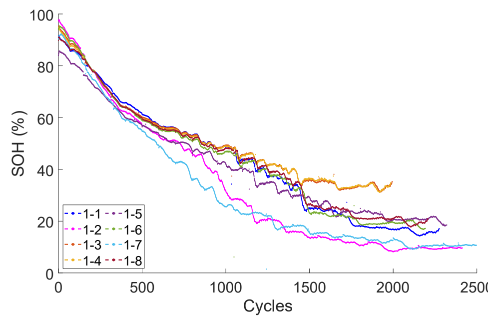

Fig. 5. Degradation trajectory from non-accelerated experiments

Specifically, the non-accelerated experiment is consisted of continuous and alternating charge-discharge periods. The charge period has a constant current constant voltage (CC-CV) profile, and the discharge period has a constant current profile. The current setting in the CC charge and discharge period is 1/3 C, the voltage setting in the CV charge period is 4.2 V, and the cut-off voltage setting in the CC discharge period is 2.7 V.

The whole experiment was implemented from Apr. 2021 to Mar. 2022 for over 10 months (7200 hours), the overall degradation trajectory is shown in Fig. 5. The experiment equipment is installed in an in-house environment with no specific insulation measures (the environment temperature varies in season and day-night).

In industrial applications, it is 80% SOH that is selected as the lifetime termination of Lithium-ion battery [32]. However, Lithium-ion battery has the advantage of high energy density, which is 4∼6 times that of a Lead-acid battery, thus the testing is continuously implemented until it degrades to approximately its 20% SOH (at this status, the lithium-ion battery still has strong competitiveness compared with a new lead-acid battery). These acquired degradation data have a wide SOH range (from 100% to 20%), thus also have the potential value for cascade utilization related research.

During the implementation process of the long-lasting experiment, we check the status of the batteries almost every week, thus we found some interesting phenomena which tend to be ignored in previous public datasets. As shown in Fig. 6, there exist periodic small waves in the degradation process of each battery. Besides, the fluctuations in overall trend also have some similarities between each other.

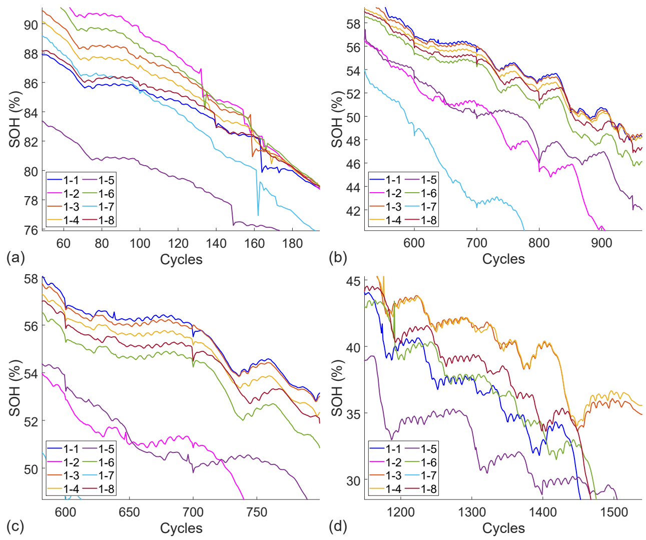

Fig. 6. Periodic similarity between different batteries

Following the investigation in one of our previous works [8], we initially would like to treat those waves and fluctuations as uncertainties, and then introduce some "timely detection" and "properly management" for those uncertainties, or develop an adaptive approach to make adaption regarding those uncertainties. After that, we also would like to make some "transfer" discussions with those non-accelerated degradation data. Above mentioned are widely used, well-developed, and straightforward research routines.

However, we found those waves and fluctuations might be related to the environment temperature, because we suddenly realized that the small waves in the degradation trajectory appear every day. To better illustrate this periodic degradation characteristic, Fig. 7a shows the degradation trajectories of different batteries regarding date-time, and the vertical line represents the beginning of the new year.

Clearly, there show significant consistency between different batteries. Fig. 7b represents the enlargement of the box part in Fig. 7a, it shows that the fluctuations in different degradation processes have similar occurrence times and amplitudes. Then, Fig. 7c represents the enlargement of the box part in Fig. 7b. These small waves appear periodically (once a day) in Fig. 7c, as these vertical line represent the beginning of the new day.

This is very interesting, actually, those waves and fluctuations in the public degradation dataset are hard to explain. Thus, their solutions have always been limited to "detection", "management", "adaption" or other aftertreatment solutions. For example, [19] recently proposed a prognosis approach that is able to detect those upward fluctuations in the degradation process of Lithium-ion batteries.

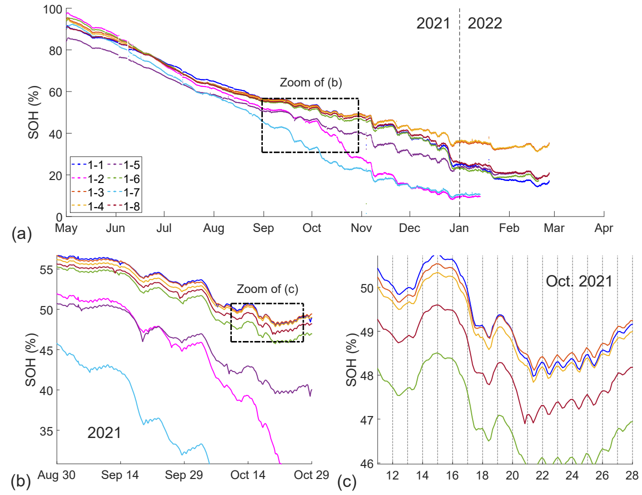

Fig. 7. SOH degradation process with respect to date time

Generally, explainability has always been regarded as the common difficulty for the further in-depth investigation of uncertainty, thus we would like to initiate some theoretical analysis for this. Then, above mentioned "transfer" motivations and solutions will be left for our future research.

IV. Explainable Uncertainty by Delayed Correlation

Due to some realistic reasons, we did not install specific sensors to monitor the surface temperature of our batteries. We think that the massive adoption of temperature sensors is not economic and realistic for practical applications. Instead, we acquired the meteorological data from the national ordinary meteorological station. The station is 20 km (approximately 20 minutes for driving) away from the actual location of the experiment.

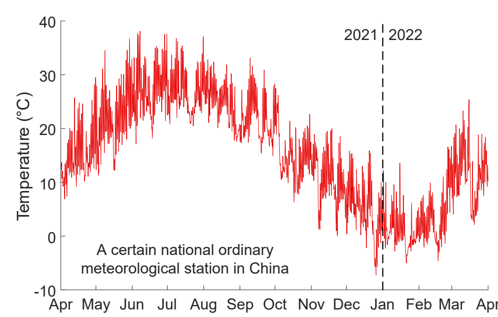

Fig. 8. Local temperature data

The acquired meteorological data is recorded at the synoptic hours, including the daily routine observations such as temperature, pressure, humidity, wind speed and direction, and precipitation amounts. The data is exchanged among different countries via the Global Telecommunications System (GTS), under the framework of World Meteorological Organization. In United States, it is publicly available from NOAA National Centers for Environmental Information [33]. The temperature date during the implementation of non-accelerated degradation experiments is shown in Fig. 8.

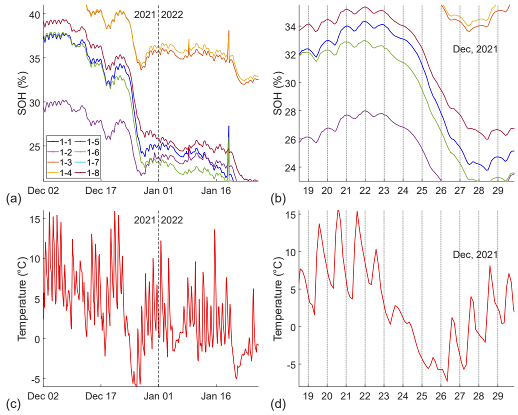

Fig. 9. Correlation between SOH and temperature

To highlight the similarity between SOH degradation process and changing environmental temperature, Fig. 9 shows their details information. Note different from that in Fig. 5, the SOH data in fig. 9 adopt the date-time as its horizontal axis, then the degradation trajectory from different batteries shows strong consistency. There show small waves and significant fluctuations in both dynamic processes, which also appear to be very similar in detail.

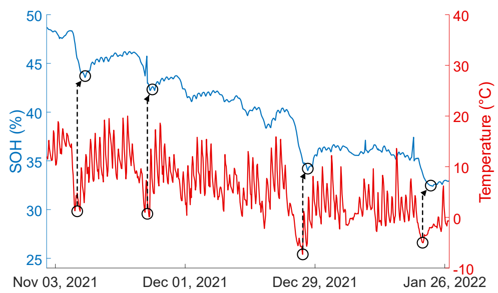

Fig. 10. Delayed correlation between SOH and temperature

For these small waves in temperature data, the lowest value is located at around 8 o'clock (sunrise), and the highest value is located at around 14 o'clock, and this is consistent with real-life common sense. While for these small waves in SOH data, the lowest value is located around 10 o'clock, the highest value is located at around 22 o'clock, which lags behind the variation of environmental temperature for several hours. For the changing temperature data shown in Fig. 9d, the valley is located in Dec. 26, due to a cold snap. Then for the SOH degradation data shown in Fig. 9b, the valley is located in Dec. 28, lags several days after the occurrence of temperature valley.

In conclusion, there exists a delayed correlation between SOH degradation and changing environmental temperature, and Fig. 10 selected several typical fluctuations to show in detail this relationship.

To proceed further investigation on this phenomenon, Differential Model Decomposition [8] is adopted here for the theoretical uncertainty analysis. Differential Model Decomposition can decompose the uncertainty information step by step from original data, its technical details can be found in [8]. Following step (2) of its implementation procedure, Fig. 11a shows the extracted uncertainty from the SOH degradation process, Fig. 11b shows the extracted uncertainty from the environmental temperature variation process, and the uncertainty in SOH degradation process has a different standard deviation from that in the environmental temperature variation process. Then Fig. 11c shows their comparison after normalization, and it shows strong correlation and lag effect.

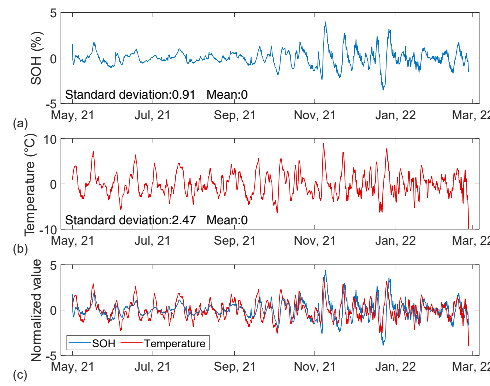

Fig. 11. Extracted uncertainties through Differential Model Decomposition

These uncertainties shown in Fig. 11 represent the waves and fluctuations in the original data. Clearly, these significant fluctuations in SOH degradation appear tens of hours later than that in the changing environmental temperature. In conclusion, these waves and fluctuations in the environmental temperature variation process have a causal relationship with that in SOH degradation process, and the former is the cause of the latter one. Most importantly, there exists a finite delay in this causal relationship. Thus it is possible to predict these fluctuations in SOH degradation several hours ahead of their happen.

The possible mechanism of this lag effect might be originated from the heat transfer process between battery and the environment. Actually, the battery itself need to transfer heat with the environment, and the heat transfer speed depends on several factors, thus the variations in environmental temperature can not immediately change the self temperature of battery. This is very realistic in practical application and has not been given enough attention so far.

In our implementation, we adopt only the recorded meteorological temperature data for analysis, and this solution is able to warn the risk of suddenly SOH dropping several hours before it really happen. Note even the surface temperature of battery can be recorded by temperature sensors, there still exists a finite transfer delay between surface temperature and body temperature of the battery.

Further, the meteorological forecast is also a publicly available service and is very reliable in modern life, then the alarm can be issued much earlier with pre-forecasted temperature.

V. Conclusion

In this paper, we present a non-accelerated degradation experiment with Lithium-ion batteries. With these practical

SOH degradation data and collected meteorological temperature data from NOAA, we demonstrate that some uncertainties in SOH degradation process can be explained by the variation in environmental temperature. We then provide an in-depth analysis about delayed correlation with Differential Model Decomposition. The theoretical analysis shows that the early warning of sudden SOH drop is possible and has significant meaning in practical applications, such as being used to avoid the "sudden death" of the smartphone or "sudden break down" of the electric vehicle.

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REFERENCES

[1] Jiusi Zhang, Yuchen Jiang, Xiang Li, Mingyi Huo, Hao Luo, and Shen Yin. An adaptive remaining useful life prediction approach for single battery with unlabeled small sample data and parameter uncertainty. *Reliability Engineering & System Safety*, 222:108357, 2022.

[2] F. Cadini, C. Sbarufatti, F. Cancelliere, and M. Giglio. State-of-life prognosis and diagnosis of lithium-ion batteries by data-driven particle filters. *Applied Energy*, 235:661–672, 2019.

[3] John Weddington, Guangxing Niu, Renxiang Chen, Wuzhao Yan, and Bin Zhang. Lithium-ion battery diagnostics and prognostics enhanced with dempster-shafer decision fusion. *Neurocomputing*, 458:440–453, 2021.

[4] Kai ZHANG, Peng ZHAO, Canfei SUN, Youren WANG, and Zewang CHEN. Remaining useful life prediction of aircraft lithium-ion batteries based on f-distribution particle filter and kernel smoothing algorithm. *Chinese Journal of Aeronautics*, 33(5):1517–1531, 2020.

[5] Robert R. Richardson, Michael A. Osborne, and David A. Howey. Gaussian process regression for forecasting battery state of health. *Journal of Power Sources*, 357:209–219, 2017.

[6] Yang Chang, Jianxiao Zou, Shicai Fan, Chao Peng, and Huajing Fang. Remaining useful life prediction of degraded system with the capability of uncertainty management. *Mechanical Systems and Signal Processing*, 177:109166, 2022.

[7] Xiaosong Hu, Le Xu, Xianke Lin, and Michael Pecht. Battery lifetime prognostics. *Joule*, 4(2):310–346, 2020.

[8] Dongzhen Lyu, Guangxing Niu, Enhui Liu, Tao Yang, Gang Chen, and Bin Zhang. Uncertainty management and differential model decomposition for fault diagnosis and prognosis. *IEEE Transactions on Industrial Electronics*, 69(5):5235–5246, 2022.

[9] Penghua Li, Zijian Zhang, Qingyu Xiong, Baocang Ding, Jie Hou, Dechao Luo, Yujun Rong, and Shuaiyong Li. State-of-health estimation and remaining useful life prediction for the lithium-ion battery based on a variant long short term memory neural network. *Journal of Power Sources*, 459:228069, 2020.

[10] Jinpeng Tian, Rui Xiong, and Weixiang Shen. State-of-health estimation based on differential temperature for lithium ion batteries. *IEEE Transactions on Power Electronics*, 35(10):10363–10373, 2020.

[11] Guijun Ma, Yong Zhang, Cheng Cheng, Beitong Zhou, Pengchao Hu, and Ye Yuan. Remaining useful life prediction of lithium-ion batteries based on false nearest neighbors and a hybrid neural network. *Applied Energy*, 253:113626, 2019.

[12] Sai Li, Huajing Fang, and Bing Shi. Remaining useful life estimation of lithium-ion battery based on interacting multiple model particle filter and support vector regression. *Reliability Engineering & System Safety*, 210:107542, 2021.

[13] Kristen A. Severson, Peter M. Attia, Norman Jin, Nicholas Perkins, Benben Jiang, Zi Yang, Michael H. Chen, Muratahan Aykol, Patrick K. Herring, Dimitrios Fraggedakis, Martin Z. Bazant, Stephen J. Harris, William C. Chueh, and Richard D. Braatz. Data-driven prediction of battery cycle life before capacity degradation. *Nature Energy*, 4(5):383–391, 2019.

[14] Taichun Qin, Shengkui Zeng, Jianbin Guo, and Zakwan Skaf. State of health estimation of li-ion batteries with regeneration phenomena: A similar rest time-based prognostic framework. *Symmetry*, 9(1):4, 2017.

[15] Matthew B. Russell, Evan M. King, Chadwick A. Parrish, and Peng Wang. Stochastic modeling for tracking and prediction of gradual and transient battery performance degradation. *Journal of Manufacturing Systems*, 59:663–674, 2021.

[16] Dong Wang, Jin Zhen Kong, Yang Zhao, and Kwok Leung Tsui. Piecewise model based intelligent prognostics for state of health prediction of rechargeable batteries with capacity regeneration phenomena. *Measurement*, 147:106836–106836, 2019.

[17] Zewang Chen, Na Shi, Yufan Ji, Mu Niu, and Youren Wang. Lithium-ion batteries remaining useful life prediction based on BLS-RVM. *Energy*, 234:121269, 2021.

[18] Datong Liu, Jingyue Pang, Jianbao Zhou, Yu Peng, and Michael Pecht. Prognostics for state of health estimation of lithium-ion batteries based on combination Gaussian process functional regression. *Microelectronics Reliability*, 53(6):832–839, 2013.

[19] Q. Ma, Y. Zheng, W. Yang, Y. Zhang, and H. Zhang. Remaining useful life prediction of lithium battery based on capacity regeneration point detection. *Energy*, 234:121233, 2021.

[20] Zhi-Xin Yang, Guokuan Yu, Jing Zhao, Pak Kin Wong, and Xian-Bo Wang. Online Equivalent Degradation Indicator Calculation for Remaining Charging-Discharging Cycle Determination of Lithium-Ion Batteries. *IEEE Transactions on Vehicular Technology*, 70(7):6613–6625, 2021.

[21] Guang Jin, David E. Matthews, and Zhongbao Zhou. A Bayesian framework for on-line degradation assessment and residual life prediction of secondary batteries inspacecraft. *Reliability Engineering & System Safety*, 113:7–20, 2013.

[22] Marcos E. Orchard, Matías S. Lacalle, Benjamín E. Olivares, Jorge F. Silva, Rodrigo Palma-Behnke, Pablo A. Estévez, Bernardo Severino, Williams Calderon-Muñoz, and Marcelo Cortés-Carmona. Information-Theoretic Measures and Sequential Monte Carlo Methods for Detection of Regeneration Phenomena in the Degradation of Lithium-Ion Battery Cells. *IEEE Transactions on Reliability*, 64(2):701–709, 2015.

[23] Benjamín E. Olivares, Matías A. Cerda Munoz, Marcos E. Orchard, and Jorge F. Silva. Particle-Filtering-Based Prognosis Framework for Energy Storage Devices With a Statistical Characterization of State-of-Health Regeneration Phenomena. *IEEE Transactions on Instrumentation and Measurement*, 62(2):364–376, 2013.

[24] Peng Wang and Robert X. Gao. Prognostic Modeling of Performance Degradation in Energy Storage by Lithium-ion Batteries. *Procedia Manufacturing*, 34:911–920, 2019.

[25] Fu-Kwun Wang and Tadele Mamo. A hybrid model based on support vector regression and differential evolution for remaining useful lifetime prediction of lithium-ion batteries. *Journal of Power Sources*, 401:49–54, 2018.

[26] Danhua Zhou and Bin Wang. Battery health prognosis using improved temporal convolutional network modeling. *Journal of Energy Storage*, 51:104480, 2022.

[27] Jianbo Yu. State of health prediction of lithium-ion batteries: Multiscale logic regression and Gaussian process regression ensemble. *Reliability Engineering & System Safety*, 174:82–95, 2018.

[28] Xiaoqiong Pang, Rui Huang, Jie Wen, Yuanhao Shi, Jianfang Jia, and Jianchao Zeng. A Lithium-ion Battery RUL Prediction Method Considering the Capacity Regeneration Phenomenon. *Energies*, 12(12):2247, 2019.

[29] Liming Deng, Wenjing Shen, Hongfei Wang, and Shuqiang Wang. A rest-time-based prognostic model for remaining useful life prediction of lithium-ion battery. *Neural Computing and Applications*, 33(6):2035–2046, 2021.

[30] Yapeng Zhou and Miaohua Huang. Lithium-ion batteries remaining useful life prediction based on a mixture of empirical mode decomposition and arima model. *Microelectronics Reliability*, 65:265–273, 2016.

[31] Jian Liu and Ziqiang Chen. Remaining Useful Life Prediction of Lithium-Ion Batteries Based on Health Indicator and Gaussian Process Regression Model. *IEEE Access*, 7:39474–39484, 2019.

[32] Man-Fai Ng, Jin Zhao, Qingyu Yan, Gareth J. Conduit, and Zhi Wei Seh. Predicting the state of charge and health of batteries using data-driven machine learning. *Nature Machine Intelligence*, 2(3):161–170, 2020.

[33] NCEI GIS NOAA. Noaa national centers for environmental information: Global surface hourly, May 2022. Dataset available at https://www.ncei.noaa.gov/access/search.