Applied Energy Symposium 2022: Clean Energy towards Carbon Neutrality (CEN2022)
April 23-25, 2022, Ningbo, China
Paper ID: 0007

Unsupervised Extraction of Degradation Related Features from Battery Cycling Data via a Conditional Temporal Convolutional Autoencoder

Jianxiang Wang[1], Shijie Weng[1], Xuesong Feng[1], Xiaoli Peng[1], Yong Xiang[1*]

1 School of Materials and Energy, University of Electronic Science and Technology of China, Chengdu, China (*Corresponding Author)

ABSTRACT

Clean energy production is often accompanied by battery storage systems that undergo complex degradation processes. Incremental capacity and differential voltage peaks are traditionally used for degradation analysis, but are sensitive to current rate, deep degradation, and battery chemistry. To enhance the robustness of degradation feature tracking, this study proposes a conditional temporal convolutional autoencoder. The unsupervised nature of the proposed method enables the extraction of degradation related features from data that have no peak features. Results show that the proposed method can extract features and reconstruct battery cycling curves with high fidelity. Furthermore, the extracted features are highly correlated with peak locations of incremental capacity and differential voltage curves. The extracted features also have less noise and no missing values compared to the peak locations. Prediction of peak locations from single encoding achieves mean absolute errors of 0.019 V and 2.4% state-of-charge. The proposed method is therefore potentially useful for battery degradation analysis and health assessment.

Keywords: lithium-ion battery, differential voltage analysis, incremental capacity analysis, neural network, unsupervised learning

NONMENCLATURE

Abbreviations	
ADAM	Adaptive moment estimation
ANN	Artificial neural network
CC	Constant current
CPU	Central processing unit
CTCA	Conditional temporal convolutional autoencoder
CV	Constant voltage
DCA	Deep convolutional autoencoder
DVA	Differential voltage analysis
GPU	Graphic processing unit
ICA	Incremental capacity analysis
LIB	Lithium-ion battery
MAE	Mean absolute error
RAM	Random access memory
RUL	Remaining useful life
SOC	State-of-charge

1. INTRODUCTION

LIBs have become widely used in consumer electronics [1, 2], transportation [3, 4], and energy storage [1, 5] due to their high energy density, power density, and relatively long lifetime. LIBs are considered especially promising as an energy storage component in clean and sustainable energy production for the regulation of uncertain power demands and renewable power supplies such as solar and wind [6]. However, LIBs degrade after extended usage due to factors including the depth of discharge, current load, and external temperature [6], which leads to reduced battery performance. Therefore, an accurate understanding of the degradation mechanism of LIBs is crucial to the development of high-performance battery materials and sustainable energy systems.

Previous studies used ICA and DVA to reveal the underlying mechanism of battery degradation. In ICA and DVA, the peak features of differential cycling curves are related to the battery intercalation process and correspond to degradation modes such as loss of lithium inventory and loss of active materials [7, 8]. Due to the peaks' correlation with degradation modes, many

discharging $\mathrm{d}Q/\mathrm{d}V$ peak initially near 4.0 V decreases faster in the predicted part after step 120 than the charging peak increases, which is consistent with this observation. In Fig. 4b, the $\mathrm{d}V/\mathrm{d}Q$ peaks slightly shift towards higher SOC during aging, possibly because the increase of polarization causes charging to be cut off earlier at high voltage than discharging is cut off at low voltage.

5. CONCLUSION

This paper proposes a CTCA for the extraction of degradation related features from battery cycling data. The extracted CTCA encodings highly resemble the peak locations of incremental capacity and differential voltage curves, but are more stable and less noisy compared to the peaks. Prediction of peak locations from single encoding achieves MAEs of 0.019 V and 2.4% SOC. Because the features of battery cycling curves often reflect the evolution of battery degradation modes, an accurate extraction of these features allows a precise analysis of battery degradation, which can in turn enable the development of higher-performance battery materials and more sustainable energy systems. Future work should therefore investigate the relationship between the CTCA encodings and measured battery degradation modes and explore the assessment of battery health using these encodings.

ACKNOWLEDGEMENT

We thank Professor Jingjing Li for helpful suggestions.

REFERENCES

[1] Stroe DI, Swierczynski M, Stroe AI, Kaer S, Teodorescu R. Lithium-ion battery power degradation modelling by electrochemical impedance spectroscopy. IET Renew Power Gen, 2022;11(9):1136-1141.

[2] Kabir MM, Demirocak DE. Degradation mechanisms in Li-ion batteries: a state-of-the-art review. Int J Energ Res, 2017;41:1963-1989.

[3] Pastor-Fernández C, Yu TF, Widanage WD, Marco J. Critical review of non-invasive diagnosis techniques for quantification of degradation modes in lithium-ion batteries. Renew Sust Energ Rev, 2019;109:138-159.

[4] Tian H, Qin P, Li K, Zhao Z. A review of the state of health for lithium-ion batteries: Research status and suggestions. J Clean Prod 2020;261:120813.

[5] Xu B, Oudalov A, Ulbig A, Andersson G, Kirschen DS. Modeling of lithium-ion battery degradation for cell life assessment. IEEE T Smart Grid 2016:9(2):1131-1140.

[6] Ahmadian A, Sedghi M, Elkamel A, Fowler M, Golkar MA. Plug-in electric vehicle batteries degradation modeling for smart grid studies: Review, assessment and conceptual framework. Renew Sust Energ Rev 2018;81: 2609-2624.

[7] Chen J, Marlow MN, Jiang Q, Wu B. Peak-tracking method to quantify degradation modes in lithium-ion batteries via differential voltage and incremental capacity. J Energy Storage 2022;45:103669.

[8] Weng C, Feng X, Sun J, Peng H. State-of-health monitoring of lithium-ion battery modules and packs via incremental capacity peak tracking. Appl Energ 2016; 180:360-368.

[9] Weng C, Cui Y, Sun J, Peng H. On-board state of health monitoring of lithium-ion batteries using incremental capacity analysis with support vector regression. J Power Sources 2013;235:36-44.

[10] Li X, Yuan C, Wang Z. State of health estimation for Li-ion battery via partial incremental capacity analysis based on support vector regression. Energy 2020;203: 117852.

[11] Lee S, Kim Y. Li-ion battery electrode health diagnostics using machine learning. Amer Contr Conf 2020:1137-1142.

[12] Li X, Wang Z, Yan J. Prognostic health condition for lithium battery using the partial incremental capacity and Gaussian process regression. J Power Sources 2019; 421:56-67.

[13] Fly A, Chen R. Rate dependency of incremental capacity analysis (dQ/dV) as a diagnostic tool for lithium-ion batteries. J Energy Storage 2020;29:101329.

[14] Wang J, Xiang Y. Fast modeling of the capacity degradation of lithium-ion batteries via a conditional temporal convolutional encoder-decoder. IEEE T Transp Electr, in press.

[15] She C, Wang Z, Sun F, Liu P, Zhang L. Battery aging assessment for real-world electric buses based on incremental capacity analysis and radial basis function neural network. IEEE T Ind Inform 2020;16(5):3345-3354.

[16] Zhang S, Zhai B, Guo X, Wang K, Peng N, Zhang X. Synchronous estimation of state of health and remaining useful lifetime for lithium-ion battery using the incremental capacity and artificial neural networks. J Energy Storage 2019;26:100951.

[17] Cheng Z, Sun H, Takeuchi M, Katto J. Deep convolutional autoencoder-based lossy image compression. Picture Coding Symposium 2018:253-257.

[18] Maures M, Capitaine A, Delétage JY, Vinassa JM, Briat O. Lithium-ion battery SOH estimation based on incremental capacity peak tracking at several current levels for online application. Microelectron Reliab 2020; 114:113798.