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State of Charge Monitoring and Estimation in Electric Vehicles: A Comprehensive Review

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Abstract: The state of charge (SOC) of a battery is a key parameter for the safe and efficient operation of electric vehicles (EVs), as it directly affects driving range estimation, energy management, and battery protection. Accurate SOC estimation is challenging due to the nonlinear behavior of batteries, variations in operating conditions, temperature effects, and aging phenomena. This paper presents a comprehensive review of SOC monitoring and estimation techniques for electric vehicle applications. First, the fundamental concepts of battery SOC, key battery characteristics, and the role of SOC in battery management systems are discussed. Subsequently, a detailed review of conventional, model-based, and data-driven SOC estimation methods is provided, highlighting their underlying principles and practical applications. The performance of existing approaches is then compared in terms of estimation accuracy, robustness, computational complexity, and suitability under real-world driving and charging conditions. Key challenges and limitations associated with current SOC estimation techniques are identified. Finally, emerging research trends and future directions toward intelligent, adaptive, and real-time SOC estimation frameworks are outlined, followed by concluding remarks on the development of reliable SOC estimation strategies for next-generation electric vehicles.

Keywords: State of Charge (SOC), Electric Vehicles, Battery Management System (BMS), SOC Estimation, Lithium-Ion Batteries, Model-Based Estimation, Data-Driven Methods, Machine Learning, Battery Monitoring.

I. INTRODUCTION

The rapid growth of electric vehicles (EVs) has intensified the demand for reliable and efficient battery management systems to ensure safety, performance, and user confidence. Among various battery state parameters, the state of charge (SOC) plays a crucial role, as it represents the available capacity of a battery relative to its rated capacity. Accurate SOC information is essential for estimating driving range, optimizing energy management strategies, enabling safe charging and discharging, and preventing overcharging or deep discharging of the battery.Unlike conventional fuel gauges, SOC cannot be measured directly and must be estimated using battery terminal measurements such as voltage, current, and temperature. However, the electrochemical behavior of lithium-ion batteries is highly nonlinear and influenced by several factors, including operating conditions, temperature variations, load dynamics, and battery aging. These complexities make SOC estimation a challenging task, particularly under real-world driving scenarios where current profiles are highly dynamic and unpredictable.

Accurate SOC estimation is critical not only for vehicle-level functions but also for advanced applications such as fast charging, regenerative braking, energy optimization, and vehicle-to-grid interactions. Inaccurate SOC estimates may lead to range anxiety, reduced battery lifespan, safety risks, and inefficient utilization of energy resources. Consequently, improving the accuracy and robustness of SOC estimation techniques has become a major research focus in the development of next-generation EV battery management systems.Over the past decades, a wide range of SOC monitoring and estimation methods have been proposed, ranging from conventional techniques such as Coulomb counting and open-circuit voltage–based approaches to advanced model-based and data-driven methods. Recently, artificial intelligence and machine learning techniques have gained significant attention due to their ability to capture complex nonlinear relationships and adapt to varying operating conditions. Despite these advancements, no single SOC estimation method can universally satisfy the requirements of accuracy, robustness, computational efficiency, and real-time applicability.

In this context, this paper presents a comprehensive review of SOC monitoring and estimation techniques for electric vehicle applications. The review aims to summarize the fundamental concepts of battery SOC, systematically classify existing estimation methods, and critically analyze their performance and limitations. Furthermore, current challenges and emerging research directions are discussed to provide insights into the development of intelligent, adaptive, and reliable SOC estimation frameworks for future electric vehicles.

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II. BACKGROUND AND FUNDAMENTALS OF BATTERY STATE OF CHARGE

A. Definition of State of Charge

The state of charge (SOC) is a key indicator used to describe the available energy in a battery relative to its nominal or rated capacity. It is typically expressed as a percentage, where 100% SOC represents a fully charged battery and 0% SOC corresponds to a fully discharged state. Mathematically, SOC can be defined as the ratio of the remaining charge to the maximum charge capacity of the battery. Since direct measurement of stored charge is not feasible, SOC must be estimated using measurable battery parameters such as terminal voltage, current, and temperature.

B. Battery Characteristics Relevant to SOC Estimation

Lithium-ion batteries, which are widely used in electric vehicles, exhibit complex electrochemical behavior that significantly influences SOC estimation. Key battery characteristics include nonlinear voltage–SOC relationships, rate-dependent capacity, hysteresis effects, internal resistance variation, and thermal sensitivity. Additionally, battery capacity degrades over time due to aging mechanisms such as solid electrolyte interface formation and lithium plating, leading to changes in internal parameters. These characteristics vary with operating conditions and battery chemistry, making accurate SOC estimation challenging under real-world driving scenarios.

Table No: 1 Background and Fundamentals of Battery State of Charge (SOC)

Aspect	Description	Relevance to SOC Estimation
Definition of SOC	SOC represents the ratio of remaining battery capacity to its nominal capacity, usually expressed as a percentage.	Forms the basis for energy availability, range prediction, and battery protection.
Battery Characteristics	Includes nonlinear voltage–SOC relationship, internal resistance variation, hysteresis, temperature sensitivity, and aging effects in lithium-ion batteries.	Strongly influences SOC estimation accuracy and model selection.
Temperature Effects	Battery performance and parameters vary with temperature, affecting voltage response and capacity.	Causes estimation errors if not compensated in SOC algorithms.
Battery Aging	Capacity fades and increases in internal resistance over time due to electrochemical degradation.	Leads to parameter mismatch and long-term SOC drift.
Measurement Uncertainties	Sensor noise and errors in current, voltage, and temperature measurements.	Accumulates errors, especially in integration-based methods.
Dynamic Load Conditions	Rapid current changes due to acceleration, regenerative braking, and fast charging.	Challenges real-time SOC estimation under practical EV operation.
Role in BMS	SOC is a core input for battery management functions such as charge control, thermal management, and cell balancing.	Enables safe operation, efficient energy use, and extended battery life.
Application Impact	Influences driving range estimation, fast charging strategies, and vehicle-to-grid operations.	Critical for user confidence and system-level optimization.

C. Factors Affecting SOC Estimation Accuracy

Several factors impact the accuracy and reliability of SOC estimation methods. Measurement errors in current, voltage, and temperature sensors can lead to cumulative estimation errors, particularly in integration-based methods. Temperature variations affect internal resistance and battery dynamics, while aging alters capacity and model

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parameters over time. Dynamic load conditions, regenerative braking, and fast charging further complicate SOC estimation due to rapidly changing current profiles. Model uncertainties and parameter mismatches also contribute to estimation inaccuracies, emphasizing the need for adaptive and robust estimation techniques.

D. Role of SOC in Battery Management Systems

SOC estimation is a fundamental function of the battery management system (BMS) in electric vehicles. Accurate SOC information enables reliable driving range prediction, safe charging and discharging control, and effective energy management strategies. It also supports advanced BMS functions such as cell balancing, thermal management, fault diagnosis, and protection against overcharge and deep discharge. Furthermore, SOC plays a critical role in emerging applications such as fast charging, regenerative energy recovery, and vehicle-to-grid operations. Therefore, improving SOC estimation accuracy and robustness is essential for enhancing battery safety, performance, and lifespan in electric vehicle systems.

III. SOC MONITORING AND ESTIMATION TECHNIQUES

SOC estimation techniques for electric vehicle batteries can be broadly classified into conventional methods, model-based approaches, and data-driven techniques. Each category differs in terms of estimation accuracy, computational complexity, robustness, and suitability for real-time implementation in battery management systems as shown in figure 1.

A. Conventional SOC Estimation Methods

Conventional SOC estimation methods are widely used due to their simplicity and ease of implementation. One of the most common techniques is Coulomb counting, which estimates SOC by integrating the battery current over time. While this method is straightforward and computationally efficient, it is highly sensitive to current measurement errors and initial SOC uncertainty, leading to error accumulation over long-term operation.Another widely used approach is the open-circuit voltage (OCV) method, which estimates SOC based on the relationship between battery OCV and SOC. This method provides good accuracy under equilibrium conditions; however, it requires the battery to remain at rest for a sufficient period, making it unsuitable for real-time EV operation. Hybrid approaches combining Coulomb counting and OCV correction are often employed to improve estimation accuracy in practical applications.

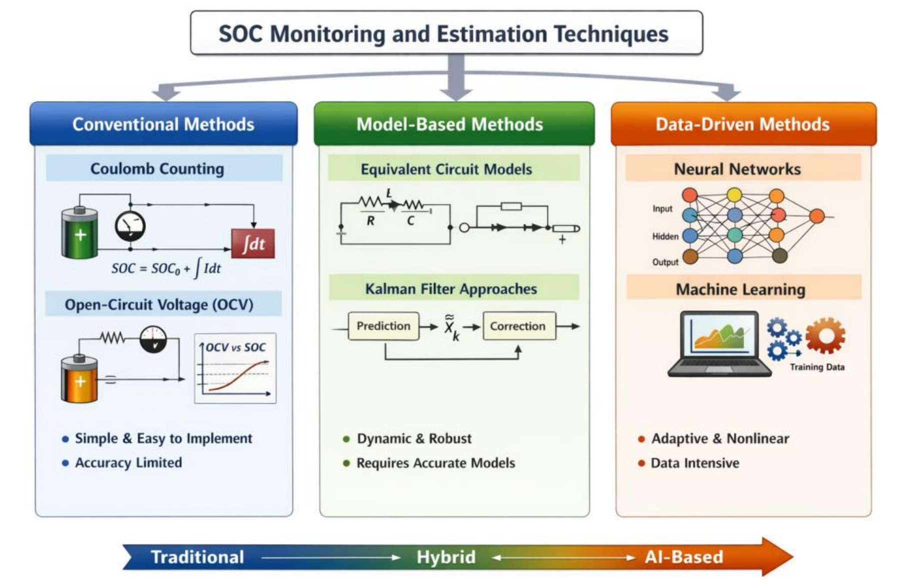

Figure no 1: SOC estimation techniques overview

B. Model-Based SOC Estimation Techniques

Model-based SOC estimation methods utilize mathematical battery models to represent the dynamic behavior of the battery. Equivalent circuit models, such as the Rint model and Thevenin-based models, are commonly adopted due to their balance between accuracy and computational efficiency. These models are often combined with estimation algorithms such as Kalman filters, extended Kalman filters (EKF), unscented Kalman filters (UKF), and particle filters to estimate SOC in real time.

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Electrochemical models provide a more detailed representation of battery internal processes and offer higher estimation accuracy. However, their high computational complexity and parameter identification requirements limit their real-time applicability in EV battery management systems. Model-based approaches generally offer improved robustness and adaptability compared to conventional methods but require accurate model parameterization and continuous updating to account for battery aging and temperature effects.

C. Data-Driven and Artificial Intelligence–Based Methods

Data-driven SOC estimation techniques have gained significant attention in recent years due to advances in machine learning and computational intelligence. These methods rely on historical and real-time battery data to learn the nonlinear relationship between input variables such as voltage, current, and temperature, and the corresponding SOC. Commonly used techniques include artificial neural networks, support vector machines, fuzzy logic systems, and deep learning models. Machine learning–based approaches can achieve high estimation accuracy under complex and dynamic operating conditions without requiring explicit battery models. However, their performance strongly depends on the quality and diversity of training data, and they may suffer from poor generalization when operating conditions deviate from the training dataset. Hybrid methods that combine model-based and data-driven techniques are increasingly explored to leverage the strengths of both approaches while mitigating their individual limitations as shown in figure 2.

IV. CHALLENGES, PERFORMANCE COMPARISON, AND EVALUATION METRICS

Accurate and reliable SOC estimation remains a challenging task due to the complex and nonlinear behavior of lithium-ion batteries and the demanding operating conditions of electric vehicles. This section discusses the major challenges associated with SOC estimation, compares the performance of existing approaches, and outlines commonly used evaluation metrics.

A. Key Challenges in SOC Estimation

One of the primary challenges in SOC estimation is the nonlinear and time-varying nature of battery characteristics. Factors such as temperature fluctuations, battery aging, and varying charge–discharge rates significantly affect battery dynamics and degrade estimation accuracy. Sensor noise and measurement errors in current, voltage, and temperature further introduce uncertainty, particularly in long-term operation.Real-world driving conditions present highly dynamic current profiles due to frequent acceleration, regenerative braking, and fast charging, which pose difficulties for both conventional and model-based estimation methods. Additionally, battery aging leads to capacity fade and internal resistance changes, causing parameter mismatch in model-based approaches and reducing the effectiveness of fixed-parameter estimators.

B. Performance Comparison of SOC Estimation Methods

Conventional methods, such as Coulomb counting and OCV-based techniques, are computationally efficient and easy to implement but suffer from limited robustness and long-term accuracy. Coulomb counting is prone to drift over time, while OCV-based methods are unsuitable for real-time operation due to relaxation requirements.Model-based methods generally offer improved accuracy and robustness under dynamic conditions by incorporating battery dynamics into the estimation process. Kalman filter–based approaches can effectively handle measurement noise and system uncertainty; however, their performance depends heavily on accurate battery models and parameter tuning. Electrochemical model–based methods provide high accuracy but are computationally intensive, limiting their practical use in real-time battery management systems.

Data-driven and artificial intelligence–based methods demonstrate strong capability in capturing nonlinear relationships and adapting to complex operating conditions. These approaches often outperform traditional methods in terms of estimation accuracy; however, they require large, high-quality datasets and significant computational resources. Their generalization ability under unseen operating conditions and aging effects remains a key concern.

C. Evaluation Metrics for SOC Estimation

The performance of SOC estimation techniques is commonly evaluated using quantitative metrics such as root mean square error (RMSE), mean absolute error (MAE), and maximum estimation error. Robustness is assessed by examining performance under varying temperatures, aging conditions, and dynamic load profiles. Computational complexity and memory requirements are critical metrics for real-time implementation in embedded battery management systems.

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Additional evaluation criteria include convergence speed, stability, sensitivity to initial SOC errors, and adaptability to battery degradation. Comprehensive performance assessment under realistic driving and charging scenarios is essential to determine the suitability of SOC estimation methods for practical electric vehicle applications.

Figure no 2: Challenges, Performance Comparison, and Evaluation Metrics

D. Limitations of Existing Approaches

Despite significant advancements, no single SOC estimation method can simultaneously achieve high accuracy, robustness, low computational complexity, and adaptability under all operating conditions. Conventional methods lack long-term reliability, model-based approaches suffer from parameter dependency, and data-driven techniques face challenges related to data availability and interpretability. These limitations highlight the need for hybrid and adaptive SOC estimation frameworks that can balance performance and practicality.

V. FUTURE RESEARCH DIRECTIONS

Despite significant progress in SOC monitoring and estimation techniques, several open research challenges remain that warrant further investigation. One important research direction is the development of adaptive and self-learning SOC estimation algorithms that can automatically update model parameters to account for battery aging, temperature variations, and changing operating conditions. Such approaches are essential for maintaining long-term estimation accuracy throughout the battery lifespan.The integration of artificial intelligence with physics-based battery models represents another promising trend. Hybrid methods that combine model-based estimators with machine learning techniques can exploit both physical interpretability and data-driven adaptability. These methods have the potential to improve robustness under dynamic driving conditions while reducing reliance on extensive training datasets.

Advanced sensing and data acquisition technologies, including high-precision sensors and cloud-based monitoring platforms, are expected to enhance SOC estimation accuracy. In addition, the use of digital twin technology for batteries may enable real-time monitoring, predictive analysis, and fault diagnosis, thereby supporting more intelligent battery management strategies.Future research should also focus on reducing computational complexity and improving real-time feasibility for embedded battery management systems. Lightweight algorithms capable of operating efficiently on resource-constrained hardware are critical for large-scale EV deployment. Furthermore, standardized evaluation frameworks and benchmark datasets are needed to enable fair comparison and validation of SOC estimation methods under realistic driving and charging scenarios.

VI. CONCLUSION

This paper presented a comprehensive review of state of charge monitoring and estimation techniques for electric vehicle applications. The fundamental concepts of battery SOC, key influencing factors, and the role of SOC in battery management systems were discussed. Conventional, model-based, and data-driven SOC estimation methods were systematically reviewed and compared in terms of accuracy, robustness, computational complexity, and practical applicability. Although significant advancements have been achieved, existing SOC estimation approaches continue to

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face challenges related to nonlinear battery behavior, aging effects, sensor uncertainties, and real-world operating conditions. No single method can fully satisfy all performance requirements, highlighting the need for hybrid, adaptive, and intelligent SOC estimation frameworks. Continued research in this area will play a crucial role in improving battery safety, extending battery lifespan, and enhancing the overall reliability and efficiency of future electric vehicles.

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