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Review on Robust State of Charge Estimation of EV Battery using Advanced Control Technique

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ABSTRACT: Battery technology has been a bottleneck in electric cars, and whether in theory or practice, research on battery management is extremely important, particularly for estimating the battery's state-of-charge. In fact, the battery has strong time-varying and non-linear properties, which are extremely complex. As a result, accurately estimating the state of charge is a challenging task. This study provides a comprehensive review of State of Charge (SOC) estimation methods for Lithium-Ion (Li-Ion) batteries, focusing specifically on Electric Vehicles (EVs). The increasing interest in EVs and the need for efficient battery management have driven advancements in SOC estimation techniques. Various approaches, such as data-driven techniques, advanced filtering methods, and machine learning algorithms, have been explored to enhance SOC estimation accuracy. The integration of artificial intelligence and hybrid models has shown promising results in improving performance. However, challenges persist in addressing non-linear battery behavior, temperature variations, and diverse operating conditions. Researchers continue to study ways to improve the robustness and adaptability of SOC estimation methods to overcome these challenges. The primary ideal of this study is to give an over- to- date summary of the rearmost Advancements in SOC estimation, offering perceptivity into innovative approaches and developments in the field. A comprehensive examination of all being SOC styles, along with their advantages, challenges, and operation rates, has been conducted, with a specific focus on EV battery operation systems. The future development direction is to establish a comprehensive database, improve hardware technology, create a better battery model, and fully leverage the advantages of each algorithm.

I. INTRODUCTION

When it comes to environmental pollution, many people associate it with cars. Indeed, traditional fuel-powered cars have contributed to issues such as the greenhouse effect and haze. As a result, attention is once again shifting toward new energy vehicles, especially electric-powered vehicles, which are expected to be the new trend in the future [1].In the early 2000s, EVs were still in the development stage. Limited progress in battery technologies resulted in low range capacities and high battery pack costs, which, in turn, led to a lack of interest in EVs [2]. However, since the 2010s, advancements in battery technologies, longer range capabilities, and fast charging technologies have significantly boosted the appeal of EVs. From the 2020s onwards, especially with the increase in range capacities, EVs have become a strategic focus for automotive manufacturers. Many automotive companies have shifted their focus to EV models, which has led to accelerated infrastructure development and an increase in the number of charging stations. According to the 'Global EV Outlook 2023' report published by the International Energy Agency, the total number of EVs worldwide has notably increased between 2010 and 2022 [3].

EVs provide a cleaner and more sustainable transportation option, but ensuring the safe operation of the batteries, their reliability, and driving safety is of utmost importance [4]. Li-Ion batteries, a type of rechargeable battery that relies on the movement of lithium ions between electrodes, have gained popularity due to their high energy density, lightweight design, and fast charging and discharging capabilities [5]. As the EV market has grown and developed, the cost of Li-Ion batteries has decreased, while their efficiency has increased. Consequently, Li-Ion batteries have become a widely used and effective energy storage solution for EVs. By using Li-Ion batteries, EV manufacturers can produce vehicles with higher performance, longer range, and better driving experiences. Based on data extracted from the Global Electric Vehicle Battery Market for 2023, the market size in this domain was \$50.5 billion. Projections suggest significant growth, with a substantial rise expected to reach \$500 billion by 2032 [6].

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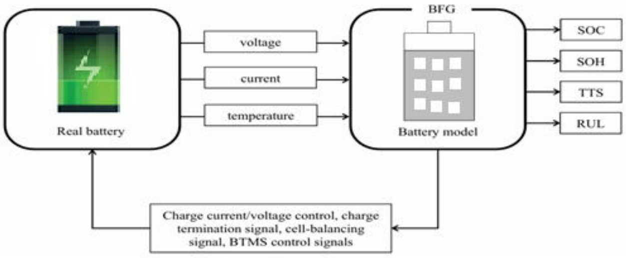

Figure 1. The general function of a battery management system (BMS)

The state of charge (SOC) of batteries in a battery management system is similar to the fuel meter in a conventional fuel car. The primary function of the SOC is to communicate the battery's status to the driver while also preventing issues such as overcharging and over-discharging. The state of charge (SOC) of batteries in a battery management system is similar to the fuel meter in a conventional fuel car. The primary function of the SOC is to inform the driver of the battery's status while also preventing issues such as overcharging and over-discharging [7, 8].

In fact, the estimation of SOC has been a topic of ongoing study. As we know, the battery is a highly complex and non-linear electrochemical element, and its performance depends on both its internal and external conditions. In fact, the estimation of SOC has been a topic of ongoing study. As we know, the battery is a highly complex and non-linear electrochemical element, and its performance depends on both its internal and external conditions. At the same time, the battery's performance should consider not only the performance of the individual battery but also the inconsistency of performance within the battery pack. Additionally, factors such as battery aging, cycle life, and temperature pose significant challenges to accurately estimating the battery's state of charge [9, 10]. In fact, scholars and researchers began studying SOC in the 1960s. Over the past half-century, there has been extensive scientific research on SOC estimation for batteries, yet this problem still requires a more effective solution [11, 12].

Therefore, this paper examines the existing SOC estimation methods to provide valuable insights for scholars, researchers, and automotive enterprises.

The structure of this paper is as follows: Section 1: Abstract, Introduction, and BMS. Section 2: Introduction to the concept of SOC. Section 3: Classification of SOC estimation methods, along with an analysis of their advantages and disadvantages. Section 4: Conclusion and suggestions.

Introduction to batteries state of charge (SOC)

SOC, typically expressed as a percentage (%), represents the maximum discharge capacity of a battery under specific temperature and discharge rate conditions, indicating the remaining capacity relative to the rated capacity and ensuring the battery remains undamaged [13].

$$\mathrm{SOC} = \frac{Q_c}{Q} \times 100\% = 100\% - \frac{Q_e}{Q} \qquad (1)$$

Where, Q_c is the remaining capacity of a battery, and Q is the maximum possible discharge capacity at rated temperature and C-rate. As the battery ages, this capacity decreases. Due to factors such as charge rate, discharge rate, temperature, self-discharge, efficiency factor, and battery aging, the definition of SOC requires adjustments in practical applications. The difficulty lies in understanding both the numerator and the denominator of the equation, where the denominator of Equation (1) represents the battery capacity. The definition of battery capacity is not consistent here. Typically, the denominator of Equation (1) uses the rated capacity, factory capacity, cycle capacity, or the current actual capacity of the battery [14, 15]. In theoretical analysis, the most commonly used capacity is the rated capacity, which serves as the classic definition for the denominator of Equation (1). This method treats the rated capacity as a fixed value, with SOC calculated by subtracting the amount of charge added ordischarged from the rated capacity [16]. Currently, most electric vehicles define SOC based on electric charge quantity. In this equation, Qc represents the residual power of the battery at the time of calculation, with its unit in Ah. Q refers to the total capacity of the battery,

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also measured in Ah [17], while Qe represents the battery charge. In fact, the battery typically varies with many factors, so this equation needs modification [18]. Equation (2) is more commonly used.

$$SOC\,(t) = SOCt_0 - \int_{t0}^{t} \frac{\eta I}{C_n} d_\tau \tag{2}$$

In this equation, SOC(t) represents the nominal capacity of the battery, with its unit in Ah. The coulomb efficiency, also known as discharged efficiency, refers to the ratio of the discharge capacity of a battery to the charge capacity in one loop (= Q/Qn). The entered charge often cannot convert all the active substances into electricity due to certain losses, such as irreversible side reactions in the battery. As a result, the value is usually less than 100%. In fact, current lithium-ion batteries have a coulomb efficiency of 99.9% or higher. This value can be obtained using the Peukert equation, by combining the measured residual charge and discharge current of thetwo batteries. However, in practice, measuring the coulomb efficiency is challenging, as it is highly influenced by factors like charge and discharge current, temperature, battery aging, and the internal resistance of the battery [19].

When discussing SOC, another important parameter to consider is the state of health (SOH), which reflects the aging degree of the battery. SOH is influenced by various factors. During the use of battery-powered vehicles, differences in temperature, ventilation conditions, self-discharge, electrolyte concentration, and other factors within the battery pack can increase inconsistencies in parameters such as battery voltage, internal resistance, and capacity, ultimately affecting the SOH value. The relationship between the two is as follows.

$$SOC\,(t) = SOH\,(t) - DOD\,(t) \tag{3}$$

In Equation (3), SOH(t) represents the state of health. When the battery is new, SOH is considered 100%. DOD(t) (depth of discharge) refers to the percentage of the battery's discharge relative to its rated capacity. DOD is considered when the discharge exceeds at least 80% of the battery's rated capacity.

II. LITERATURE REVIEW

State of Charge (SOC) estimation is a critical function in electric vehicle (EV) battery management systems (BMS), directly affecting performance, safety, and longevity. Among the various methods employed for SOC estimation, the Kalman Filter (KF), Extended Kalman Filter (EKF), and Deep Learning (DL) approaches represent three major technological paradigms—model-based linear, model-based non-linear, and data-driven, respectively.

The Kalman Filter is a widely used estimation algorithm for linear systems with Gaussian noise. It has been applied in early SOC estimation models, particularly when the battery is represented by a linear equivalent circuit model. KF is computationally efficient and easy to implement, making it suitable for real-time applications. However, it suffers from poor accuracy in highly non-linear systems such as lithium-ion batteries, where the voltage-SOC relationship is inherently non-linear. The foundational work by Plett (2004) demonstrated KF's potential, although its limitations led to the development of more advanced techniques.

The Extended Kalman Filter extends KF by allowing for non-linear dynamics through local linearization of the system around current estimates. EKF has become a standard in SOC estimation due to its balance between accuracy and computational efficiency. It is typically used with non-linear battery models, such as 2-RC or Thevenin models. EKF improves estimation accuracy over KF but still suffers from issues like sensitivity to model inaccuracies and tuning of noise parameters. It may also produce suboptimal results if the system exhibits high degrees of non-linearity. Literature by Zhang et al. (2017) has sought to improve EKF performance by introducing adaptive elements to counter battery aging effects.

In contrast, Deep Learning methods represent a shift from model-based to data-driven approaches. Neural networks, including Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs), have been leveraged to directly learn the relationship between input features (voltage, current, temperature) and SOC from historical battery data. These methods offer superior accuracy and adaptability, especially under complex driving conditions and battery degradation. However, they come with challenges such as the need for large datasets, high computational demand, and a lack of transparency in model decisions. Studies such as those by Li et al. (2020) and

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Zhang et al. (2021) illustrate the effectiveness of DL approaches, particularly when integrated with physics-informed constraints for better robustness and generalization.

Comparatively, KF is best suited for applications with limited computational resources and relatively simple system dynamics. EKF strikes a good balance for real-time onboard systems with moderate complexity, while DL-based methods are ideal for cloud-enabled or hybrid systems where high accuracy and adaptability are required. Each method carries trade-offs in terms of accuracy, computational load, interpretability, and robustness to battery aging. Emerging research increasingly focuses on hybrid methods that integrate model-based and data-driven approaches, aiming to leverage the strengths of both EKF and deep learning.

Aspect	Kalman Filter	Extended Kalman Filter	Deep Learning methods
Handling Non-linearity	Limited	Good	Excellent
Accuracy	Moderate	High	Very High
Computational Demand	Low	Moderate	High
Model Dependency	Linear Models required	Accurate battery models required	Data-driven (minimal model dependence)
Robustness to aging	Limited	Moderate	High
Real time feasibility	High	Moderate	Low-Moderate
System Type	Linear	Non-linear	Non-linear, data driven
Interpretability	High	Medium	Low

Table no 01: Comparative table for SOC estimation methods

III. METHODOLOGY OF PROPOSED SURVEY

The methodology of this survey involves a structured and comparative analysis of existing literature on Kalman Filter (KF), Extended Kalman Filter (EKF), and Deep Learning (DL) approaches used for State of Charge (SOC) estimation in electric vehicle (EV) batteries. The survey begins with a systematic literature review using academic databases such as IEEE Xplore, ScienceDirect, SpringerLink, and Google Scholar. Keywords including "SOC estimation," "Kalman Filter," "Extended Kalman Filter," "Deep Learning," "Electric Vehicle Batteries," and "Battery Management System" are employed to identify relevant studies published in the past two decades. Articles are filtered based on relevance, citation count, and the specificity of their contribution to SOC estimation techniques.

Each selected study is categorized according to the methodological approach: KF, EKF, or DL. For each category, we extract key performance indicators such as estimation accuracy, computational complexity, robustness to temperature and aging effects, real-time applicability, and data/model dependency. In addition to quantitative performance metrics, qualitative aspects such as interpretability, scalability, and integration potential with battery management systems are analyzed. For Kalman-based methods (KF and EKF), emphasis is placed on the battery modeling techniques used, such as equivalent circuit models and parameter identification strategies. For DL methods, attention is given to the network architecture (e.g., LSTM, CNN), dataset characteristics, training methodology, and generalization ability under varying conditions.

To ensure consistency in evaluation, a comparative framework is developed that aligns each method's strengths and limitations under common criteria. Where available, benchmark datasets or real-world testing scenarios are referenced to provide context. Finally, the survey synthesizes current research trends, identifies existing gaps in literature—such as lack of standardized datasets or hybrid model development—and offers directions for future research aimed at enhancing SOC estimation performance under practical EV operating conditions.

1. Kalman Filter

The fundamental concept of the Kalman Filter (KF) is the optimal design aimed at minimizing the variance of the power system's state.[20-21].It uses real-time measurements of battery voltage, current, and temperature to estimate the state of charge (SOC). The KF method for SOC estimation models the battery as a power system. The KF statistically models the battery's internal state and the correlation between measurements to deliver the most accurate estimate. [22].The measured voltage and current values are treated as state variables, with a system model applied accordingly. First, the KF employs the battery model and previous SOC estimates to predict the upcoming SOC. Next, the discrepancies between the actual measurements and the predicted SOC are analyzed, and an update process adjusts the estimated SOC, accounting for measurement errors to achieve the most accurate value [23]. The KF provides a real-time, adaptive approach for SOC estimation, effectively managing noise, errors, and uncertainties in system measurements to deliver a more reliable estimate.

The general mathematical representation of the battery model is as follows.
Equation of state:

$$X_{k+1} = f(X_{k,}U_K) + V_k \tag{4}$$

Equation of observation:

$$y_{k+1} = g(x_k, u_k) + w_k \tag{5}$$

In equation (4) and (5), u_k is the system input, typically representing variables such as current, temperature, residual charge, and internal resistance. yk+1 is the system output, typically representing the voltage, while xk is the system's state variable, including the estimated SOC. The functions f(xk, uk) and $g(x_k,u_k)$ represent the nonlinear equations derived from the battery model, which must be linearized during the calculation process.

The method's principle is illustrated in Figure 2. It represents the battery as a system with an equation of state and an observation equation, treats the SOC as an internal state, develops a state-space model, and performs minimum variance estimation for the SOC.

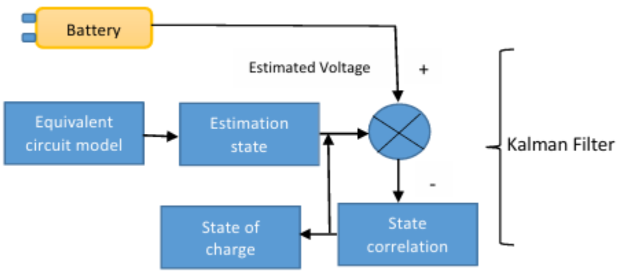

Figure 2. Principal of operation of the Kalman Filter

The KF algorithm is represented using the electrical equivalent model, as shown below, based on the PNGV model presented in Fig. 3. The state equations for the battery are provided in the following (6) and (7) and kalman filter algorithm to calculate its coefficient matrix.

$$\begin{bmatrix} u_b \\ u_2 \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ 0 & -\dfrac{1}{R_2\ C_2} \end{bmatrix} \begin{bmatrix} u_b \\ u_2 \end{bmatrix} = \begin{bmatrix} \dfrac{1}{C_b} \\ \dfrac{1}{C_2} \end{bmatrix} I \tag{6}$$

$$U_{ocv} = [-1\ -1] \begin{bmatrix} u_b \\ u_2 \end{bmatrix} + (-R_1 I) + U_{ocv} \tag{7}$$

where ub rep resents the voltage across the capacity Cb, u2 denotes the voltage across the circuit composed of R2//C2, R1 is the internal resistance, and Uocv represents the open-circuit voltage.

Its advantage lies in eliminating the error that accumulates over time in the ampere-hour integral method.

At the same time, it does not require high accuracy for the initial SOC. In other words, even with some deviation in the initial value, it can still converge effectively to the true value. Additionally, it can provide strong correction even in the presence of noise.

Its disadvantage is that the accuracy heavily depends on the construction of the battery equivalent model, with errors mainly arising from three factors: the model's time variability, its non-linearity, and the approximation of noise. In practical applications, it is commonly used in various types of batteries, particularly in hybrid-electric vehicles where current fluctuations are significant.

Currently, many improved methods have been developed based on this approach [23–25]. For instance, the Extended Kalman Filtering (EKF) method linearizes the nonlinear system, the Unscented Kalman Filtering (UKF) method modifies the KF by incorporating the transformation of U to address the nonlinear problem with a probability distribution, and the Central Difference Kalman Filtering (CDKF) method applies the central difference approach to the KF, among others.

2. Extended Kalman Filter

The EKF is a highly effective model-based method for state estimation, commonly applied in battery-related applications. SoC estimation using EKF is discussed in [26]–[27].

The EKF (Extended Kalman Filter) employs a two-stage predictor-corrector algorithm. In the first stage, the most recent state estimate and the error covariance are projected forward in time to generate a predicted state estimate. In the second stage, this predicted estimate is corrected by incorporating the latest process measurement. [32].

$$\begin{bmatrix} \frac{dU_1}{dt} \\ \frac{dU_2}{dt} \\ \frac{dsoc}{dt} \end{bmatrix} = \begin{bmatrix} \frac{-1}{R_1C_1} & 0 & 0 \\ 0 & \frac{-1}{R_1C_2} & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} U_1 \\ U_2 \\ SOC \end{bmatrix} + \begin{bmatrix} \frac{1}{C_1} \\ \frac{1}{C_2} \\ \frac{\eta}{Q} \end{bmatrix} [i\ Batt] \tag{8}$$

$$U = [-1 \ -1 \ \ E_m] \begin{bmatrix} U_1 \\ U_2 \\ SOC \end{bmatrix} + R_0\, [i\ Batt] \tag{9}$$

Principal of operation of the extended Kalman filter

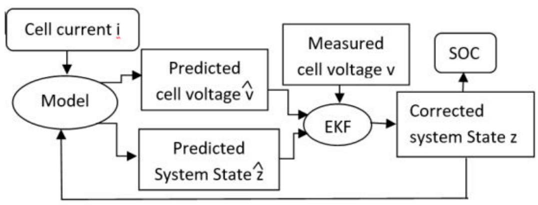

Figure. 3 Principal of operation of the extended Kalman filter

The EKF compares the measured cell voltage with the cell voltage predicted by a battery model. The model also predicts internal, immeasurable states, one of which is the SoC of the battery cell. In the second step, the EKF corrects

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the internal states by considering the estimated accuracies of both the measurement and the model prediction. This process results in a corrected estimation of the SoC.

3. Deep Learning

The black box battery model treats the battery as an unknown system, using measurable inputs such as current, voltage, temperature, and other parameters, while the battery's State of Charge (SOC) serves as the output. By applying intelligent algorithms, the model learns the relationship between the input and output data, as shown in Figure 4. Typically, the black box battery model utilizes techniques like neural networks, support vector machines, fuzzy algorithms, deep learning, and others to estimate the battery's SOC based on the input state parameters.

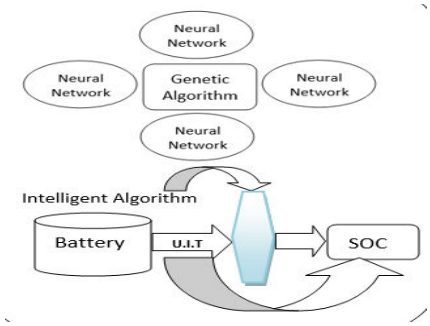

Figure 4. SOC estimation method based on black box battery model

The neural network model, inspired by the animal nervous system, adapts well to nonlinear systems. It typically includes an input layer, hidden layer, and output layer, as shown in Figure 5. The neural network model, inspired by the animal nervous system, is adaptable to nonlinear systems and consists of an input layer, hidden layer, and output layer.It supports multiple inputs and outputs, fault tolerance, self-learning, and is suitable for various batteries.However, it requires extensive training data and performs well only within the range of training samples.SOC estimation errors depend on the training data and methods, limiting its application.Often, it is combined with data clustering algorithms like fuzzy c-means (FCM) to reduce complexity and improve performance. [33,34].

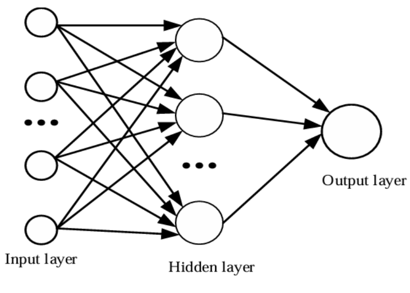

Figure 5. Typical neural network model structure

The support vector machine (SVM) is a well-established machine learning algorithm that minimizes structured risk to improve generalization, even with limited data. SVM is divided into support vector classification (SVC) for classification and support vector regression (SVR) for regression. It performs well in nonlinear, high-dimensional battery modeling and accurately estimates battery SOC.

Fuzzy algorithms mimic human reasoning and decision-making, using fuzzy variables to estimate battery SOC. Battery voltage, current, and temperature are converted into fuzzy values, which are processed through fuzzy rules based on experience. The result is then defuzzified to obtain the battery SOC value [35, 36].

Deep learning is a neural network with multiple layers that automatically extracts abstract features, enabling complex nonlinear mapping between input and output data. It uses simple neurons to form complex networks with strong

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generalization and parallel processing capabilities. Battery data like voltage, current, and temperature are input into the network, and the SOC is calculated through the hidden layers. While deep learning models offer high accuracy, they are computationally intensive and require significant resources. Algorithms such as deep belief networks (DBN), convolutional neural networks (CNN), and recurrent neural networks (RNN) implement deep learning. DBN combines unsupervised and supervised learning, reducing training error and improving prediction accuracy [37].A typical CNN architecture includes an input layer, convolutional layers, pooling layers, fully connected layers, and an output layer, as illustrated in Figure 5b. Through successive convolution and pooling operations using multiple filters, the CNN effectively extracts features from the data. However, in CNN and DBN networks, neurons within each layer are not interconnected, and their one-to-one input-output structure is not suitable for handling time series problems. In contrast, an RNN consists of an input layer (X), a hidden layer (Y), and an output layer (H). What sets RNNs apart is the presence of a delay mechanism that allows them to retain historical information [38] as shown in figure 5 c.RNNs are widely used to address time series data problems. However, they suffer from issues such as gradient explosion and vanishing gradients, which limit their ability to handle long sequences and restrict their effectiveness in practical applications. To overcome these limitations, models like Gated Recurrent Units (GRU) and Long Short-Term Memory (LSTM) networks have been developed. These models enhance the capabilities of RNNs by improving the functionality of hidden nodes. As a variant of the RNN, the LSTM model introduces a cell state mechanism that effectively addresses the shortcomings of traditional RNNs, offering a more robust solution for time series prediction [39].

GRU, a variant of LSTM, is designed to overcome the short-term dependency limitations of standard RNNs. It demonstrates strong robustness when the initial state of charge (SoC) is uncertain and effectively adapts to variations in ambient temperature [40].GRU-RNN can automatically learn network parameters using adaptive gradient descent algorithms. Unlike electrochemical and equivalent circuit models, which rely on complex differential equations and require extensive manual effort for modeling and parameter tuning, GRU-RNN eliminates the need for such hand-engineering [41].Compared to LSTM-RNN, GRU-RNN has a simpler architecture with fewer parameters, making it more effective on smaller datasets.

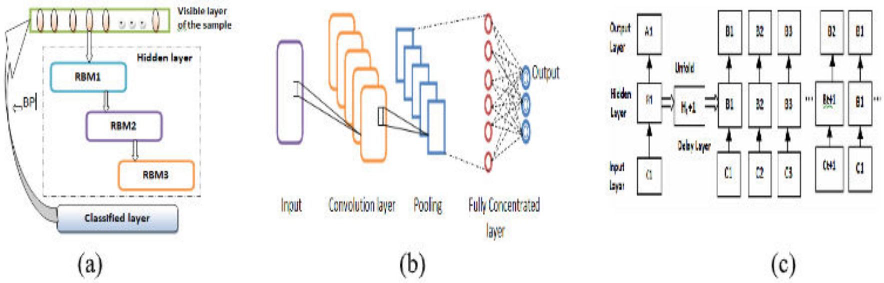

Fig.6 Deep learning structure: (a) structure of DBN; (b) structure of typical CNN; (c) structure of RNN

Genetic Algorithm (GA) is an intelligent optimization technique designed to solve both constrained and unconstrained, stochastic, and nonlinear problems, aligning with the ongoing advancement of optimization theory. GA features a high level of parallelism in its computational processes, allowing parallel execution during offspring generation and fitness evaluation. It possesses capabilities such as self-organization, self-adaptation, self-learning, and group-based evolution. Moreover, GA is characterized by its implicit parallelism and strong ability to explore the global solution space [42].The fitness function is the most critical component of a Genetic Algorithm (GA), as it directly determines the evaluation of each individual's performance within the population. There are no strict standards for designing a fitness function—it can be any function that appropriately reflects the objective of the optimization task. Since the algorithm relies entirely on the fitness function to guide the selection process, its design significantly influences both the efficiency and outcome of the GA. Compared to traditional identification methods, GA offers greater robustness, requiring only the objective function's value to randomly search for optimal parameters that satisfy given conditions. This makes it a feasible and efficient approach for optimizing the noise matrix in Extended Kalman Filter (EKF) applications [43].

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Genetic Algorithm (GA) is introduced for the online optimization of the system noise covariance and measurement matrix in the Extended Kalman Filter (EKF), enabling real-time estimation of the battery's State of Charge (SOC) with minimal model error. While GA is known for its complexity and relatively slow global search speed, it is also prone to getting trapped in local optima when facing multiple extreme values. However, through mechanisms such as selection, crossover, and mutation, GA can effectively escape local optima and perform a comprehensive global search. To enhance optimization efficiency, a hybrid intelligent identification method combining GA with Particle Swarm Optimization (PSO) is employed. This multi-algorithm collaborative approach leverages PSO's rapid convergence and GA's global search capabilities, allowing for efficient exploration of the feasible solution space and accurate identification of battery model parameters [44].The GA-based optimization method for the lithium-ion equivalent circuit model effectively captures the high dynamic behavior of lithium-ion batteries [45].

Genetic Algorithms (GA) are often integrated with neural networks to enhance the online optimization of system and measurement noise covariance matrices in the Extended Kalman Filter (EKF), enabling accurate real-time estimation of battery State of Charge (SOC) with minimal model error. Although GA has high computational complexity and a relatively slow global search process, it is capable of escaping local optima—common in multi-extreme-value problems—through evolutionary operations such as selection, crossover, and mutation. To further improve optimization performance, a hybrid intelligent identification approach that combines GA with Particle Swarm Optimization (PSO) is employed. While PSO tends to converge quickly but may get stuck in local optima, GA complements it by enhancing global search capabilities. This collaborative method efficiently explores the feasible solution space and achieves high-accuracy identification of battery model parameters [44].GA is also frequently combined with neural network algorithms for estimating the State of Charge (SOC) of power batteries. A novel approach has been proposed that integrates an Immune Genetic Algorithm (IGA) with a Back propagation (BP) neural network for improved SOC estimation [44, 45].

Advantages of Deep learning

I. Able to model complex nonlinear relationships between input variables and the state of charge (SOC).
II. Effectively captures the complex nonlinear interactions between input variables and the state of charge (SOC)
III. Has the ability to learn and represent complex nonlinear relationships between input variables and the state of charge (SOC)

Challenges of Deep learning

I. The performance largely relies on access to high-quality and diverse training data.
II. Choosing the right network architecture, learning rate, and other hyperparameters demands careful optimization and expert knowledge.
III. Without proper regularization or validation, ANNs may overfit the training data, leading to poor generalization on unseen data.

IV.CONCLUSION AND FUTURE WORK

Kalman Filter (KF), Extended Kalman Filter (EKF), and Deep Learning (DL) methods each offer unique advantages and challenges for estimating the State of Charge (SOC) of electric vehicle batteries.

- **Kalman Filter** is effective for linear systems with Gaussian noise, providing real-time, computationally efficient SOC estimation. However, its performance degrades when the battery system exhibits nonlinear behavior.
- **Extended Kalman Filter** extends KF to handle nonlinear dynamics by linearizing around the current estimate, improving accuracy in SOC estimation for nonlinear battery models. Despite this, EKF can struggle with strong nonlinearities and model inaccuracies, requiring careful tuning.
- **Deep Learning methods** excel at capturing complex nonlinear relationships in battery behavior without explicit modeling. They can achieve high accuracy in SOC estimation when trained on large, diverse datasets. However, DL approaches demand substantial computational resources, extensive training data, and may lack transparency compared to model-based filters.

In summary, while KF and EKF are well-suited for real-time SOC estimation in systems with known or moderately nonlinear dynamics, Deep Learning offers powerful capabilities for handling complex, nonlinear battery behaviors when sufficient data and computational resources are available. The choice depends on the specific application requirements, including accuracy, computational capacity, and availability of training data.

Future work in the domain of State of Charge (SOC) estimation for electric vehicle (EV) batteries is expected to explore several promising directions across Kalman Filter (KF), Extended Kalman Filter (EKF), and Deep Learning (DL) methodologies. For KF and EKF-based approaches, future research will likely focus on improving robustness to model uncertainties and battery aging. This includes developing adaptive or self-tuning Kalman filters that can adjust parameters in real time based on operating conditions, thereby reducing the reliance on precise battery models. Moreover, efforts will continue toward enhancing the accuracy of equivalent circuit modeling and parameter identification, potentially incorporating machine learning techniques to support model adaptation.

In the case of EKF, future studies may aim to integrate more advanced nonlinear filtering techniques, such as the Unscented Kalman Filter (UKF) or Particle Filter (PF), to better handle the strong non-linearities and non-Gaussian noise characteristics observed in real-world battery systems. There is also growing interest in hybrid models that combine physics-based EKF structures with data-driven learning modules, offering the benefits of physical interpretability and improved adaptability.

For deep learning methods, future work is anticipated to address key challenges related to data availability, generalization, and explainability. More extensive and standardized datasets covering diverse battery chemistries, aging states, and operational conditions are needed to train models that can generalize well across different scenarios. Additionally, integrating physics-informed neural networks (PINNs) and model-constrained architectures can help balance predictive power with physical plausibility. Research will also focus on improving the interpretability and trustworthiness of deep learning models, making them more viable for safety-critical applications in EVs.

Finally, cross-disciplinary efforts combining signal processing, control theory, and artificial intelligence are likely to lead to the development of next-generation hybrid SOC estimation frameworks. These would ideally leverage the strengths of both model-based and data-driven approaches, offering enhanced accuracy, real-time performance, and long-term adaptability in practical EV applications.

REFERENCES

1. Bilgin, B.; Magne, P.; Malysz, P.; Yang, Y.; Pantelic, V.; Preindl, M.; Korobkine, A.; Jiang, W.; Lawford, M.; Emadi, A.Makingthecaseforelectrified transportation. IEEE Trans. Transp. Electrif. 2015, 1, 4–17. [CrossRef]
2. V. Chobanov, K. Bojkov, Evaluation of economic and social effects of integrating a BMS system in residential and commercial housing, in: ISMSIT 2021 - 5th Int. Symp. Multidiscip. Stud. Innov. Technol. Proc, 2021, pp. 74–77, https://doi.org/ 10.1109/ISMSIT52890.2021.9604703.
3. International Energy Agency, Global EV Outlook 2015, Geo, 2015, pp. 9–10.
4. C.C. Chan, An overview of electric vehicle technology, Proc. IEEE 81 (1993) 1202–1213, https://doi.org/10.1109/5.237530.
5. J. Kim, V. Mathew, B. Sambanam, M.H. Alfaruqi, S. Kim, Recent developments of zinc-ion batteries, Energy-Sustainable Adv. Mater. 33 (2021) 27–57, https://doi. org/10.1007/978-3-030-57492-5_2.
6. Electric vehicle battery market sales projected to grow at 26.52% CAGR by 2032 driven by decreasing costs of lithium-ion batteries. https://www.globenewswire. com/en/news-release/2023/04/06/2642915 (accessed June 5, 2023).
7. Chaoui, H.; Golbon, N.; Hmouz, I.; Souissi, R.; Tahar, S. Lyapunov-based adaptive state of charge and state of health estimation for lithium-ion batteries. IEEE Trans. Ind. Electron. 2014, 62, 1610–1618. [CrossRef]
8. Lu,L.; Han, X.; Li, J.; Hua, J.; Ouyang, M. A review on the key issues for lithium-ion battery management in electric vehicles. J. Power Sources 2013, 226, 272–288. [CrossRef]
9. Bhatt, D.K.; Darieby, M.E. An Assessment of Batteries form Battery Electric Vehicle Perspectives. In Proceedings of the 2018 IEEE International Conference on Smart Energy Grid Engineering (SEGE), Oshawa, ON, Canada, 11–13 August 2018.

10. Meng,J.; Luo, G.; Breaz, E.; Gao, F. A robust battery state-of-charge estimation method for embedded hybrid energy system. In Proceedings of the IECON 2015-41st Annual Conference of the IEEE Industrial Electronics Society, Okohama, Japan, 9–12 November 2015.
11. Sun, F.; Xiong, R.; He, H. A systematic state-of-charge estimation framework for multi-cell battery pack in electric vehicles using bias correction technique. Appl. Energy 2016, 162, 1399–1409. [CrossRef].
12. Cai, C.; Du, D.; Liu, Z.; Ge, J. State-of-charge (SOC) estimation of high power Ni-MH rechargeable battery with artificial neural network. In Proceedings of the 9th International Conference on Neural Information Processing, Singapore, 18–22 November 2002.
13. C.F. Oeste, Battery state of charge calculation with EPC converters, in: Appl. Note - AN026. 5, 2020. www.epicpower.es
14. Dincer, I.; Hamut, H.S.; Javani, N. Thermal Management of Electric Vehicle Battery Systems; John Wiley & Sons: Hoboken, NJ, USA, 2016.
15. Rahn, C.D.; Wang, C.-Y. Battery Systems Engineering; Mechanical Industry Press: Beijing, China, 2018.
16. Xiaojun, T. Electric vehicle Battery Management System Design; Sun Yat-sen University Press: Guangzhou, China, 2011.
17. Fang, W.; Jun, X. Design and Manufacture of Battery Management System for Electric Vehicle, 2nd ed.; Science Press: Beijing, China, 2017.
18. Plett, G.L. Extended Kalman filtering for battery management systems of LiPB-based HEV battery packs: Part 3. State and parameter estimation. J. Power Sources 2004, 134, 277–292. [Cross Ref]
19. Gholizadeh, M.; Salmasi, F.R. Estimation of state of charge, unknown nonlinearities, and state of health of a lithium-ion battery based on a comprehensive unobservable model. IEEE Trans. Ind. Electron. 2013, 61, 1335–1344. [CrossRef]
20. Hiwa, S. Secondary Battery state-of-Charge Estimating Device and Secondary Battery State-of-Charge Estimating Method. WO Patent 2016129248A1, 18 August 2016.
21. Takechi, H. State-of-Charge Calculation Device, Computer Program, and State-of-Charge Calculation Method. WO Patent 2017183241A1, 26 October 2017.
22. P. Spagnol, S. Rossi, S.M. Savaresi, Kalman filter SoC estimation for Li-ion batteries, in: Proc. IEEE Int. Conf. Control Appl, 2011, pp. 587–592,
https://doi. org/10.1109/CCA.2011.6044480.
23. M. Mer, M.O. Gülbahçe, Batarya S ¸arj Durumu Kestirim Y¨ontemleri Üzerine ˙ Inceleme Review on the SOC Estimation Methods, 2022.
24. Zhang, X.; Wang, Y.; Yang, D.; Chen, Z. An on-line estimation of battery pack parameters and state-of-charge using dual filters based on pack model. Energy 2016, 115, 219–229. [CrossRef]
25. Cheng, S.; Zhang, Y.; Cheng, X.-F.; Zhang, X. State estimation using physics-based equivalent circuit models of a Li-ion cell and Kalman filter. In Proceedings of the IECON 2017-43rd Annual Conference of the IEEE Industrial Electronics Society, Beijing, China, 29 October–1 November 2017.
26. M. Rubagotti, S. Onori, and G. Rizzoni. Automotive Battery Prognos tics Using Dual Extended Kalman Filter. pages 257–263, Oct 2009
27. Amir Vasebi, Maral Partovibakhsh, and S. Mohammad Taghi Bathaee. A novel combined battery model for state-of-charge estimation in lead-acid batteries based on extended kalman filter for hybrid electric vehicle applications. Journal of Power Sources, 174(1):30– 40, 2007. Hybrid Electric Vehicles.
28. Xu,X.M.; Zhang, L.; Jiang, Y. Active Control on Path Following and Lateral Stability for Truck–Trailer Combinations. Arab. J. Sci. Eng. 2019, 44, 1365–1377. [CrossRef].
29. Yi, M.Q.; Zhao, W.G.; Pei, Y.M. Research on SOC estimation of lithium-ion battery based on DBN algorithm. Heilongjiang Electr. Power 2019, 41, 125–128.
30. Bai,S.ResearchonLi-ionBattery Life Prediction Method Based onDeepLearning. Master'sThesis, HarbinInstitute of Technology, Harbin, China, 2020.
31. Yang, F.; Song, X.; Xu, F. State-of-Charge Estimation of Lithium-Ion Batteries via Long Short-Term Memory Network. IEEE Access 2019, 7, 53792–53799. [CrossRef].
32. I.U. Khalil, SOC prediction of lithium-ion battery using extended Kalman filter, in: Encycl. Ocean Eng, 2022, pp. 517–521, https://doi.org/10.1007/978-981-10- 6946-8_300259.
33. Tong, S.; Lacap, J.H.; Park, J.W. Battery state of charge estimation using a load-classifying neural network. J. Energy Storage 2016, 7, 236–243. [CrossRef]

34. Zahid, T. Research on Estimation Algorithm of Power Battery State of Charge. Master's Thesis, University of Chinese Academy of Sciences (Shenzhen Institute of Advanced Technology, Chinese Academy of Sciences), Shenzhen, China, 2018.
35. Xu,X.M.; Zhang, L.; Jiang, Y. Active Control on Path Following and Lateral Stability for Truck–Trailer Combinations. Arab. J. Sci. Eng. 2019, 44, 1365–1377. [CrossRef]
36. Sheng, H.; Xiao, J. Electric vehicle state of charge estimation: Nonlinear correlation and fuzzy support vector machine. J. Power Sour. 2015, 281, 131–137. [CrossRef].
37. Yi, M.Q.; Zhao, W.G.; Pei, Y.M. Research on SOC estimation of lithium-ion battery based on DBN algorithm. Heilongjiang Electr. Power 2019, 41, 125–128.
38. Yi, M.Q.; Zhao, W.G.; Pei, Y.M. Research on SOC estimation of lithium-ion battery based on DBN algorithm. Heilongjiang Electr. Power 2019, 41, 125–128.
39. Bai,S.Research on Li-ion Battery Life Prediction Method Based onDeepLearning. Master's Thesis, Harbin Institute of Technology, Harbin, China, 2020.
40. Duan,W.; Song, C.; Peng, S.; Xiao, F.; Shao, Y.; Song, S. An Improved Gated Recurrent Unit Network Model for State-of-Charge Estimation of Lithium-Ion Battery. Energies 2020, 13, 6366. [CrossRef].
41. Li, C.; Xiao, F.; Fan, Y. An Approach to State of Charge Estimation of Lithium-Ion Batteries Based on Recurrent Neural Networks with Gated Recurrent Unit. Energies 2019, 12, 1592. [CrossRef].
42. Mu,J.Y.ResearchonModelErrorofLi-ionBatterySOCEstimationBasedonKF.Master'sThesis, JilinUniversity, Jilin, China, 2019.
43. Zhou, W.R.; Jiang, W.G. SOC estimation of lithium battery based on genetic algorithm to optimize extended Kalman filter. J. Chongqing Univ. Technol. 2019, 33, 33–39. [CrossRef] [PubMed].
44. Ma,J. Research on Online Estimation Algorithm of Electric Vehicle Power Battery Remaining Capacity Based on Data. Master's Thesis, Tianjin Polytechnic University, Tianjing, China, 2019.
45. Victor, P.-C.; Sandra, C.-S.; Marcelo, C.-C.; Fraile-Ardanuy, J.; Jimenez-Bermejo, D. GA-based approach to optimize an equivalent electric circuit model of a Li-ion battery-pack. Expert Syst. Appl. 2021, 172, 114647.