Lithium-ion batteries have become a chosen energy solution for many types of systems including consumer electronics, electric vehicles, and military and aerospace electronics, due to their high energy density, high galvanic potential, lightness of weight and long lifetimes compared to lead-acid, nickel-cadmium, and nickel-metal-hydride cells. As the demand for lithium-ion batteries increases so does the need to evaluate their reliability. This process requires an understanding of battery degradation and how it can be monitored and predicted under different environmental and usages conditions. With this knowledge, decisions regarding maintenance and warranty can be made.

Introduction

Monitoring battery reliability during usage may be viewed in two different contexts. The first involves state of charge (SOC). SOC is analogous to the battery indicator on a cell phone. SOC indicates how much charge a battery has available before it needs to be recharged. The second context, which is the focus of this work, is state of health (SOH). SOH indicates the remaining useful charge/discharge cycle life of a battery. As a battery undergoes cycling, the amount of charge it can hold in a fully charged state begins to decrease. The available charge that a battery can deliver is known as the battery’s capacity. The decrease in capacity during usage is brought on by side reactions that occur between the battery’s electrodes and electrolyte which bind lithium, thus removing it from the Faradic process. Solid precipitates arise as the product of these side reactions and adhere to the electrodes, increasing the internal resistance of the cell. Additionally, expansion and contraction of the electrodes during lithium insertion and de-insertion can bring on mechanical damage. The combined effects of these reactions reduce the battery’s ability to store electrical energy. For many applications, failure is considered to occur when the capacity of the battery is reduced to below 80% of its rated value. At this point, the battery is considered as an unreliable power source and should be replaced, because it tends to exhibit an exponential decay of capacity after it passes this point.

There are two main approaches to battery SOH predictions: physics-of-failure (PoF) and data-driven. PoF-based prognostic methods utilize knowledge of a product’s life cycle loading conditions, geometry, material properties, and failure mechanisms to estimate its remaining useful life (RUL). PoF models have been developed, incorporating film resistance, exchange current density and overvoltage of parasitic reaction to predict capacity fade in lithium-ion batteries [1]. However, these models tend to be computationally intensive and are not well suited for real-time battery monitoring. Data-driven techniques extract features from performance data such as current, voltage, time, and impedance, using statistical and machine learning techniques to track the product’s degradation and estimate its RUL. Data-driven methods do not require specific knowledge of material properties, constructions or failure mechanisms, and avoid developing high-level physical models of the system, so that they are less complex than PoF based approaches. Data-driven methods can capture the inherent relationships and learn trends available in the data to provide RUL prediction. Relevance vector machine (RVM) and particle filter have been implemented to predict the SOH and RUL of Lithium-ion batteries based on impedance spectroscopy data [2]. However, the impedance
measurement requires expensive equipments and is time consuming. In addition, the battery should be disconnected to the charger or load during the measurement. These shortcomings confine its application in real practice.

Experiment

In this work, capacity is adopted as the indicator of the SOH of batteries. Capacity can be measured as the integral of current over the time from fully charged state to fully discharged state. In order to investigate the degradation of lithium-ion batteries, the battery aging experiments were conducted. The batteries were cycled under the ambient temperature. Their rated capacity is 0.9 ampere hour (Ah). During the charging period, a constant current of 0.5C (0.45A) was supplied to the batteries until the voltage reached an upper limit of 4.2 volts. The power supply was then switched to a constant voltage mode and the cells were held at 4.2 volts until the charging current decreased to 0.045A. At this point the batteries were considered fully charged. During discharge a load was placed on the battery to draw a constant current of 0.5C (0.45A) until the voltage decreased to 2.7V. The capacity of the cells were estimated and recorded at each cycle.

Model

Capacity data were then analyzed and used to establish a parametric model to model the battery degradation. It was found that an exponential model in the form of

\[ Q(k) = a \cdot \exp(b \cdot k) + c \cdot \exp(d \cdot k) \]

can well capture the capacity fade trend with the discharge cycle, where \( a, b, c, \) and \( d \) are the model parameters to be estimated; \( Q(k) \) is the capacity measured at the cycle \( k \). In this model, parameters \( a \) and \( b \) controls the value of the initial capacity, \( c \) and \( d \) determines the degradation rate. The goodness of fit statistics of this model to the capacity fade data with discharged cycles was estimated. The R-square and adjusted R-square were both greater than 0.99, which means the proposed model is well suitable to represent capacity fade data. Thus as long as the parameters of this model are accurately estimated, the model will be able to provide good predictions of the battery’s capacity at a given cycle number.

Algorithms have been proposed to estimate the parameters of a model [3]. The most popular one is non-linear least square regression (NLSR). NLSR has well-developed theoretical foundation and can fit a broad range of functions. However, it is strongly sensitive to outliers. The presence of one or two outliers in the data can seriously affect the results of NLSR. In addition, the starting values should be provided before NLSR, and must be reasonably close to the as yet unknown parameter estimates, or the algorithm may not converge.

Recently, Kalman filters have been used for parameter estimation, especially estimating parameters from noisy data [3]. In this work, Kalman filter was adopted due to the following advantages: first, it is computational efficient and can be implemented for real-time monitoring; secondly, it takes into account the measurement uncertainties or noise, and it can incorporate prior knowledge of the system; an third, it provides dynamic estimation error bounds on these estimations, so that the confidence level of the prognostics can be accessed.

There are several variations of Kalman filter, like the standard Kalman filter, extended Kalman filter (EKF) and unscented Kalman filter (UKF). The EKF was used in this study, because is a specially designed for
solving non-linear problem. EKF was initially proposed by researches for tracking the nonlinear stochastic process of a system. It requires a system function which characterizes the evolving of the state parameters of the system with time, and an observation function, which represents the measurements of the system as a function of the state parameters. The EKF approach is to apply the standard Kalman filter to nonlinear system with additive white noise by continually updating a linearization around the previous state estimate starting with an initial guess. In other words, a linear Taylor approximation of the system function at the previous state estimate is considered and the observation function is evaluated at the corresponding predicted position. This approach gives a simple and efficient algorithm to handle a nonlinear model.

In order to fit in the EKF framework, the model parameters $a, b, c, d$ can be considered as state parameters, and the observation function is $Q_k = a_k \cdot \exp b_k \cdot k + c_k \cdot \exp d_k \cdot k$. By defining an initial guess $[a_0, b_0, c_0, d_0]$ for the model parameters, EKF can recursively update them at each cycle $k$ based on the newest capacity measurement. The purpose of EKF is to produce the optimal parameter estimates that tend to provide the closer $Q_k$ to the actual measurement. The more update of the parameters, the more accurate they will be. After the model parameters being estimated, the exponential model can be extrapolated to the failure threshold to predict the failure time of the battery.

Fig.1 shows the prediction result using the EKF at the cycle 120. The first 120 capacity measurements were used to estimate the model parameters. The blue points are the actual capacity measurements, and the red curve is prediction based on the exponential model, whose parameters were estimated by EKF. The actual failure cycle and the predicted failure cycle are 189 and 179 respectively. Hence, the prediction error is 10 cycles.

![Fig. 1 The prediction result at cycle 120 using extended Kalman filter.](image-url)
For comparison, Fig.2 shows the prediction result obtained by using NLSR. It can be seen from Fig.2 that NLSR greatly underestimated the actual failure cycle. The prediction error is 46 cycles. The relative large noise at between the cycle 10 to 70 is a possible cause resulting in the poor performance of NLSR. On the contrary, the EKF takes the measurement noise into account during the estimation, so it is more robust and provides more accurate estimation for the model parameters.

Conclusions

The state of health of a lithium-ion battery can be evaluated by the capacity it can deliver. Experiments were conducted to investigate the degradation of lithium-ion batteries, and an exponential model was found to be suitable for modeling the capacity fade trend. An extended Kalman filtering approach was proposed to estimate the parameters of the exponential model. Extended Kalman filter is robust to measurement noise and can provide better estimation than the nonlinear least square approach. After determining the parameters, the exponential model can be extrapolated to the failure threshold to predict the failure time.

References