International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 10 Issue: 03 | March - 2026 SJIF Rating: 8.659 ISSN: 2582-3930

A Detailed Survey on State of Health Estimation Methods

D venkatesh[1], B Kumar Raju[1], G Durga Prasad[1], B Suresh[1], T S Kishore[2], M Santosh Kumar[2]
[1]B. Tech Student Department of Electrical and Electronics Engineering, GMRIT Deemed to be University, Rajam, Vizianagaram - 532127, Andhra Pradesh, India.
[2]Department of Electrical and Electronics Engineering, GMRIT Deemed to be University, Rajam, Vizianagaram - 532127, Andhra Pradesh, India.
Email: kumarsaivajuladurga@gmail.com

---***---

Abstract - Lithium-ion batteries are widely used in electrical vehicles, renewable energy storage systems, and long cycle life. However, with each charge-discharge cycle, their performance gradually degrades, impacting reliability and safety. A key parameter to evaluate battery degradation is the State of Health (SOH), which cannot be measured directly and must be estimated using advanced Battery Management System (BMS) techniques. This article presents a comprehensive survey of the state of the art in SOH estimation for lithium-ion batteries. It classifies methods into three categories: direct measurement methods, model-based prediction methods and data-driven methods using machine learning. Each method is analyzed in terms of advantages, limitations, and implementation challenges. The study also highlights emerging hybrid approaches combining electrochemical models with AI for improved SOH estimation accuracy.

Key Words: Lithium-ion Battery, State of Health (SOH), Battery Management System (BMS), Battery Degradation, Machine Learning, Energy Storage Systems

1.INTRODUCTION

Energy Storage Technologies are essential components of today’s electrical/electronic systems. They're found in electric vehicle industry, smart grid infrastructure and among other applications when integrating with renewable energy sources like wind or solar power. Lithium-Ion batteries are the most dominant type of energy storage tech because they have high energy density, long life span, low weight, and very low self-discharge rate. This combination makes them ideal for use in both portable and large-scale applications; however, lithium-ion batteries are chemically/thermally stressed (degraded) over time by chemical reactions and mechanical stress thus causing the battery capacity to be reduced, internal resistance to be increased, and power capability (Kw/h) to decrease.

Degradation has a direct effect on the safety, efficiency, and reliability of all battery powered systems; therefore, continuous monitoring of the condition of a battery is critical to its optimal performance and lifetime. A major parameter being used to evaluate battery aging is the State-of-Health (SOH) of a battery, which represents its current capacity compared to when it was new. Estimating SOH accurately would help with predictive maintenance, optimizing charging methods, and better management of safety issues. However, estimating SOH is difficult due to the impact of many variables on batteries, including temperature change, charge and discharge cycles, depth of discharge, and the cycle life of the battery; therefore, advanced monitoring (in real-time) and intelligent estimation techniques need to be included as part of the Battery Management System in order to calculate the SOH as accurately as possible.

To understand how complex SOH monitoring (state of health monitoring) actually is, first it is imperative to know how batteries degrade and how they work from a physics perspective. Lithium polymer (Li Pol) batteries charge and discharge repeatedly by moving lithium ions between the anode and the cathode, or between the anode and cathode through the electrolyte. Percentage of total available capacity of battery versus maximum nominal capacity (new)) is used as a means of measuring the state of health of lithium-ion batteries. This number reflects how old the battery is (compared to when it was new), which also corresponds to the amount of charge remaining that the battery can deliver at its maximum discharge rate. Therefore, the main role of a BMS (battery management system) is to take the external input that it receives (terminal voltage, load current, and temperature) and calculate the internal SOH state (for the battery). The state of charge, internal electrochemical state of the battery, and all of this information cannot be measured directly by simple physical sensors as they are not in contact with the outside of the battery (either electronically or mechanically).

2 PROBLEM STATEMENT

A significant challenge faced by SOH evaluations of lithium-ion based battery systems lies in their non-linear and time varying behaviours based on the dynamic conditions present in the real-world. Periodically charging and discharging battery cells results in increased internal resistance as well as a decrease in the maximum amount of energy that can be stored over many (i.e., hundreds) charging / discharging cycles, which left uncontrolled may eventually lead to catastrophic structural failure from within the batteries themselves. The SOH of batteries that have degraded such that the SOH data is no longer reliable do not allow the use of static state estimation models to accurately produce an operating battery management system. Additionally, measurement noise generated by the use of low-cost components (e.g. thermocouples, etc.) commonly used as watch elements within the standard BMS hardware further complicate efforts to provide an accurate adaptive-to-degradation low-computation battery management system that can operate using limited microcontroller platform resources.

3. LITERATURE REVIEW

Initially, our methods for checking the State of Health (SoH) of batteries were relatively simple - looking at them physically. However, now the methods used to check SoH have moved into more complex and intelligent frameworks. Originally, SoH checking methods were based on coulomb counting techniques. With the introduction of intelligent methods, SoH and charge are now estimated simultaneously (Ng et al. [8]). Most traditional methods of measuring SoH directly do not yield accurate results due to sensor drift so they have been replaced by closed-loop observers. Makuwatsine and Singh [6] presented an example of how the introduction of an Extended Kalman Filter (EKF) model to capture the nonlinear characteristics of batteries (which vary as they age) has improved the accuracy of SoH predictions. Many researchers have begun to use large databases to develop models that analyze battery degradation processes and provide health indicators, including capacity and internal resistance. The health indicators can be combined with large data platforms and used to provide real-time detection of trends associated with battery aging [4]. Also, according to Sylvestrin et al. [10], Long Short Term Memory (LSTM) neural networks are particularly good at capturing long-term temporal dependencies in battery data. Du et al.'s research [3] demonstrated that NARX models used during charging can reduce prediction errors by over 50%.

Recently, there has been a tendency to use hybrid modeling approaches to combine modern computational methods that are cost effective, accurate, and able to model the state of health (SoH) for a battery. For example, Mumtaz Noreen and others [7] reported using advanced filtering techniques for state estimation, and reported using state-of-the-art AI (artificial intelligence) techniques that resulted in error rates as low as 0.32%. Dineva [1] highlighted that machine learning (ML) using neuromorphic technology (NMT) is a promising alternative to less effective, traditional (linear filtering) methods of processing large data sets from multiple sources of data commonly found in battery systems of electric vehicles (EVs). Swarnkar and others [9] have stated that accurately assessing the SoH of batteries will be a critical success factor for second-life battery applications. Researchers have determined that deep convolutional neural networks (CNNs) effectively reduce the overall computation associated with SoH estimates for battery technology [5]. Dini et al. [2] reviewed current methodologies used for different battery chemistries and noted that factors associated with each chemistry drive the decision of an approach (model-based or AI-based) to estimate accurately the SoH value.

4 RESEARCH GAPS

- Resource Limits: The computation needs of high precision algorithms are much greater than those of traditional low-cost microcontrollers operating in a BMS, such that these traditional algorithms require significantly less processing resources to operate.
- Completely Independent Estimates of SOC and SOH: The fact that there are no algorithms capable of independently estimating both SOC and SOH means that the estimate made for one of the two variables

will affect the estimate made for the other variable.

- Temperature Extremes: Due largely to the fact that there are currently very few models that are capable of accurately simulating battery performance at either extremely low and/or high temperature extremes, existing models will have a lack of accuracy in these environments and therefore a lack of accuracy in estimating battery SOC.
- Experimental Validation of New Approaches: The literature currently available to us does not have much experimentally validated data relative to new techniques when tested and measured in a controlled laboratory environment, nor does it include any measure of the level of high frequency noise that is present in most workplace environments.

5. CONCLUSION

Continuous monitoring of lithium-ion energy storage systems (LIESS) State of Health (SoH) is critical for keeping these systems safe, efficient and economical over the long term. There has been a shift away from using static estimation techniques towards dynamic/self-correcting ones. Model-based observers are still the best means of achieving accurate and efficient estimates of SoH, though it is anticipated that Battery Management Systems (BMS) will become more hybrid; however, cloud-based intelligent solutions will likely increase as battery management technologies advance. A promising means of developing more accurate SoH estimates across a wider range of operating conditions is through the use of hybrid/electrochemical models in conjunction with deep learning methods.

6. FUTURE SCOPE

In the future, SoH (State of Health) determination will be focused on finding increasingly accurate, real-time adaptive techniques to estimate the health status of lithium battery cells. In addition, combining state-of-the-art "Artificial Intelligence" (AI) & machine learning with 'electrochemical' modelling techniques should improve how well we are able to predict "SoH" under different environmental and operational conditions. Some future research will also focus on lightweight software algorithms implemented in resource-limited Battery Management Systems (BMS). Finally, standardizing SoH estimation methods and diagnostics will be critical for second use battery applications.

REFERENCES

[1] A. Dineva, “The assessment of progress in the prediction of battery health for electric vehicles, compared from prior linear filtering to recent machine learning techniques,” *Batteries*, vol. 10, no. 10, pp. 356, 2024. DOI: https://doi.org/10.3390/batteries10100356

[2] P. Dini, A. Colicelli, and S. Saponara, “A review of modelling and ascertaining the state of charge and state of health for batteries used in automotive applications,” *Batteries*, vol. 10, no. 1, pp. 34, 2024. DOI: https://doi.org/10.3390/batteries10010034

[3] D. Du, R. Qi, Z. Ren, and D. Xiao, “Research into estimating the state of health for lithium-ion batteries through the charging cycle,” *Energies*, vol. 16, no. 3, pp. 1420, 2023. DOI: https://doi.org/10.3390/en16031420

[4] M. Li, W. Xu, S. Zhang, L. Liu, A. Hussain, E. Hu, J. Zhang, Z. Mao, and Z. Chen, “A review of battery management processes for estimating battery health using indicators and machine learning,” *Materials*, vol. 18, no. 1, pp. 145, 2025. DOI: https://doi.org/10.3390/ma18010145

[5] S. S. Madani, C. Ziebert, P. Vahdatkhah, and S. K. Sadrnezhaad, “Recent progress of deep learning methods for health monitoring of lithium-ion batteries,” *Batteries*, vol. 10, no. 6, pp. 204, 2024. DOI: https://doi.org/10.3390/batteries10060204

[6] T. T. Makuwatsine and M. Singh, “State of charge and state of health estimation for electric vehicle battery,” in *Proc. IC2E3*, 2024, pp. 1–6. DOI: https://doi.org/10.1109/ic2e362166.2024.10827735

[7] M. T. Mumtaz Noreen, M. H. Fouladfar, and N. Saeed, “Evaluation of battery management systems for electric vehicles using traditional and modern estimation methods,” *Network*, vol. 4, no. 4, pp. 586–608, 2024. DOI: https://doi.org/10.3390/network4040029

[8] S. B. Sarmah, P. Kalita, A. Garg, X. Niu, X. Zhang, X. Peng, and D. Bhattacharjee, “A review of state of health estimation of energy storage systems: Challenges and solutions for lithium-ion battery packs in electric vehicles,” *J. Electrochem. Energy Convers.*

Storage, vol. 16, no. 4, 2019. DOI: https://doi.org/10.1115/1.4042987

[9] R. Swarnkar, H. Ramachandran, S. H. M. Ali, and R. Jabbar, "A systematic literature review of state of health and state of charge estimation methods for batteries in electric vehicles," *World Electric Vehicle Journal*, vol. 14, no. 9, pp. 247, 2023.

[10] G. R. Sylvestrin, J. N. Maciel, M. L. M. Amorim, J. P. Carmo, J. A. Afonso, S. F. Lopes, and O. H. Ando Junior, "State of the art in electric batteries' state-of-health estimation with machine learning: A review," *Energies*, vol. 18, no. 3, pp. 746, 2025. DOI: https://doi.org/10.3390/en18030746