State-of-Charge and State-of-Health Estimation for Li-Ion Batteries of Hybrid Electric Vehicles under Deep Degradation

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ABSTRACT

In recent industry, hybrid vehicles are gaining more recognition as a practical means for future transportation due to the longer distance, reduced charging time, and less charging stations dependency. The batteries in the hybrid vehicles, however, undergo more complex operation of charge depleting and sustaining modes alternately, which may need more accurate battery state estimation. In this study, a model based method is explored for the Li-ion batteries in the hybrid electric vehicles to estimate State-of Charge (SOC) and State-of-Health (SOH) accurately. While there have been widespread studies for this topic in the batteries research, not many are found that have investigated hybrid operation modes. Also the estimations are mostly limited to normal batteries or shallow degradation with the SOH higher than 90%. In this study, an algorithm based on the dual extended Kalman filter (DEKF) and enhanced self-correcting (ESC) model is developed for the simultaneous estimation of the SOC and SOH. Degradation data for plug-in hybrid vehicle (PHEV) are taken for the study, which undergo the deep degradation of 30%. In order to maintain the accuracy such that the root mean square error (RMSE) of the SOC is within 5% over the entire degradation cycles, two practical methods are proposed: First, the SOH is estimated separately during the battery charging, and is used as a constant in the SOC estimation in the discharging cycles. Second, battery modeling is conducted and the parameters are reset in every intermittent cycles at which the SOH is reduced by 10% initially and by 5% thereafter.

1. INTRODUCTION

Lithium-ion batteries have been applied extensively in various fields, including portable electronic devices, road transportation, and power supply systems, expecting their future role in energy sustainability (Zubi et al., 2018). As battery-powered vehicles such as pure electric and hybrid electric vehicles gain popularity, the development of battery management systems (BMS) estimating the state-of-charge (SOC) and state-of-health (SOH) of the batteries becomes crucial to ensure reliable and efficient battery operation (Mishra et al., 2021). In the BMS research, most SOC and SOH estimators have been developed for pure electric vehicles that primarily operate in charge-depleting (CD) mode. However, there is an increasing demand for hybrid vehicles that can handle higher loads and longer distances, which involves switching between CD and charge-sustaining (CS) mode during the operation. This can make the SOC estimation more difficult than those in the CD mode alone. Therefore, SOC and SOH estimation under combined mode is necessary for improved accuracy (Yoo et al., 2023).

Fundamentally, it is impossible to measure the SOC and SOH of batteries directly, thus methods are designed for estimating them based on measurable data such as current, voltage and temperature. Among the many achievements, Kalman Filter-based algorithms, which belong to the model-based approach, have proven their effectiveness and account for more than half of the SOC estimation methods (Shrivastava et al., 2019). Nevertheless, it is a challenge to estimate SOC for degraded batteries, which requires the SOH estimation as well (Hannan et al., 2017). Investigations into the simultaneous estimation of SOC and SOH, in view of both the effectiveness and efficiency, have remained relatively

Table. 1. Literature using model-based SOC and SOH estimation with aged battery data.

Author	Year	Battery Model	Methods (SOC-SOH)	Estimation Factor	Results of Estimation	Level of Degradation
R. Xiong	2014	1 RC model	EKF-EKF (multi-scale)	SOC, All Parameters	SOC, Capacity	100%, 82.6%, 82.1% and 72.1%
N. Wassiliadis	2018	2 RC model	EKF-EKF	SOC, Capacity, Resistance	SOC, Capacity, Resistance	100%, 97%, 85%, 78% and 49%
J. Wu	2019	2 RC model	AEKF-KF	SOC, Resistance	SOC	96.5%, 93.9%, and 92.4%
X Hu	2018	fractional second-order model	EKF-EKF	SOC, Capacity, Resistance	SOC, Capacity, Resistance	86.1%, 81.7% and 74.5%
L. Ma.	2022	fractional second-order model	MIUKF-UKF (multi-scale)	SOC, Capacity, Resistance	SOC, Capacity	98.1%, 94.7%, and 91.5%

insufficient (Wang et al., 2021). Even in the simultaneous estimation of SOC and SOH, substantial portion have targeted normal batteries (Campestrini et al., 2016; H. Guo et al., 2017; R. Guo & Shen, 2022; Hossain et al., 2022; C. Hu et al., 2012; Lee et al., 2008; Plett, 2004, 2006; Shrivastava et al., 2022; Ye et al., 2023; Zhang et al., 2016)

Model-based SOC and SOH estimation for aged battery can be categorized into two groups. The first involves updating the model's parameters to account for battery aging (Li et al., 2019; Sepasi et al., 2014; Shrivastava et al., 2019; Xu et al., 2022). While it is possible to update the model through optimization, using which the SOC is estimated, it comes at the cost of high computational burden. Additionally, there is a challenge in determining an appropriate updating period. The second approach involves co-estimation of the states and parameters of a battery model (X. Hu et al., 2018; Ma et al., 2022; Wassiliadis et al., 2018; Wu et al., 2019; Xiong et al., 2014). While this can be achieved using the dual filter algorithms (Yoo et al., 2023), it presents a significant challenge due to the substantial number of parameters in the model. This is further compounded by the fact that the only directly measurable output is the voltage under the given currents. Consequently, only a few parameters such as the capacity, i.e., the SOH, and internal resistance are estimated, while the others are held at fixed values. However, this approach may result in a less accurate model of aged battery.

Upon the survey of relevant literature, it follows that the approaches on the co-estimation of SOC and SOH by the dual filters need a comprehensive discussion in various aspects: battery model, type of filters, specific settings of these filters, initial values of state and parameters, and the level of degradation. Regarding the battery model, used models are Thevenin model with first-order (1RC) (Xiong et al., 2014) or second-order (2 RC) (Wassiliadis et al., 2018; Wu et al., 2019), or fractional second-order model (X. Hu et al., 2018; Ma et al., 2022). While the extended Kalman filter (EKF) is usually used, other filters such as adaptive extended Kalman filter (AEKF) or unscented Kalman filter (UKF) have sometimes been used, and there is a case where a dual filter has different time intervals considering the characteristics of state and parameter. Regarding the settings of filter (such as error, noise and measurement covariance), many did not specify values and conditions, except (X. Hu et al., 2018; Wassiliadis et al., 2018).This may make the results less trusted in terms of practical application. In view of the degradation levels, only one paper (Wassiliadis et al., 2018) has explored capacity fade over 50%, but the results are given without confidence intervals. As a result, despite the abundance of literature, these limitations pose challenges in adopting a practical approach to BMS development. Table 1 summarizes the representative papers in terms of model, methods, results of estimation, and level of degradation.

This study presents a more practical methodology to co-estimate the SOC and SOH by the dual Kalman filter for the batteries undergoing hybrid operations. Two key insights are applied for this research. First, it is observed that the co-estimation of SOC and SOH may yield inaccurate results due to the poor observability of the capacity. To mitigate this, a

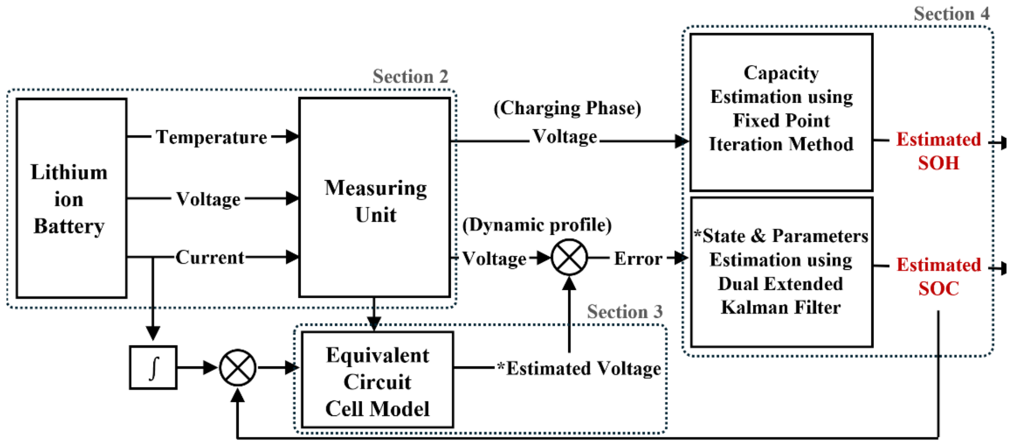


Figure 1. An overview of the core methodology

practical solution is developed by separating the SOC and SOH estimation, namely, estimating the SOC using the Dual Extended Kalman Filter (DEKF) in the discharging phase while estimating the SOH using the Fixed-Point Iteration Method (FPIM) in the charging phase. The reason is that the capacity estimation during the charging process is generally standardized and exhibit less dynamics as opposed to the discharging process. Second, when the batteries degrade by more than 10% in capacity, even the performance of this approach falls below acceptable level. Therefore, remedial action is applied by updating the parameters of battery model periodically.

The approach is validated by utilizing thirty battery cell datasets. These datasets are obtained through tests conducted under three distinct dynamic profiles representing plug-in hybrid electric vehicles (PHEVs), captured at ten points throughout the cycles ranging from 0% to 30% of capacity fade. Section 2 outlines the experimental method to measure temperature, voltage and current, and three types of dynamic profiles in charging phase. In Section 3, two battery models: Thevenin and Enhanced Self-Correcting (ESC) are addressed, which is to estimate voltage from the measured data. Section 4 explains the procedure of SOC and SOH estimation by the DEKF and FPIM respectively. An overview of the key methodology proposed in this paper can be found in Figure 1. Finally, key findings are summarized in Section 5, providing comprehensive insights and limitations.

2. Battery Cell Test

In this study, the same battery cell and equipment described in the literature (Yoo et al., 2023) are used for the test, which is a Samsung SDI, 18650-35E lithium-ion battery cell with nominal capacity of 3.5 Ah and a nominal voltage of 3.7 V. The battery is operated by a DC electronic load (Kikusui, PLZ1004W), a DC power supply (Kikusui, PWR800L) and a charge-discharge system controller (Kikusui, PFX2512) as shown in Figure 2. The test profiles are divided into dynamic test and aging test. The dynamic profiles comprise of three scenarios of Plug-in Hybrid Electric Vehicles (PHEV) as shown in Figure 3: City, Highway, and High-speed. City and Highway profiles consist of charge-depletion (CD) mode and charge-sustaining (CS) mode, while High-speed has CD mode only.

Figure 2. Experimental setup

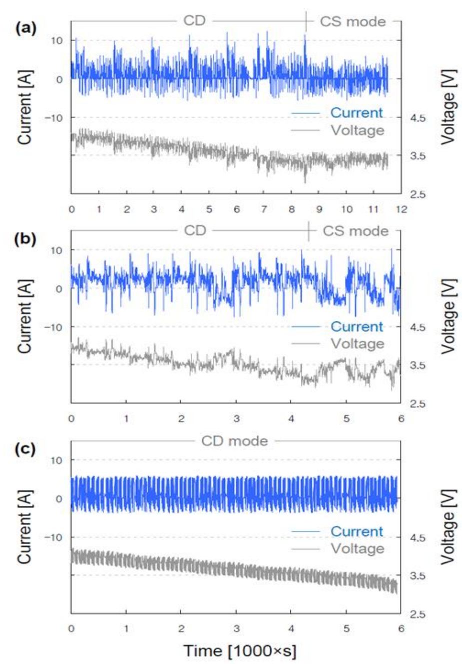


Figure 3. Voltage response to the current profiles adopted: (a) City, (b) Highway, and (c) High-speed

Aging test is performed to acquire aged battery data, by repeating charging and discharging cycles up to the capacity degradation of 30% as shown in Figure 4. Once the battery cell exhibits a noteworthy degree of capacity fade, three different dynamic profiles are applied. Before proceeding the aging test, static test is conducted to obtain the relation between the open circuit voltage (OCV) and SOC as shown in Figure 5. In the aging test, 2100 cycles are used to make capacity fade of 30%. Dynamic tests are conducted at 10 time points with the intervals of every 100 cycles during the period from the initial to the 300th cycles, and with the intervals of every 300 cycles from the 300th to the end of the cycles, which is depicted in Figure 6. The failure threshold for SOH is given at the 80% of initial capacity as shown in the dotted horizontal line in the figure. The capacity decreases mostly in linear fashion, except from 1200 to 1500 cycles where it is constant. The dynamic test data at each cycle, which are 0, 300, 1200 and 2100 cycles, are presented in Figure 7. For each cycle, three dynamic profiles are applied with the initial SOC set at approximately 0.9 (90%). As the degradation proceeds, each profile exhibits an abrupt termination because the cutoff voltage is reached earlier, indicating that the capacity has faded.

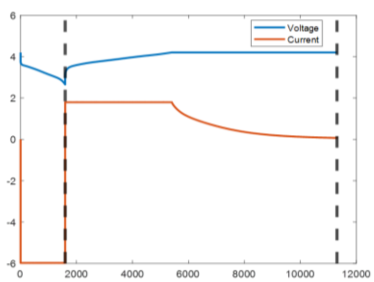


Figure 4. Aging test profiles

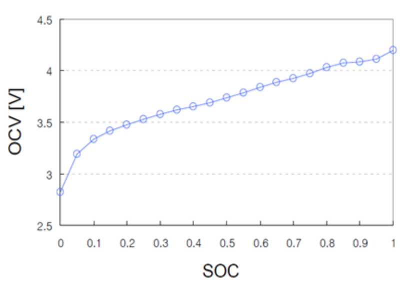


Figure 5. OCV-SOC relationship

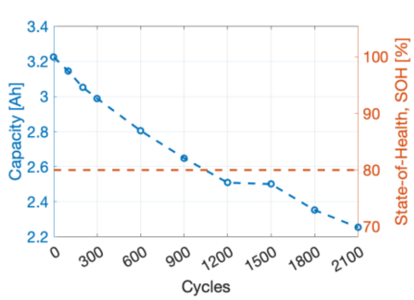
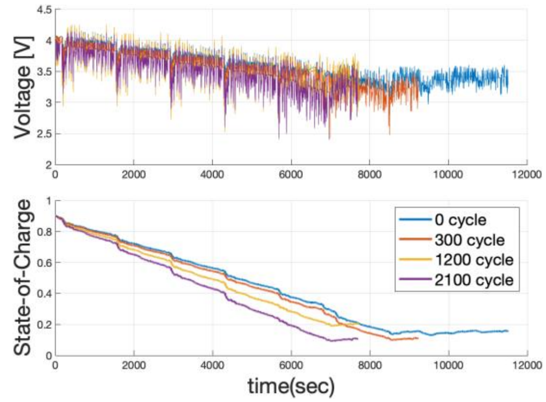


Figure 6. Capacity degradation in the aging test



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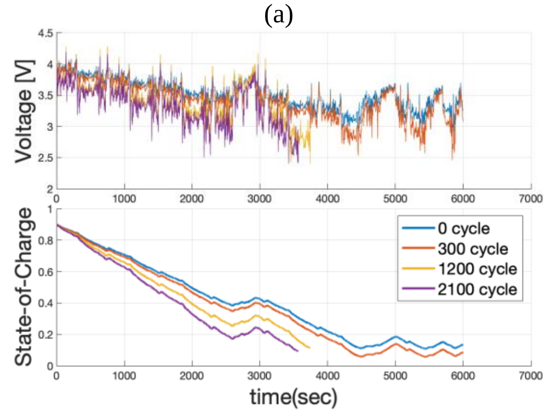

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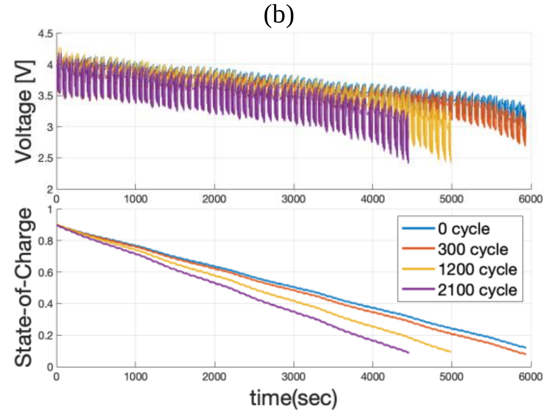

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Figure 7. Voltage response to the current profiles adopted at each cycle: (a) City, (b) Highway, and (c) High-speed

3. Battery Model

In this study, Thevenin and Enhanced Self-Correcting (ESC) models are reviewed to select a suitable battery model based on the gathered test data. The Thevenin model, one of the most widely utilized equivalent circuit models (ECMs) for model-based estimation of batteries, describes battery behavior by accounting for voltage drop through a resistor element and time-varying polarization voltages through one or more parallel resistor-capacitor (RC) elements.

The ESC model, proposed by Plett (2015), extends the Thevenin model by incorporating a hysteresis term to describe the hysteresis voltage of batteries with empirical modeling. Its configuration is shown in Figure 8, where v_T is terminal voltage, v_{oc} is open-circuit voltage, z is SOC, i is current (current bias ib is ignored in this study) flowing through R_0 (ohmic resistance), i_R is the current flowing through R_j and C_j (polarization resistance and capacitance), h is hysteresis, M is maximum hysteresis voltage, M_0 is instantaneous hysteresis voltage, and s is sign function of i.

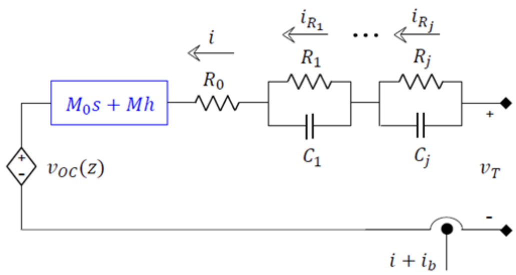
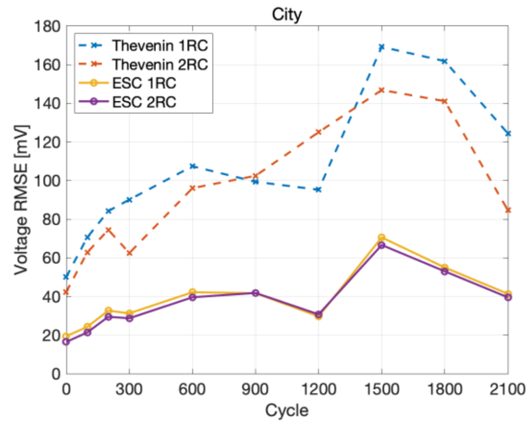


Figure 8. Circuit schematic for the ESC model which is the same as the Thevenin model except the addition of hysteresis voltages (in blue)

This study considers cases with 1 or 2 RC pairs for both the Thevenin and ESC models, denoted as Thevenin 1RC/2RC, and ESC 1RC/2RC. In order to estimate the model parameters, method by Plett, (2015) and Yoo et al., (2023) is employed, using the dynamic data for each cycle. Consequently, the models enable calculation of terminal voltage under the given current. The performance of each model is summarized in Figure 9 by the root mean square error (RMSE) between measured and estimated voltage. It is noteworthy that the ESC model outperforms the Thevenin model consistently for all the collected data. This superiority becomes more remarkable as the battery is aged. It is found that the hysteresis term in the model is useful to describe aging of the battery. Another observation is that the incorporation of additional RC pairs primarily yields a positive effect in the case of the Thevenin models, whereas it does not in the ESC model. This is from the fact that the hysteresis term diminishes the relative influence of additional RC pairs in the ESC model. This observation supports that adding the hysteresis term is better than adding the number of RC pairs. Therefore, the ESC 1RC model is chosen in this study. However, it is important to note that even the performance of the ESC model experiences accuracy loss in the aged batteries, which means that the model error increase is inevitable as the battery ages.



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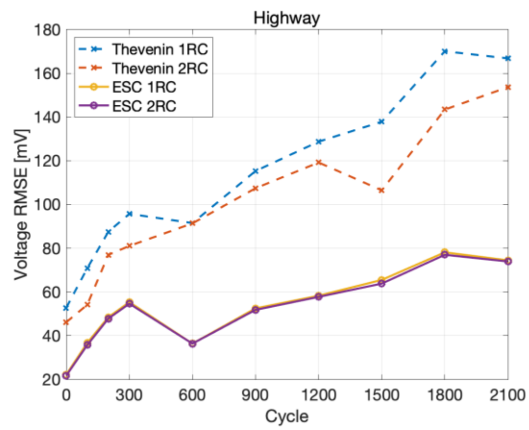

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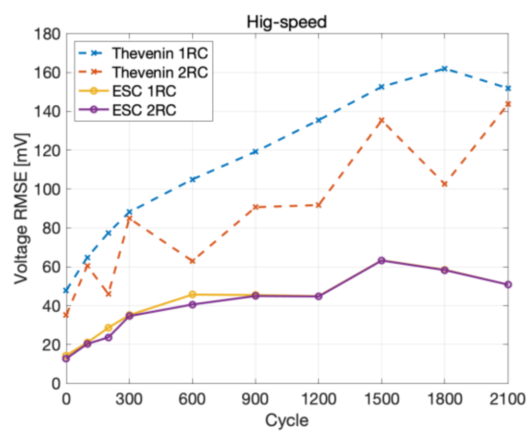

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Figure 9. Modeling performance of each model: (a) City, (b) Highway, and (c) High-speed

4. SOC AND SOH ESTIMATION

In this section, the procedure of SOC and SOH estimation by the DEKF and FPIM are outlined along with the corresponding result. The initial step involves the application of a general DEKF as reviewed in Section 1, based on the

ESC 1 RC model as determined in Section 3. Subsequently, the inherent weak observability of capacity in the DEKF algorithm is identified. To address this, the FPIM, a capacity estimation technique, is integrated into the DEKF framework. However, despite this integration, there exsists a decline in estimation performance for deep degraded battery cells. Therefore, remedial solution is proposed: an initial parameter estimation update is recommended after a 10% capacity loss to enhance estimation performance. Estimation results are summarized in each step of this process. In summary, the contribution of this study is to improve and validate methodologies to estimate SOC and SOH for test datasets with various dynamic profiles, including hybrid operation modes, and various degradation levels, up to 30% of capacity loss of battery cells.

The dual extended Kalman filter (DEKF), one of the approaches to generalize the extended Kalman filter (EKF) for simultaneous estimation of state and parameters, comprises of two filters: one for estimating the state and the other for estimating the parameters (Plett, 2005, 2015). Each filter executes the steps, and they are linked by exchanging information during the time update sequence. In this research, we propose a hybrid approach incorporating the DEKF and the capacity estimation technique to overcome the inherent weak observability of the capacity in the DEKF algorithm (Wassiliadis et al., 2018). The capacity estimation is implemented by the fixed-point iteration method (FPIM) during battery charging, and the estimated capacity value is used as a known value in the DEKF during the battery discharging (Sung & Lee, 2018).

At first, the DEKF is applied for the co-estimation of SOC and SOH, and the results are evaluated by the RMSE in the case of SOC and the last estimated value in the case of SOH in each dynamic profile, whose true values were obtained through coulomb counting of current during the conducted profiles and capacity testing after the profiles, respectively. Then, our proposed approach is applied, where the SOH estimation is separated from the DEKF and is made by the FPIM during the charging cycle.

Estimation Results of SOC and SOH using DEKF

By applying the DEKF based on the ESC 1RC Model to all 30 datasets, estimation results are obtained for SOC and SOH. Regarding the SOC, the RMSE for each profile and cycle is illustrated in Figure 10. It was observed that prior to 600 cycles, the estimation performance exhibits RMSE of less than 3% for all datasets. However, beyond 600 cycles, a significant degradation in estimation performance become evident. As the degradation progresses, it can be observed that the error in the initial SOC gradually increases.

Involving OCV-SOC tests at specific time intervals and subsequently updating the battery model can mitigate inaccuracies in estimation. Nevertheless, static tests for acquiring OCV-SOC lookup tables are time-consuming, and selecting suitable test time points poses a challenge.

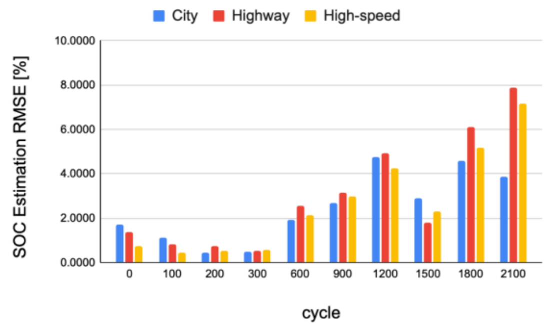


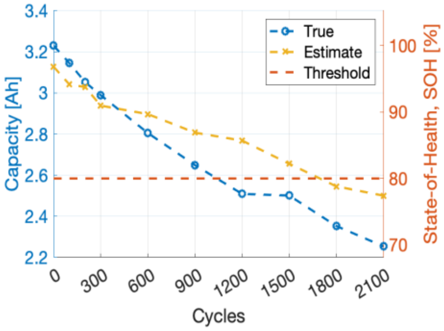
Figure 10. Estimation results of SOC using DEKF

Table. 2. Initial SOC estimation of each dataset

Cycle	City	Highway	High Speed
0	0.88	0.88	0.88
100	0.88	0.88	0.88
200	0.87	0.88	0.88
300	0.87	0.87	0.87
600	0.85	0.85	0.85
900	0.84	0.83	0.83
1200	0.81	0.82	0.82
1500	0.81	0.82	0.83
1800	0.79	0.80	0.80
2100	0.79	0.78	0.78

In this paper, a methodology is explored to mitigate inaccuracies in estimation without additional static tests. Hence, the inaccurate initial SOC estimation due to the battery aging remains as an inherent error in estimation without updating the battery model.

In the SOH estimation, it was observed that, except for the early degradation stage, the capacity generally does not satisfy the acceptable level of performance. Figure 11 depict the results of SOH estimation as the battery ages for each profile. It is observed that the capacity has low observability, and its estimation depends on the specific profile. This may be due to the fundamental issues in estimating various states and parameters based on limited measurement data. Meanwhile, for internal resistance, overall estimation performance was found to be superior when compared to the reference values. It is noted that the internal resistance has high observability compared to the capacity. Thresholds for failure based on each SOH were established at 80% of the initial capacity and twice the initial value for the internal resistance. Reference values of internal resistance were derived from battery modeling results rather than obtained through power tests. In this investigation, capacity was regarded as the indicator of SOH since the true capacity was measured at each time point. Consequently, the failure point of the battery is estimated to occur around 1,000 cycles, coinciding with the battery's capacity dropping below 80% of its initial capacity, as shown Figure 12. This failure point couldn't be accurately predicted due to the low observability of capacity in this estimation algorithm.



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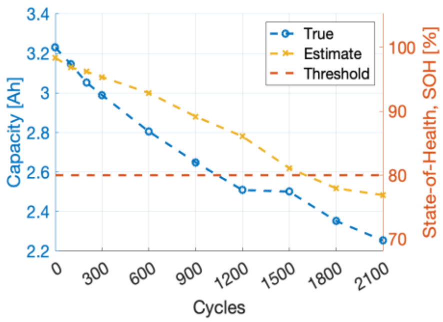

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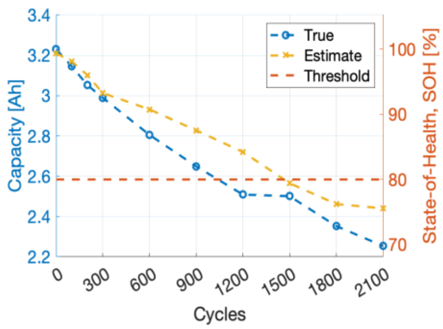

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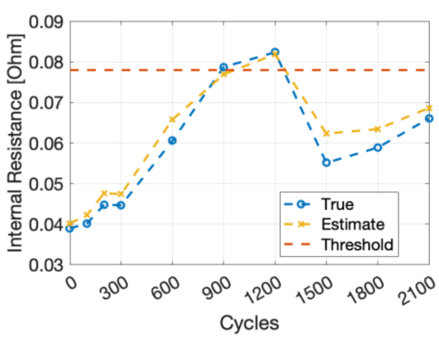
Figure 11. Capacity estimation results of PHEV datasets (a) City, (b) Highway and (c) High-speed



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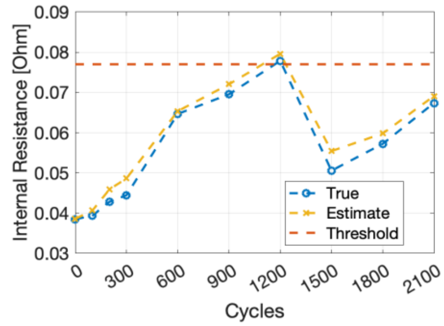

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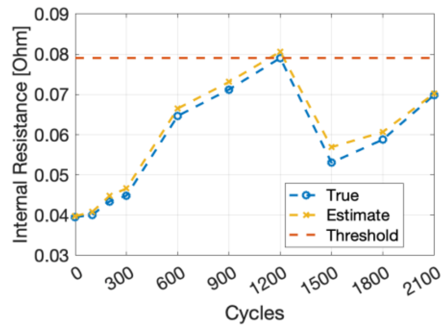

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Figure 12. Resistance estimation results of PHEV datasets (a) City, (b) Highway and (c) High-speed

Estimation Results of SOC and SOH using DEKF and FPIM

SOH Estimation

To overcome the low performance in capacity estimation, we have applied capacity estimation techniques separately using the charging profile data. Among various techniques, fixed-point iteration method (FPIM) was selected to estimate capacity during charging. Since there is only one type of profile in the charging, we can obtain a single capacity estimation result, as shown in Figure 13.

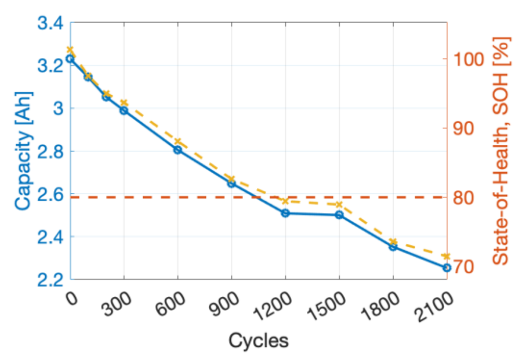


Figure 13. Results of the SOH estimation.

The estimation error was confirmed to be within 3%, indicating a significant improvement in estimation performance compared to the DEKF methodology, which estimates simultaneously from each profile.

SOC Estimation

Utilizing the estimated capacity during charging as a fixed value for SOC estimation using DEKF, the performance of SOC estimation is depicted in Figure 14. Unfortunately, despite improvements in capacity estimation performance, there is no corresponding enhancement observed in SOC estimation. It is observed that the performance significantly deteriorates with RMSE exceeding 5% after 600 cycles.

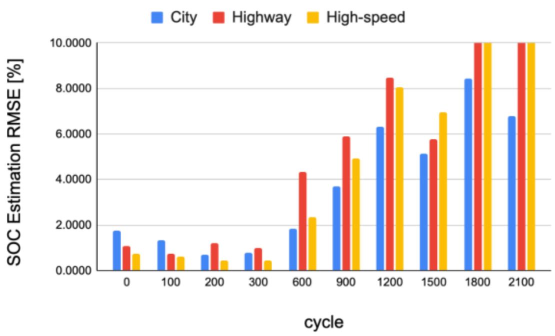


Figure 14. Estimation results of SOC using DEKF and FPIM

The everlasting decrease in the performance of SOC estimation as battery ages, despite the capacity being so close to the true value, can be attributed to several factors. These encompass the initial SOC estimation error and inaccuracies in model assumptions, as previously mentioned. Additionally, nonlinearities in the battery behavior and limitations in the estimation algorithms employed contribute to this phenomenon. Moreover, the interaction among these factors can exacerbate the complexity of the estimation process, further impeding the accurate SOC estimation. In the battery modeling of Figure 9, it has been observed that the ESC 1RC demonstrates sufficient capability to simulate the behavior of aged batteries. Consequently, there is an expectation that the SOC estimation would perform well if the parameters were estimated to optimal values. However, the challenge arises when attempting to simultaneously estimate the states and parameters to their optimal values within the filter algorithm, especially based on the limited measurement data. To address them, the initial parameter estimation values were set as the last parameter estimation values from the former dataset for each profile. This approach aimed to leverage the previous dataset's knowledge and fine-tune the initial parameter values for improved estimation accuracy in subsequent cycles. By initializing the parameters with values derived from the previous dataset, it was expected that the model could benefit from the accumulated insights and trends observed in earlier profiles, thereby enhancing the robustness and reliability of the estimation process. However, while it has been noted that internal resistance exhibits high observability in the estimation algorithm, the majority of parameters display low observability. Furthermore, unlike capacity or internal resistance, there is no discernible trend for each parameter during degradation. This lack of observable trends makes the efforts useless in the estimation process.

Estimation Results of SOC using DEKF, FPIM and initial parameter estimation update

SOC Estimation

To address the issue of deteriorating SOC estimation performance despite the improvement in SOH estimation through separate estimation, a method was applied to conduct the battery model at specific time points and reset the initial parameter estimation values.

Based on the degradation threshold of 20% capacity loss as the failure point for SOH, the battery modeling was conducted using dynamic profiles at intervals of 10% capacity loss initially, and 5% capacity loss subsequently. This method involved conducting the battery model at 600, 1200, and 1800 cycles to reset the initial parameter values. As a result, the SOC estimation performance was improved to within RMSE 5% after 600 cycles. The SOC estimation performance and the SOC estimation errors at 0, 600, 1200, and 2100 cycles are illustrated in Figure 15. Internal resistance estimation showed no significant impact compared to the previous method, as confirmed in Figure 16.

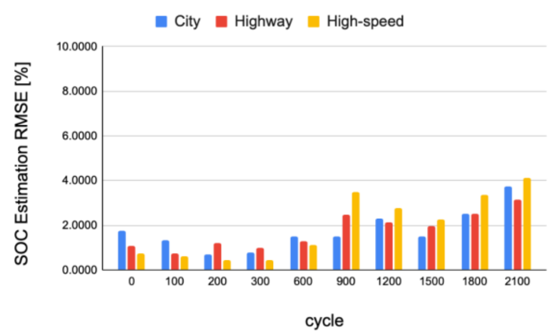
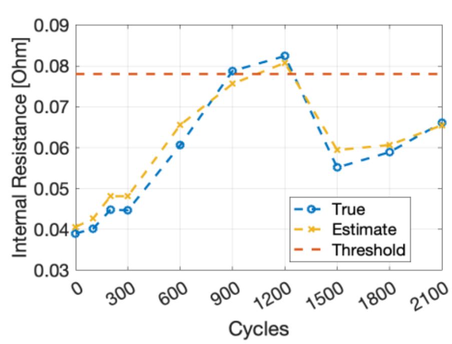


Figure 15. Estimation results of SOC using DEKF, FPIM and initial parameter estimation update



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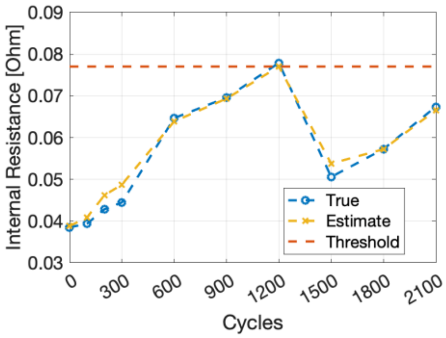

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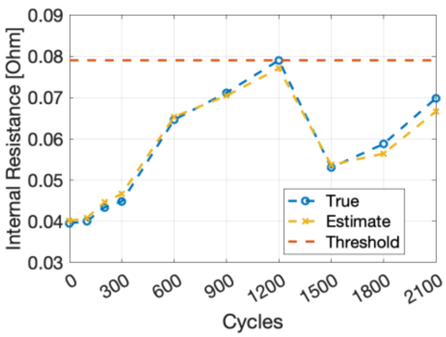

(c)

Figure 16. Resistance estimation results of PHEV datasets (a) City, (b) Highway and (c) High-speed

5. Conclusion

In this study, a methodology is investigated to estimate SOC and SOH of the battery whose capacity degraded from 0 to 30%. A hybrid approach is proposed that the DEKF and the capacity estimation technique are incorporated to overcome the inherent weak observability of the capacity in the DEKF algorithm. The capacity estimation is implemented by the fixed-point iteration method (FPIM) during the battery charging, and the resulting estimated capacity value is held constant in the process of DEKF during battery discharging. However, we observed a decline in estimation performance beyond a 10% capacity loss, prompting us to propose an initial parameter estimation update to address this issue. As a result, the proposed methodology achieves an accurate and reliable co-estimation of SOC and SOH, even in the battery aging with SOC estimation error lower than 5% and SOH estimation error lower than 3%, even for a battery cell with a capacity fade of 30% for three profiles including hybrid operation modes.

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