State of Health Prediction of Li-ion Batteries using Incremental Capacity Analysis and Support Vector Regression

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***Abstract*—Lithium-ion battery is introduced recently as a key solution for energy storage problems both in stationary and mobile applications. However, one main limitation of this technology is the aging, i.e., the degradation of storage capacity. This degradation happens in every condition, whether the battery is used or not, but in different proportions dependent on the usage and external conditions. Due to the complexity of aging phenomena to characterize, lifetime modeling and state of health (SoH) prediction of Li-ion cells attract the attention of researchers in recent years. This paper investigates the use of incremental capacity analysis (ICA) method to estimate the SoH for NCA lithium-ion batteries. To find the IC curves, it is essential to calculate the dQ/dV of the V-Q curves of the battery, which is infeasible due to the presence of noise and sampling intervals in the voltage measurements. Therefore, a simple and robust smoothing method is proposed, based on support vector regression (SVR), to fit a continuous function to the noisy voltage curves of the battery. By differentiating the fitted function, it is shown that the peak values of the IC curves can predict the SoH of the batteries cycled with different temperature, current rate, and state of charge. More than five hundred Q-V curves from testing 22 different cells in 8 different testing conditions are investigated. An average error of 1.86% for the SoH prediction shows that the developed SoH estimator is able to robustly predict the SoH of the cells cycled under different conditions. This technique can use partial charging voltage curves, and therefore testing time can be largely reduced, making it possible to be implemented in the battery management system (BMS).**

***Index Terms*—State of Health (SoH), Support Vector Regression (SVR), Incremental Capacity Analysis (ICA), Li-ion batteries, Prediction**

I. Introduction

Lithium-ion (Li-ion) batteries have become the most promising solution for energy storage in various applications, from laptops and smartphones to EVs and grid storages. Regardless of recent developments, the cost portion of these batteries is still high in many applications, making the battery lifetime a critical point in reaching profitability. However, these batteries are recognized as complex electrochemical devices with a nonlinear behavior that depends on various internal and external conditions, therefore, difficult to model and analyze. In addition, in these storage systems, capacity decrease and power fading do not originate from the same phenomena, but from several various processes and interactions. Since many of these processes cannot be studied independently and have similar timescales, investigation of aging mechanisms becomes more complicated.

The aging tests by using real operation conditions for every single application are very time and cost intensive. Lifetime prediction using aging models can overcome this challenge as they have to be done only once per cell type. However, a lack of knowledge on the aging processes in Li-ion batteries restricts the development of accurate lifetime prediction models. Accelerated aging tests in combination with the simulation of aging models, in order to extrapolate the aging test results to real-life conditions, are needed to provide a lifetime model that can be used to develop operational strategies and business models. In this regard, several approaches are introduced in the literature including impedance-based estimations [1], Kalman filters [2], Artificial Neural Networks [3], etc., to be applied in different applications including smart grids [4], electric and hybrid vehicles [5], and second-life stationary applications [6] to name a few.

Incremental capacity analysis (ICA) is one of the methods used for modeling the aging of Li-ion batteries by employing differential mathematical tools. In this method, the differentiation of the charged or discharged battery capacity with respect to the terminal voltage dQ/dV is performed and thereafter, by focusing on how the peaks and valleys of the obtained curves change, different degradation modes can be distinguished and quantified. The ICA approach is mainly used in investigating the behavior of a battery in a laboratory environment as a non-invasive tool, which does not require the physical separation of each electrode. The experimental studies have shown the feasibility of using the ICA to observe how the amplitude and position of the curve peaks change during the cell lifetime, with the intention of detecting the different aging mechanisms inside the cell [7]. This method is also able to classify the different degradation modes, i.e., loss of active material, loss of lithium, kinetic degradation, and the increase in the polarization resistance. The main advantage of this method is

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its universality, as it can be applied to different chemistries, cell designs, battery sizes, and operating conditions [8].

One of the main drawbacks and limitations of ICA is the fact that the cell has to be charged or discharged with a constant low current in the entire voltage region where the peak is located. If ICA is applied to a charge voltage curve obtained under high current rates, the possibility to detect the peaks corresponding to phase transformation of the cathode becomes limited. Regardless of this drawback, analyzing battery aging by IC curves still has the potential to be implemented in a battery management system (BMS) which measures voltage, current, and temperature. ICA curves can be obtained by real-time calculations in the slow constant current charging process of the battery. The differences in the curves between the fresh battery and the aged one can identify the internal aging mechanisms of the batteries in real time and give an estimate of the battery SoH.

Till now, the ICA method for Li-ion batteries has been mostly focused on the electrochemical aging mechanism analysis, while only a handful of research has been carried out for online SoH estimation [9]. The main difficulty in the ICA originates from processing the differentiations of the voltage data which is a sampled discrete signal with the measurement noises. Differentiating of a noisy signal can simply result in large fluctuations with values near zero and infinity. In order to solve this problem, the curve fitting methods are used to calculate the IC curves. The main idea here is to approximate the discretized voltage signal with a smooth continuous curve that can represent the original noisy voltage curve with minimum error. Thereafter, the differentiation function is performed on the smooth continuous fitted signal [10].

The possibility of using ICA in a BMS for on-board SoH estimation has been recently introduced by [11]. The support vector regression (SVR) method, which is a machine learning method, is used for curve fitting on the voltage signal and it is shown that SVR provides the most consistent identification results with a moderate computational load. The machine learning based methods are usually used for predicting the capacity loss (SoH) [3], rather than fitting the battery voltage curves. However, the SVR has shown advantages in the following properties: (1) insensitive to measurement noises; (2) robust to data range and size; (3) effective in extracting a signature that shows strong dependence to battery age, making it promising for further online ICA on diagnosing the battery SOH [10]. The authors in [11] investigated the lifetime of 8 LFP cells which are cycled at the same conditions. An online, SVR based fitting process of the charging Q–V curves is accomplished, and then a numerical differentiation of the curve is carried out in order to obtain the location and height of ICA peaks. The height of the peak is then compared with the offline data to obtain an estimation of the battery capacity. To be able to use this method online, it is assumed that it is possible to occasionally have a charge curve with a low constant current while charging the batteries of PHEVs and EVs, and therefore, they chose to apply ICA only during the charging process and in a defined voltage range. Afterwards, the analysis in [12] shows that the SVR methods developed for single cell capacity estimation can also be used for a module or pack that has parallel-connected cells. In addition, [13] investigates the ICA and differential voltage analysis (DVA) methods for on-board battery state of charge and capacity estimation. A simple and robust smoothing method for IC curves, in order to reduce the noise, is proposed in [9] based on Gaussian filters. Reference [10] has conducted parametric studies to investigate the influence of the key parameters in the SVR algorithm on the performance of curve fitting.

In this paper, the ICA method is used in order to estimate the SoH of NCA battery cells. Due to the measurement noise and discrete nature of a sensor measurement, it is not possible to calculate the derivation directly from V-Q curves. Therefore, a smoothing method based on support vector regression (SVR) is proposed in order to fit a continuous function to the noisy voltage curves of the battery. By differentiating the fitted function, it is shown that the peak values of the IC curves can predict the SoH of the batteries. This method is applied to 523 V-Q characteristic curves of 22 cells which are tested with 8 different cycling conditions. The main improvement in this work is the different cycling conditions that were considered in evaluating the prediction model, while [9], [11]–[13] only considered the aging in one specific temperature and current rate. Although the SoH prediction error is increased for different aging scenarios, it is shown that the error margin remains in an acceptable range, proving the feasibility of using this method for on-board SoH prediction.

II. Cycling degradation of Li-ion batteries

State of health (SoH) is a metric to evaluate the aging level of batteries, by describing the current state of the battery compared to its state as a new one, measured as a percentage.

$$\mathrm{SoH(t)} = \frac{\text{remaining capacity at time t}}{\text{initial capacity}} (\%) \tag{1}$$

SoH is not a measurable quantity so accurate estimation is essential for this parameter. Such estimations could be achieved through various online and offline methods with different complexity and accuracy.

In general two different degradation process types can be distinguished in a battery. The first type of degradation is related to wearing of mechanical or electrical components, e.g. Breakdowns or failures of single elements (the cooling system, sensors, ...). A gradual degradation can be observed in different components of the batteries until a malfunction or safety issue arises. Such degradation problems can be avoided during the battery lifetime by having an appropriate design, using high-quality components, and regular maintenances.

The second type of degradation is related to electrochemical processes inside Li-ion cells, called cell aging, and is the scope of this document. The two main effects of battery aging are identified as capacity fade and impedance increase. The chemical causes and origins of these two effects are different, implying a nonlinear behavior for the aging of the batteries. For the battery capacity fade, two main mechanisms can be

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Table I
TEST ROUTINES

Test	Temperature (°C)	Starting SoC (%)	DoD (%)	Discharge rate (C)	Validation
1	5	100	100	3	3
2	5	100	100	1	2
3	25	100	100	3	5
4	25	90	20	3	2
5	25	60	20	3	2
6	25	40	20	3	2
7	25	100	100	1	3
8	45	100	100	1	3

identified [14]: 1- The loss of cyclable lithium which increases cell imbalance. Loss of cyclable lithium is related to side reactions that can occur at both electrodes, as the SEI grows at carbon anode due to electrolyte decomposition. (SEI (solid electrolyte interface) is the formation of a thin resistive layer on the cell electrode surfaces), and 2- The loss of electrode active materials, possibly a material dissolution, structural degradation, particle isolation, and electrode delamination. The impedance increase of the cell can occur due to passive films at the active particle surface as well as loss of electrical contact within the porous electrode.

The aging of a cell can be divided into two categories: aging during storage, i.e. calendar aging, and aging because of utilization (charge or discharge), i.e. cycle aging. Calendar aging is the irreversible proportion of lost capacity during storage. Self-discharge rate, or more precisely, effects occurring within the battery during storage, varies highly according to storage conditions. These condition factors include temperature, storage voltage (or SoC), and time. Cycle aging happens when the battery is either in charge or in discharge. The main factor in cycle aging is the depth of discharge (DoD) which is the changes in SoC during discharge. Other effective factors include the current rate, SoC, and temperature. In this paper, the cycle aging is analyzed.

In this work, the commercially available Lithium nickel cobalt aluminum oxide (NCA) cathode chemistry with graphite anode is tested under the conditions given in Table.I. Between two to five cells were tested at each of the testing conditions to provide more validated results, therefore, 24 tests were performed in total. These testing conditions include three different temperatures (5°C, 25°C, and 45°C), four different SoCs at the beginning of the test (100%, 90%, 60%, and 40%), two different DoDs at 100% and 20%, and two different discharge rates (1C and 3C). Here, 1C is defined as the current rate that can discharge a new and fully-charged cell in one hour. The constant current charge rates were 1C for 1C discharge rate and 1.5C for 3C discharge rate. The rated capacity is 6 Ah for the NCA cells which defines the 1C current rate as 6 A. The capacity characterization test (measuring the remaining capacity) is performed at 25°C with C/10 current rate after continuous cycling of 100 to 200 cycles or loss of 4% to 5% of cell capacity. For the characteristic tests, first, the battery is charged with a constant current/constant voltage charging algorithm, until the battery

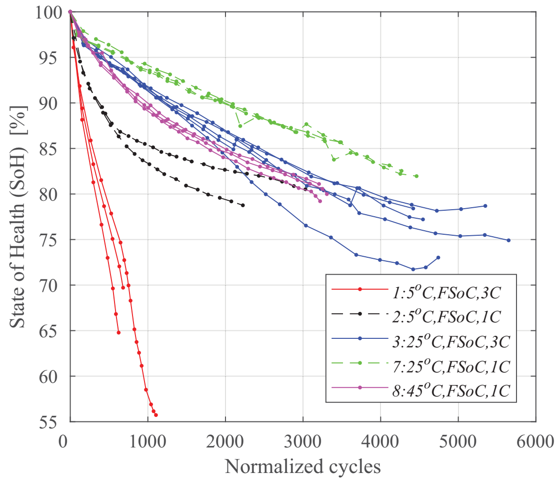

Figure 1. Cycle aging of NCA cells in full cycles.

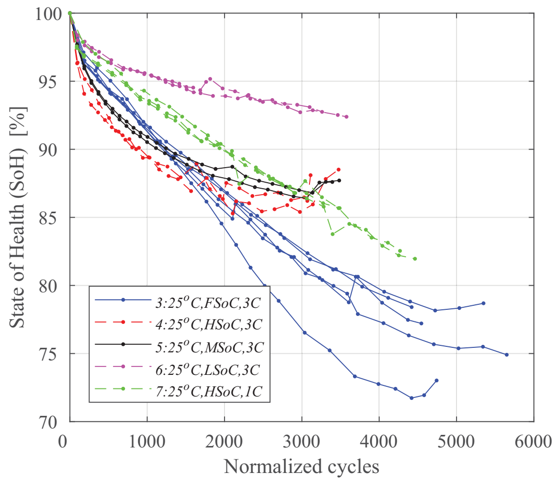

Figure 2. Cycle aging of NCA cells in 25°C temperature.

reaches the maximum threshold voltage. Then, the battery is discharged with C/10 until the minimum threshold voltage is reached while the charge flow is measured by using the Coulomb counting algorithm. The degradation in SoH of the NCA cells over normalized cycles (equivalent full cycles) are shown in Fig. 1 for the cells with full cycles and in Fig. 2 for the cells cycled in 25°C.

The charging and discharging curves of all the characteristic tests are shown in Fig. 3 and Fig. 4, respectively, for one of the cells cycled in 5°C, 1C current rate, and 0-100% SoC. It is possible to observe that the charge and discharging capacity gradually decrease as the number of cycles increases (the curves move from right to left). In this paper, the charging curves in characteristic tests (same as Fig. 3) are used for ICA calculations in the next sections.

III. ICA BY USING SVR

Support vector machine (SVM) is a powerful supervised learning model for prediction and classification. There are two

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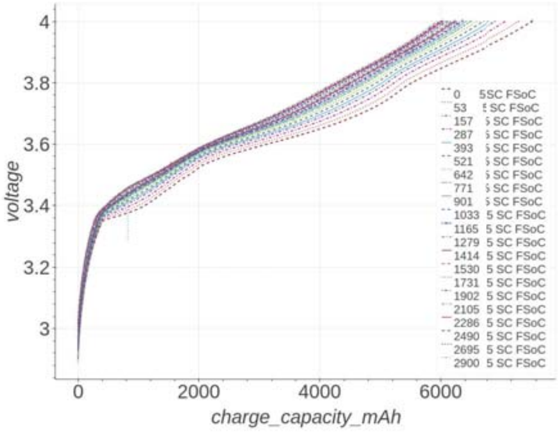

Figure 3. Charge curves for characteristic tests with C/10 current rate.

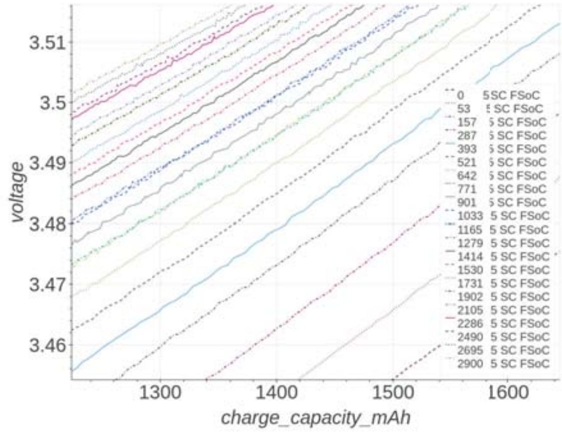

Figure 5. A zoom in of charge curves for characteristic tests with C/10 current rate.

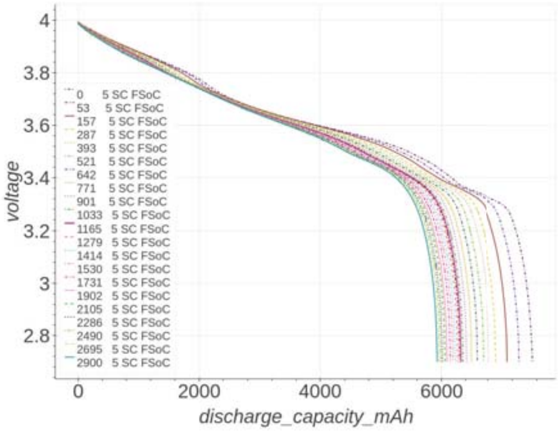

Figure 4. Discharge curves for characteristic tests with C/10 current rate.

main categories for support vector machines: support vector classification (SVC) and support vector regression (SVR). SVM is a learning system which uses a high dimensional feature space. The basic idea of SVM for classification is to map the training data into higher dimensional space using a nonlinear mapping function and then perform linear regression in higher dimensional space in order to separate the data. Data mapping is performed using a predetermined kernel function while the data separation is done by finding the optimal hyperplane (called the Support Vectors) with the maximum margin from the separated classes. This way, there is no need to use all training samples to construct the decision boundaries, but the few samples, i.e, the support vectors, are important, as the cost function for building the model does not care about training points that lie beyond the margin. On the other hand, the cost function for building the model ignores any training data that is close (within a threshold ε) to the model prediction.

Assuming that the training data is represented by $\{(x_1,y_1),...,(x_l,y_l)\}$, the goal in SVR method is to find a function $f(x)$ that has at most ε deviation from the actually obtained targets y_i for all the training data, and at the same time is as flat as possible. In other words, the errors are not important as long as they are less than ε, but any error larger than this will not be accepted [15]. To illustrate the idea in a simple way, we assume the f to be a linear function in the form of $f(x) = \langle \omega, x \rangle + b$ where $\langle .,. \rangle$ denotes the dot product. The flatness condition is satisfied by seeking for a small ω which can be ensured by minimizing the norm $\|\omega\|^2 = \langle \omega, \omega \rangle$. This can be represented as the following convex optimization problem:

$$\begin{array}{ll} \text{minimize} & \frac{1}{2}\|\omega\|^2 \\ \text{subject to} & \begin{cases} y_i - \langle \omega, x_i \rangle - b \le \varepsilon \\ \langle \omega, x_i \rangle + b - y_i \le \varepsilon \end{cases} \end{array}$$

It is possible that the above optimization problem is not feasible, i.e., the function f that approximates all pairs (x_i, y_i) with ε precision does not exist. To deal with infeasible constraints of the above optimization problem, slack variables ξ_i, ξ_i^* are introduced, and the optimization problem is improved as:

$$\begin{array}{ll} \text{minimize} & \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{l}(\xi_i + \xi_i^*) \\ \text{subject to} & \begin{cases} y_i - \langle \omega, x_i \rangle - b \le \varepsilon + \xi_i \\ \langle \omega, x_i \rangle + b - y_i \le \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \ge 0 \end{cases} \end{array}$$

where the constant $C > 0$ determines the trade-off between the flatness of f and the amount up to which deviations larger than ε are tolerated.

Incremental capacity is calculated by differentiating the change in the battery load to the changes in terminal voltage during either charging or discharging, as follows:

$$\frac{dQ}{dV} \approx \frac{\Delta Q}{\Delta V} = \frac{Q_t - Q_{t-1}}{V_t - V_{t-1}} \tag{2}$$

where Q_t is the Ampere-hour (Ah) charge and V_t is the battery voltage at time t. By calculating (2) in the whole voltage range of the cell, the charging/discharging V-Q curve can be transformed into peaks and valleys on the IC curve. Each peak in the curve can be identified with its features, such as intensity and location, and it can represent a specific electrochemical process taking place in the cell. Specifically, the value of the

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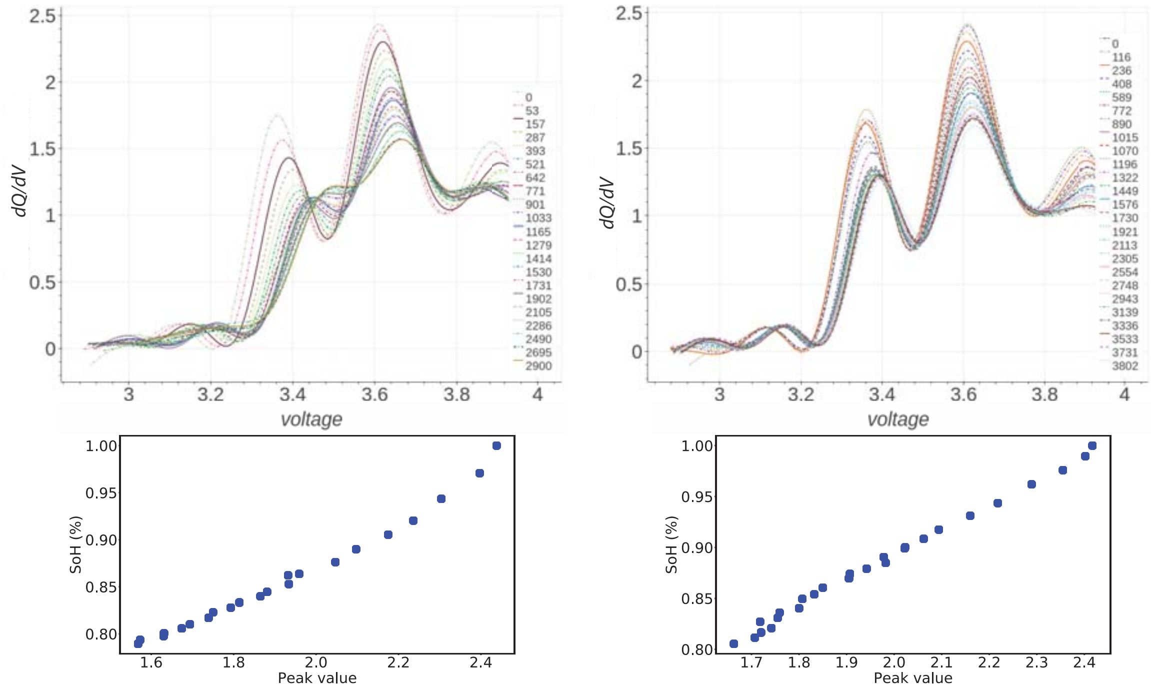

(a) 5°C SC FSoC (b) 45°C SC FSoC

Figure 6. dQ/dV curves for charging of characteristic tests with C/10 (top) and corresponding ICA peak values (bottom).

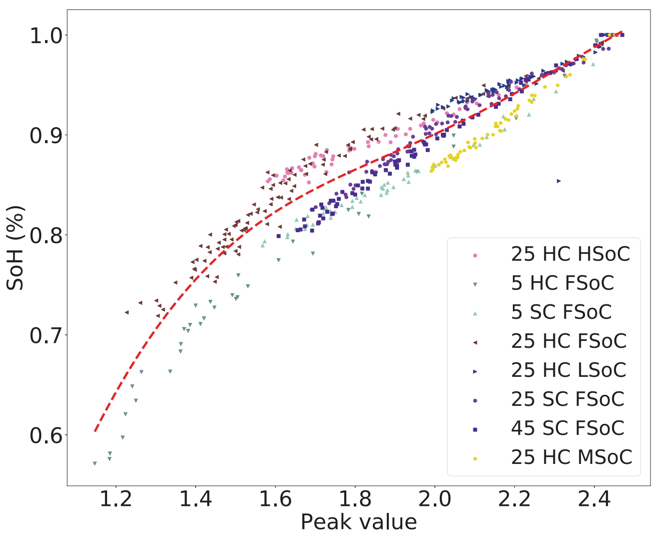

Figure 7. ICA peaks for all cells under accelerated lifetime tests.

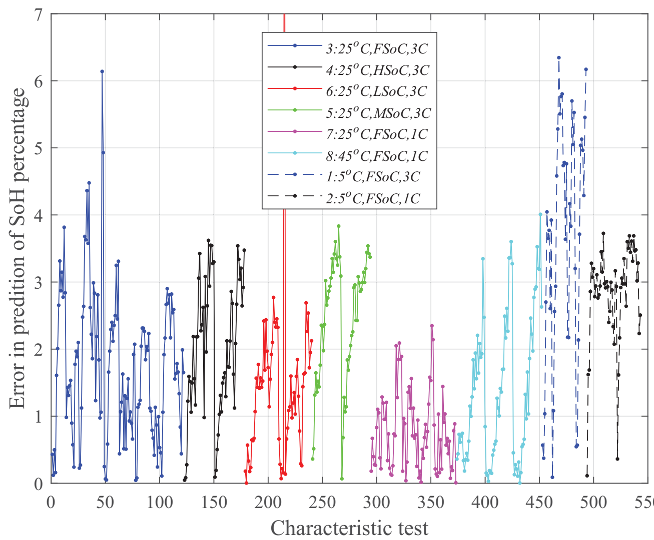

Figure 8. Errors in prediction of SoH based on ICA peaks by using SVR.

highest peak in the IC curve is closely related to the battery aging, and therefore, can be used to monitor the SoH of the battery. In addition, some of the degradation mechanisms inside the cell can be distinguished by analyzing the changes in the peaks of the IC curves, observing how the battery degrades over time in different operational conditions. This can not only help in predicting faults and maintenances but also can help the operator to change the operation condition of the battery, prolonging its lifetime.

However, as mentioned before, it is not feasible to calculate the derivation in (2) directly from the V-Q curves. Fig. 5 represents a zoom of the curves in Fig. 3 which shows that the voltage signal is very noisy and the derivation of such a signal will have very small or very large values. To avoid this problem, it is necessary to approximate the signals with a smooth continuous function with the minimum fitting error. In this paper, the SVR method is used for fitting and differentiating the V-Q curves.

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IV. Results and discussion

In this section, all the 22 cells tested under 8 different cycling conditions, presented in Table I, are considered for ICA with using SVR method. In total, 543 characteristic tests are performed on these cells during their lifetime, and the corresponding V-Q curves, while charging with C/10 current rate in 25°C, is used for calculating the IC curves. Fig.6 presents the IC curves for the cells tested in 5°C, 1C, 0-100%SoC (test 2) on the left, and 45°C, 1C, 0-100%SoC (test 8 in Table I) on the right. The number of cycles before each characteristic test is shown on the right side of the figures. It is possible to observe that the highest peaks move down and to the right as the cell ages. The peak value and corresponding SoH of the cell are shown in the bottom part of the Fig. 6, which shows an almost linear trend for each defined testing temperature, i.e., the peak values of IC curves decreases linearly with decreasing the SoH.

The IC peaks of all the 543 characteristic tests are shown in Fig. 7 which represents cycling under different temperature, current rate, state of charge, and depth of discharge. Although it can be seen that for each cycling condition, the relation between peak value and SoH is linear, the whole dataset is not following a linear fit. However, it still can be observed that the whole data follows the trend of decreasing in the peak value while the SoH decreases. To represent this trend, the SVR method is again applied to the data, and the fitted line is shown in Fig. 7.

In Fig. 8, the error in the prediction of SoH using the SVR based fitted function in Fig. 7 is presented. It can be concluded that the SoH prediction by SVR has smaller errors when the battery cell is new, compared to an aged one. In fact for each cell, the error value starts from 0% for the cell with SoH=100% (as expected), and increases by the aging of the cell, until it reaches the maximum error, which is generally below 4%. It should be noted that the error is especially high for the cell cycled in 5°C with the 3C current rate, with maximum errors of around 6%. The average error for prediction of all the 543 states of health is around 1.86%. This concludes that it is possible to predict the SoH of NCA cells by using SVR tools, by measuring the voltage and current of the battery cells (V-Q curves), calculating the IC curves and peaks, and finding the SoH based on the predicting function found by fitting the lifetime test data using the SVR method.

Acknowledgments

We Acknowledge the Research Council of Norway (project no. 228739) for funding through the project "Life and Safety for Li-ion batteries in Maritime conditions (SafeLiLife)" and within MoZEES, a Norwegian Center for Environment-friendly Energy Research (FME), co-sponsored by the Research Council of Norway (project no. 257653) and 40 partners from research, industry and public sector.

V. Conclusion

In this paper, the incremental capacity analysis method is used to predict the SoH of NCA cells by only having voltage-current measurements from BMS. First, the testing scenarios for accelerated aging of the cells are described. 523 V-Q characteristic curves from 22 cells aged under 8 different testing condition are considered. Support vector regression tool is used to smooth the noisy V-Q curves in order to make the signal differentiation feasible. It is shown that a clear linear trend can be observed between IC peak height and SoH for each cell. However, for all the cells cycled under different conditions, the trend is more nonlinear. SVR tool is used again to fit a function to the ICA peaks of all tested cells, reaching an average error of 1.86% in predicting the SoH of all cells.

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