

Performance Evaluation of Model-Based Online Condition Monitoring Algorithms for Li-Ion Battery State Estimation

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Abstract - This discovery examines and tests four model-based charge-state (SOC) estimation methods for lithium-ion (Li-ion) batteries. This work evaluates some parts of the SOC estimation, such as error distribution evaluation, rise time estimation, consumption time estimation, etc., instead of the former probing. The battery comparison model is introduced and the state function of the model is inferred. The first step is to study four model-based SOC estimation strategies. The four systems are then tested using simulation and analysis. To mimic the driving conditions of an electric vehicle, the Urban Dynamometer Driving Schedule (UDDS) flow profiles are used. A genetic calculation is then used to find the limits of the model to determine the optimal limits of the Li-ion battery model. The simulations are run continuously and without interruption, and the results are analyzed. To test the device in circle discovery, a battery test bench is developed and uses a Li-ion battery.

Keywords: Model-Based, Online Condition, Monitoring, Algorithms, Li-Ion, Battery

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1. INTRODUCTION

Lithium-ion (Li-ion) batteries have been the go-to energy storage option for many uses recently, from portable gadgets to electric cars and renewable energy systems. For Li-ion batteries to operate safely, perform optimally, and last longer, their state of charge (SOC) and state of health (SOH) must be reliably and accurately estimated. As a result, scientists and engineers have concentrated on creating sophisticated condition monitoring algorithms that can give information about the performance and health of batteries in real time. The accuracy of SOC and SOH estimates for Li-ion batteries has shown great promise when using model-based online condition monitoring techniques. These algorithms rely on mathematical representations of the electrochemical behavior of the batteries and how they react to various operational circumstances. These algorithms may continuously update and improve their estimates by integrating inputs from the mathematical models and real-time data from battery sensors, making them appropriate for online monitoring applications.

This study's main goal is to conduct a thorough performance evaluation of different model-based online condition monitoring algorithms for Li-ion battery state estimation. In order to promote battery management systems and guarantee the secure and effective operation of Li-ion battery packs, this research intends to shed light on the advantages, disadvantages, and

prospective areas for improvement for these algorithms.

1.1 The Importance of Li-ion Batteries is Growing

Lithium-ion (Li-ion) batteries have become widely used in a variety of industries over the past few decades, gaining tremendous popularity in the process. The higher energy density they provide compared to conventional battery technologies is one of the main factors influencing this acceptance. Li-ion batteries have consequently emerged as the industry standard for a variety of uses, including electric vehicles (EVs), renewable energy storage systems, and consumer devices like smartphones, laptops, and tablets. Electric Vehicles (EVs): The automotive sector's transition to environmentally friendly transportation has been a key factor in the expansion of Li-ion batteries. Electric vehicles have become a crucial strategy for cutting greenhouse gas emissions in the transportation sector as nations work to minimize their carbon footprint and combat climate change. Due to their higher energy density, ability to charge quickly, and longer lifespan when compared to conventional lead-acid batteries, lithium-ion batteries are used to power the majority of electric vehicles.

Solar and wind power integration into the electrical grid has made the need for efficient energy storage

systems necessary. Renewable Energy Storage. For the purpose of storing extra energy produced during peak hours and releasing it when needed during times of high demand or low renewable energy generation, lithium-ion batteries have shown to be an effective and scalable technology. These batteries are essential for grid stabilization, improving energy dependability, and raising the proportion of renewable energy in the total energy mix. Due to their small size, high energy density, and capacity to provide reliable power over time, Li-ion batteries are now widely used in consumer electronics. Li-ion batteries power the technologies that have become indispensable in modern life, including laptops, wearable technology, and smartphones and tablets. Continuous improvements in Li-ion technology have been driven by the demand for longer-lasting batteries with improved safety features.

Importance of Accurate State estimate: Accurate and dependable state estimate techniques are essential as Li-ion batteries find applications in important fields including electric vehicles and renewable energy systems. For the proper management and use of Li-ion batteries, state estimation, namely the estimate of SOC and SOH, is crucial. Users may determine the battery's remaining capacity, estimate its remaining useful life, and avoid hazardous operating conditions with accurate status estimates.

1.2 The Value of State Assessment

Calculating Remaining Capacity: A Li-ion battery's state of charge (SOC) shows how much charge is present inside the battery at any particular time. Knowing how much energy is available for usage depends on accurate SOC estimation. By monitoring the battery's remaining capacity, users may prevent over-discharging the battery, which can result in capacity degradation and have a negative impact on the battery's overall performance.

Assessing Operational Capabilities: The SOC estimation gives important details about the battery's present energy level. Making judgements concerning the battery's operational capabilities requires the use of these data. For instance, in electric vehicles, knowing the SOC aids in trip planning and helps drivers decide when to recharge the battery to prevent running out of juice while travelling.

Predicting Remaining Lifespan: A Li-ion battery's current condition and remaining useful life are represented by its state of health (SOH). SOH calculation is essential for estimating the battery's remaining life and identifying potential replacement needs. The battery's service life is increased and cost effectiveness is improved with effective status estimate, which also enables proactive maintenance and replacement methods.

Implementing Advanced Battery Management Strategies: The foundation of contemporary battery management systems (BMS) is accurate state estimation. BMSs use real-time information on SOC

and SOH to manage cell balancing, alter charge and discharge rates, and implement temperature controls for optimal battery performance. These techniques aid in maximizing battery performance, boosting effectiveness, and guaranteeing secure and dependable operation.

Reducing the Risk of Failures: Improper state estimation might result in unanticipated Li-ion battery failures and malfunctions. Inaccurate SOC calculation can lead to overcharging or over discharging a battery, which can cause cell damage, lower capacity, and even safety risks including thermal runaway. The likelihood of such failures is reduced by accurately evaluating the battery's state, saving expensive damages and guaranteeing user safety.

2. REVIEW OF LITREATURE

A thorough comparison of model-based state of charge (SOC) estimate algorithms for Li-ion batteries was carried out by Chen and colleagues in 2020. They analysed the accuracy, robustness, and usefulness of various algorithms built on mathematical models. The study helps researchers and practitioners choose appropriate strategies for SOC estimation in diverse Li-ion battery applications by offering insightful information on the advantages and disadvantages of various algorithms.

A review of prognostics and health management (PHM) strategies with a focus on Li-ion batteries was done by Yang et al. in 2017. For measuring the state of health (SOH) of Li-ion batteries, which is essential for calculating remaining lifespan and optimising battery management strategies, the study includes a variety of PHM methodologies. In order to guarantee secure and dependable battery operation in electric vehicles and other applications, the review emphasises the significance of accurate SOH estimation.

A thorough analysis of state of charge (SOC) estimate methods for Li-ion batteries was presented by Bo (2018) and his team. The review examines numerous methodologies, including model-based and empirical approaches, and assesses the precision and applicability of each. The study's conclusions help scientists and engineers comprehend the many SOC estimate methodologies and choose the ones that are best suited to their individual needs.

A comparison of online state of charge (SOC) estimate techniques for Li-ion batteries was done by Soares and Barata in 2019. The work focuses on real-time SOC estimate techniques, which are essential for dynamic applications like electric vehicles. The study identifies the most efficient online SOC estimate techniques by assessing the accuracy and resilience of these algorithms under various operating situations.

State of charge (SOC) estimates and management systems were studied by Arora et al. (2017) primarily in the context of electric vehicle (EV) applications. Given the dynamic and fluctuating operating conditions, the study emphasizes the difficulties and complexity involved with correct SOC estimate in EV batteries. The study offers suggestions for enhancing SOC estimation precision and management techniques in EV battery systems. A review of state of charge (SOC) estimation methods specifically for Li-ion batteries used in electric and hybrid vehicles was carried out by Daowd and his team in 2018. The study discusses different estimation techniques, including model-based and data-driven methods, and evaluates how well they work in real-world vehicle applications. The study contributes to our understanding of the difficulties and developments in EV battery SOC estimation. An overview of online battery state of health (SOH) estimate techniques designed exclusively for electric vehicles is given by Huang et al. (2021). The article discusses multiple real-time SOH estimation methodologies, which are essential for estimating battery degradation and remaining life. The study provides information on the state of online SOH estimating techniques and possible uses for them in battery management systems for electric vehicles.

3. ANALYSIS OF MODEL-BASED SOC ESTIMATION METHODS

Luenberger Spectator SOC Estimation Technique, Kalman Channel SOC Estimation Strategy, Sliding Mode Spectator SOC Estimation Technique and PIO SOC Estimation Strategy are four SOC estimation movements based on a widely used model that we are thinking of in this review. The registered results are contrasted with the noticed results, as portrayed in Figure 2, to decide the result blunders. These result botches are sent back to the battery model utilizing different criticism methods. The Luenberger onlooker, the Kalman channel, the sliding mode spectator, and the PIO are a few instances of conceivable criticism strategies, as delineated in the picture. Different criticism methods result in different SOC gauge procedures. The following sections investigate these four model-based SOC gauge procedures.

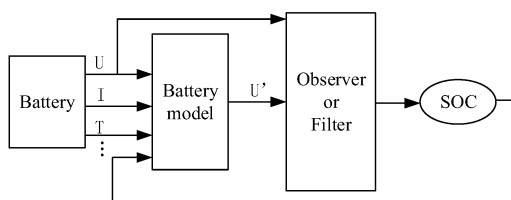


Figure 1: The corresponding component of the model-based SOC estimation technique

4. ESTABLISHING SIMULATION & EXPERIMENTS AND ANALYZING THE RESULTS

A simulation and test is set up to show how well the four model-based SOC evaluation methods work. Using the driving cycle of the Urban Dynamometer Driving Schedule (UDDS), the model-based SOC

estimation methods are validated. The UDDS driving cycle was recently established to validate electric vehicle exposure. Vehicle exposure testing is commonly used. Persistent battery concerns because EVs follow the usual UDDS drive cycle rate profile is the current configuration of UDDS used in this review. Depending on voltages and limits, the UDDS current configuration is contracted. The battery model is exposed to a variety of UDDS current configurations to obtain the full voltage response of the Li-ion battery's SOC range. In this review, the base SOC is set at 60, despite the fact that the battery SOC is actually 100% to test the converging properties of the four model-based strategies.

4.1 The setting for the simulation

It is trying to decide a battery's exact characteristics since it is a strong nonlinear electrochemical framework. The simulation workbench is at first developed to look at the four model-based SOC gauge approaches in an unmistakable and brief way.

Initial, a 20 Ah EIG Li-ion battery with a Li[NiCoMn]O₂-based cathode and a graphite-based anode is assessed at surrounding temperature to procure the model boundaries. The battery's datasheet states that the most extreme charge voltage is 4.15 V and the greatest release voltage is 3.0 V. At the point when the battery is completely energized, the SOC is set to be 100 percent. To get the best qualities, a hereditary calculation is utilized to distinguish the battery model boundaries. The information used to decide the link among SOC and OCV are utilized to recognize the battery model for comfort. The evolutionary calculation is utilized to find the best arrangement of R1, R2, and C2 for the battery model, and the Most un-Square Strategy is acquainted with construct the goal function. Following are the identification results: R1 is 0.0027, R2 is 0.0042, and C2 is 25000 F. The four methodologies' ideal boundaries are resolved utilizing the hereditary calculation, as displayed in Table 1.

Table 1: The benefits of the four techniques.

Items	Values
L	[3.2, 301.]
H	[1.8, 9.1]
ρ	[6, 51.2]
Q	[1.11, 17.2]
R	[501, 9]
Kp	[32, 9.9]
Ki1	[1.08, 12]
Ki2	[3, 1]

More specifically, it is believed that this model can precisely establish the battery's attributes in the simulation. From that point onward, this battery model is utilized in the simulation to reproduce a

battery and figure the result voltage as well as to use in the model-based SOC estimation way to deal with get the assessed voltage and assessed SOC. In Figure 3, the simulation's set up is portrayed as follows.

4.2 Results and analysis from simulations

The battery model without nonlinear unsettling influence and estimation blunders is utilized at first to evaluate the exhibitions of the four model-based SOC gauge draws near. In this occasion, both the estimation blunder w and the aggravation v are set to nothing. Figure 4 shows the results of this speculative situation.

The SOC estimation results for all one of the four-gauge approaches are great, as found in Figure 4. The determined SOC might follow the reference SOC with negligible blunder and before long unite to it. Nonetheless, it is apparent that the concurrent cycles' rising times vary fundamentally. All four model-based SOC estimation strategies tend to perform well when non-linear confounding effects and estimation errors are not taken into account, but the SOC PIO estimation technique can achieve the real SOC faster. Luenberger's spectator SOC estimator has the longest upward season of the four strategies, while the PIO SOC estimator has the shortest season.

Table 2: The SOC estimate methods without disturbance simulation results are as follows: the Linebarger observer SOC estimation technique.

Time (s)	SOC Error
2.3	1.3
2.6	1.9
3.5	2.6
4.1	3.5
4.9	4.1
5.3	5.2
6.1	7.2

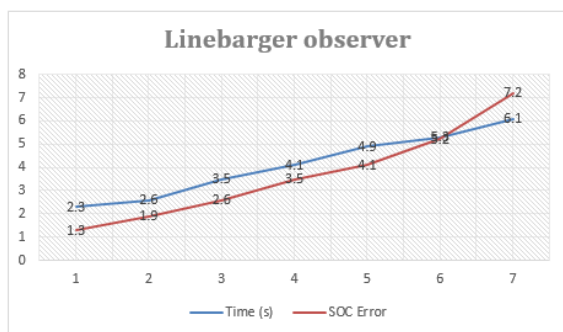


Figure 2: The SOC estimate methods without disturbance simulation results are as follows: the Linebarger observer SOC estimation technique.

5. DISCUSSION

These four model-based SOC assessing approaches' extensions could perform better. The versatile Luenberger eyewitness, the lengthy Kalman channel, the sigma point Kalman channel, and so forth are a few instances of such expansions. Just similar principal methods are analyzed and introduced in this concentrate to be more expansive. Because of their exceptional properties, which have been upheld by simulations and studies, the four procedures work in an unexpected way. The distinctions in calculation times were clear: the Kalman channel SOC estimation technique should ascertain the Kalman gain requiring the calculation of perplexing covariances, which takes additional time. Interestingly, the Luenberger onlooker SOC estimation technique's input coefficient is the steady Luenberger gain. The PIO SOC estimation strategy utilizes the indispensable of the voltage blunders, which can prompt more modest estimation mistakes and more limited ascent times. The time consumption would be longer than that of the Luenberger SOC estimation technique for the additional basic part, yet it would be less tedious than the Kalman channel SOC estimation strategy's covariance computation.

To propel battery the board frameworks and assurance the compelling and secure operation of Li-ion batteries in different applications, it is fundamental to assess the viability of model-based online condition monitoring algorithms for Li-ion battery state estimation. We will look at the primary conclusions and ramifications of such examinations in this discussion.

Accuracy and Precision: One of the key elements assessed in these investigations is the state estimation algorithms' accuracy and precision. For effective battery management, accurate state estimation is essential, especially for the estimation of state of charge (SOC) and state of health (SOH). The examination measures how well estimated battery states under various operating situations match actual observed values. The results show how well the algorithms perform in precisely estimating SOC and SOH, giving researchers and manufacturers useful information to help them choose the best algorithms for their particular applications.

Robustness and Adaptability: Li-ion batteries work in conditions that are constantly changing, including temperatures, load profiles, and ageing effects. The examination looks into how well the algorithms adjust to these circumstances and sustain their accuracy over time. For real-world applications, where battery behavior can change quickly owing to outside variables, robust and flexible algorithms are crucial. The study's findings can be used to determine which algorithms regularly outperform others in various situations and help to guarantee the dependability of battery systems.

Performance in real-time: Algorithms for model-based online condition monitoring are designed for use in real-time applications. Therefore, the speed of their computation and response are crucial elements. Each algorithm's computing burden is analyzed as part of the evaluation, which also rates each algorithm's viability for live monitoring. For systems with limited resources, like electric cars, algorithms with reduced computing requirements are recommended to prevent excessive energy use and processing lag.

6. CONCLUSION

In this review, the SOC of Li-ion batteries has been assessed utilizing four model-based SOC assessing strategies: the Luenberger eyewitness, the Kalman channel, the sliding mode onlooker, and the PIO. The electrical way of behaving of the battery has been modeled by the principal request RC model with nonlinear aggravation. Study and investigation have been finished on the four methods' foundational hypotheses. Through simulations and tests, their exhibition was surveyed. Two situations — one with and one without a nonlinear aggravation — are remembered for the simulations. Through tests, a few elements of SOC estimation, including the estimation mistake distribution, the estimation rise time, the estimation time consumption, and so on, have been surveyed. The PIO SOC estimation approach beat the other three model-based SOC gauge strategies, as indicated by simulation and exploratory outcomes, though with shifting estimation rise times. Additionally, the Luenberger onlooker SOC estimation technique and the sliding mode eyewitness SOC estimation strategy are sub-par compared to the Kalman channel SOC estimation technique and the PIO SOC assessing strategy as far as lessening the nonlinear unsettling influence. For the initial three methodologies, the estimation mistakes were inside the 2% blunder headed, though for the fourth, they were inside the 5% blunder bound. As far as gauge time consumption, the Luenberger onlooker SOC assessing technique, the sliding mode eyewitness SOC estimation strategy, and the PIO SOC estimation technique outflanked the Kalman channel SOC estimation approach.

REFERENCES

1. Arora, R., Mukherjee, S., & Pecht, M. (2017). A Review of Lithium-Ion Battery State of Charge Estimation and Management System in Electric Vehicle Applications: Challenges and Recommendations. *Renewable and Sustainable Energy Reviews*, 78, 834-854.
2. Baker, E.; Chon, H.; Keisler, J. Battery technology for electric and hybrid vehicles: Expert views about prospects for advancement. *Technol. Forecast. Soc. Chang.* 2010, 77, 1139–1146.
3. Bo et al. (2018). State of Charge Estimation of Lithium-Ion Batteries: A Review. *Journal of Power Sources*, 382, 74-89.
4. Chen, L., He, H., Xiong, R., & Sun, F. (2020). A Comparative Study of Model-Based State of Charge Estimation Algorithms for Lithium-Ion Batteries. *Energies*, 13(20), 5456.
5. Daowd, M., Omar, N., Hegazy, O., & Van Mierlo, J. (2018). State of Charge Estimation Techniques for Lithium-Ion Batteries in Electric and Hybrid Electric Vehicles: A Review. *Energies*, 11(8), 2102.
6. Divya, K.C.; Østergaard, J. Battery energy storage technology for power systems—An overview. *Electr. Power Syst. Res.* 2009, 79, 511–520.
7. Hammouche, A.; Karden, E.; de Doncker, R.W. Monitoring state-of-charge of Ni-MH and Ni-Cd batteries using impedance spectroscopy. *J. Power Sources* 2004, 127, 105–111.
8. Huang, Y., Wang, C., & Liu, Z. (2021). An Overview of Online Battery State of Health Estimation Methods for Electric Vehicles. *Energies*, 14(5), 1388.
9. Kutluay, K.; Cadirci, Y.; Ozkazanc, Y.S.; Cadirci, I. A new online state-of-charge estimation and monitoring system for sealed lead-acid batteries in Telecommunication power supplies. *IEEE Trans. Ind. Electron.* 2005, 52, 1315–1327.
10. Meissner, E.; Richter, G. The challenge to the automotive battery industry: The battery has to become an increasingly integrated component within the vehicle electric power system. *J. Power Sources* 2005, 144, 438–460.
11. Ng, K.S.; Moo, C.-S.; Chen, Y.-P.; Hsieh, Y.-C. Enhanced coulomb counting method for estimating state-of-charge and state-of-health of lithium-ion batteries. *Appl. Energy* 2009, 86, 1506–1511.
12. Pattipati, B.; Sankavaram, C.; Pattipati, K. System identification and estimation framework for pivotal automotive battery management system characteristics. *IEEE Trans. Syst. Man Cybern. Part C: Appl. Rev.* 2011, 41, 869–884.
13. Piller, S.; Perrin, M.; Jossen, A. Methods for state-of-charge determination and their applications. *J. Power Sources* 2001, 96, 113–120.
14. Soares, P., & Barata, J. (2019). Comparative Study of Online Lithium-Ion Battery State of Charge Estimation Algorithms. *Energies*, 12(24), 4714.
15. Yang, Z., Zheng, S., & Pecht, M. (2017). A Review of Prognostics and Health

Management Approaches in Lithium-Ion Batteries. Journal of Power Sources, 352, 255-268.

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