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► **To cite this version:**

Rania Aboulfadl, Christophe Roman, Guillaume Graton, Mustapha Ouladsine. End of Life Detection of Li-ion Primary Cell Battery Based on Closed-Loop Voltage and Ambient Temperature. SAFE-PROCESS 2024, Jun 2024, Ferrara, Italie, Italy. hal-04543534

HAL Id: hal-04543534

<https://hal.science/hal-04543534>

Submitted on 15 Apr 2024

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End of Life Detection of Li-ion Primary Cell Battery Based on Closed-Loop Voltage and Ambient Temperature

Rania ABOULFADL ^{*,**} Christophe ROMAN ^{**}
Guillaume GRATON ^{**,***} Mustapha OULADSINE ^{**}

^{*} *Telaqua, 19 Quai de Rive Neuve, F-13007 Marseille, France*

^{**} *Aix Marseille Université, CNRS, LIS (UMR 7020), Avenue Escadrille Normandie-Niemen, F-13397 Marseille Cedex 20, France*

^{***} *Centrale Méditerranée, Technopôle de Château-Gombert, 38 rue Frédéric Joliot-Curie, F-13451 Marseille Cedex 13, France
(email: rania.aboulfadl@lis-lab.fr).*

Abstract:

This paper deals with the detection of Lithium-ion battery end of life based on its voltage and ambient temperature measured every 1 hour. A methodology for classifying the battery status (normal or degradation mode) is presented. The battery's entropy and enthalpy have also been estimated. The classification has been performed using three algorithms: Interquartile, Isolation Forest, and One-Class SVM. The metrics used to compare these methods are F1-score and Average F-measure. The findings showed that enthalpy has promising results in detecting the battery end of life.

Keywords: AI and FDI methods, Filtering and estimation, Power plants and power systems.

1. INTRODUCTION

Industrial systems use communicating devices to collect and send information about their states. This information can be used to trigger alerts or plan predictive maintenance. In this context, the efficiency of data transmission in various applications relies on long-range radio communications and extended device lifespan. Due to these requirements, battery-powered devices are commonly used in the industry. These devices play a key role in monitoring and controlling different systems. However, the device battery discharge can cause faults (Isermann (1997)) that may lead to system dysfunctions such as actuation loss. 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 charge of lithium batteries are: Discharge test (Chen and Li (2014)), Amper-hour balance (Keil and Jossen (2016)), and the open circuit voltage (Piller et al. (2001)). These first two methods use the current drawn from the battery to determine the State of Charge (*SoC*). Measuring this current requires a battery gauge or a specific measurement circuit. The Open Circuit Voltage (*OCV*) can be determined by measuring the voltage across the battery when no current is flowing through it, providing an indication of its unloaded state. These measurements are not always embedded in low cost, low power and low maintenance systems. Whereas, closed-loop battery voltage and ambient temperature are easier to measure. The battery *SoC* is often used in literature (Piller et al. (2001); and Srinivas Singirikonda (2020)) as a feature to detect the battery end of life. Another effective method to determine

the battery *SoC* consists in using artificial neural networks (Wang et al. (2020)). Indeed, these models can learn and predict the battery behavior based on historical data. The Kalman filter is also used to estimate the *SoC* (Wang et al. (2020)), by measuring the current and/or open circuit voltage. However, the access to the information required by these approaches such as the *SoC* specifications, features, and capabilities is not always available.

The contribution of this paper is an approach to detect the end of life of a lithium battery based only on its closed-loop voltage and the ambient temperature, which is new up to our knowledge.

This approach is applied to the case of battery powered devices used in irrigation systems. Their batteries are used to power the irrigation monitoring and controlling system (collect irrigation data and activate valves to start or stop irrigation). These batteries have a limited amount of energy and the discharge results in the loss of the automatic irrigation system operations. Hence, early detection of the end of battery life allows the improvement of the system overall performance and reliability. Unnecessary replacements or maintenance of the batteries may result in wasted money and lower accessibility of the service, hence it is essential to find a trade off between detecting battery end of life too early and missing it. The aim of the approach proposed in this paper is to detect the degradation mode associated with the end of battery life before it is fully discharged.

The remainder of this paper is organized as follows. The approach to detect the battery end of life and the main detection indicators are described in Section 2. In

Section 3, the comparison between different algorithms and methods is described. Finally, concluding remarks are presented in Section 4.

2. DETECTION APPROACH OF THE BATTERY END OF LIFE

The battery model illustrated in Fig. 1 simplifies the complex dynamics of battery behavior, see Vermeer et al. (2021). It is assumed that the following equations hold

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

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

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, $V_0 \in \mathbb{R}$ is the voltage across the internal battery resistor R_0 and $T_0 \in \mathbb{R}$ is the temperature offset. It is assumed that $w_i \sim \mathcal{N}(0, \sigma_i)$, and that w_v and w_T are independent. These equations model the battery temperature and voltage evolution over time and in the following both values are measured and recorded every hour.

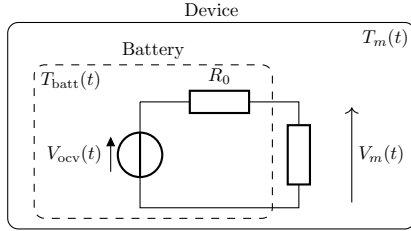


Fig. 1. Model of a Lithium-ion battery.

2.1 Entropy and enthalpy estimation

Despite lacking access to the data for estimating *SoC* (such as current and *OCV*), there exists a relationship between the entropy, enthalpy and *SoC*. This relationship, as given by the theorem of Yazami (Manane and Yazami (2017)), indicates that enthalpy ΔH and entropy ΔS are indicators of battery status:

$$\text{SoC}(t) := \alpha + \beta \Delta S(t) + \gamma \Delta H(t), \quad (3)$$

α , β and γ are coefficients that depend on the battery technology.

The entropy and enthalpy of the battery (Maher and Yazami (2014); and Manane and Yazami (2017)) are respectively defined as follows

$$\Delta S(t) := F \frac{\partial V_{\text{ocv}}(t)}{\partial T_{\text{batt}}(t)}, \quad (4)$$

$$\Delta H(t) := F \left(V_{\text{ocv}}(t) - T_{\text{batt}}(t) \frac{\partial V_{\text{ocv}}(t)}{\partial T_{\text{batt}}(t)} \right), \quad (5)$$

where F represents the Faraday constant. To detect the end of battery life, the approach of this paper uses $V_m(t)$, as well as an estimation of both the entropy $\Delta S(t)$ and the enthalpy $\Delta H(t)$ as inputs of the model. The battery voltage can be modeled on the sliding window given by $t_c \in [t - \Delta t, t]$, see (Forgez et al. (2010)):

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

where A , B and C are constants with respect to t_c but take different values on each sliding window considered. Δt is

the size of the sliding window, its determination is detailed in Section 3.2. The equations (1), (2), and (6) give:

$$V_m(t_c) = \bar{A}(t) + B(t)T_m(t_c) + C(t)t_c - B(t)w_T(t_c) + w_v(t_c), \quad (7)$$

where $\bar{A}(t) = A(t) - B(t)T_0 + V_0$. In order to validate the conformity of the data to the regression equation (7), we decided to evaluate the correlation between voltage and temperature, which makes it possible to perform a linear regression to estimate the equation coefficients. Using (6) in (4) and (5), one gets $\forall t_c \in [t - \Delta t, t]$

$$\Delta S(t_c) = F B(t), \quad (8)$$

$$\Delta H(t_c) = F(A(t) + C(t)t), \quad (9)$$

We suggest to monitor the following estimates for $t_c = t$ of $\Delta S(t)$ and $\Delta H(t)$:

$$\Delta \hat{S}(t) := B(t). \quad (10)$$

$$\Delta \hat{H}(t) := \bar{A}(t) + C(t)t. \quad (11)$$

These estimations are related to $\Delta S(t)$ and $\Delta H(t)$ by a proportional factor and a linear relation respectively. Let us consider, these equations in discrete time with $t = kT_e, k \in \mathbb{N}$, with T_e the step time. Defining $\theta_k := [\bar{A}(kT_e) \ B(kT_e) \ C(kT_e)]^T$, one gets that

$$Y_k = X_k \theta_k + W_k, \quad Y_k := \begin{bmatrix} V_m(kT_e) \\ V_m((k-1)T_e) \\ \vdots \\ V_m((k-n)T_e) \end{bmatrix},$$

$$X(t) := \begin{bmatrix} 1 & T_{\text{batt}}(kT_e) & kT_e \\ 1 & T_{\text{batt}}((k-1)T_e) & (k-1)T_e \\ \vdots & \vdots & \vdots \\ 1 & T_{\text{batt}}((k-n)T_e) & (k-n)T_e \end{bmatrix}, \quad (12)$$

$$W_k := \begin{bmatrix} w_v(kT_e) \\ w_v((k-1)T_e) \\ \vdots \\ w_v((k-n)T_e) \end{bmatrix} - B(kT_e) \begin{bmatrix} w_T(kT_e) \\ w_T((k-1)T_e) \\ \vdots \\ w_T((k-n)T_e) \end{bmatrix},$$

in which n is the number of point in the sliding window. In the data under consideration the step time is $T_e = 1$ hour. An estimation of θ_k can be made using ordinary least square estimation

$$\hat{\theta}_k = (X_k^T X_k)^{-1} X_k^T Y_k. \quad (13)$$

Ordinary least square estimation is known to be sensitive to outliers, which can negatively impact the accuracy of the estimation (Huber (2004); and Maronna et al. (2019)). To address this issue, there are various methods that can be employed. This study employs the Weighted Least Squares method, as introduced in Gervini and Yohai (2002), specifically for time-series modeling. After estimating $\theta(t)$, five different indicators are investigated to detect the battery end of life using a classification: (i) the voltage, (ii) the entropy estimation, (iii) the enthalpy estimation, (iv) the Hotelling's T^2 statistic and (v) the square prediction error Q statistic. The two last indicators are based on the principal component analysis (PCA) on $(V_m, \Delta \hat{S}, \Delta \hat{H})$, where $\Delta \hat{S}$ and $\Delta \hat{H}$ are defined in (10) and (11). Principal component analysis is used for detecting faults, as demonstrated by Harrou et al. (2013), Mansouri et al. (2016), and Hashim et al. (2020).

2.2 Detecting the degradation mode

The detection of the degradation mode consists in finding the time index when any of the indicators surpasses its respective threshold. Let's denote this indicator as x , defined as the time series: $x[k] \in \mathbb{R}$ for $k \in \mathbb{N}$. The objective is to determine the value of k for which the system transitions from normal mode behavior to degradation mode, based on the value of the indicator x . It is important to note that this value of k cannot be precisely identified because the degradation has a continuous behavior. The effects of degradation start mild and become progressively more severe. In this analysis, the aim is to understand the normal behavior of a system and monitor whether the current value of x corresponds to a normal operation or a degraded state. To identify a model based on normal data behavior, the use of semi-supervised methods and one-class model is considered. Three different approaches are explored to detect anomalies from normal system behavior and establish a degradation threshold for each indicator, as detailed in the following sections.

a) *Interquartile:* The first evaluated method to identify abnormal data is the boxplot method (Adam et al. (2018)). This method uses the first and third quartiles, respectively Q_1 and Q_3 and interquartile range $I_{QR} = Q_3 - Q_1$ to identify outliers. The IQR method defines a data point as an anomaly if it falls below $T_{low} = Q_1 - 1.5I_{QR}$, or above $T_{high} = Q_3 + 1.5I_{QR}$. The anomaly detection rule is as follows:

$$\text{Anomaly} = \begin{cases} \text{True,} & \text{if } x < T_{low} \text{ or } x > T_{high} \\ \text{False,} & \text{otherwise.} \end{cases} \quad (14)$$

b) *One Class SVM classification:* One class support vector machine (OCSVM) is one of the kernel-based methods that is part of the support vector machines (SVMs) (Schölkopf et al. (2001)). OCSVM model is trained only on data annotated by an expert as representing the system not in a degraded mode. The One-Class SVM seeks to identify a hyperplane that optimally isolates the normal data from the origin (Lang et al. (2020)). The hyperplane should aim to effectively separate regular data points from potential anomalies by maximizing the space between the hyperplane and the regular points. This can be written as a constrained optimization problem

$$\min_{\mathbf{w}} \left(\frac{1}{2} \mathbf{w}^T \mathbf{w} - \nu \left(\sum_{i=1}^N \xi_i \right) \right), \quad (15)$$

$$\mathbf{w}^T \mathbf{x}_i \geq 1 - \xi_i, \quad i = 1, 2, \dots, N,$$

$$\xi_i \geq 0, \quad i = 1, 2, \dots, N.$$

The decision function is defined as

$$D(\mathbf{x}) = \mathbf{w}^T \mathbf{x} - \rho. \quad (16)$$

where \mathbf{w} is the weight vector of the hyperplane, \mathbf{x}_i is the feature vector of the i -th data point, ν is a control parameter for the number of anomalies, and ρ is the decision threshold for classifying the data. If $D(\mathbf{x}) > 0$, \mathbf{x} is considered normal. Otherwise, it is considered as an anomaly.

c) *Isolation Forest:* The iForest or Isolation Forest is an anomaly detection algorithm. It operates by isolating anomalies from the rest of the dataset (Liu et al. (2008))

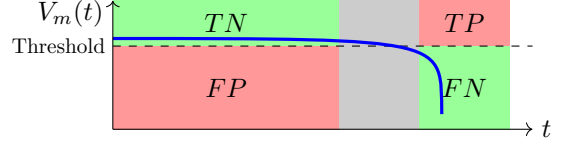


Fig. 2. Algorithm evaluation.

through the construction of multiple decision trees, each created by randomly selecting a feature and a split value.

Anomalies, being rare and distinct, are particularly isolated using fewer splits than regular observations. The procedure to create the iTree (Mao et al. (2018)) is as follows: First, a random feature q and a random split point p are selected. Second, the data is split into two subsets,

$$X_l = \{\mathbf{x}_i \in X : x_i(q) \leq p\}, X_r = \{\mathbf{x}_i \in X : x_i(q) > p\}.$$

These two steps are repeated recursively until a stopping criterion is met.

The anomaly score of the sample j is calculated as:

$$s(f(j), n) = 2^{-\frac{E(f(j))}{c(n)}}, \quad (17)$$

where $E(f(j))$ is the expected path length of j in a single isolation tree $f(j)$ and $c(n)$ is a normalization factor derived from the average expected path length over all trees in the forest.

Anomalies are identified by comparing the anomaly score to $s(f(j), n)$ a predefined threshold. Data points with scores lower than the threshold are considered as anomalies. First, when $E(f(j)) \rightarrow 0$, $s \rightarrow 1$, the probability of j being an anomaly is high. Then if $E(f(j)) \rightarrow c(n)$, $s \rightarrow 0.5$, whether j is an anomaly is uncertain. Finally, when $E(f(j)) \rightarrow n - 1$, $s \rightarrow 0$, the probability of j being normal is high.

2.3 Evaluation Metric

$F1$ - score represents the harmonic mean of precision and recall as in (Sokolova et al. (2006)). This metric is particularly useful when both false positive and false negative are important. In general, the $F_{\beta measure}$ represents a more generalized form of the $F1$ - score:

$$F_{\beta measure} = \frac{(1 + \beta^2)TP}{(1 + \beta^2)TP + \beta^2FN + FP}. \quad (18)$$

Fig. 2 displays three distinct phases: the normal mode, the degradation mode, and the transient phase in between. An expert has labeled the battery charge phases as follows: $d = 0$ for the normal mode and $d = 1$ for the degradation mode. The model output is denoted as r : if the model classifies the battery as charged, $r = 0$, while $r = 1$ indicates it is in its end of life. Refer to Table 1 for the corresponding confusion matrix.

Table 1. Confusion matrix

	$r = 0$	$r = 1$
$d = 0$	True Negative (TN)	False Positive (FP)
$d = 1$	False Negative (FN)	True Positive (TP)

Since the $F_{\beta measure}$ only considers three of the four elements of the confusion matrix and is sensitive to class imbalances, the Average F-measure (AGF) metric was developed to address these limitations in (Maratea et al.

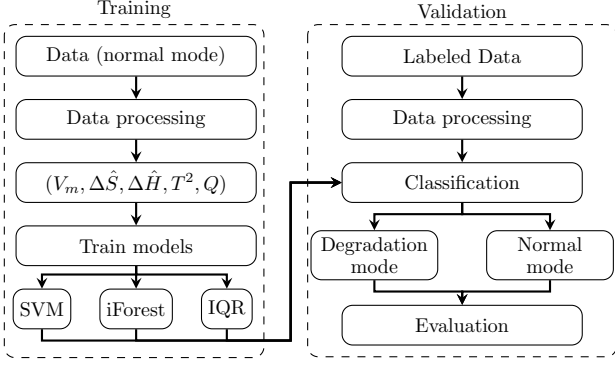


Fig. 3. Training and Validation procedure

(2014)). This metric uses all elements of the confusion matrix and gives a higher weight to samples that are correctly classified in the minority class. This metric is defined as follows:

$$AGF = \sqrt{F_2 InvF_{0.5}}, \quad (19)$$

where F_2 is the F-measure with $\beta = 2$ and $InvF_{0.5}$ is calculated by constructing a new confusion matrix in which the class label of each sample is switched (i.e. positive samples become negative and vice versa) and $\beta = 0.5$.

2.4 Diagram system

In order to address the objective of capturing system degradation and synthesizing a threshold, the following approach is proposed.

Training process: The first step is to find and calculate the features (V_m , $\Delta\hat{S}(t)$, $\Delta\hat{H}(t)$, Hotelling's T^2 , Q statistic) designed to capture and represent the battery degradation. Then, the models mentioned in Subsection 2.2 are trained to recognize normal mode using a dataset consisting of 125 time series of charged batteries. This training phase allows the models to learn the patterns and characteristics of charged battery behavior. Then, thresholds for each indicator are set to classify normal mode from degradation mode. Please refer to Fig. 4 for the training dataset.

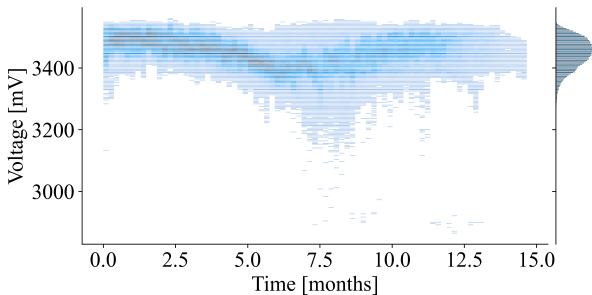


Fig. 4. Voltages of the training dataset: 125 time series.

Validation process: Once the thresholds are set, they are applied to 34 time series to classify the battery statuses. The most suitable algorithm and indicator for detecting degraded mode are selected based on $F1$ -score and AGF metrics. Please refer to Fig. 5 for an illustration of the testing dataset and to Fig. 3 for the training and validation

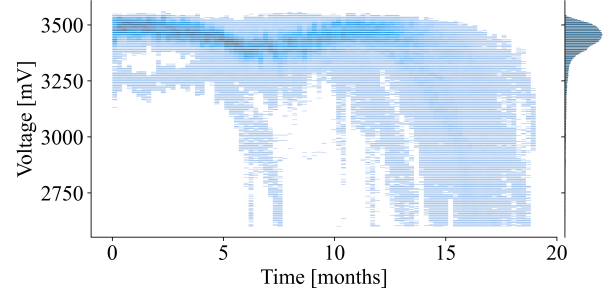


Fig. 5. Voltages of the testing dataset: 34 time series.

process. By following this approach, an indicator that captures battery end of life is identified providing actionable information for maintenance or replacement decisions.

3. APPLICATION

3.1 End of life detection using voltage

Fig. 5 shows the hourly voltage measurements taken for a sample of discharged batteries, which have an average lifespan of about 15 months. The method outlined in Section 2 is used to detect the battery end of life. The analysis of the data reveals the presence of a distinct voltage spike during the winter period. This voltage anomaly makes the determination of an appropriate threshold for anomaly detection a challenging task. Setting a high threshold would trigger false alarms, introducing unnecessary investigations. Whereas, employing a low threshold might delay the detection of genuine anomalies, potentially impacting the system reliability and performance. Therefore, finding a balance between the threshold values becomes crucial to find a compromise between minimizing false alarms and ensuring timely detection of actual anomalies.

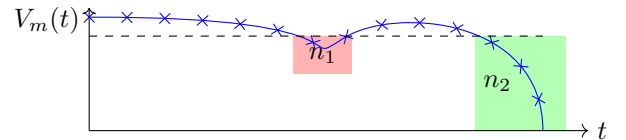


Fig. 6. Illustration of the voting process.

Let's consider a numerical time series, denoted as $X = (x[0], x[1], x[2], \dots, x[k_{end}])$, where k_{end} is the total number of data points and a threshold τ . Using a voting operation as described in Tajti (2020), an alarm is triggered whenever a certain number n of consecutive points in the sequence fall strictly below the threshold τ . This operation can be formulated as follows:

For each $x[k_i]$, where $i \in (n, n+1, \dots, end)$: we verify if all the previous n points are less than τ , i.e. $x[k_{i-n+1}], x[k_{i-n+2}], \dots, x[k_i] < \tau$.

If this condition is true, an alarm is triggered at index i . In other words, we are looking for the smallest index i that satisfies the above condition. A smaller n can lead to more frequent alarms and may also increase the rate of false alarms, while a larger n can reduce the rate of false alarms and also delays the detection of events. Choosing a suitable n can also enhance the robustness of this method

towards outliers. Since outliers would need to persist over n consecutive points to trigger an alarm, transient spikes in the data, which could be due to noise or temporary fluctuations, are less likely to result in false alarms. See Fig. 6 for an illustration of the voting process.

3.2 Correlation between voltage and temperature

In order to assess the conformity of our data with the regression equation (7), we examined the correlation between battery voltage and temperature across all 125 devices. The correlation coefficients, ranging from 0.60 to 0.96 for every device, indicate a strong correlation between these two variables as outlined in Asuero et al. (2006). To determine the optimal sliding window Δt , the correlation is calculated at various time intervals, ranging from 1 to 30 days. For each device, the time interval with the highest correlation is determined. The sliding window Δt is then the average of these time intervals with the highest correlation. Using the aforementioned selection technique, the sliding window width Δt obtained was 14 days and this value is used in the rest of this paper.

3.3 End of life detection using entropy

Fig. 7 illustrates the variation of the entropy $\Delta\hat{S}(t)$ for a single device. This entropy is determined by using (10). It is observed that a significant increase in the entropy tends to be associated with battery degradation. Then, the degradation mode is detected using the threshold determined by the method outlined in Section 2.

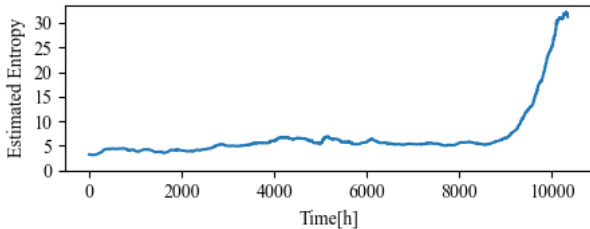


Fig. 7. Illustration of the estimated entropy.

3.4 End of life detection using enthalpy

Fig. 9 illustrates the variation of the estimated enthalpy over time, by using (11). The enthalpy curve is smoother than the voltage one presented in Fig. 8 and there is no bump related to the drop in temperature during the winter period. The degradation mode is detected using threshold by the method outlined in Section 2.

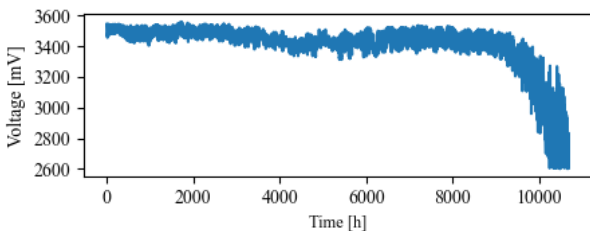


Fig. 8. Illustration of the battery voltage.

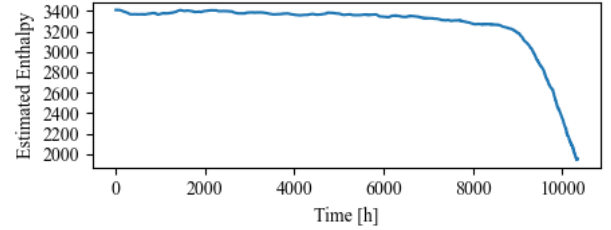


Fig. 9. Illustration of the estimated enthalpy.

3.5 End of life detection using PCA model

Principal Component Analysis (PCA) can be employed as an advanced technique to explore the relationships between voltage, entropy, and enthalpy, as well as to reduce the dimensionality of the dataset (Harrou et al. (2013); Mansouri et al. (2016); and Hashim et al. (2020)). The application of PCA in our context enables the extraction of meaningful patterns and the identification of potential correlations between these variables. To ensure the reliability and validity of the PCA model, the T2 and Q coefficients can be used for assessing model quality and detecting outliers as described below.

a) Hotelling's T2 method: The Hotelling's T2 statistic is a multivariate measure that calculates the distance of an observation from the center of the model. A high T2 value may signify that a data point is substantially distant from the model center, possibly suggesting an outlier or deviation from expected behavior.

$$T^2 = (\mathbf{X} - \boldsymbol{\mu})^T \mathbf{C}^{-1} (\mathbf{X} - \boldsymbol{\mu}), \quad (20)$$

where \mathbf{X} is a PCA space data point, $\boldsymbol{\mu}$ is the mean and \mathbf{C} is the covariance matrix of the PCA scores.

b) Squared Prediction Error Q method: The Q coefficient, also known as the Q statistic, quantifies the residual variance not captured by the PCA model. A large Q value may indicate that the data point does not fit the model adequately, potentially due to the presence of unmodeled variations or noise.

$$Q = \|\mathbf{X} - \mathbf{X}_{\text{reconstructed}}\|^2, \quad (21)$$

where X is an observed data point, and $X_{\text{reconstructed}}$ is the reconstructed data point from the PCA model.

4. RESULTS AND DISCUSSIONS

The IQR, OCSVM, and iForest algorithms are compared to determine the threshold of each indicator, in order to classify whether batteries are in normal or degradation mode. The results are grouped into the four categories mentioned earlier in Section 2: FN, TN, TP and FP. F1 Score and AGF are computed for each signal and Table 2 represents their weighted averages since the signals do not have the same lengths.

According to Table 2, the enthalpy indicator defined in Maher and Yazami (2014), and in Manane and Yazami (2017), when paired with the iForest algorithm, consistently outperformed the others. Indeed, using F1 Score and AGF as the performance metrics, enthalpy achieved the highest average weighted scores, indicating its potential as a key indicator for effective detection of the battery end of

Table 2. Results

	Voltage		Entropy		Enthalpy		T2		Q	
	F1-score	AGF	F1-score	AGF	F1-score	AGF	F1-score	AGF	F1-score	AGF
IQR	81%	85%	72%	87%	90%	94%	63%	69%	74%	76%
OC-SVM	80%	88 %	74 %	86%	91%	93%	70%	75%	74%	78%
iForest	82%	88%	73 %	87 %	93%	97%	68%	78%	72%	76%

life. It is worth mentioning that the F1 Scores and AGFs of enthalpy displayed the smallest dispersion among all indicators, hinting at a lower variability and suggesting it as a more consistent measure to detect the battery end of life. In conclusion, this study suggests that enthalpy, in conjunction with the iForest algorithm, delivers the best performance to detect the battery end of life.

5. CONCLUSION

This paper presents a comparative analysis of various algorithms for classifying whether the Lithium-ion primary cells batteries are in normal or in degradation mode based only on voltage and temperature. The proposed approach consists in feeding the model with the estimated entropy and enthalpy. The results show that combining enthalpy and the iForest algorithm yields promising results in the detection of battery end of life. After detecting the degradation mode, the prediction of battery Remaining Useful Life (RUL) is an interesting area for further research.

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