JREE: Vol. 5, No. 3, (Summer 2018) 60-63

Journal of Renewable Energy and Environment

Research Article

Journal Homepage: www.jree.ir

Development of Lifetime Prediction Model of Lithium-Ion Battery Based on Minimizing Prediction Errors of Cycling and Operational Time Degradation Using Genetic Algorithm

Mohammad Zarei-Jelyani, Mohammad Sarshar*, Mohsen Babaiee, Nima Tashakor

Institute of Mechanics, Iranian Space Research Center, Shiraz, Iran.

P A P E R I N F O

Paper history:
Received 10 June 2019
Accepted in revised form 22 September 2019

Keywords:
Lithium-Ion Battery
Capacity Loss
Lifetime Prediction
Cycle-Life
Operational Time

A B S T R A C T

Accurate lifetime prediction of lithium-ion batteries is a great challenge for the researchers and engineers involved in battery applications in electric vehicles and satellites. In this study, a semi-empirical model is introduced to predict the capacity loss of lithium-ion batteries as a function of charge and discharge cycles, operational time, and temperature. The model parameters are obtained by minimizing the prediction errors of experimental capacity loss for each charge/discharge cycle at 25 ^{o}C, 35 ^{o}C, and 45 ^{o}C.The optimum values of the model parameters are obtained using genetic algorithm, one of the optimization tools in Matlab software. The model accurately predicts the capacity loss of lithium-ion battery for more charge and discharge cycles at 25 °C with an average error of 4 %. The mentioned cycles are used only to validate the prediction.

1. INTRODUCTION

The lithium-ion battery (LIB) is the main option to store electrical energy due to their high energy density, long cycle life, wide operating temperature, and environmental suitability [1, 2]. Batteries with such advantages amongst other types are used in cell phones, laptops, electrical vehicles, telecommunication systems, and satellites [3, 4]. Battery lifetime is an important issue regarding practical utilization of LIBs [5, 6]. Accurate prediction of the useful lifetime avoids LIBs malfunctioning and failures and ensures the stability and safety of the developed system [7]. Generally, lifetime prediction methods for industrial LIBs improve the reliability of system design. For example, an accurate lifetime prediction model decreases the system cost by minimizing the allowed capacity of the installed battery instead of requiring a large safety margin [8]. In a spacecraft, LIB is one of the most important sub-systems in that its accurate lifetime prediction helps realize the maintenance schedule and provides a failure warning before reaching critical levels. In particular, for those low-cost and long-life space applications or instant launching missions, an above-ground decay or lifetime test is not permitted. Therefore, capacity fade modeling and lifetime prediction of LIB have drawn much attention in reliability engineering [9].

In the case of developing an LIB with a long cycle life, product verification requires considerable time, which may exceed the total scheduled time of battery development. Hence, with an accurate model of lifetime prediction, the battery verification can be done and developed accurately based on the limited number of experiments.

LIBs lifetime prediction models are classified into three categories: empirical models, mechanistic models, and semi-empirical models. Empirical models are relatively easy to use; however, they do not describe the details of the physical processes that occur in the system (such as adsorption, diffusion, and migration) [9, 10]. Furthermore, these fully empirical data fitting are precise only in cases where numerous experiments have been performed [11, 12].

Mechanistic models for lifetime prediction are generally obtained by physical degradation models describing electrochemical reactions in LIB. These models usually include a lot of parameters to properly indicate complex failure mechanisms. In addition, parameters are not constant under different operating conditions of LIB, which make it more difficult to determine the parameters of the mechanistic models [13, 14]. These challenges result in remarkable deviations regarding the precision of lifetime prediction. However, the semi-empirical models are relatively easy to develop and have a certain physical concept. In fact, semi-empirical models are considered to be intermediates between completely empirical and mechanistic models for LIB lifetime prediction [15].

Minghui Hu et al. [16] proposed a model for rapid determination of battery lifetime. The model is arranged to predict battery capacity using Arrhenius formula, temperature accelerated stress, and charge/discharge current accelerated stress. They obtained a fitted model to estimate the rate of battery capacity fade as a function of battery charge/discharge cycle numbers. Their model predicted the battery lifetime with a relative error of 40 %.

Yapeng Zhou et al. [17] found a linear correlation between mean voltage falloff and LIB capacity. They presented a new index of LIB degradation modeling and predicted the LIB useful life based on the mean voltage falloff with a relative error of 9 %.

Zarei-Jelyani et al. [10] proposed a model considering Arrhenius law for temperature and square root function for

*Corresponding Author's Email: m.sarshar@isrc.ac.ir (M. Sarshar)

cycle number dependencies, as the effective factors in lifetime prediction of LIBs. The relative error of the proposed model is 20 % at 25 ^{o}C.

Zarei-Jelyani et al. [7] proposed a semi empirical model to estimate the LIB capacity loss using the concept of the power law. The parameters of this model are obtained based on minimizing the prediction error using Marquardt-Levenberg algorithm. Their proposed model predicted the maximum charge/discharge cycles at the LIB's decay point with a relative error of 15 %.

In this study, a semi-empirical model of lifetime prediction is proposed to estimate the LIB's total capacity loss based on the number of charge/discharge cycles and operational time degradation. The parameters of the model are obtained based on minimizing the prediction error using Genetic algorithm. The calculation is performed using Matlab 2016a tool box.

2. EXPERIMENTAL

Aging experiments were carried out on Panasonic LIB cylindrical cells (NCR18650B). Sixteen charge/discharge cycles were carried out on three LIBs at temperatures of 25 ^{o}C, 35 ^{o}C, and 45 ^{o}C according to the manufacturer's instructions. The LIB capacities are measured and recorded by a multi-channel battery testing system (BTS3000, Neware Co.). Table 1 presents the LIBs characteristics used in this study.

Table 1. LIB characteristics used in this study.

Nominal capacity (mAh)		Minimum	3250
		Typical	3350
Nominal voltage (V)		3.6	
Charging method		Constant current-Constant voltage	
Charging voltage (V)		4.2	
Ambient temperature (^{o}C)	Charge	$10 \sim +45$ °C	
	Discharge	$-20 \sim +60$ °C	
	Storage	$-20 \sim +50$ °C	
Maximum weight (g)		47.5	
Volumetric energy density (Wh/l)		676	

The following stepwise charge/discharge procedure is used for aging experiment.

1. The battery is charged to 4.2 V at constant current of 975 mA.
2. It is charged with constant voltage of 4.2 V until the current decreases to 65 mA.
3. Twenty minutes of battery rest is needed.
4. LIB is discharged to 2.5 V at constant current of 3250 mA.

3. MATHEMATICAL MODELING

Generally, two mechanisms are taken into account for the LIB capacity loss. The first one is a degradation resulting from the expansion and contraction of anode and cathode during charging and discharging happening in each cycle. The second one is a degradation caused by electrochemical reactions, which is progressive over time, regardless of whether the LIB is charged, discharged, or even at rest. Since these two mechanisms are independent of each other, the LIB's overall capacity loss is assumed to be their function. Therefore, in LIB's lifetime prediction model, the operating time and charge/discharge cycle number are considered as the independent parameters.

Further, both degradation of cycling and operational time develop more quickly at higher temperatures. Hence, temperature is taken into account in the lifetime prediction model.

Eq. (1) is the general expression of the capacity loss model as a function of operating time (t_{op}), the number of cycles (N_{cyc}), and ambient temperature (T).

$$Q_{\rm loss} = A_{\rm op} \times e^{\frac{-E_{\rm op}}{RT}} \times t_{op}{}^{z_1} + A_{\rm cyc} \times e^{\frac{-E_{\rm cyc}}{RT}} \times N_{cyc}{}^{z_2} \quad (1)$$

where Q_{loss} is capacity loss, and A_{op} and A_{cyc} are the pre-exponential factors corresponding to degradation of operational time and cycling, respectively. E_{op} and E_{cyc} are the active energies corresponding to degradation of the operational time and cycling, respectively. T is the absolute temperature in Kelvin, R is the ideal gas constant, and z_1 and z_2 are the power exponents.

The parameters of Eq. (1) are A_{op}, A_{cyc}, E_{op}, E_{cyc}, z_1, and z_2 that are based on aging experimental data. Depending on the charge/discharge procedure, each cycle is carried out at time of τ. Hence, the operating time is considered to be $t_{\rm op} = N_{\rm cyc} \times \tau$. Therefore, the capacity loss model is expressed in the following equation.

$$Q_{\rm loss} = A_{\rm op} \times e^{\frac{-E_{\rm op}}{RT}} \times (N_{\rm cyc} \times \tau)^{z_1} + A_{\rm cyc} \times e^{\frac{-E_{\rm cyc}}{RT}} \times N_{\rm cyc}{}^{z_2} \quad (2)$$

The capacity loss model is converted to Eq. (3) by considering $A'_{\rm op} = A_{\rm op} \times \tau^{z_1}$ as a new parameter:

$$Q_{\rm loss} = A'_{\rm op} \times e^{\frac{-E_{\rm op}}{RT}} \times N_{\rm cyc}{}^{z_1} + A_{\rm cyc} \times e^{\frac{-E_{\rm cyc}}{RT}} \times N_{\rm cyc}{}^{z_2} \quad (3)$$

4. RESULTS AND DISCUSSION

The experimental data of the charge/discharge cycles (60 cycles at 25 ^{o}C, 35 ^{o}C, and 45 ^{o}C) are used to determine the parameters of the capacity loss model. Figure 1 shows the discharge capacity of three fresh LIBs versus the cycle number at different temperatures of 25 ^{o}C, 35 ^{o}C, and 45 ^{o}C. The discharge capacity levels at 25 ^{o}C and 35 ^{o}C are almost similar to each other, and the initial discharge capacities at 25 ^{o}C and 35 ^{o}C are 3283 and 3270 mAh, respectively. After 60 charge/discharge cycles, the discharge capacity reaches 3172 and 3166 mAh at 25 ^{o}C and 35 ^{o}C, respectively. The level of discharge capacity at 45 ^{o}C is different from that at two other temperatures so that its initial value is 3338 mAh and, after 60 cycles, it reaches 3216 mAh. However, the discharge capacity loss at 45 ^{o}C is 3.65 % after 60 cycles, which is more than the capacity loss at 25 ^{o}C (3.38 %) and 35 ^{o}C (3.18 %).

Figure 2 represents the charge capacity of three fresh LIBs versus the cycle number at different temperatures of 25 ^{o}C, 35 ^{o}C, and 45 ^{o}C. As shown in Figure 2, the trend of charge capacity during cycling is similar to that of the discharge capacity at different temperatures. Similar to the discharge process, both of charge capacity level and charge capacity loss at 45 ^{o}C are more than those at 25 ^{o}C and 35 ^{o}C.

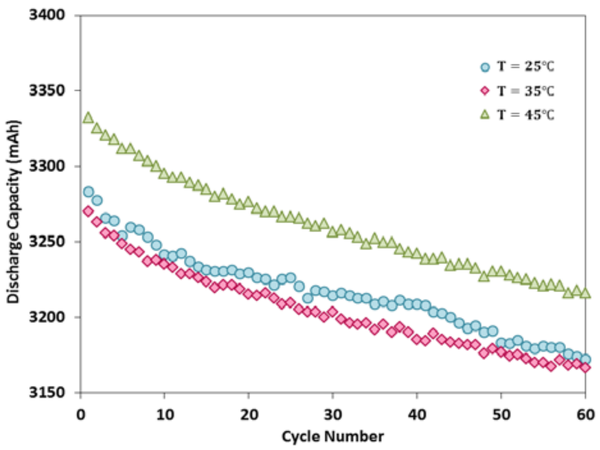

Figure 1. Discharge capacity of three fresh LIBs versus cycle number at different temperatures of 25 ^{o}C, 35 ^{o}C, and 45 ^{o}C.

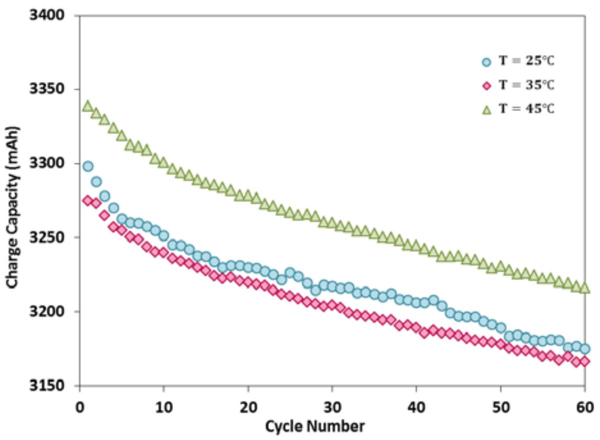

Figure 2. Charge capacity of three fresh LIBs versus cycle number at different temperatures of 25 ^{o}C, 35 ^{o}C, and 45 ^{o}C.

The optimum values of the model parameters are obtained by minimizing the prediction errors using the genetic algorithm in optimization tools of Matlab 2016a software. The capacity loss model with the optimum parameters is shown in Eq. (4).

$$Q_{loss} = 0.063 \times e^{\frac{9.111}{T}} \times N_{cyc}^{0.66} + 0.168 \times e^{\frac{-1.51}{T}} \times N_{cyc}^{0.651} \quad (4)$$

The accuracy of the developed model is shown in Figures 3 and 4. Figure 3 indicates the experimental and calculated data of capacity loss of Panasonic LIB cells at different temperatures of 25 ^{o}C, 35 ^{o}C, and 45 ^{o}C for sixteen charge/discharge cycles. As shown in Figure 3, the capacity losses simulated by Eq. (4) are in agreement with the experimental data.

In order to validate the model, the capacity losses of 300 charge/discharge cycles are calculated at 25 °C. Figure 4 shows the comparison between the experimental and calculated data at 25 ^{o}C for 300 cycles. The results indicate that the model accurately predicts the LIB capacity loss with a very good average relative error of 4 %.

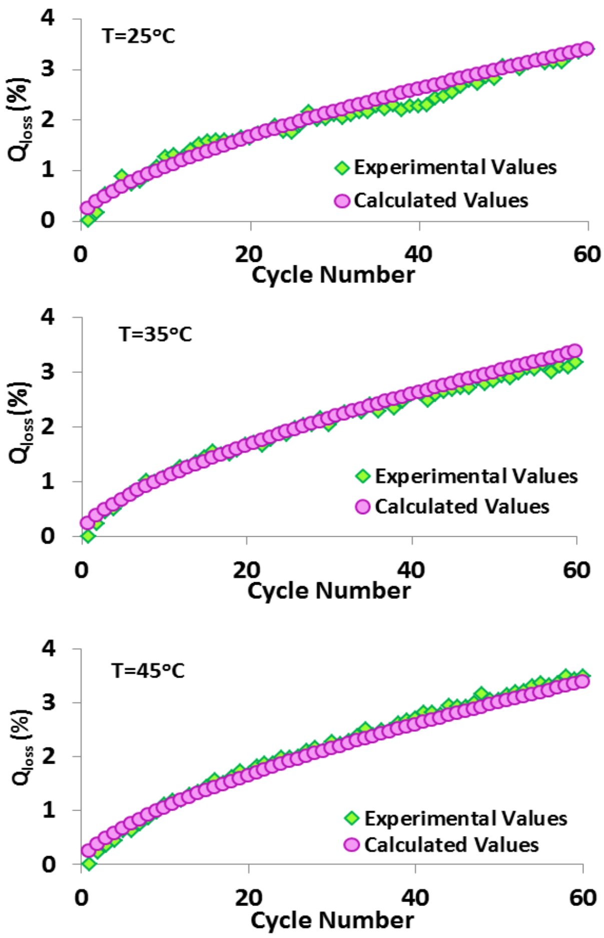

Figure 3. Experimental and calculated (based on Eq. (4)) capacity losses of LIBs at different temperatures of 25 ^{o}C, 35 ^{o}C, and 45 ^{o}C for 60 charge/discharge cycles.

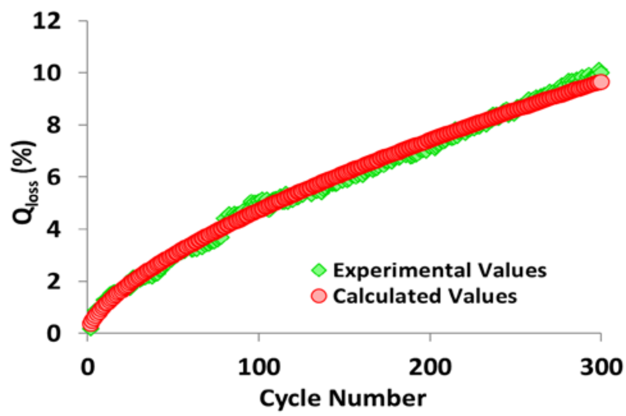

Figure 4. Comparison between the experimental data and calculated values of capacity loss at 25 ^{o}C for 300 cycles.

5. CONCLUSIONS

In this work, a model was developed to predict the capacity loss of lithium-ion batteries. The reliability of battery design increased with this model. The optimum values of the model parameters were obtained based on minimizing the prediction errors using the genetic algorithm optimization tools of Matlab 2016 software. The developed model accurately predicted the LIB capacity loss with a very good relative error of 4 %. Therefore, the LIB lifetime can be estimated according to the requirements of battery missions such as allowable capacity loss and operating temperature.

6. ACKNOWLEDGEMENT

This work was mainly supported by the Iranian Space Research Center.

REFERENCES

1. Yuchen, S., Datong, L., Yandong, H., Jinxiang, Y. and Yu, P., "Satellite lithium-ion battery remaining useful life estimation with an iterative updated RVM fused with the KF algorithm", ***Chinese Journal of Aeronautics***, Vol. 31, (2018), 31-40. (Doi: 10.1016/j.cja.2017.11.010).
2. Dehghan, F., Mohammadi-Manesh, H. and Loghavi, M.M., "Investigation of lithium-ion diffusion in $LiCoPO_4$ cathode material by molecular dynamics simulation", ***Journal of Structural Chemistry***,Vol. 60, (2019), 727-735. (Doi: 10.1134/S0022476619050044).
3. Lee, S., Cho, Y., Song, H.K., Lee, K.T. and Cho, J., "Carbon-coated single-crystal $LiMn_2O_4$ nanoparticle clusters as cathode material for high-energy and high-power lithium-ion batteries", ***Angewandte Chemie***, Vol. 124, (2012), 8878-8882. (Doi: 10.1002/anie.201203581).
4. Sarshar, M., Zarei-Jelyani, M. and Babaiee, M., "Application of semi empirical and multiphysics models in simulating lithium ion battery operation", ***Proceedings of 10th International Chemical Engineering Congress and Exhibition***, Isfahan, Iran, (2018).
5. Ecker, M., Nieto, N., Käbitz, S., Schmalstieg, J., Blanke, H., Warnecke, A. and UweSauer, D., "Calendar and cycle life study of Li $(NiMnCo)O_2$-based 18650 lithium-ion batteries", ***Journal of Power Sources***, Vol. 248, (2014), 839-851. (Doi: 10.1016/ j.jpowsour.2013.09.143).
6. Xie, Y., Li, J. and Yuan, C., "Multiphysics modeling of lithium ion battery capacity fading process with solid-electrolyte interphase growth by elementary reaction kinetics", ***Journal of Power Sources***, Vol. 248, (2014), 172-179. (Doi: 10.1016/j.jpowsour.2013.09.059).
7. Zarei-Jelyani, M., Sarshar, M., Babaiee, M. and Ghasemi, A., "Experimental study and empirical modeling of capacity loss in space lithium-ion battery", ***Journal of Modeling in Engineering***, Vol. 55, (2018), 3-3. (Doi: 10.22075/jme.2018.13281.1304).
8. Yoshida, T., Takahashi, M., Morikawa, S., Ihara, C., Katsukawa, H., Shiratsuchi, T., and Yamaki, J.I., "Degradation mechanism and life prediction of lithium-ion batteries", ***Journal of The Electrochemical Society***, Vol. 153, (2006), A576-A582. (Doi: 10.1149/1.2162467).
9. Cui, Y., Du, C., Yin, G., Gao, Y., Zhang, L., Guan, T., Yang, L. and Wang, F., "Multi-stress factor model for cycle lifetime prediction of lithium ion batteries with shallow-depth discharge", ***Journal of Power Sources***, Vol. 279, (2015), 123-132. (Doi: 10.1016/j.jpowsour. 2015.01.003).
10. Zarei-Jelyani, M., Sarshar, M., Babaiee, M., Ghasemi, A. and Eqra, R., "Lifetime prediction of lithium-ion battery", ***Proceedings of 3rd Symposium of Scientific and Technical Achievements of ISRC***, Tehran, Iran, (2017).
11. Wright, R.B., Christophersen, J.P., Motloch, C.G., Belt, J.R., Ho, C.D., Battaglia, V.S., Barnes, J.A., Duong, T.Q. and Sutula, R.A., "Power fade and capacity fade resulting from cycle-life testing of advanced technology development program lithium-ion batteries", ***Journal of Power Sources***, Vol. 119, (2003), 865-869. (Doi: 10.1016/S0378-7753(03)00190-3).
12. Fellner, J., Loeber, G., Vukson, S. and Riepenhoff, C., "Lithium-ion testing for spacecraft applications", ***Journal of Power Sources***, Vol. 119, (2003), 911-913. (Doi: 10.1016/S0378-7753(03)00222-2).
13. Santhanagopalan, S., Zhang, Q., Kumaresan, K. and White, R.E., "Parameter estimation and life modeling of lithium-ion cells", ***Journal of The Electrochemical Society***, Vol. 155, (2008), A345-A353. (Doi: 10.1149/1.2839630).
14. Safari, M., Morcrette, M., Teyssot, A. and Delacourt, C., "Multimodal physics-based aging model for life prediction of Li-ion batteries", ***Journal of The Electrochemical Society***, Vol. 156, (2009), A145-A153. (Doi: 10.1149/1.3043429).
15. Wang, J., Liu, P., Hicks-Garner, J., Sherman, E., Soukiazian, S., Verbrugge, M., Tataria, H., Musser, J. and Finamore, P., "Cycle-life model for graphite-$LiFePO_4$ cells", ***Journal of Power Sources***, Vol. 196, (2011), 3942-3948. (Doi: 10.1016/j.jpowsour.2010.11.134).
16. Hu, M., Wang, J., Fu, C., Qin, D. and Xie, S., "Study on cycle-life prediction model of lithium-ion battery for electric vehicles", ***International Journal of Electrochemical Science***, Vol. 11, (2016), 577-589.
17. Zhou, Y., Huang, M., Chen, Y. and Tao, Y., "A novel health indicator for on-line lithium-ion batteries remaining useful life prediction", ***Journal of Power Sources***, Vol. 321, (2016), 1-10. (Doi: 10.1016/j.jpowsour.2016.04.119).