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Lithium-ion primary cell battery end of life detection using charge voltage and temperature data.

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1 Introduction

Industrial systems have a crucial need for communication to collect and send information about their state, trigger alerts or prevent maintenance. In the specific context of farms, data transmissions require long-range radio communications and extended lifetime. To overcome these challenges, energy battery-powered devices are used. These devices play a key and decisive role in monitoring irrigation related data and activating valves to start or stop irrigation. However, the discharge of the device battery can cause faults[1] that lead to the loss of essential data needed to monitor the system and automate irrigation. It is therefore essential to detect the battery end of life before it is fully discharged to avoid any loss of service. The most commonly used methods in analyzing the state of lithium batteries are Discharge test, Ah balance and Open circuit voltage [2]. All of these methods use the current drawn from the battery to determine the battery SoC (State of Charge). However, measuring this current mainly requires a battery gauge or a specific measurement circuit that are not always embedded in low cost, low power and low maintenance systems. On the other hand, battery voltage and temperature are easier to measure and more commonly used. Another effective method to determine the battery SoC is by using artificial neural networks [3] as they can learn and model the battery behavior based on historical data and non linear relations between several variables. The Kalman filter can be used to estimate the SoC [3], which relies on measuring the current and/or open circuit voltage. Unfortunately, we do not have access to the necessary information regarding the SoC specifications, features, and capabilities. This lack of data is preventing us from accurately estimating the SoC. The choice of the method to analyze the state of life of a lithium battery mainly depends on the available information: battery voltage and ambient temperature since access to current and historical data of SoC is not always available. This led us to explore alternative methods that can effectively detect the end of life of batteries without relying on current measurements or historical data of SoC and compare them to the more conventional methods. Battery SoC is often used in literature [2, 5] as an indicator of battery life, but in our case we cannot estimate it for the lack of access to data information. For these reasons, we focus on the detection of the battery end of life behavior.

2 Objective and assumptions

The objective of this work is to detect the degradation mode associated with the end of life behavior of the battery before it is fully discharged by proposing a method for detecting it using only the measured battery voltage and ambient temperature.

The battery model is illustrated in Figure 1. The following equation holds

$$T_m(t) = T_{\text{batt}}(t) + T_0 + w_T(t), \quad (1)$$

$$V_m(t) = V_{\text{ocv}}(t) + V_0 + w_v(t), \quad (2)$$

where V_m and T_m are respectively the measured voltage and the measured temperature, V_{ocv} is the open-circuit voltage, T_{batt} is the battery temperature, V_0 is the voltage across the resistor R_0 and T_0 is the associated temperature. We assume that $w_i \sim \mathcal{N}(0, \sigma_i)$, and that w_v and w_T are independent.

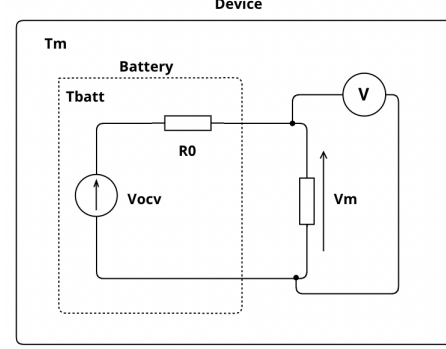


FIG. 1: Model of a Lithium-ion battery

3 Methodology approach

We have the following definition for the entropy and the enthalpy [6, 8] of the battery

$$\Delta S(t) = F \frac{\partial V_{\text{ocv}}(t)}{\partial T_{\text{batt}}(t)}, \quad (3)$$

$$\Delta H(t) = F \left(V_{\text{ocv}}(t) - T_{\text{batt}} \frac{\partial V_{\text{ocv}}(t)}{\partial T_{\text{batt}}(t)} \right), \quad (4)$$

where F represents the Faraday constant and T_{batt} is the battery temperature. The relationship between the entropy, enthalpy and SoC is given by the theorem of Yazamy [8]:

$$\text{SoC}(t) = \alpha + \beta \Delta S(t) + \gamma \Delta H(t). \quad (5)$$

Thus, to detect the battery end of life, we propose to use the measured voltage $V_m(t)$, along with an estimation of the entropy $\Delta S(t)$ and a biased estimation of the enthalpy $\Delta H(t)$. The contribution of this paper is a proposition on how to estimate $\Delta S(t)$ and $\Delta H(t)$ and the associated methods to detect the battery end of life. Using [7], the battery voltage can be modeled using the following equation, for $t_c \in [t - \Delta t, t]$:

$$V_m(t_c) = A(t) + B(t)T_{\text{batt}}(t_c) + C(t)t_c, \quad (6)$$

where A , B and C are constants with respect to t_c . Note that Δt corresponds to the size of the sliding window which is defined as one week. Using (6), we can deduce the estimator of $\Delta S(t)$ and $\Delta H(t)$ with $\Delta \hat{S}(t) = B$, and $\Delta \hat{H}(t) = A + Ct$. These estimators are related to $\Delta S(t)$ and $\Delta H(t)$ by a proportional factor and an affine relation respectively. Moreover, the equation holds with experimental data. Furthermore, we use the correlation computation in order to determine the window length Δt . This means that for any t , we estimate the equation associated with a backward window of length Δt . Considering $y(t_c) = b(t)x(t_c)$, $b(t)$ is estimated using ordinary least square estimation $b(t) = (X^T X)^{-1} X^T Y$.

Ordinary least square estimation is known to be sensitive to outliers, which can negatively impact the accuracy of the estimation [9, 10]. To address this issue, there are various methods that can be employed. In this study, we propose using the Weighted Least Squares presented in [4], specifically for time-series data. After estimating $b(t)$, we suggest investigating four different battery end of life detection methods, namely: first we will set a threshold based on voltage by analyzing the available data, then entropy, enthalpy, and finally the proposed approach will also be used to set the thresholds for fault detection indices, Hotelling's T^2 statistic and Q statistic which is squares prediction error (SPE) [11, 12, 13] by performing principal component analysis (PCA) on the three parameters $(V, \Delta S, \Delta H)$.

By considering these different methods, we aim to enhance the accuracy and reliability of our results in detecting battery end of life. To validate the accuracy of our chosen threshold determination method, we will test these thresholds on batteries that have reached their end of life.

Figure 2 shows the hourly voltage measurements taken for a sample of discharged batteries, which have an average lifespan of about 15 months.

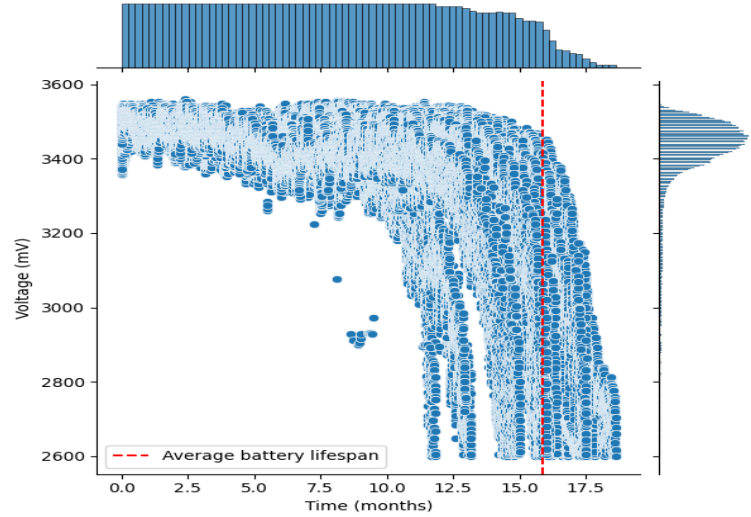


FIG. 2: Voltage time series

4 Conclusions and perspectives

In conclusion, the detection of the battery end of life is a crucial task for ensuring the reliability and safety of various applications. By leveraging the measured voltage, entropy, and enthalpy estimations, a more accurate and comprehensive understanding of the battery health can be achieved. This approach, based on Yazamy's theorem and statistical methods, allows for the estimation of $\Delta S(t)$ and $\Delta H(t)$, which are parameters for monitoring the battery performance. Our objective is to achieve less than 10% false alarm and less than 5% missed detection rates. We will discuss, in future work, threshold determination, remaining end of life estimation, and provide a statistical comparison of the methods.

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