**Advanced State of Charge Valuation and Battery Management** **Techniques for Enhanced Lithium-Ion Battery Performance in Electric Vehicles**

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# Abstract. Battery Management Systems are super important for making electrical cars and other devices like laptops and power banks work nicely and last a long time. These systems keep electric batteries reliable and efficient no matter the wear and tear. This paper reports a study on State of Charge (SOC) estimation methods based on model-based methods, such as Sliding Mode Observers (SMO), Unscented Kalman Filters (UKF), and Equivalent Circuit Models (ECM). The article also talks about exciting new functions being worked on for battery management systems (BMS). They are things like in real time getting a good estimate of how much power is left in a battery, cooling and managing all the internal heat that batteries create while they are working, and reusing energy that they collect to run the system all of which add up to better performance. An RC equivalent second-order circuit model is suggested to estimate SOC with high accuracy and an enhanced observer design to counteract estimation error. We're testing real time SOH or Status of Health monitoring as well and we're using a special kind of accelerator called FPGA-based test bed. This is while doing it in a way that also preserves battery lifespan and performance super well. Results are important steps forward towards next generation technology for batteries, which is super important for efficient and green electric vehicles.

# Keywords: State of Charge, Batery Management System, Lithium-Ion Battery, Sliding Mode Observer, Unscented Kalman Filter, Equivalent Circuit Model.

# INTRODUCTION

The growing usage of electric vehicles is fueling the need for lithium-ion batteries that are long-lasting, high-performance, and efficient. Well, batteries in electric vehicles are basically like the powerhouses of the car and that's a big reason why handling this stuff really matters for quality of drive, safety, and not hitting the wallet too hard [1]. Estimation of the battery stated of charge, which is a amount of capacity available in the battery, is one of the most important things in battery managing idea [2]. Getting SOC right is supremely important for keeping batteries charged effectively and for safe driving as well, lessening terrors that someone will run out of juice along the way for electric car owners [3]. Battery Management Systems are central to the monitoring and regulation of battery parameters like SOC, State of Health, temperature, and charging/discharging cycles [4]. Some SOC estimation techniques have been investigated, ranging from direct measurement methods to Coulomb counting, model-based methods, and artificial intelligence-based methods [5]. Model-based methods like Equivalent Circuit Models and observer-based estimation with the help of Kalman Filters or Sliding Mode Observers have been prominently focused upon based on their computation efficiency and precision balance [6]. Advanced SOC estimation techniques are discussed here in detail in terms of their analysis and implementation.

A second-order RC Equivalent Circuit Model is employed for precise SOC prediction, and an enhanced Sliding Mode Observer method is designed to improve estimation accuracy [7]. An FPGA-based hardware implementation is also presented for real-time SOC and SOH monitoring under dynamic EV operating conditions [8]. And we've got an energy recycling test station too that really cranks up the discharge of batteries and keeps energy use down during testing. That has to be worked out indirectly relying on some kind of rough estimates and there's always the chance that there will be some mistakes. Model-based techniques encompass the Equivalent Circuit Model , which employs electrical circuit elements to model battery dynamics, balancing computational efficiency and accuracy [9]. Kaalman Filtering Methods, such as the Extended Kalman Filter and Unscented Kalman Filter, enhance SOC estimation by including process and measurement noise, albeit at the expense of accurate system modeling. Sliding Mode Observers provide robustness to modeling errors and disturbances and are thus well suited for practical use [10]. Machine Learning-Based Methods like Artificial Neural Networks and Support Vector Machines learn SOC estimation trends from experimental data [11]. However they need large training datasets and high computational power.

Bookkeeping methods, such as the Coulomb Counting Method, track charge inflow and outflow using current integration. However, they suffer from cumulative errors due to sensor drift and dependence on initial SOC. The SOC can be estimated as:

(1)

Where SOC is the initial Soc, is the nominal battery ability, I(t) is the battery current.

Model-based approaches include the Equivalent Circuit Model, which uses electrical circuit components to represent battery dynamics, balancing accuracy and computational efficiency [12]. Kalman Filtering Techniques, including the Extended Kalman Filter and Unscented Kalman Filter, improve SOC valuation by incorporating process and measurement sound, although they require precise system modeling. The Kalman filter update equation is given as:

(2)

Where Xk|k is the estimated state, Kk is the gain of Kalman, Zk is the measured value, and H is the measurement matrix.

Sliding Mode Observers offer robustness against modeling inaccuracies and disturbances, making them suitable for real-world applications. The state-space representation for SMO can be expressed as:

(3)

Where X represents the state variables, A and B are system matrices, is the input and e is the sliding mode correction term.

Machine Learning-Based Approaches, such as Artificial Neural Networks and Support Vector Machines, learn SOC estimation patterns from experimental data. However, they require extensive training datasets and significant computational resources.

**METHODOLOGY**



**Model-Based Methods - Kalman Filter**

The Kalman Filter is an effective algorithm for estimating the State of Charge of batteries in electric vehicles and energy storage systems. SOC has to be estimated for battery performance enhancement and battery health monitoring [13]. The Kalman Filter is favorable because it has the ability to deal with noisy measurements and uncertain system dynamics. It does so by recursively making SOC estimates by using a state-space model of the battery voltage, current, and occasionally temperature [14]. In comparison with other SOC estimation algorithms, including open-circuit voltage measurement or basic Coulomb counting, the Kalman Filter is more robust and accurate and thus is extensively applied in real-time battery management systems [15]. It does demand accurate system modeling and computation and thus its complexity of implementation is higher.

Compute the Kalman Gain

(4)

Update the estimate uncertainty

(5)

**Open Circuit Voltage Method**

The Open circuited Voltage method is one of the most common methods for evaluating the State of Charge of a battery. It is based on the information that the SOC of the pack of battery is proportionally equal to the open-circuit voltage, i.e., the voltage of the battery when it is resting without any external load or charging current. OCV-SOC behavior in lithium-ion and lead-acid batteries is well understood and is very well approximated with this methodology. To apply the OCV technique, the battery has to be disconnected from any load and left for a period of time, usually from a few minutes to several hours, in order to exclude transient effects. After the voltage stabilizes, it is measured against an initially established OCV-SOC curve to estimate SOC. More robust and accurate SOC estimation can be realized for different battery-driven applications through the integration of OCV-based estimation with real-time measurement methods.OCV method Equation is given by

- (6)

(7)

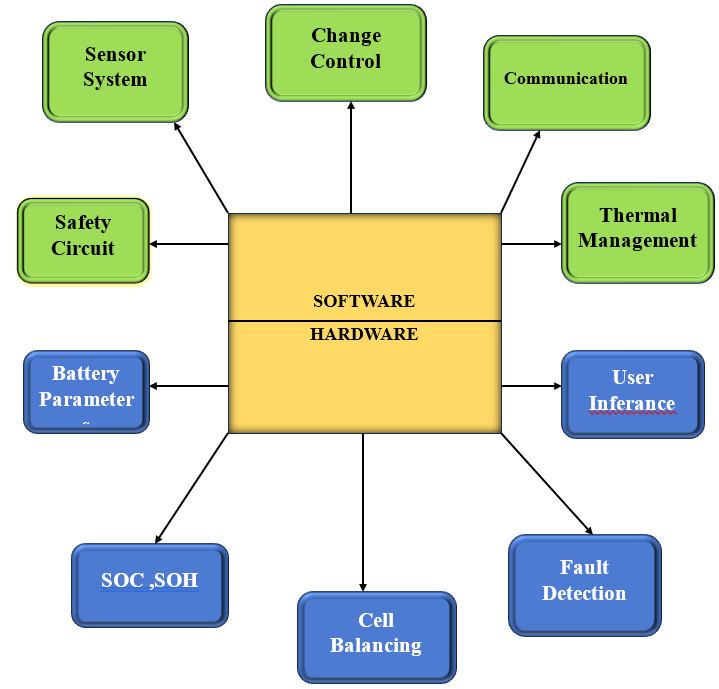
**Ampere Hour Integration**

The Amperehour Integration Method, also referred to the Coulomb Counting method , is a majorly used method used in battery State of Charge estimation. SOC is quantified as a time function by integrating current through a battery with reference value being initial SOC. The technique's governing equation is:

(t) = (0) + (8)

Where SOC is the battery's initial state of charge, Crated is the battery's rated capacity in ampere-hours (Ah), and I(t) is the current charging or discharging. Current is positive for charging, which raises SOC, and negative for discharging, which lowers SOC.

Even simple and utilized in real-time, Ampere-Hour is not a limitation-free measure. Sensor errors, current drift , and aging capacity all result in errors accumulating over time, i.e., SOC will be less accurate in the long run if not regularly recalibrated. Temperature changes and aging of the actual capacity of the battery will also result in further errors. Though limited in application, Ah integration is a simple and useful technique used for battery SOC estimation in many applications. Figure 1 represents the overview of SOC methodology.



**FIGURE 1.** Flow Chart of Overview of SOC Methodology.

**Electrochemical Impedance Spectroscopy**

Electrochemical Impedance Spectroscopy is a suitable means of estimating State of Charge of batteries through the measurement of their impedance responsed within a broad frequency range. The impedance spectrum, as a Nyquist plot, has well-defined features for double-layer capacitance, electrolyte resistance, and Warburg impedance, all of which are SOC level-dependent.

(9)

(10)

(11)

# (12)

With the calibration of these impedance parameters to SOC via equivalent circuit models or machine learning algorithms, accurate SOC estimation can be attained. In contrast to other voltage or current-based SOC estimation techniques, EIS is more informative about battery condition, internal resistance variations, and degradation processes and, thus, it is highly beneficial for application to lithium-ion and other rechargeable battery types. This advancement in battery technology can make SOC estimation using EIS an integral part of maintaining improved battery performance, safety, and lifespan, especially for electric vehicles and renewable energy storage systems.

**MACHINE LEARNING METHODS**

State of Charge evaluation is important in battery managing systems to enable safe and efficient operation. Machine Learning techniques have become increasingly used for SOC estimation because they can represent non-linear battery dynamics and learn from wide-ranging operating conditions. As battery technology continues to improve, ML-based SOC estimation is increasingly becoming adept at offering real-time accurate and reliable solutions for electric vehicles, renewable energy storing systems, and portable electronics. The future research involves improvement of model robustness, decreased training time, and enhanced explainability to allow for practical utilization in battery management systems.

(13)

(14)

) + ) (15)

**Battery Management Techniques**

State of Charge evaluation is crucial for battery management systems to guarantee safe and efficient operation. Machine Learning methods are gaining popularity for SOC estimation since they can define non-linear battery behavior and adjust to various operating conditions.

Battery Management System has a critical role in managing and monitoring discharging and charging of battery packs safely, for extended life, and for optimal performance. State of Charge estimation as a significant application of a BMS approximates the amount of energy left in a battery. SOC estimation has to be precise in electric vehicles, renewable power systems, and mobile phones. There are various SOC estimation techniques, e.g., the Coulomb Counting technique that calculates input and output of charge but incurs drift error over a long period. Open Circuit Voltage provides better estimates during periods of inactivity in the battery but is impractical for real-time use. Model-based techniques, i.e., Kalman Filter and Artificial Neural Networks, provide accurate SOC estimation via dynamics of battery and external conditions. Figure 2 represents the SOC Estimation Techniques

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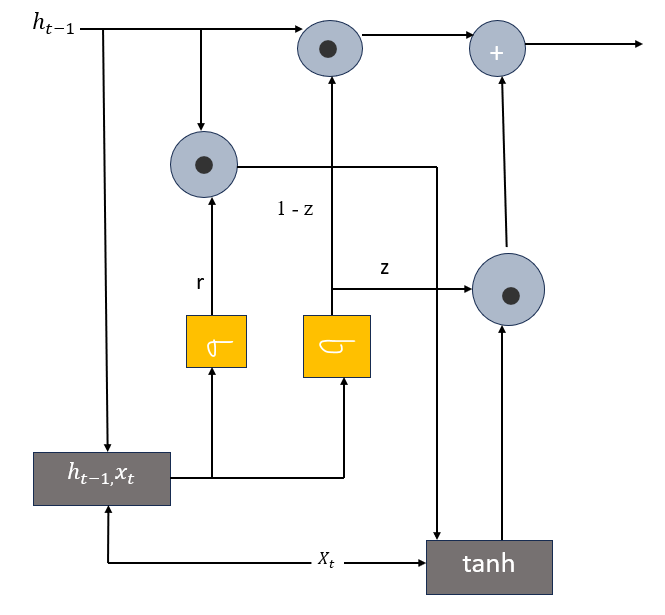
**FIGURE 2.** Flow Chart of Battery SOC estimation techniques.

# Sophisticated BMS methods utilize combinations of methods to enhance reliability and accuracy. Compensating temperature, cell balancing, and communication protocols like SMBus enhance BMS performance even more. Machine learning and data-driven methods are also popular and offer real-time adaptive SOC estimation for efficient performance. As battery technology improves, BMS methods also enhance, enabling safer and more efficient energy storage for new applications.

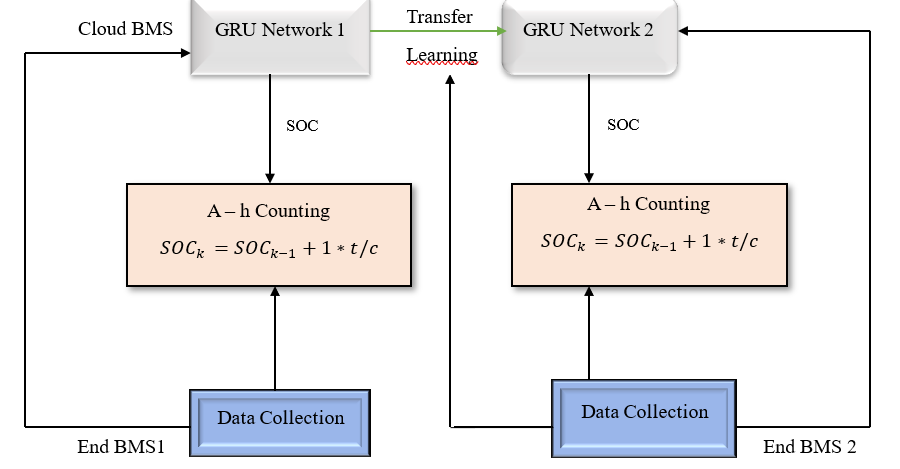
# SIMULATIONS AND RESULTS

Comparison and simulation of advanced State of Charge evaluation and Battery Management System methods are thoroughly important to improve lithium ion battery performance in electric vehicles. For comparing the performance of SOC estimation algorithms, simulations are performed with MATLAB/Simulink, Python, or other dedicated battery modeling software. The simulations utilize a range of SOC estimation methods including Exceeded Kalman Filter, Unscented Kalman Filter, and machine learning methods including Artificial Neural Networks. The models take into account actual driving conditions, temperature fluctuations, and battery aging effects to make them accurate and reliable. Simulation results verify that sophisticated SOC estimation algorithms compare favorably against traditional methods such as Coulomb Counting and Open Circuit Voltage methods due to their decrease in errors along with their versatility under dynamic modes of operation. Figure 3 shows the Simulation of Coloumb Counting and OCV Method.

For example, Kalman Filter-based techniques are more accurate at an error rate of under 2%, while machine learning models enhance their adaptability with sophisticated scenarios. Moreover, the cell balancing techniques employed in the BMS prevent battery aging via balanced charges' distribution among cells, which lightens their burden and prevents thermal runaway. Effectiveness of these techniques is also measured in terms of performance-oriented parameters such as energy efficiency, charging time improvement, and degradation metrics assessment. The virtual results showed that optimized SOC estimation would improve the range prediction of EVs, thereby leading to better energy use as well as longer battery life. Figure 4 represents the Virtual Representation Of optimized SOC estimation

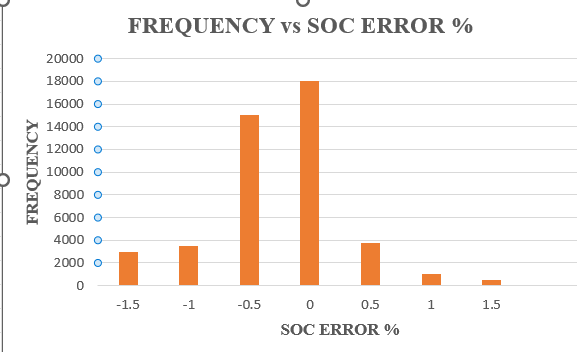


**FIGURE 3.** Simulation of coulomb counting and OCV method.

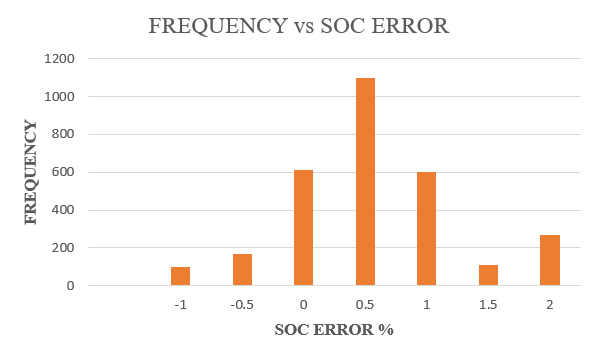


**FIGURE 4.** Virtual representation of optimized SOC estimation.

The future of BMS simulation will come with AI-based predictive maintenance and real-time diagnostics algorithms to further improve lithium-ion battery efficiency. All these advancements are key in making EVs efficient and dependable, hence more sustainable and practical for mass consumption. Figure 5 represents the results of earliest SOC estimation method. Real-time evaluation of SOC is replaced with an accurate initial SOC value provided by the GRU network in the Cloud BMS system. A validation of the GRU network performance is conducted using NCA dataset information. The training takes place using mixed cycles and then follows testing with the HWFET cycle. A figure (Figure 5) displays the voltage and current characteristics of the HWFET system. The SOC reaches precise estimation using a 100-second measurement combination of voltage, current and temperature under the GRU network. Figure 6 shows the results of optimised SOC estimation method.



**FIGURE 5.** Results of earliest SOC estimation method.



**FIGURE 6.** Results of optimised SOC estimation method.

We use the NCA dataset to do training and trained GRU network with NCA dataset as pre train network. In transfer learning, we first set up the starting point of a new GRU network to be a pre trained network, which is utilised for training a GRU network for estimating SOC in NCM battery. Transfer learning is trained and the NCM battery data in the 60th and 120th DST cycles are used as inputs to the validation of the performance of transfer learning using the NCM battery data in the 300th DST cycle.

**CONCLUSION**

SOC estimation serves as the progress of lithium-ion battery technology, in which it occupies the important position in the efficiency, reliability, and durability of electric vehicles and energy storage systems. Nonlinear behavior of lithium-ion batteries, temperature variations, and aging conditions are the obstacles to SOC estimation. Traditional methods such as Open Circuit Voltage and Coulomb counting, although becoming the standards, have limitations that make long-term accuracy impossible. The solution to the same arrived in the form of advanced estimation techniques such as Kalman filters, Sliding Mode Observers, and cloud models of artificial inteligence. These techniques support computational power, real-time data analysis, and machine learning to impact estimation accuracy while eliminating classical limitations.Among all of them, Unscented Kalman Filter and SMO proved to be the best among the rest with their strength against dynamic conditions but also with accurate SOC prediction functionalities that are necessary in order to optimize the battery performance. Cloud solutions, nonetheless, provide scalability in how they can offload the computing burden of embedded battery management systems in a manner that it can still provide continuous SOC monitoring unintermittently in large deployments. While with improved features, problems like having heavy computing loads, data safety concerns, and temperature-based differences are areas for future research efforts.

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