Battery prognostics based on discharge voltage drop for energy storage applications

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ABSTRACT

This study proposes an approach that can predict the end of Li-ion battery life using the discharge voltage drop curve during its use in the energy storage system (ESS). The approach is developed based on the findings that the voltage drop in Li-ion batteries increases as the battery undergoes cycles, and it can be related with the residual capacity. The key idea is to insert the additional cycle of full charging and discharge with constant c-rate during the usage of the ESS. In this cycle, the relation between the voltage drop and capacity is established off-line via regression technique. Then this is applied to estimate the SOH and RUL on-line during the battery cycles. Particle filter (PF) algorithm is applied to this end, in which the degradation and regression models are taken as the state and measurement models respectively, and the capacity is estimated in the form of samples. The obtained samples are then used to predict its behavior in the future, from which the RUL distribution is determined. Conclusion of the study is that the voltage drop in Li-ion batteries can be a good indicator of the battery health and PF is a useful tool that can predict the RUL accurately even when the charge-discharge conditions change in the middle of the usage cycles.

1. INTRODUCTION

Recently, Li-ion batteries are becoming increasingly popular for reliable storage of energy in a variety of applications including the energy storage system (ESS) due to numerous advantages such as energy-to weight ratios, self-discharge when not in use, energy and power densities, etc. The batteries, however, tend to degrade in its capacity as it undergoes charge and discharge cycles, and it is regarded as failure when it reaches 70~80% of its initial capacity. For the maintenance of Li-ion batteries, the state-of-health (SOH) and the remaining useful life (RUL) of the batteries needs to be estimated with acceptable accuracy. Here, the SOH means the ratio of present capacity with respect to the capacity of the fresh battery, and the RUL means the remaining time or cycle left before reaching the 70% capacity of the fresh battery capacity. (i.e. SOH=0.7).

To estimate the SOH and RUL of Li-ion batteries, the various probability-based approach have been vigorously applied. The approaches can be classified into physics-based approach and data-driven approach. In physics-based approach, the SOH and its degradation model is built using the equivalent circuit model (Seo et al. 2012, Bhagu et al., 2005, Andre et al., 2013, Dalal et al, 2011) or electrochemical model (Lee et al., 2015, Sung et al., 2016). For RUL estimation, the various Bayesian inference approaches such as Kalman filter (Seo et al, 2012), Extended Kalman filter (Bhangu et al, 2005, Andre, et al, 2013), Particle filter (Dalal et al., 2011) have been applied. The data-driven approach can overcome the uncertainties due to the simplification in the physical modeling. The various approach such as artificial neural networks (Nuhic et al., 2013), relevance vector machines (Liu et al., 2015, Yang et al, 2015), support vector machines (Li et al., 2015) have been applied for the estimation of RUL. The estimation accuracy of the physics based approach is expected to be superior to that of modeldriven approach because the model is based on the actual physical phenomenon of the capacity degradation. However, the battery system model is too much complex to build the physical model including the whole phenomenon of the capacity fade.

This paper propose the data-driven approach for the SOH and RUL estimation using the relation between the voltage drop and the battery capacity. Matsushima (2007) proposes the SOH estimation approach using the voltage drop. This relation can be used only in the same operating conditions such as temperature, voltage and c-rate. To apply this approach for the ESS used at random operating condition, the cycle having the fixed operating conditions can be inserted during the usage of the ESS. The function of the capacity with respect to the voltage drop is built using the third-order polynomial function and conventional regression technique. To build this function, the voltage curve and the measured capacity of the ESS battery pack is used as the experimental data. Next, the RUL is predicted using the Particle Filter (PF) algorithm from the data of capacity and cycle.

2. SOH ESTIMATION

This section shows how to estimate the SOH using the voltage drop of the battery. The function of capacity with respect to voltage drop is built using third-order polynomial for each fixed time (2, 4, 6, … minutes). The experimental data of ESS battery back is used to build the model, and the effectiveness of the proposed method is validated.

2.1. Function of SOH with respect to Voltage Drop

The shape of voltage curve is changes as the capacity of Li-ion batteries decreases. In the case of discharging, the voltage drop during the fixed time increases as the capacity fade as can be seen in Figure 1.

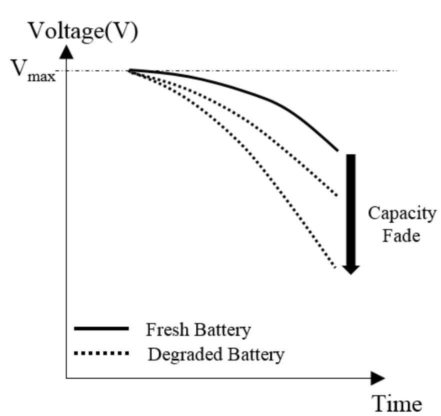

Figure 1. Changes in voltage curve by the capacity fade in Li-ion batteries.

Instead of the voltage drop at one specific time duration, the voltage drop for various time duration can be used for better estimation of SOH. Figure 2 show the voltage drop at various fixed time. Here, the polynomial function between the capacity and the voltage drop at various time duration (t_k) is built as:

$$\Delta V = a_{0k} + a_{1k} \times SOH + a_{2k} \times SOH^2 + a_{3k} \times SOH^3 \quad (1)$$

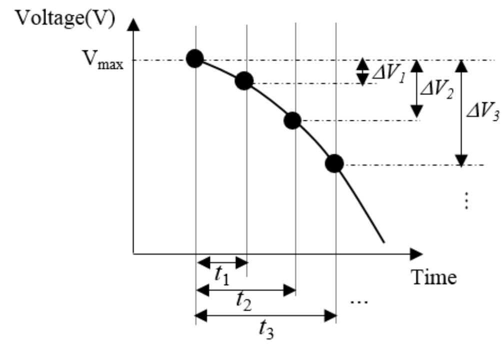

Figure 2.Voltage drop for various time duration.

Here, voltage drop is used as the output instead of input because the voltage drop is the measured value, and the SOH is the estimated one. To find the coefficient a_{0k}~a_{3k} in (1), the conventional regression approach is applied with experimental data of ESS pack test.

2.2. SOH model using Training Data

To validate the effectiveness of the proposed SOH estimation approach, the SOH model is built using the training data of ESS pack test. The test is performed using the cycle of the actual ESS usage. For every 200 cycle, the capacity is measured from the current integration of twice cycle with 1C charge and discharge. The calculated capacity is presented in. Figure. 3.

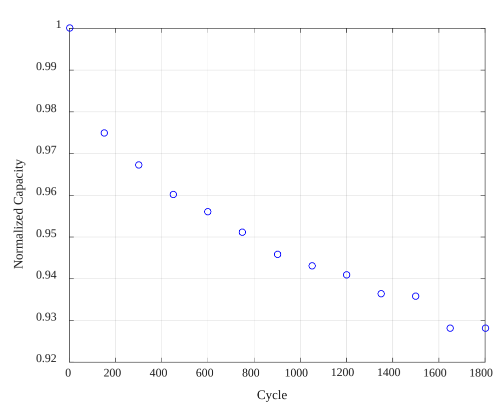

Figure 3. Measured capacity with respect to cycle.

The voltage drop for each cycle is measured from the voltage curve in the training data. Figure 4 shows the relation between the present capacity and the voltage drop during 10 minute discharging from maximum voltage. This curve shows that the voltage drop can be used as good indicator of the capacity degradation.

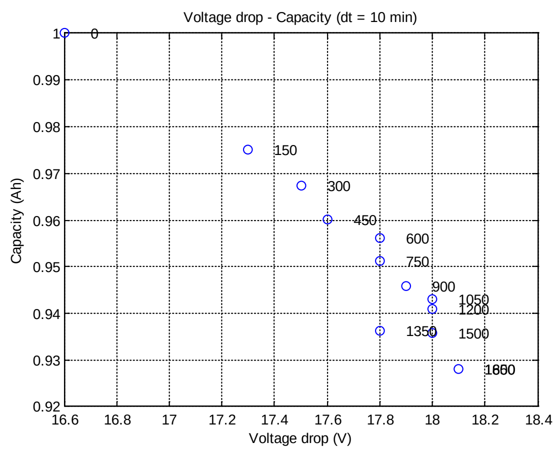

Figure 4. Relation between the present capacity (Ah) and the voltage drop (V) during 10 minute discharging

The relation in figure 4 can be model using the polynomial function (1). The coefficient of the polynomial function is calculated using the conventional regression technique. The obtained coefficients are a_0=-474, a_1=1391, a_2=-1278 a3=378. Figure 5 shows that the obtained polynomial function fits the date well. Although, the data for one time duration (10 minutes) is given in this paper, the polynomial functions for various time duration can be used together for the SOH estimation with better accuracy. To sum up, the SOH model between the present capacity and voltage drop at various time duration of discharging built by the test data can be used to estimate the SOH of ESS.

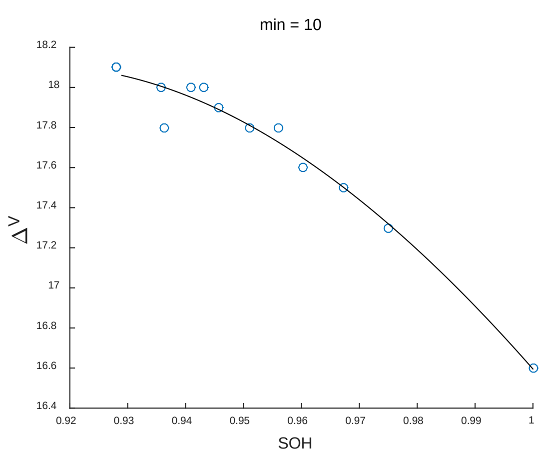

Figure 5. Polynomial function (black line) obtained using regression.

3. RUL ESTIMATION

The RUL is estimated using the particle filter algorithm. The end of life of battery is set as the time when the present capacity decreases as 70% of the fresh battery capacity. Well-known particle filter algorithm (An et al. (2013)) is applied to predict the SOH degradation. As the SOH degradation model, the exponential function (Sim et al., 2013)) is applied, and the coefficient of the exponential function and standard deviation is estimated by comparing the measured and model SOH. Figure 6 show the prediction result of SOH degradation obtained using the PF algorithm. The 95% prediction interval (P.I.) and the median of the SOH is estimated as shown in Figure 6. Figure 7 shows the probability density function of the estimated RUL. The median of RUL is estimated around 9300 cycle.

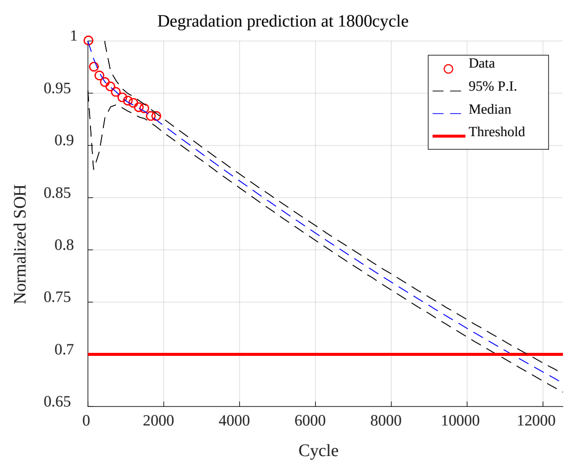

Figure 6. Prediction of SOH degradation

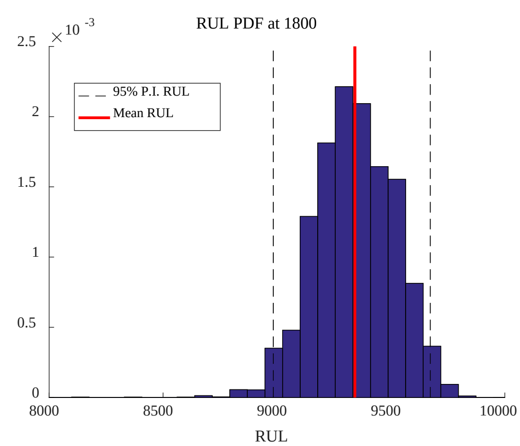

Figure 7. Probability density function of RUL

4. CONCLUSION

This paper proposes the data-driven SOH estimation approach using the voltage drop. The relation between the voltage drop and the present capacity is modeled as the polynomial function using the training data. Using this model, the present capacity can be estimated using the voltage curve of the test data. The model built using the training data is presented, and it is validated that the voltage drop can be used as good indicator to estimate the SOH. This approach is valid only when the voltage curve at fixed operating condition can be achieved. To apply this approach for the SOH estimation of ESS used at the random operating condition, the fixed cycle can be inserted during the usage. In addition, the RUL of the Li-ion battery is predicted using the particle filter algorithm. As the estimation result, the probability density function of the RUL is provided.

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