Lithium-ion battery SOH analysis

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***Abstract*— Battery State-of-Health modelling can significantly reduce the amount of costly laboratory tests in the application being analyzed. This paper discusses the prediction of the State-of-Health, an indicator of battery life, using support vector regression. This experiment is performed on a sample cell of a lithium-ion battery, which is subjected to a method known as the Constant Current Constant Voltage method, where the battery is charged and discharged at a constant current of 0.5 C. Although this method in this paper is applied in laboratory conditions and it is a controlled method, or it deviates from the battery cycling of real applications, it can be used in these applications, thus the scope of this research can predict the State-of-Health also in the areas of batteries used in mobile devices or electromobility. The State-of-Health indicator then determines whether the battery is still suitable for that primary application. Assuming that we can predict this parameter with some accuracy, it is then also possible to tell after what length of time a battery will need to be replaced and when it will be suitable for secondary applications such as stationary storage. Once it reaches that state, this calculation can be further applied to those applications as well.**

Keywords — Li-ion battery, SOH, SVR, Estimation, CCCV

I. Introduction

In recent decades, lithium-ion (Li-ion) batteries have evolved into a key technology for energy storage in a variety of applications from consumer electronics to electric vehicles and stationary power systems. Due to their high energy density, long lifetime, and ability to recharge without significant reduction in capacity, Li-ion batteries have become the preferred solution for many primary and secondary applications.

Primary applications are notably crucial for devices including electric vehicles and portable electronics, providing essential power for their core functionalities. On the other hand, in secondary applications, such as stationary energy storage, Li-ion batteries serve a supportive role, either as backup power solutions or as key elements in enhancing the reliability and stability of the electrical grid.

The life of Li-ion batteries is affected by many factors, including the temperature of the operating environment, the depth of discharge, the magnitude of the charge and discharge current and the overall number of battery cycles. Together, these factors determine how long a battery maintains its capacity and therefore how efficiently it stores electrical energy.

The State-of-Health (SOH) serves as a pivotal metric for gauging the aging process of batteries, offering insight into the extent of capacity or power reduction over time. A fresh battery boasts an SOH of 100%, indicating optimal performance and capacity. As the SOH wanes to 80%, it signals that the battery no longer possesses the requisite energy to fulfil the demands of specific e-mobility applications, marking its transition to the end-of-life (EOL). The intricacy of SOH lies in its non-measurable nature, necessitating the development of estimation techniques to ascertain this critical parameter accurately. Ensuring precise estimation of SOH is paramount for the maintenance of safety and reliability in e-mobility operations, highlighting the significance of ongoing research in this area. [1]

SOH estimation techniques are categorized into physics-based and data-driven methods. The physics-based category includes empirical, equivalent circuit, and electrochemical models, with the crucial aspect being the updating of model parameters. On the other hand, data-driven methods rely less on physical understanding and more on operational data to capture the degradation characteristics of SOH. Data-driven strategies aim to establish a relationship between SOH and various features. These features comprise both direct attributes such as voltage, current, and temperature, and indirect attributes, which typically consist of statistical analyses of direct features. In the field of estimating the SOH a variety of data-driven methodologies have been employed. Among these tools, recurrent neural network (RNN), support vector regression (SVR), relevance vector machine (RVM) and Gaussian process regression (GPR) are most significant. Specifically, the SVR approach is used in this study due to its robust performance in predictive accuracy and computational efficiency. These methods have been documented extensively for RNN [2], SVR [3,4], RVM [5], and GPR [6].

II. Experiment

A. Measurement

The estimation of SOH is investigated for a Samsung INR18650-35E battery with lithium-nickel-manganese-cobalt-oxides (NMC) as a cathode material and graphite as an anode material, 300 cycles were measured using the constant current constant voltage (CCCV) method. The battery was charged and discharged at 0.5 C which corresponds to a current of 1.7 A at a battery capacity of 3400 mAh and in a voltage range of 2.65 – 4.20 V. Voltage profiles during charging and discharging are shown in Fig. 1 and 2, respectively, where the dark blue color curve is the first cycle and the dark red color curve is the last cycle. Detailed information for the battery cell used in this paper is listed in Table I.

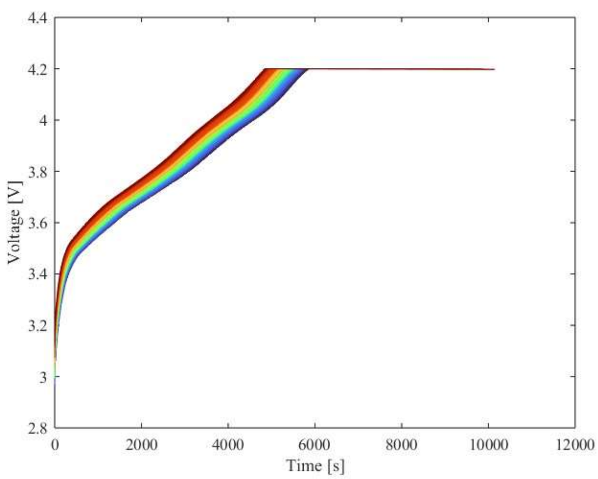

Fig. 1: Battery voltage dependence on time during charging (the dark blue curve is the first cycle and the dark red is the last cycle).

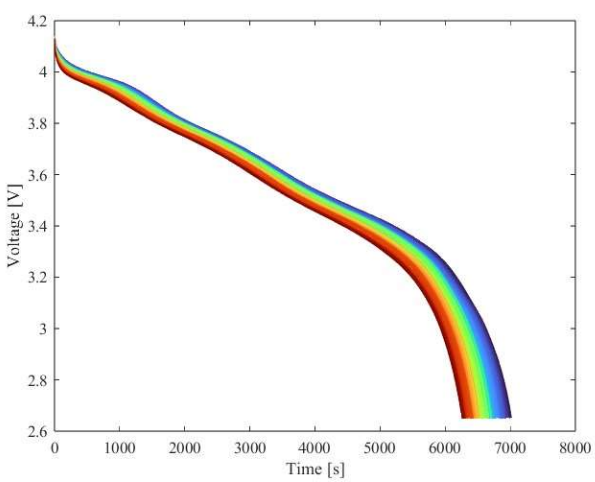

Fig. 2: Battery voltage curves during discharging (the dark blue curve is the first cycle and the dark red is the last cycle).

The CCCV approach is widely recognized as the default protocol for cycling Li-ion batteries. This method unfolds in two key stages: initially, the battery is charged at a consistent current rate until it hits a predetermined voltage threshold. Following this, the charging mode switches to a constant voltage, maintaining this voltage level while gradually reducing the current. The switch from constant current to constant voltage occurs once the cell's voltage reaches its maximum value, a level often set based on the specific application's demands or the battery's nominal capacity. It is during the constant voltage phase that the battery's SOH can be particularly impacted, as slower charging rates may enhance longevity and reduce stress on the battery.

The CCCV method is sensitive to the charge/discharge current rate (C-rate), temperature, and the battery's intrinsic chemistry, with higher C-rates potentially limiting lithium diffusion within the electrodes and thus, affecting the battery's capacity and lifespan. This limitation underscores the importance of optimizing the C-rate for rapid charging while also balancing the trade-off between charge speed and battery health. [7]

TABLE I: LI-ION BATTERY PARAMETERS

Samsung INR18650-35E	
Parameter	***Value***
Type	Cylindric
Nominal Capacity	3.4 Ah
Nominal Voltage	3.6 V
Maximum Voltage	4.2 V
Minimum Voltage	2.5 V
Maximum Current	8 A

B. *Data selection*

Data separation is performed in about 1/3 of the measured cycles, of which 95 are selected for training and the rest for validation. The data has been separated into individual charge and discharge cycles where a parameter is extracted from each cycle, the set of which forms the input data for the support vector regression.

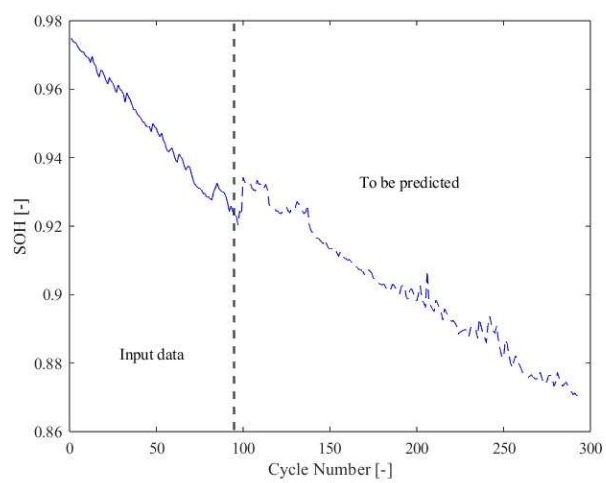

Fig. 3: Measured and separated SOH to Input data and Validation data

C. Feature extraction

In this study, we evaluate two parameters that can be measured in real time: Time Interval of an Equal Charging Voltage Difference (TIECVD) and Time Interval of an Equal Discharging Voltage Difference (TIEDVD). These indicators tend to degrade as the battery ages, which implies that they could provide insights into the battery's capacity. TIECVD is calculated as the duration it takes for the battery voltage to increase from 3.5 V to 4.2 V during the charging process. Conversely, TIEDVD measures the time it takes for the voltage to decrease from 3.8 V to 3.6 V during discharge. It is important to mention that only assuming the battery is discharging at a constant current, so TIEDVD has a major impact. Otherwise, TIECVD becomes the sole indicator of battery health used for SOH estimation. [8]

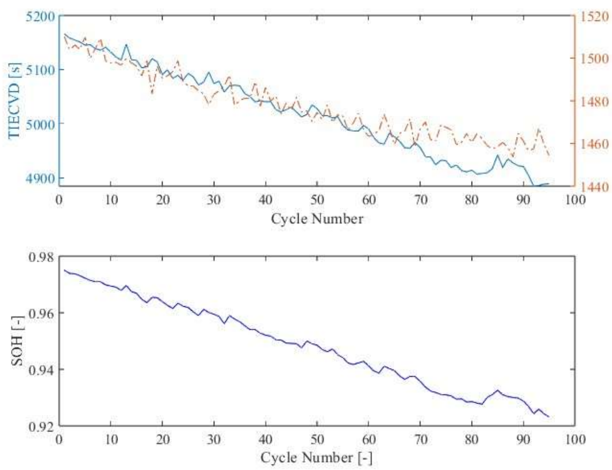

Fig. 4: Input features (TIECVD, TIEDVD) compared with SOH.

D. SOH estimation

SOH represents the ratio between actual capacity Q_i and nominal capacity Q_0 of the battery.

$$SOH_i = \frac{Q_i}{Q_0} \tag{1}$$

Support Vector Regression (SVR) represents an adaptation of Support Vector Machines (SVM) for regression tasks, allowing the methodology to address issues with small sample sizes and non-linear data. SVR constructs hyperplanes in a high-dimensional space, which serves as a decision surface to predict output values with high accuracy. When applied to the evaluation of a battery's SOH, feature data is non-linearly mapped and subsequently regressed within a multi-dimensional space to estimate the SOH value.

There is a sample set $S = \{(x_i, y_i), i = 1,2, \dots, N\}(x_i \in R^n, y_i \in R)$, where x_i and y_i are the i-th input and output feature values. N denotes the sample size, and n stands for the feature dimensionality. The mapping function employed by SVR transforms the original low-dimensional data into a higher-dimensional space, following the equation:

$$f(x) = \omega \cdot \varphi(x) + b, \tag{2}$$

where ω denotes the weight vector, b signifies the bias, and $\varphi(x)$ is the nonlinear mapping function. If the relaxation variables ζ_t and ζ_i are inserted into the equation, the solution to the problem of finding ω and b can be explained mathematically as below:

$$\min R(\omega, b, \bar{\zeta}) = \frac{1}{2} \parallel \omega \parallel^2 + C \sum_{i}^{n} (\bar{\zeta}_t + \bar{\zeta}_t^*), \tag{3}$$

The deviation of the predicted values from the actual values is within the specified error epsilon ϵ for each data point as specified in the equations:

$$\text{s.t} \begin{Bmatrix} y_i - \omega \cdot \phi(x) - b \leq \varepsilon + \bar{\zeta}_i \\ \omega \cdot \phi(x) + b - y_i \leq \varepsilon + \bar{\zeta}_i^* \\ \zeta_r \bar{\zeta}_t^* \geq 0. \end{Bmatrix}, \tag{4}$$

Where C denotes the penalty term reflecting the trade-off between model complexity and the degree to which deviations larger than ϵ are tolerated. By introducing Lagrange multipliers and using the kernel function, the SVR function can be redefined as:

$$f(x) = \sum_{i=1}^{N} (\alpha_i - \alpha_i^*) K(x_i, x_j) + b, \tag{5}$$

In this equation $K(x_\mathrm{i}, x_j)$ is the kernel function, where x_i are the input vectors for training samples, and x_j are input vectors for test samples. Lagrange operators are represented by α_i and α_i^*.

Various kernel functions are usually used in the SVR model: separate linear kernel function, polynomial kernel function, RBF kernel function and sigmoid kernel function. Gaussian or Radial Basis Functions (RBF) are chosen to solve the SOH estimation.

$$K_{\mathrm{RBF}}(x_i, x_j) = \exp\left(-\frac{1}{2\sigma^2} \|x_i - x_j^2\|\right), \tag{6}$$

where the width of the RBF kernel function is represented by σ. [4]

III. Results

To achieve the best results, it is chosen automatic optimization of hyperparameters: Kernel function width, penalty factor and error tolerance. The results of the optimization are shown in Table II and their progress is plotted in Fig. 5.

The 'Min observed objective' represents the lowest value of the objective function achieved during the hyperparameter tuning process, serving as a direct measure of model performance under various parameter settings. The 'Estimated min objective' reflects the predictive model's extrapolation of the minimum objective value based on current trends observed throughout the optimization iterations. The sharp peak observed initially suggests a suboptimal set of hyperparameters, which the optimization algorithm rapidly adjusts in subsequent evaluations.

TABLE II: HYPERPARAMETER OPTIMIZATION RESULTS

Parameter	***Value***
Width of kernel function σ	129.54
Penalty factor C	225.03
Tolerated error ϵ	$1.28 \cdot 10^{-3}$

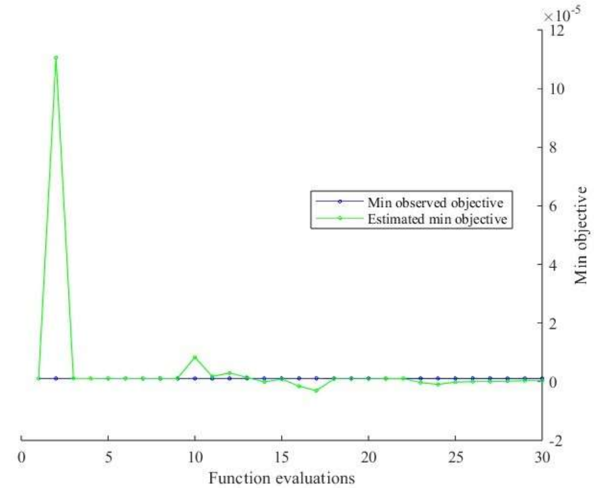

Fig. 5: Min objective vs. number of function evaluations.

The result of SOH prediction using the SVR method with hyperparameter optimization is plotted in Fig. 6. It is clear that the predicted curve maintains the same trend as the measured curve, although there is a certain deviation in the predicted data from the 100th cycle when continuous cycling is interrupted and other battery tests are performed. At this point, the battery rests before it is reconnected to continuous cycling, which is reflected by an increase in SOH.

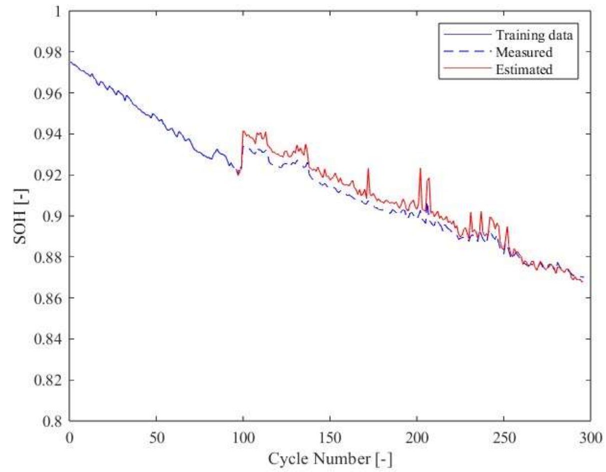

Fig. 6: Comparison between predicted and measured SOH.

A. Evaluation

The root mean square error (RMSE) graph in Fig. 7 shows the deviation of the predicted SOH and measured values as a function of each cycle.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}$$

Where n is cycle number, y_i represents measured data and $\hat{y}_i$ is the estimated SOH value. The initial values are close to zero, where it is directly linked to the training data by the prediction. However, this is followed by a battery rest at cycle 100, where the RMSE value increased rapidly. This rest is not included in the training dataset as it would significantly change the gradient of the predicted curve. The predicted data tends to decrease the RMSE value in the later stage, which is precisely the most important part of the prediction, and the resulting trend of decrease in predicted SOH is thus almost equivalent to the measured one. The overall RMSE of the entire predicted dataset compared to the measured one is equal to $5.3 \cdot 10^{-3}$.

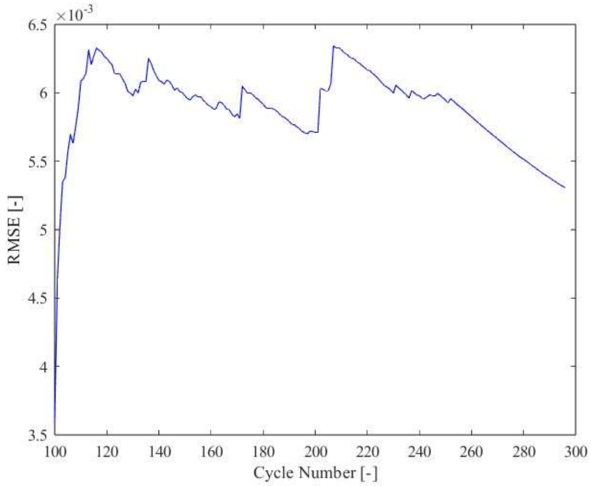

Fig. 7: Evaluation of RMSE between estimated SOH and validation data in each cycle

IV. Conclusion

This paper focuses on the SOH estimation of Li-ion batteries using the SVR method with hyperparameter optimization. A deviation of real from measured data was observed, which may be caused by the battery resting at 100 cycles when additional tests were performed on the battery and it stopped cycling continuously for a period of time. However, this rest period was not included in the test data in response to it deviating from the resulting predicted curve vector. Although this phenomenon is considered to be natural battery behaviour, it occurred only once in the dataset. On the other hand, this situation could be resolved by making it more frequent throughout the dataset, thus further optimizing the resulting model. Nevertheless, despite this fact, the resulting RMS error of the predicted SOH parameter with respect to the measured one is equal to $5.3 \cdot 10^{-3}$, it is clear that the SOH parameter can be effectively predicted using this method. The accuracy could be further improved by using more sophisticated data-driven methods in deep learning.

Acknowledgment

This work was supported by the BUT specific research program (project No. FEKT-S-23-8286).

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