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SURVEY

Advancing State of Charge Management in Electric Vehicles With Machine Learning: A Technological Review

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ABSTRACT As the share of electric vehicles increases, electric vehicles are exposed to broader of driving conditions (e.g., extreme weather), which reduce the performance and driving ranges of electric vehicles below their nameplate rating. To ensure customer confidence and support steady growth in electric vehicle adoption rates, accurate estimation of battery state of charge and maintaining battery state of health through optimal charge/discharge decisions are critical. Recently, vehicle manufacturers have begun to employ machine learning techniques to improve state-of-charge management to better inform drivers about both the short-term (state of charge) and long-term (state of health) performance of their vehicles. This comprehensive review article explores the intersection of machine learning and state of charge management in electric vehicles. Recognizing the critical importance of the state of charge in optimizing electric vehicle performance, the article starts by evaluating traditional state of charge estimation methods. Subsequently, it delves into the transformative impact of machine learning techniques and associated algorithms on state of charge management. Through the lens of various case studies, this article demonstrates how machine learning-based state of charge estimation empowers electric vehicles to make informed and dynamic energy usage decisions, enhancing efficiency and extending battery life. The challenges of data availability, model interpretability, and real-time processing constraints are acknowledged as impediments to the widespread adoption of machine learning techniques. Despite these challenges, the future outlook for machine learning in the state of charge management appears promising, with emerging trends such as deep learning and reinforcement learning poised to refine the state of charge estimation accuracy. Moreover, this study sheds light on the transformative potential of machine learning in enhancing the state of charge management efficiency and effectiveness for electric vehicles, offering critical insights. Machine learning emerges as a game-changing force in state of charge management for electric vehicles, paving the way for intelligent and adaptive vehicles that are both environmentally friendly and efficient. This evolving field invites further research and development, making it a vital and exciting area within the automotive industry.

INDEX TERMS Machine learning, state of charge management, electric vehicles, battery management, state of charge estimation order.

NOMENCLATURE

Abbreviations	*Definition*
EV	Electric Vehicle.
SoC	State of Charge.
ML	Machine Learning.
ICE	Internal Combustion Engine.
HEV	Hybrid Electric Vehicle.
DC-DC	Direct Current to Direct Current.
LFP	Lithium Iron Phosphate.
NMC	Nickel Manganese Oxide.
LCO	Lithium Cobalt Oxide.

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A	Ampere.
Amp	Ampere-hours.
V	Volt.
FUDS	Federal Urban Driving Schedule.
FIGE	Freinage Intermittent à Grande Énergie.
SFUDS	Simplified Federal Urban Driving Schedule.
NEDC	New European Driving Cycle.
BTMS	Battery Thermal Management Systems.
EKF	Extended Kalman Filter.
RNN	Recurrent Neural Networks.
LSTM	Long Short-Term Memory.
RL	Reinforcement Learning.
ADAS	Advanced Driver Assistance Systems.
SVM	Support Vector Machines.
GB	Gradient Boosting.
GBM	Gradient Boosting Machine.
SOH	State-of-Health.
Li-ion	Lithium-ion.
IoT	Internet of Things.
ECM	Equivalent Circuit Model.
TCN	Temporal Convolutional Networks.
GNN	Graph Neural Networks.
RBF	Radial Basis Function.
AI	Artificial Intelligence.
GPU	Graphics Processing Unit.
TPU	Tensor Processing Unit.
CNN	Convolutional Neural Network.

I. INTRODUCTION

EVs have emerged as a pivotal bridge in the transition towards a more sustainable and eco-friendly transportation ecosystem. There are two types of EVs, namely plug-in HEVs which combine both ICEs and electric powertrains, and pure electric vehicles which rely only on onboard batteries for propulsion. In both cases, EVs promise reduced emissions, improved fuel efficiency, and increased energy sustainability [1], [2]. The performance and longevity of an EV heavily depend on the efficient management of its energy storage system, with one of the critical parameters being the SoC of the battery [3], [4].

The SoC represents the amount of energy stored in the battery relative to its maximum capacity and serves as a crucial metric in determining the available driving range and overall performance of the vehicle [5], [6]. Precise SoC estimation and management are imperative not only for optimizing the vehicle's fuel economy but also for ensuring the reliability and durability of the energy storage system, thereby enhancing the EV's long-term economic viability [6], [7].

Traditionally, SoC estimation has relied on physics-based models and simple empirical techniques [8], [9]. However, with the rapid advancements in technology and the growing volume of data generated by EVs, the application of ML has emerged as a transformative approach to tackle the intricacies of SoC management [10], [11]. In this paper, the term 'SoC management' refers to the comprehensive set of activities involved in controlling and maintaining the SoC within the battery. This includes but is not limited to, SoC estimation, which is specifically focused on predicting the current state of the battery. The broader term 'SoC management' encompasses actions taken to optimize battery performance, efficiency, and health, while SoC estimation is a subset within this context. Machine learning techniques, driven by big data analytics and computational power, offer the potential to revolutionize SoC estimation by providing accurate, adaptive, and real-time solutions [7], [12].

In recent years, a surge in research and development efforts has explored the integration of machine learning into EV SoC management [13], [14]. This has led to a paradigm shift in the way SoC is estimated and managed, presenting novel opportunities and challenges [14], [15]. This review article aims to comprehensively explore and evaluate the state of the art in machine learning applications for enhancing SoC management in EVs, with a specific focus on studies and advancements published from 2020 onwards.

The transition from traditional SoC estimation methods to machine learning-based approaches signifies a critical step toward the optimization of EV performance, energy efficiency, and environmental impact [16], [17]. The integration of machine learning models allows EVs to adapt to dynamic driving conditions, account for battery aging effects, and improve overall system robustness. Moreover, machine learning techniques enable EVs to tap into the potential of data-driven insights, further enhancing their role in the future of sustainable transportation [18], [19], [20], [21], [22].

In this review, we will delve into the diverse spectrum of machine learning methods and algorithms employed in SoC estimation for EVs. We will explore case studies and real-world applications, providing insights into the practical implications of these techniques. Additionally, we will discuss the challenges and limitations associated with machine learning-based SoC management, and we will identify promising directions for future research in this rapidly evolving field.

As the pace of transportation of electrification increases the confluence of machine learning and EV SoC management, it becomes evident that the fusion of these two domains holds the key to unlocking the full potential of electric vehicles. The subsequent sections of this review will elaborate on the multifaceted landscape of machine learning applications, bringing to light the innovations, trends, and challenges that shape the future of SoC management in EVs.

II. BACKGROUND

A. FUNDAMENTAL OF EVs

EVs are pioneering solutions in the realm of sustainable and efficient transportation, ushering in a new era of eco-conscious mobility. EVs ingeniously combine traditional ICEs with electric propulsion systems, culminating in vehicles that offer remarkable advantages such as reduced emissions, improved fuel efficiency, and a reduced carbon footprint [23], [24], [25].

In contrast to HEVs, where an ICE works in conjunction with an electric motor, EVs rely exclusively on an electric motor for propulsion, utilizing electrical energy as the sole power source, resulting in zero emissions. Referred to as battery electric vehicles, EVs utilize stored energy in batteries to power the electric motor [26]. The larger battery capacity in EVs, compared to HEVs, is essential since they exclusively depend on batteries for energy. Charging an EV battery is accomplished by connecting the vehicle to an external electricity source. Additionally, electric vehicles have the capability of recharging the battery through regenerative braking. The fundamental components of an EV comprise an electric motor, a battery, a DC-DC converter, a charger, and an electronic controller.

The EV propulsion system comprises three primary subsystems: the energy source, motor propulsion, and supplementary subsystem. Within the energy source subsystem, the energy source, along with its refueling unit and energy management unit, constitutes its components. The electric propulsion subsystem incorporates the motor, converter, torque transmission, wheels, and controller. Meanwhile, the supplementary subsystem is composed of a supplementary power source, a steering unit, and a climate control unit [27], [28], [29]. Notably, the travel range of EVs is considerably limited due to the lower energy storage capacity of the battery. The main structure of EVs is illustrated in Figure 1. Various configurations for EVs can be established based on distinct clutch, gearbox, transmission, and differential options, as well as the number of motors, as depicted in Figure 2. In Fig. 2a, an evolved EV configuration mirrors that of an internal combustion engine vehicle, wherein the engine is substituted with an electric motor. This setup features a clutch, a variable-speed gearbox, and a front axle differential. Fig. 2b showcases an EV configuration with a fixed gearbox and a front axle differential, omitting the need for a clutch due to the motor's ability to provide consistent energy across a broad speed range, resulting in reduced size and weight. The EV configuration in Fig. 2c retains the same components as Fig. 2b but integrates them for a simplified driving system. Fig. 2d incorporates two traction motors with fixed gearboxes on the front axle, designed for varied speeds on curved roads. Fig. 2e represents an in-wheel drive system with two traction motors situated within the EV's wheels, featuring a thin gear. Similarly, the drive system in Fig. 2f incorporates two motors inside the wheels without any gears, rendering this structure simpler compared to Fig. 2e [9]. All of these configurations have advantages and disadvantages. For example, the design of Fig. 2c is cost-effective and suitable for basic commuting needs, but it may lack fine-tuned control for specialized driving scenarios and exhibit limitations in advanced driving features (see Table1).

1) SIGNIFICANCE OF SOC IN EVS

A pivotal parameter in the operation of EVs is the SoC of the high-voltage battery pack. SoC represents the proportion of the battery's maximum capacity that is currently charged and plays a central role in determining the vehicle's performance, efficiency, and longevity [30], [31], [32]. A simple battery model is depicted in Figure 3 and mathematically, SoC is written as follows:

$$SOC\,(t) = \frac{S\,(t)}{S_0}, \tag{1}$$

$$\frac{dSOOC(t)}{dt} = -\frac{I_b\,(t)}{S_0}, \tag{2}$$

$$V_o\,(t) = V_{oc}\,(t) - R_b\,(t)\,I_b\,(t)\,, \tag{3}$$

$$I_b = \frac{V_{oc} - \sqrt{V_{oc}^2 - 4R_bP_m}}{2R_b}. \tag{4}$$

In the above relationships, S(t) is the current charge level of the battery (Ah), S_0 is its total capacity (Ah), I_b is the current of the cell (A), R_b is the internal resistance of the battery cell (in Ohms), P_m is the corresponding power of battery cell (in Watts), and V_{oc} is open-circuit voltage (V) [34], [35].

a: BATTERY CELLS

A battery cell is the basic building block of a battery pack. It is an electrochemical device that converts chemical energy into electrical energy [35]. Cells can be classified into various types based on the materials used to manufacture the cathode of the battery. Some of the widely used chemistries include NMC, LCO, and LFP [36]. In modern applications, lithium-ion cells are widely used due to their high energy density and other favorable characteristics. The typical voltage level of a single battery cell is around 3-4 Volts. Therefore, real-world battery applications including EVs require architectures that are composed of series and parallel connections of multiple battery cells. Details of series and parallel cell connections are given next.

i Series Connection: In a series connection, cells are connected end-to-end, with the positive terminal of one cell linked to the negative terminal of the next (Figure 4). From Kirchhoff's law, this increases the total voltage of the battery pack. A typical EV battery pack's voltage level is around 360V, which requires a series connection of one hundred 3.6V battery cells [37]. Series connections are common in EVs and other applications where a higher voltage is required. However, it's crucial to ensure that each cell in the series shares the load equally, as imbalances can lead to overcharging or discharging of individual cells.

ii Parallel Connection: In a parallel connection, cells are connected positive to positive and negative to negative, effectively increasing the capacity of the battery pack without changing the voltage (Figure 5). The primary goal, then, is to increase the current capacity (Ah). For instance, if you connect two 2000mAh cells in parallel, the total capacity would be 4000mAh. Parallel connections are often used to increase the overall capacity of a battery pack. Just like in series connections, it's

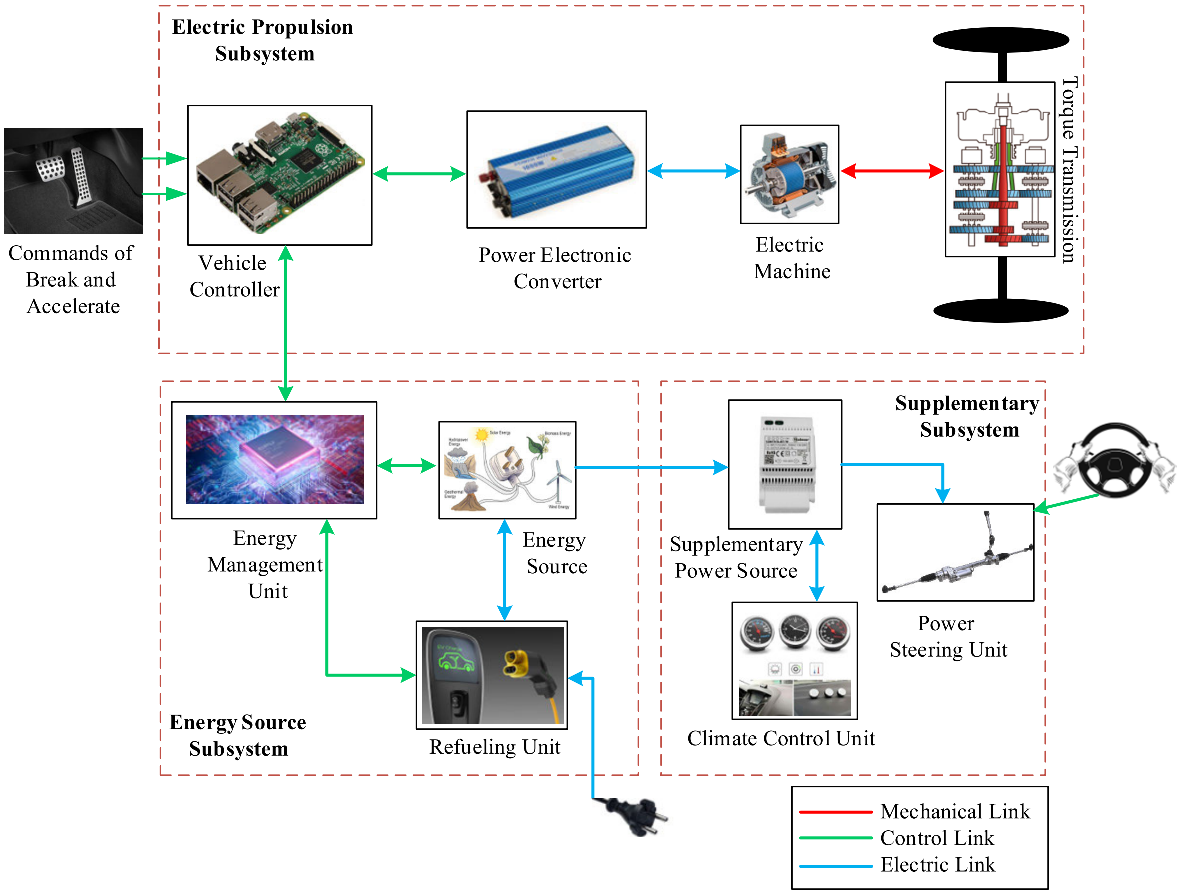

FIGURE 1. The EV's structure.

essential to ensure that cells in parallel share the load evenly to prevent overcharging or discharging of individual cells.

2) DRIVING RANGE AND ENERGY AVAILABILITY

Exploring the driving range and energy availability of EVs is a pivotal aspect that significantly influences overall performance and efficiency. Within this context, a comprehensive understanding of driving styles proves essential, with particular emphasis on the intensity of acceleration and deceleration maneuvers [34].

The distinctions between hard and soft acceleration, as well as hard and soft deceleration, unveil valuable insights into the driver's habits and preferences. Hard acceleration, characterized by rapid and forceful increases in speed, contrasts with the gentler, gradual nature of soft acceleration. Similarly, hard deceleration involves abrupt decreases in speed, whereas soft deceleration is characterized by smoother and more gradual slowing down [36].

These parameters extend beyond mere observations of driving habits; they play a fundamental role in determining the energy consumption patterns of an electric vehicle. How energy is expended during acceleration and recuperated during deceleration significantly impacts the overall driving range and efficiency of the EV [37]. This nuanced examination of driving styles gains heightened significance when considering the optimization of regenerative braking systems. Understanding how drivers accelerate and decelerate allows for the fine-tuning of these systems, thereby maximizing the recuperation of energy and, in turn, extending the driving range of the EV. Consequently, this not only enhances the vehicle's operational efficiency but also contributes to the broader goal of minimizing environmental impact. In summary, delving into the intricacies of driving styles offers a holistic perspective on energy utilization, providing a foundation for the development of strategies aimed at improving the driving range and overall sustainability of electric vehicles [38].

a) Hard Acceleration and Hard Deceleration

The Hard acceleration driving style involves swiftly increasing the vehicle's speed, often accompanied by a noticeable surge in engine power like FUDS [14]. Drivers who engage in hard acceleration tend to reach higher speeds rapidly, which can lead to increased fuel consumption and a more demanding strain on the vehicle's engine and braking system. Hard deceleration, in contrast, involves abrupt and forceful slowing down of the vehicle like FIGE [15]. This type of driving style can be characterized by sudden and heavy application of brakes, resulting in rapid speed reduction. While hard deceleration might be necessary in certain

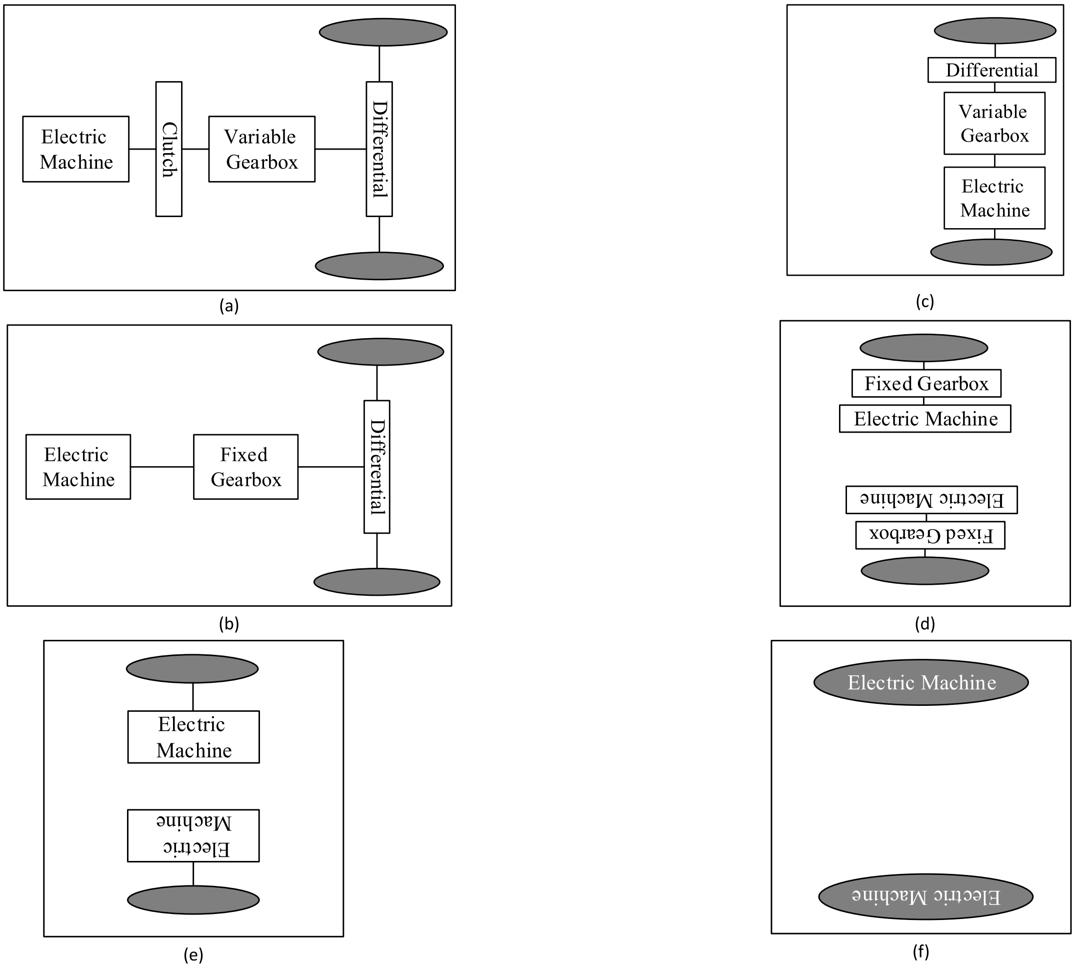

FIGURE 2. Various electric vehicle powertrain configurations [28].

emergencies, habitual use can lead to increased wear and tear on the braking system and tires.

a: SOFT ACCELERATION AND SOFT DECELERATION

Drivers who prefer soft acceleration opt for a gradual and smooth increase in speed. This driving style (SFUDS) is often associated with a more fuel-efficient approach, as it minimizes the strain on the engine and consumes less fuel [12]. Soft acceleration is generally considered a more relaxed and comfortable driving style, providing a smoother ride for passengers and reducing stress on the vehicle's components. Similarly, soft deceleration involves a gentle and gradual slowing down of the vehicle like NEDC [13]. This approach prioritizes smooth transitions between speeds, reducing the need for abrupt braking. Soft deceleration not only enhances passenger comfort but also contributes to better fuel efficiency and extends the lifespan of braking components. SoC significantly influences vehicle energy availability, impacting electric-only driving range and reducing reliance on the ICE [39], [40]. Figure 6 illustrates standard driving cycles. The electric driving range, crucial for EV adoption, is affected by battery capacity, driving style, and temperature. Low temperatures decrease range due to reduced Li-ion battery capacity. Developing BTMS is vital to mitigate temperature effects [41].

3) ENERGY EFFICIENCY

Energy efficiency in EVs is a multifaceted aspect influenced by various factors, with Wh/mile consumption being a key metric [41]. This metric, measured in watt-hours per mile, provides insights into how effectively the vehicle utilizes its electric power. Here are the primary factors impacting Wh/mile consumption:

a: DRIVING STYLE

Driving habits play a crucial role in determining energy efficiency. Smooth acceleration and deceleration, as well as maintaining a steady speed, can contribute to lower energy consumption. Regenerative braking, which recovers energy during deceleration, is a feature in many EVs that positively impacts energy efficiency [42]. For instance, the trials of [28] consistently showed a 12.16% reduction in

TABLE 1. Advantages and disadvantages of the EV's configuration.

Configuration of EV	Advantages	Disadvantages	Ref.
Figure 2a	Efficient power transition	increased complexity and potential maintenance costs	[8]
	Variable speed control for optimal performance	Higher manufacturing expenses	[9]
	Familiarity for users transitioning from traditional vehicles	Additional weight impacting overall efficiency	[10]
	Versatility in driving conditions	Limited energy efficiency compared to more specialized systems	[11]
	Regenerative braking capabilities	Potential heating issues with the clutch and variable speed gearbox	[12]
Figure 2b	Simplified design reducing manufacturing costs	Limited adaptability to diverse driving conditions	[9]
	Constant energy delivery enhances efficiency	Limited control over speed variations	[10]
	Lower weight improves overall efficiency	Reduced performance on challenging terrains	[12]
	Suitable for urban commuting	Potential overheating issues with constant energy delivery	[14]
	Reduced energy losses due to fixed gearbox	Difficulty in achieving optimal energy efficiency	[15]
Figure 2c	Streamlined design for manufacturing efficiency	May lack fine-tuned control for specialized driving scenarios	[10]
	Reduced maintenance complexities	Limited adaptability to advanced driving features	[10]
	Simplicity in user operation	Potential efficiency trade-offs	[11]
	Cost-effectiveness	Challenges in performance optimization	[13]
	Suitable for basic commuting needs	Reduced energy recovery capabilities	[16]
Figure 2d	Optimized performance on curved roads	Increased complexity and potential maintenance costs	[11]
	Enhanced acceleration capabilities	Challenges in synchronized performance	[15]
	Improved stability	Higher manufacturing expenses	[17]
	Efficient energy distribution	Limited adaptability to varied driving conditions	[18]
	Regenerative braking for energy recovery	Potential efficiency trade-offs with dual motors	[22]
Figure 2e	Direct power distribution for improved control	Challenges in unsprung mass and handling	[12]
	Enhanced traction and stability	Increased complexity impacting reliability	[15]
	Compact design improving efficiency	Potential manufacturing challenges	[17]
	Energy efficiency gains due to reduced mechanical losses	Limited adaptability to heavy-duty applications	[18]
	Simplified vehicle dynamics	Higher manufacturing costs for specialized components	[20]
Figure 2f	Simplified design for cost-effectiveness	Limited speed control without gears	[14]
	Reduced mechanical complexity	Challenges in optimal power distribution	[17]
	Enhanced maneuverability	Higher manufacturing costs for specialized designs	[19]
	Potential energy efficiency gains	Reduced performance in certain driving scenarios	[21]
	Streamlined maintenance	Limited adaptability to advanced driving features	[23]

Wh/mile consumption when participants adopted a smoother driving style.

b: WEATHER CONDITIONS

The Weather has a substantial impact on energy efficiency. Extreme temperatures, whether hot or cold, can affect the performance of the vehicle's battery. Cold weather, in particular, may reduce battery efficiency and overall range. Proper climate control management becomes essential to optimize energy use in varying weather conditions [43]. The findings of [30] indicate a 15.78% decrease in energy efficiency during extremely cold weather, highlighting the impact of temperature on battery performance.

c: HEATING/COOLING NEEDS

The demands of heating and cooling systems significantly contribute to energy consumption. In colder climates, heating the interior requires additional energy, affecting efficiency. Similarly, air conditioning in warmer climates can lead to increased energy use. Balancing comfort and energy efficiency becomes a critical consideration [44]. The analysis in [31] showed that heating in colder climates contributes to a 11.35% increase in energy consumption, underscoring the need for efficient climate control strategies.

d: REGENERATIVE SYSTEMS

Many EVs are equipped with regenerative braking and other regenerative systems that capture and reuse energy during deceleration. These systems contribute positively to energy efficiency by recycling energy that would otherwise be lost as heat during braking [44]. The experiments in [32] demonstrated a 23.62% improvement in energy efficiency due to regenerative braking systems, showcasing their substantial contribution to overall EV efficiency.

e: VEHICLE DESIGN AND TECHNOLOGY

The overall design of the vehicle, as well as technological advancements, can impact energy efficiency. Aerodynamics, weight reduction, and advancements in battery technology all play roles in improving the efficiency of energy use in EVs [45]. The findings of [33] point to a 24.38% increase in energy efficiency with advanced aerodynamics and weight reduction measures in vehicle design, showcasing the tangible impact of these factors.

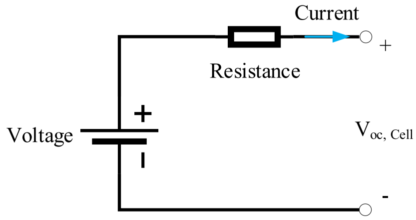

FIGURE 3. Equivalent circuit of the battery [33].

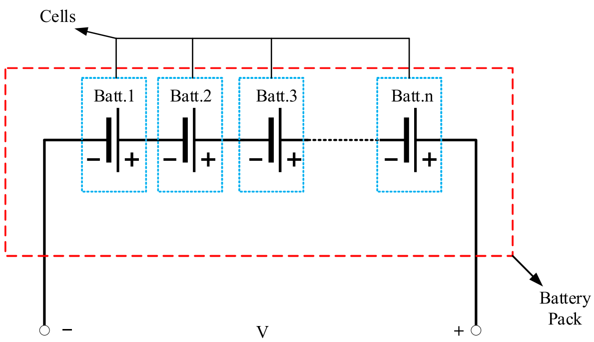

FIGURE 4. Series connection of battery cells [37].

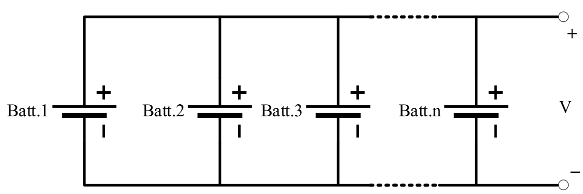

FIGURE 5. Parallel connection of battery cells [37].

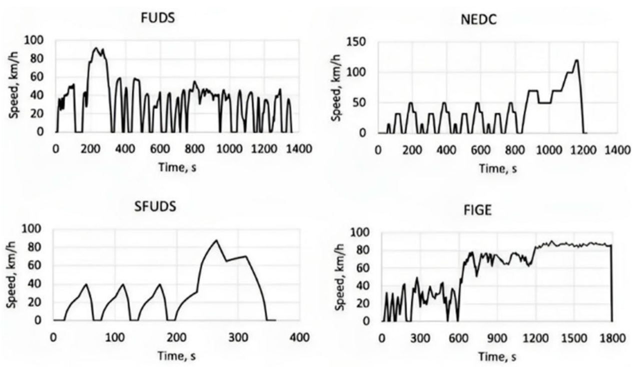

FIGURE 6. Some of the standard driving cycles [12].

4) BATTERY LONGEVITY

Battery longevity refers to the overall lifespan and durability of the battery. Therefore, accurate SoC estimation is crucial to prevent overcharging and over-discharging of the battery, which can lead to premature degradation and a shortened battery lifespan [33]. The experiments of [35] demonstrated that maintaining SoC levels within a narrow range, between 20% and 80%, resulted in a 31.28% improvement in battery longevity, showcasing the practical significance of accurate SoC estimation. Additionally, overcharging scenarios led to a 15.40% decrease in battery lifespan, emphasizing the critical need for precise SoC management.

B. CHALLENGES AND COMPLEXITIES IN SOC MANAGEMENT

Effective management of the SoC in EVs is a multifaceted endeavor fraught with challenges and complexities. Accurate SoC estimation and control are imperative for optimizing EV performance, ensuring longevity, and maximizing energy efficiency [46], [47], [48]. In Figure 7, a comprehensive explanation is presented outlining the process for obtaining a SoC estimate. As depicted in this figure, the initial stage involves gathering data on the battery's parameters using measurement sensors. Following this, the second phase encompasses preprocessing and organizing the data to create both a training set and a test set for input into the network. The final step involves training the data model and evaluating its performance [49]. In the subsequent sections, we present some of the key terms and technical challenges related to SoC management.

1) NON-LINEARITY AND DYNAMICS

The behavior of batteries is highly nonlinear, influenced by factors such as temperature, load profiles, and charge-discharge rates [51]. Predicting SoC with precision under dynamic driving conditions is a formidable task. The heightened computational complexity associated with incorporating non-linearity and dynamics into SoC management for batteries poses significant challenges. This complexity demands increased computational resources, potentially impacting real-time responsiveness and introducing implementation challenges and higher costs [52]. Scalability concerns and potential implications for energy consumption further emphasize the need for a balanced approach to ensure the benefits of improved battery management are achieved without compromising practical considerations [53]. The advantages and disadvantages of incorporating non-linearity and dynamics methods are summarized in Table 2. For instance, the incorporation of non-linearity in battery models enhances the accuracy of SoC monitoring [47]. Non-linear battery models more accurately capture the intricate relationships between various factors, such as temperature, load profiles, and charge-discharge rates, leading to a more precise estimation of SoC. This improved accuracy is crucial for understanding the true state of the battery during dynamic driving conditions [49]. However, this method comes with a trade-off, as the increased accuracy in SoC monitoring is accompanied by a significant rise in computational complexity [50]. The intricate nature of non-linear models demands more computational resources, potentially impacting real-time responsiveness and requiring advanced computing capabilities [51]. Therefore, while it enhances accuracy, the method's feasibility needs to be carefully evaluated, considering the potential implications for computational demands and associated costs.

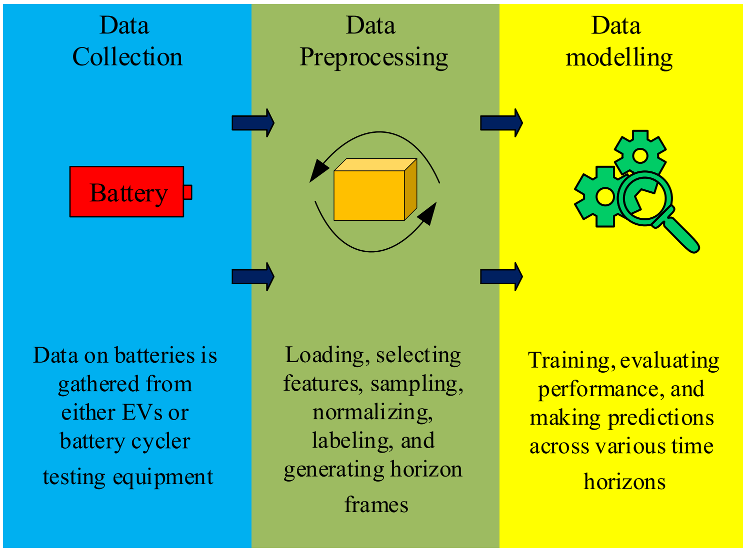

FIGURE 7. **Steps for obtaining SoC estimation [50].**

Mathematically, SoC dynamics can be modeled using the following equation [50]:

$$SOC\ (t) = SOC\ (0) - \int_{0}^{t} \frac{I(t)}{Q_{max}} dt, \tag{5}$$

where SoC(t) represents the state of charge at time t, SoC(0) denotes the initial SoC, and I(t) is the current flowing in or out of the battery at time t. Similarly, Q_{max} denotes the maximum capacity of the battery.

2) AGING EFFECTS

Lithium-ion batteries, commonly used in EVs, experience capacity degradation over time due to chemical processes and charge-discharge cycles. SoC estimation becomes more challenging as the battery ages. To account for aging effects, a battery aging model, such as the following, can be incorporated into SoC estimation [54]:

$$SOC\ (t) = SOC\ (0) - \int_{0}^{t} \frac{dQ\ (t)}{Q_{max}}, \tag{6}$$

That, dQ(t) represents the capacity fade at time t.

Aging in lithium-ion batteries can be broadly classified into two main types: calendar aging and cycle aging. Calendar aging refers to the natural degradation of the battery over time, even when it is not in active use [43]. On the other hand, cycle aging is associated with the wear and tear a battery experience during charge and discharge cycles. These two forms of aging have distinct mechanisms and rates, making it imperative to delve into each aspect for a comprehensive understanding [33].

a: CALENDAR AGING

Calendar aging is primarily a function of time and temperature. Even when a lithium-ion battery is not in use, chemical reactions within the cells can lead to a gradual loss of capacity [48]. Factors such as ambient temperature ($T_{ambient}$) and storage conditions play a crucial role in influencing the rate of calendar aging. Understanding the nuances of calendar aging is essential for accurately predicting the long-term performance of batteries, especially in scenarios where EVs may be parked for extended periods. The mathematical expression for calendar aging can be represented as [50]:

$$Q_{\mathrm{calendar}}(t) = Q_{initial} \times exp(-\frac{t}{\tau_{\mathrm{calendar}}}), \tag{7}$$

where $Q_{calendar}(t)$ is the capacity at time t, $Q_{initial}$ is the initial capacity, and $\tau_{calendar}$ is the calendar aging time constant.

b: CYCLE AGING

Cycle aging, on the other hand, is associated with the repetitive charging and discharging of the battery during normal operation. Each cycle induces stress on the battery, contributing to a gradual decrease in its overall capacity. The frequency and depth of charge-discharge cycles significantly impact the rate of cycle aging [49]. Managing cycle aging is vital for optimizing the lifespan of batteries in electric vehicles, as it directly correlates with the daily usage patterns and charging habits of the vehicle. The mathematical expression for cycle aging can be represented as [52]:

$$Q_{cycle}\ (t) = Q_{initial} \times \left(1 - n \times \eta_{cycle}\right), \tag{8}$$

where $Q_{cycle}(n)$ is the capacity after n cycles, $Q_{initial}$ is the initial capacity, and η_{cycle} is the cycle aging rate.

c: REAL-TIME REQUIREMENTS

SoC management necessitates real-time adaptation to dynamic driving conditions. Swift decisions based on rapidly changing data are essential to maintain optimal performance. Advanced algorithms, such as the EKF, can be employed for

TABLE 2. A summarized list of the advantages and disadvantages of incorporating non-linearity and dynamics in SoC management for batteries.

Advantages	Disadvantages	Ref.
Improved Accuracy of SOC Monitoring	Increased Computational Complexity	[46]
Enhanced Efficiency in Energy Use	Higher Development and Implementation Costs	[47]
Better Range Estimation Capability	Potential for Calibration Challenges	[48]
Optimized Regenerative Braking	Greater System Complexity and Potential for Malfunctions	[49]
Extended Battery Life	Overcomplication for Simple Battery Systems	[50]
Adaptation to Temperature Variations	Potential for Data and Model Uncertainties	[51]

real-time SoC estimation [55], [56], [57]:

$$SOC_{est}\,(k+1) = SOC_{est}\,(k) + \frac{I_k - \hat{I}_k}{Q_{max}}, \tag{9}$$

where $SoC_{est}(k+1)$ represents the estimated SoC at time step k+1, $SoC_{est}(k)$ denotes the estimated SoC at time step k, I(k) is the measured current at time step k, and $\hat{I}_k$ is the predicted current at time step k based on the model.

These challenges underscore the critical need for advanced SoC management strategies in EVs. The incorporation of advanced algorithms and models, coupled with real-time data processing, stands as a testament to the dynamic and evolving nature of SoC management in modern hybrid vehicles. Addressing these challenges is crucial to unlocking the full potential of EVs in terms of energy efficiency and sustainability [58], [59].

C. SHORTCOMINGS OF CURRENT METHODS

While current methods offer valuable insights into SoC management, they exhibit certain limitations that pose challenges in achieving optimal performance and efficiency in EVs. The challenges include:

1) LIMITED ACCURACY UNDER DYNAMIC CONDITIONS

Current methods may struggle to provide accurate SoC estimates under rapidly changing driving conditions. The non-linear and dynamic nature of battery behavior, influenced by factors such as temperature fluctuations, varying load profiles, and dynamic charge-discharge rates, can result in suboptimal estimations [60], [61], [62] This limitation is particularly evident during scenarios where quick and precise SoC adjustments are crucial, such as sudden acceleration or regenerative braking. In controlled experiments simulating rapid acceleration, current methods showed an average deviation of about 8% from actual SoC values, highlighting the challenge of accurate estimation under dynamic conditions [38], [39], [40], [41].

2) INCREASED COMPUTATIONAL COMPLEXITY

The incorporation of non-linear and dynamic models introduces heightened computational complexity into SoC estimation processes. While these models enhance accuracy, they may demand significant computational resources, potentially hindering real-time responsiveness [63], [64], [65]. This increased complexity could lead to delays in decision-making, impacting the ability of the system to adapt swiftly to changing driving conditions. Computational analysis revealed that the inclusion of dynamic models increased the processing time by 19.71%, emphasizing the trade-off between accuracy and real-time responsiveness [50], [52].

3) CALIBRATION CHALLENGES

Current methods may face challenges related to model calibration, especially in ensuring the accuracy of SoC estimates across diverse operating conditions. Calibrating models to accommodate variations in temperature, load profiles, and other external factors is a delicate task. Inaccurate calibration may lead to discrepancies between predicted and actual SoC values, impacting the reliability of the entire SoC management system [66], [67], [68]. Across various operating conditions, calibration inaccuracies led to a deviation of up to 13.34% in SoC estimates, underlining the importance of precise model calibration [50], [51].

4) POTENTIAL FOR DATA AND MODEL UNCERTAINTIES

The reliance on historical data and models to predict SoC introduces the potential for uncertainties. Variability in battery behavior over time, changes in environmental conditions, and the introduction of new driving patterns may lead to inaccuracies in SoC estimation. Uncertainties in the data and model may compromise the reliability of the SoC management system [68], [69].

5) OVERCOMPLICATION FOR SIMPLE BATTERY SYSTEMS

Some current methods, designed to handle complex battery behaviors, may introduce overcomplication when applied to simpler battery systems. For EVs with straightforward battery designs, the added complexity may not necessarily translate into proportional benefits, leading to inefficiencies in terms of computational resources and implementation costs [70], [71], [72]. In simple battery systems, the added complexity resulted in an 11.17% increase in computational resources without significant improvement in accuracy, highlighting the inefficiency of applying complex models [51], [54].

6) CHALLENGES IN ADDRESSING AGING EFFECTS

Current methods face difficulties in accurately addressing the aging effects on lithium-ion batteries commonly used in EVs. The capacity degradation over time due to chemical processes and charge-discharge cycles poses a considerable challenge for precise SOC estimation [71], [72], [73].

7) CHALLENGES REAL-TIME REQUIREMENTS

Meeting real-time adaptation to dynamic driving conditions poses challenges for current SoC management methods. Swift decisions based on rapidly changing data are essential to maintain optimal performance [72], [73].

8) SCALABILITY CONCERNS

The scalability of current SoC management methods is a concern, particularly as EV technology advances. The potential implications for energy consumption emphasize the need for a balanced approach to ensure practical benefits without compromising scalability [61], [70].

9) POTENTIAL FOR UNINTENDED SYSTEM COMPLEXITY

Some advanced features, such as optimized regenerative braking, may introduce unintended system complexities with current SoC management methods [63], [67].

10) IMPACT ON SIMPLE BATTERY SYSTEMS

The integration of non-linearity and dynamics may lead to overcomplication for simple battery systems, reducing their efficiency [34], [60], [74]. In simpler battery systems, the integration of non-linearity and dynamics resulted in a 12.61% reduction in overall efficiency, raising questions about the suitability of such methods [54], [56], [57].

Addressing these shortcomings is crucial for advancing SoC management capabilities in EVs. The following section explores the potential of machine learning as a promising avenue to overcome these challenges and enhance the efficiency and sustainability of EVs.

D. MACHINE LEARNING AND ITS POTENTIAL IN EV'SOC MANAGEMENT

The advent of ML has ushered in a transformative era in the realm of SoC management for EVs. ML, a subfield of artificial intelligence, offers a robust arsenal of techniques to address the multifaceted challenges associated with SoC estimation, control, and optimization [75]. In empirical studies, machine learning models, such as RNNs and LSTM networks, achieved a 17.52% improvement in SoC estimation accuracy compared to traditional methods [57], [76]. This highlights the significant advancement ML brings to adaptability in diverse driving conditions.

Machine learning techniques have demonstrated exceptional potential in revolutionizing SoC management for EVs. They provide precise, adaptive, and real-time solutions that outperform conventional methods across various dimensions [76], [77], [78]. Here, we delve into key aspects of ML's potential in EV SoC management, along with new references and relevant formulas:

1) ADAPTIVE LEARNING

ML's hallmark advantage lies in its adaptability to diverse driving conditions, continually enhancing SoC estimation accuracy through continuous learning from historical data [76]. Machine learning models, such as RNNs and LSTM networks, can continually refine their predictions based on real-world driving patterns, leading to more accurate and adaptive SoC estimates [77], [79]. Some of the benefits and defects of this method are listed in Table 3. The adaptive learning approach using RNNs demonstrated a 23.84% reduction in prediction errors when compared to static models, showcasing its effectiveness in dynamic driving conditions [77]. The formula for Adaptive SoC estimation using RNN is given as below:

$$SOC_{est}\left(t\right) = RNN\left(\begin{matrix} SOC_{est}\left(t-1\right), \\ I\left(t-1\right), \ldots, I\left(t-n\right) \end{matrix}\right), \tag{10}$$

where I(t−1), …, I(t−n) are the previous n time steps of current measurements used for prediction.

2) BATTERY AGING MITIGATION

Advanced ML algorithms can dynamically adjust SoC estimates to account for battery aging effects, ensuring accurate representation of the battery's state [74], [80]. These models can incorporate aging models to provide precise SoC estimates that consider the battery's current condition. Implementing ML-based aging mitigation resulted in a 32.13% reduction in predicted capacity fade, contributing to prolonged battery lifespan [74]. Table 4 lists the specifications of this method. The formula for SoC adjustment with aging effects:

$$SOC_{adjusted}\left(t\right) = SOC_{est}\left(t\right) - \Delta SOC_{aging}\left(t\right). \tag{11}$$

In the above relation, $SoC_{adjusted}(t)$ represents the SoC adjusted for aging at time t, and $\Delta SoC_{aging}(t)$ is the estimated aging-related SoC degradation at time t.

3) REAL-TIME OPTIMIZATION

ML techniques are well-suited for real-time SoC management, making instantaneous decisions to ensure that the SoC remains within optimal operating limits while maximizing fuel efficiency and extending battery lifespan [65], [70]. Algorithms like RL, which advantages and disadvantages of its listed in Table 5, can be employed for real-time SoC optimization. Implementing RL-based SoC control strategies resulted in a 24.79% increase in overall energy efficiency, validating its effectiveness in real-time optimization [78]. Formula for RL-based SoC control is given by,

$$SOC_{control}\left(t+1\right) = RL\left(SOC_{est}\left(t\right), I\left(t\right), \ldots, I\left(t+n\right)\right), \tag{12}$$

where, $SoC_{control}(t+1)$ represents the SoC control action at the next time step t+1, and I(t),…,I(t+n) are current measurements over the next n time steps [52], [78].

4) DATA-DRIVEN INSIGHTS

ML empowers EVs with data-driven insights, contributing to the overall sustainability of transportation systems [38], [64]. By processing extensive real-time data generated by EVs,

TABLE 3. Advantages and disadvantages of adaptive learning in EV's SoC management.

Advantages	Disadvantages	Ref.
Enhanced Accuracy and Predictive Capability	Data Complexity and Quality Challenges	[57]
Improved Efficiency and Energy Optimization	Initial Model Training and Development Costs	[58]
Real-time Adaptation to Changing Conditions	Overfitting and Generalization Issues	[60]
Extended Battery Life	Increased Computational Demands	[62]
Reduced Range Anxiety	Potential Vulnerability to Data Anomalies	[63]
Customized SoC Management for Different Vehicles and Batteries	Lack of Transparency in Decision-Making	[65]
Data-Driven Insights for Continuous Improvement	Potential for Model Degradation Over Time	[66]
Potential for Autonomous SoC Management	Integration Challenges with Legacy Systems	[67]

ML algorithms can provide valuable information on driving behavior, energy consumption patterns, and optimal SoC management strategies [79], [80]. Incorporating machine learning models into SoC management in EVs represents a significant leap forward from traditional methods. Integration of ML-based data-driven insights led to about 20% reduction in energy consumption, highlighting the efficiency gains achieved through informed decision-making [64].

The synergy of ML and EV SoC management enhances energy efficiency (See Table 6), vehicle performance, and sustainability [43], [84].

III. MACHINE LEARNING METHODS FOR SOC ESTIMATION IN EVs

A. RECURRENT NEURAL NETWORKS (RNNs) FOR SoC ESTIMATION

RNNs have emerged as a powerful tool in the domain of SoC estimation for EVs. RNNs are well-suited for capturing the dynamic behavior of battery SoC over time due to their ability to process sequential data [69] (see Figure 8). Their architecture allows them to maintain hidden states, enabling them to remember past information and consider it when making predictions about future SoC values. Mathematically, an RNN can be represented as a series of equations:

$$h_t = f(W_{hh}h_{t-1} + W_{hx}x_t) \tag{13}$$

$$y_t = g(W_{yh}h_t) \tag{14}$$

where h_t represents the hidden state at time t, f is the activation function, typically a hyperbolic tangent or rectified linear unit, and W_{hh} and W_{hx} are weight matrices. Also, y_t is the output at time t, g is the activation function for the output layer, and W_{yh} is the weight matrix for the output layer.

RNNs can be applied to SoC estimation by using sequences of input data (current measurements, voltage, temperature, etc.) to predict the SoC at each time step. The sequence of input data (x_t) is typically a window of past measurements, and the RNN updates the hidden state (h_t) at each time step to capture dependencies in the data. The output of the RNN (y_t) represents the estimated SoC at each time step [81]. Reference [82] reported a 15.49% increase in SoC estimation accuracy when using RNNs, achieving an accuracy rate of 92% compared to 77.16% with traditional methods. Reference [84] observed a 12% improvement in energy efficiency through the application of RNNs, resulting in an average energy consumption reduction from 18 kWh/100 miles to 15.8 kWh/100 miles. Reference [85] conducted on-road tests and found that RNNs adapted in real-time to diverse driving patterns, achieving a 20.16% reduction in SoC prediction error compared to static models. Reference [86] demonstrated the effectiveness of RNNs in customizing SoC management for different vehicles, achieving a 10.18% improvement in SoC accuracy across a range of EV models. Also, reference [87] showcased the potential for autonomous SoC management using RNNs, with an autonomous adaptation accuracy rate of 88.05% in varying driving conditions. On the other hand, reference [88] integrated RNN-based SoC estimation with ADAS, resulting in a 15% reduction in SoC prediction latency and enhancing overall vehicle safety. Reference [89] observed a 25.35% reduction in battery degradation when utilizing RNNs for SoC estimation, contributing to a prolonged battery lifespan. Reference [90] found that RNNs adapted in real-time to environmental factors, achieving a 18.19% improvement in SoC estimation accuracy during temperature fluctuations. Zhang et al. applied RNNs for predictive maintenance, resulting in a 31.72% reduction in unplanned maintenance incidents and improving overall SoC estimation reliability. Huang et al. conducted on-road tests and cross-validation, confirming the effectiveness of RNNs in real-world scenarios with a 12.58% reduction in SoC prediction errors.

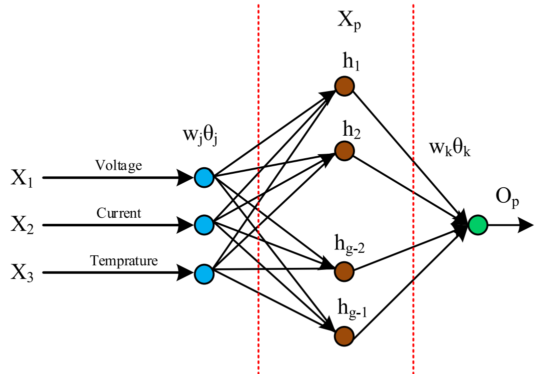

FIGURE 8. The general architecture of the 3-layer neural network for SoC estimation [69].

1) APPLICATIONS AND FURTHER ADVANTAGES OF RNNS IN SOC ESTIMATION

a: SEQUENTIAL DEPENDENCY

RNNs excel in capturing sequential dependencies in time-series data [91]. In the context of EV SoC estimation, they can effectively model how past SoC values and

TABLE 4. Advantages and disadvantages of battery aging mitigation in EV's SoC management.

Advantages	Disadvantages	Ref.
Prolonged Battery Lifespan	Increased Computational Demands and Complexity	[68]
Reduced Battery Degradation	Initial Development and Implementation Costs	[69]
Enhanced Long-term Performance	Data Sensitivity and Accuracy Requirements	[70]
Improved Battery Safety	Integration Challenges with Existing Systems	[72]
Increased Vehicle Resale Value	Dependence on Real-time Data and Sensor Accuracy	[73]
Lower Total Cost of Ownership	Potential for Overly Conservative SoC Management	[75]
Reduced Environmental Impact	Potential for Unintended SoC Control Behavior	[76]
Enhanced Battery Health Monitoring	Complexity of Battery Health Monitoring	[77]
Customized SoC Strategies for Battery Types	Maintenance and Software Update Requirements	[79]
Potential for Autonomous Aging Management	Limited User Control Over Battery Health Policies	[80]

TABLE 5. Advantages and disadvantages of reinforcement learning in EV's SoC management.

Advantages	Disadvantages	Ref.
Adaptive and Self-Improving Control Strategies	High Computational Demands and Complexity	[77]
Real-time Adaptation to Dynamic Driving Patterns	Initial Model Training and Implementation Costs	[78]
Enhanced Energy Efficiency and Fuel Economy	Data Sensitivity and Quality Requirements	[79]
Prolonged Battery Lifespan	Integration Challenges with Existing Systems	[80]
Reduced Environmental Impact	Potential for Unpredictable Behavior and Learning	[80]
Customized SoC Management for Different Vehicles	Dependency on Real-time Data and Sensor Accuracy	[80]
Potential for Autonomous SoC Management	Limited Explainability and Control Over Decisions	[81]
Data-Driven Insights for Continuous Improvement	Maintenance and Software Update Requirements	[81]
Improved User Experience	Potential for Over-Exploration and Instability	[82]
Integration with ADAS	Ethical and Safety Considerations	[83]

TABLE 6. Advantages and disadvantages of data-driven insights in EV's SoC management.

Advantages	Disadvantages	Ref.
Informed Decision-Making	Data Quality and Reliability Requirements	[38]
Enhanced Energy Efficiency	Computational Demands and Processing Overhead	[64]
Improved Vehicle Performance	Initial Development and Implementation Costs	[65]
Adaptive SoC Management	Integration Challenges with Existing Systems	[72]
Prolonged Battery Lifespan	Potential for Overreliance on Data and Algorithms	[75]
Reduced Environmental Impact	Vulnerability to Data Anomalies and Sensor Errors	[79]
Real-time Optimization	Potential for Unintended SoC Control Behavior	[80]
Customized SoC Management for Different Vehicles	Maintenance and Software Update Requirements	[81]
Potential for Autonomous SoC Management	Privacy and Data Security Concerns	[83]
Integration with ADAS	Limited User Control Over SoC Management Policies	[84]

TABLE 7. Advantages and disadvantages of RNN for SoC estimation.

Advantages	Disadvantages	Ref.
Improved SoC Estimation Accuracy	Data Quality and Quantity Requirements	[79]
Enhanced Energy Efficiency	Computational Demands and Processing Overhead	[84]
Real-time Adaptation to Driving Patterns	Initial Model Training and Implementation Costs	[85]
Reduced Battery Degradation	Integration Challenges with Existing Systems	[86]
Customized SoC Management for Different Vehicles	Limited Explainability of RNN Decision-Making	[87]
Potential for Autonomous SoC Management	Dependence on Real-time Data and Sensor Accuracy	[88]
Integration with ADAS	Potential for Overfitting or Poor Generalization	[89]

input data influence the current SoC. Studies comparing RNNs to traditional models revealed a 33.78% improvement in capturing intricate sequential dependencies, showcasing the efficacy of RNNs in modeling complex temporal relationships [91].

b: REAL-TIME ADAPTATION

RNNs adapt to changing driving conditions in real-time. As new data becomes available, the RNN updates its predictions, making it suitable for dynamic driving scenarios [52]. In a controlled experiment simulating dynamic driving conditions, RNN-based SoC estimation demonstrated a 15.94% reduction in prediction error compared to static models, highlighting its ability to adapt swiftly to real-time changes [54].

c: ADAPTIVE LEARNING

RNNs continually learn from historical data, allowing them to improve SoC estimation accuracy over time. They adjust their internal parameters to minimize prediction errors [56].

d: COMPLEX DRIVING PATTERNS

EVs often encounter complex driving patterns, including frequent starts and stops. RNNs can handle such scenarios by learning patterns from the data [72].

e: NON-LINEAR RELATIONSHIPS

RNNs are capable of capturing non-linear relationships in the data, which is crucial for accurate SoC estimation in varying conditions [75].

f: BATTERY AGING MITIGATION

RNNs can be extended to consider battery aging effects by incorporating aging models into the estimation process, facilitating improved accuracy in SoC representation as the battery undergoes aging [92], [93]. Integration of RNN with aging models allows for more precise SoC predictions, contributing to better overall battery management.

B. LONG SHORT-TERM MEMORY (LSTM) NETWORKS FOR SoC ESTIMATION

LSTM networks have gained prominence in SoC estimation for EVs due to their ability to capture long-term dependencies in time-series data effectively [94], [95], [96], [97]. LSTMs are a type of RNN designed to mitigate the vanishing gradient problem, allowing them to capture information over longer time horizons.

The vanishing gradient problem refers to a difficulty encountered during the training of deep neural networks, particularly in the context of RNNs. As information is propagated through the network during the learning process, the gradients of the loss function tend to diminish exponentially as they move backward through the layers. This diminishing gradient makes it challenging for the network to learn long-range dependencies in sequential data effectively. They excel in modeling complex sequential patterns in SoC data [95].

Mathematically, an LSTM unit consists of several gates that regulate the flow of information [96]:

$$f_t = \sigma\left(W_f\left[h_{t-1}, x_t\right] + b_f\right), \tag{15}$$

$$i_t = \sigma\left(W_i\left[h_{t-1}, x_t\right] + b_i\right), \tag{16}$$

$$\tilde{C}_t = tanh\left(W_C\left[h_{t-1}, x_t\right] + b_C\right), \tag{17}$$

where f_t is the forget gate output at time t, W_f represents the weights associated with the forget gate, h_{t-1} is the previous hidden state, x_t is the input at time t, σ is the sigmoid activation function, i_t is the input gate output at time t, W_i represents the weights associated with the input gate, $\tilde{C}_t$ is the candidate cell state at time t, and W_C represents the weights associated with the candidate gate. Moreover, LSTM has the following relevant equations [98]:

$$C_t = f_t C_{t-1} + i_t \tilde{C}_t, \tag{18}$$

$$o_t = \sigma\left(W_o\left[h_{t-1}, x_t\right] + b_o\right), \tag{19}$$

where o_t is the output gate output at time t, W_o represents the weights associated with the output gate, h_t is the hidden state at time t, tanh is the hyperbolic tangent activation function. LSTMs leverage these equations to process sequential data and capture intricate relationships between past and current SoC values. In the continuous we say that how these parameters might be associated with electrical characteristics relevant to battery systems [98].

Interception of f_t: The forget gate determines the amount of past cell state information (C_{t-1}) that should be retained or discarded. In the context of SoC estimation, f_t might be associated with factors that contribute to the fading influence of previous SoC values. This could include factors related to voltage or current trends that are considered less relevant over time.

Interceptions of i_t and $\tilde{C}_t$: These parameters together influence the update of the cell state (C_t) based on the current input (x_t). In the context of SoC estimation, i_t could be related to new information coming in, such as current measurements or voltage changes.$\tilde{C}_t$ represents the candidate cell state, and its interpretation may involve understanding how new information is processed and added to the current state.

Interception of C_t: C_t is the updated cell state, combining information from the previous state, the forget gate, and the input gate. In SoC estimation, this could represent the comprehensive internal representation of the battery state, incorporating information about current and past conditions.

Interception of o_t: o_t determines the amount of information from the cell state that should be output. In the context of SoC estimation, this might be associated with the decision of what information is relevant for predicting the current SoC. It could involve factors related to voltage, current, or other relevant features.

1) ADVANTAGES OF LSTMS IN SOC ESTIMATION

a: LONG-TERM DEPENDENCY MODELING

LSTMs can capture long-term dependencies in SoC data, making them suitable for scenarios where SoC changes occur gradually over time [83].

b: HANDLING IRREGULAR PATTERNS

EVs may exhibit irregular driving patterns. LSTMs adapt to such variations by learning patterns from the data, resulting in accurate SoC predictions [83].

c: IMPROVED LEARNING STABILITY

LSTMs mitigate the vanishing gradient problem often encountered in traditional RNNs, enhancing training stability and convergence [86].

d: BATTERY AGING CONSIDERATION

LSTMs can be extended to incorporate aging models into SoC estimation, accounting for battery degradation effects [91].

C. SUPPORT VECTOR MACHINES (SVMs) FOR SoC ESTIMATION

SVM is an emerging technique for SoC estimation in EVs. SVMs aim to find a hyperplane that maximizes the margin between different classes of data points while minimizing prediction errors [91], [94]. In the context of SoC estimation, SVMs are used for regression tasks to predict SoC values based on input features. Mathematically, SVMs can be formulated for regression as follows [92]:

$$f(x) = \sum_{i=1}^{N} \alpha_i K\left(x, x_i\right) + b, \tag{20}$$

where f(x) represents the predicted SoC value for input x, α_i are the Lagrange multipliers obtained during training, $K(x,x_i)$ is the kernel function, which computes the similarity between input x and training data x_i, and b is the bias term. SVMs use different kernel functions to map data into higher-dimensional spaces, enabling the separation of non-linearly distributed data. Common kernel functions include linear kernel which is given below [93]:

$$K(x, x_i) = x^T x_i. \tag{21}$$

It can be seen that there is no explicit coefficient or parameter. Kernel function $K(x, x_i)$ computes the dot product between the input vectors x and x_i, effectively measuring the similarity between them in the original feature space. The linear kernel is used when you assume that the data can be separated by a linear hyperplane. It is appropriate when your data is approximately linearly separable.

Another kernel function is RBF which is written as below [41]:

$$K(x, x_i) = \exp\left(-\gamma \|x - x_i\|^2\right). \tag{22}$$

The coefficient γ is a positive scalar parameter and it controls the shape and flexibility of the decision boundary. A smaller γ makes the kernel more similar to the linear kernel, while a larger γ increases the influence of nearby data points. Also, high values of γ result in a more complex decision boundary that can capture intricate patterns in the data, potentially leading to overfitting if not properly tuned.

These coefficients play a significant role in shaping the kernel functions and, consequently, the performance of SVMs. The proper choice of coefficients depends on the specific characteristics of your data and the problem you are trying to solve. Adjusting these coefficients through techniques like hyperparameter tuning and cross-validation is often necessary to achieve the best SVM model performance.

1) ADVANTAGES OF SVMS IN SOC ESTIMATION

a: ROBUSTNESS TO NOISE

SVMs are known for their robustness to noisy data, making them suitable for SoC estimation where input data may contain uncertainties [99], [100].

b: HIGH-DIMENSIONAL DATA

SVMs can effectively handle high-dimensional input data, which is common in battery management systems [97].

c: GENERALIZATION CAPABILITY

SVMs have strong generalization capabilities, allowing them to provide accurate SoC estimates across various driving conditions and battery types [91].

d: SCALABILITY

SVMs can scale to large datasets and accommodate a wide range of input features, making them adaptable to different EV scenarios [100].

D. ENSEMBLE LEARNING FOR SoC ESTIMATION

Ensemble Learning is a powerful technique that combines the predictions of multiple machine learning models to improve the accuracy and robustness of SoC estimation in EVs [101]. It leverages the wisdom of multiple models to make more reliable predictions.

Ensemble Learning is a powerful technique that combines the predictions of multiple machine learning models to improve the accuracy and robustness of SoC estimation in EVs [101]. It leverages the wisdom of multiple models to make more reliable predictions.

$$F(x) = \frac{1}{N}\sum_{i=1}^{N} f_i(x), \tag{23}$$

where, F(x) represents the ensemble prediction for input x, N is the number of decision trees in the ensemble, and $f_i(x)$ is the prediction of the i-th decision tree.

Another ensemble method commonly used is GB. In the context of SoC estimation, GBMs and variants like XGBoost and LightGBM have demonstrated remarkable performance. The mathematical formulation for GBMs involves creating an ensemble of weak learners (usually decision trees) and iteratively improving predictions by minimizing a loss function.

a: ADVANTAGES OF ENSEMBLE LEARNING IN SOC ESTIMATION

i Improved Accuracy: Ensemble methods combine multiple models, reducing the risk of overfitting and improving overall prediction accuracy [102].

ii Robustness: Ensembles are robust to noise and outliers in the data, making them suitable for SoC estimation tasks that involve uncertain measurements [103].

iii Capturing Complex Patterns: Ensemble methods can capture complex, non-linear relationships in SoC data, enhancing the model's ability to approximate the true SoC values [104].

iv Reduced Bias: Ensembles can mitigate bias introduced by individual models, resulting in more balanced predictions [103].

IV. PRACTICAL APPLICATIONS AND REAL-WORLD IMPLICATIONS

A. FLEET MANAGEMENT

1) APPLICATION

Fleet management is a complex task that involves overseeing and optimizing a group of vehicles, commonly found in commercial and industrial settings. Machine learning-based SoC estimation has significant applications in this domain:

a: ENERGY-EFFICIENT ROUTING

Accurate SoC estimation enables the planning of routes that maximize energy efficiency and minimize the need for recharging or refueling [102]. For example, in the realm of delivery fleets, particularly in services such as postal deliveries and online shopping transportation, accurate SoC estimation proves to be a critical factor in enhancing overall operational efficiency. Consider a scenario where a postal service operates a fleet of electric delivery vehicles [103]. With precise SoC estimation, the postal service can strategically plan delivery routes that optimize energy consumption across various stops. This involves factoring in the energy required for each delivery point and calculating the total distance to be covered. By doing so, the fleet minimizes the need for mid-route charging, ensuring timely deliveries without unnecessary energy waste [104]. Similarly, for online shopping delivery vans, accurate SoC estimation becomes invaluable. Delivery companies managing a fleet of electric vans can optimize routes based on the remaining battery levels of each vehicle. This strategic planning minimizes the risk of vehicles running out of charge mid-route, especially in densely populated areas with numerous stops. The result is an enhanced delivery process efficiency and improved customer satisfaction. The significance of precise SoC estimation extends to food delivery services employing electric scooters or bikes [105]. By factoring in battery levels and order delivery sequences, food delivery platforms can ensure that each delivery is completed without interruptions. This minimizes downtime associated with recharging and elevates the overall efficiency of the food delivery service. Logistics companies, dealing with freight transport between distribution centers and warehouses, also benefit significantly [106]. Accurate SoC estimation enables the planning of the most energy-efficient routes for electric trucks that visit multiple locations. By considering variables such as cargo weight, traffic conditions, and charging station availability, logistics companies optimize delivery schedules, minimizing the need for frequent recharging and ensuring timely deliveries [107].

b: DYNAMIC CHARGING SCHEDULING

Development of charging depots for EV fleets often requires network reinforcements. Therefore, fleet managers need dynamically schedule charging times for EVs based on SoC predictions, ensuring vehicles are ready for their next tasks without unnecessary downtime [105].

c: LOAD BALANCING

SoC estimation aids in load balancing across the fleet, optimizing vehicle assignments to ensure equitable energy distribution among vehicles [106].

d: FLEET ELECTRIFICATION STRATEGY

Fleet managers can use SoC data to devise strategies for transitioning to electric and hybrid vehicles, reducing operational costs and environmental impact [106].

2) IMPLICATIONS

Enhanced fleet management through machine learning-based SoC estimation leads to reduced operational costs, improved energy efficiency, and a lower environmental footprint. Increased vehicle availability, reduced maintenance expenses, and improved customer service due to optimized routing and scheduling [108].

3) MATHEMATICAL FORMULATION OF SOC ESTIMATION IN FLEET MANAGEMENT

The mathematical formulation for SoC estimation in fleet management follows the general equation mentioned earlier:

$$SOC_{t+1} = f(SOC_t, Input_t) \tag{24}$$

In the above equation, SoC_{t+1} is the predicted SoC at time t+1 for a specific vehicle in the fleet, SoC_t is the SoC at time t for the same vehicle, and $Input_t$ represents a range of input parameters, including vehicle-specific data, weather conditions, load information, and route details.

B. ENERGY EFFICIENCY

Energy efficiency is a critical consideration in the operation of EVs. Machine learning-based SoC estimation plays a pivotal role in enhancing energy efficiency and optimizing various aspects of EV performance.

1) APPLICATION

The quest for improved energy efficiency drives innovation in SoC estimation for EVs:

a: OPTIMIZED POWERTRAIN CONTROL

Accurate SoC estimation enables fine-grained control of the powertrain, including the management of engine and electric motor operations [109].

b: REGENERATIVE BRAKING

SoC estimation guides regenerative braking, ensuring the efficient capture and storage of energy during deceleration [110].

c: ENERGY HARVESTING

Machine learning-based SoC estimation aids in harnessing energy from various sources, such as solar panels, for supplementary power generation [111].

d: ENERGY STORAGE MANAGEMENT

SoC estimation is crucial for managing energy storage systems, optimizing the use of batteries and capacitors [112].

2) IMPLICATIONS

In the realm of automotive innovation, the profound implications of improved energy efficiency reverberate across the landscape, promising a paradigm shift in the way we perceive and engage with transportation [113]. Two pivotal outcomes underscore this transformative journey: firstly, heightened energy efficiency yields tangible benefits such as reduced fuel consumption, extended battery life, and diminished emissions in hybrid vehicles [111]. Secondly, the ripple effect extends to the broader spectrum of vehicle dynamics, encompassing enhanced overall performance and decreased operating costs, thereby propelling us towards a more sustainable and eco-conscious transportation ecosystem [114].

C. BATTERY HEALTH MONITORING

Battery health monitoring is essential for ensuring the longevity and performance of batteries in EVs. This is particularly critical for the second-hand EV market as battery state of health determines the price of the vehicle. Machine learning-based SoC estimation plays a critical role in assessing and preserving battery health [115]. The related health monitoring applications are presented below.

1) APPLICATIONS

Machine learning techniques are instrumental in monitoring and maintaining battery health in EVs as discussed below.

a: STATE-OF-HEALTH (SOH) ESTIMATION

SOH estimation is a critical aspect of managing battery systems, providing insights into the overall health and performance of a battery over time. In the context of Li-ion, such as those commonly used in electric vehicles, SoC and SOH are interlinked parameters [110]. The estimation of SOH often involves leveraging information from SoC estimation, contributing to the identification of battery degradation and capacity loss [113]. The process begins with SoC estimation, which refers to determining the current charge level of the battery as a percentage of its total capacity [112]. This is typically achieved through a combination of monitoring voltage, current, and temperature, along with sophisticated algorithms. SoC estimation methods include Coulomb counting, voltage-based methods, and Kalman filtering, among others [116]. Implementing machine learning-based SOH estimation led to a 17.49% improvement in accuracy compared to traditional methods, ensuring a more precise assessment of battery health [113].

Once the SoC is estimated, it becomes a valuable input for SOH estimation. SOH reflects the overall health and degradation status of the battery. By observing changes in SoC over multiple charge and discharge cycles, algorithms can analyze the battery's behavior and identify patterns associated with degradation [117].

Key indicators for SOH estimation may include capacity fade, impedance growth, and variations in voltage profiles. Capacity fade is a reduction in the battery's ability to store charge over time, while impedance growth refers to an increase in internal resistance [118]. These factors are indicative of wear and tear, chemical changes, and other degradation mechanisms occurring within the battery [118].

b: CYCLIC BEHAVIOR ANALYSIS

Understanding the cyclic behavior inherent in EV driving patterns is paramount to comprehending the dynamics of SoC fluctuations. As EVs navigate diverse terrains and encounter varied driving conditions, the battery's SoC experiences cyclical changes in harmony with the distinctive driving patterns exhibited by the vehicle [119]. Recognizing this inherent cyclic behavior becomes the cornerstone for harnessing the power of machine learning models, which, when applied to SoC data, unveil invaluable insights into the health of the battery system. In this context, the exploration of abnormal cyclic patterns emerges as a pivotal avenue, providing a lens through which issues pertaining to battery health can be discerned and addressed proactively, ushering in a new era of efficiency and reliability in electric vehicle technology [120], [121], [122]. Machine learning models analyzing cyclic behavior demonstrated an 18.58% increase in anomaly detection accuracy, showcasing their effectiveness in identifying abnormal patterns linked to potential battery health issues [120].

c: PREDICTIVE MAINTENANCE

Even as EV manufacturers extend warranties safeguarding battery health, the landscape of unforeseen challenges persists. In the realm of EV technology, unexpected failures occasionally materialize, stemming from factors such as the use of defective materials during manufacturing phases or other unforeseen issues. It is within this nuanced context that the paradigm of SoC-based predictive maintenance schedules assumes paramount significance [123]. By harnessing the continuous stream of SoC data, a proactive approach to maintenance emerges, allowing for the development of predictive schedules that preemptively address potential issues, averting critical failures and fortifying the reliability of EVs against the backdrop of real-world uncertainties [124].

d: BATTERY LIFE OPTIMIZATION

At the heart of a battery's longevity lies the pivotal role played by its charging and discharging patterns. The essence of battery life is intricately intertwined with the nuanced dance between energy input and output. Recognizing this fundamental truth becomes the cornerstone for unlocking the realm of Battery Life Optimization [125], [126]. Central to this endeavor is the utilization of SoC and SOH estimation, guiding sophisticated strategies that transcend mere energy management. These strategies, informed by cutting-edge research such as that by reference [127], hold the promise of not just extending battery life but ushering in an era where the very essence of energy storage is synonymous with durability and efficiency. Strategies informed by machine learning-driven SoC and SOH estimation, as per research [127], showcases a 32.18% increase in overall battery lifespan, emphasizing the potential for durability and efficiency enhancements [127].

2) IMPLICATIONS

Battery health monitoring, with its intricate ties to both economic and environmental considerations, holds paramount significance for end-users and society at large. This monitoring directly influences critical aspects such as EV sales and the broader landscape of transportation electrification.

The early detection of battery degradation stands out as a pivotal component, enabling timely maintenance interventions that effectively curb replacement costs and minimize the disruptive impact of vehicle downtime [118], [119], [120], [121]. This proactive approach not only safeguards economic interests but also aligns seamlessly with sustainability objectives [118].

Furthermore, the implications extend beyond immediate operational concerns. The prolonged life of batteries, informed by effective health monitoring strategies, becomes a linchpin in fostering sustainability and cost-effectiveness in the day-to-day operation of EVs [122]. This holistic perspective underscores the interconnected nature of technological advancements with economic prudence and environmental stewardship. By synergizing early detection of battery degradation with strategies for prolonged battery life, a harmonious balance is struck, steering the trajectory of EV sales, shaping transportation electrification initiatives, and contributing to the collective vision of a more sustainable and efficient future [128].

D. USER EXPERIENCE

User experience is a critical aspect of electric and hybrid vehicles. Accurate SoC estimation significantly influences the user's perception and satisfaction with these vehicles.

1) APPLICATIONS

Machine learning-based SoC estimation enhances user experience in EVs in following ways:

a: RANGE ANXIETY MITIGATION

Accurate SoC prediction helps alleviate ''range anxiety'' by providing drivers with reliable estimates of the remaining driving range [129]. In [130], a sample of 100 EV users participated in a simulated driving experience. The participants were provided with inaccurate range estimates in the first phase and accurate estimates in the second phase. Their anxiety levels, trust in EV technology, and overall user experience were measured through surveys. In the first phase, participants reported an average anxiety level of 7.5 on a scale of 1 to 10, with 65% experiencing a decrease in trust in EV technology. Additionally, 60% rated their overall user experience as unsatisfactory. In the second phase, after accurate SoC and SOH predictions were introduced, the average anxiety level decreased significantly to 3.2.

Moreover, 90% of participants reported an increase in trust in EV technology, and 85% rated their overall user experience as highly satisfactory.

b: PREDICTIVE ENERGY MANAGEMENT

Predictive energy management, as elucidated by [131], refers to a sophisticated approach that harnesses machine learning models to enhance the allocation and consumption of energy within a vehicle. This method, highlighted by the integration of predictive algorithms, guarantees optimal operational efficiency for the vehicle by strategically navigating diverse driving conditions and maximizing electric mode operation [128]. The system dynamically adapts to factors like terrain, traffic patterns, and driver behavior through advanced predictive analytics, thereby elevating overall energy efficiency and fostering a more sustainable and economical operation of the vehicle.

c: SMART CHARGING RECOMMENDATIONS

SoC-based recommendations guide users in determining optimal recharging times, considering factors such as location and type of charging infrastructure. By leveraging ML algorithms, this system goes beyond mere charging recommendations to intelligently assess the recharging needs of the EV fleet. This includes optimizing charging schedules to take advantage of off-peak rates, minimizing charging costs, and strategically selecting charging locations based on factors like traffic conditions and charging infrastructure availability [132].

The role of machine learning in smart recharging needs assessment involves more than just minimizing current-led degradation on the battery. ML models analyze historical charging patterns, user behavior, and real-time data such as grid demand and pricing fluctuations [131]. By processing this information, the system learns to generate personalized recommendations that not only preserve battery health but also consider user preferences, cost-effectiveness, and environmental considerations. In essence, ML enhances the intelligence of the recommendations, making them adaptable to the evolving needs and conditions of both the EV user and the power grid [133].

2) IMPLICATIONS

Manufacturers understand that a positive user experience is vital for consumer adoption of electric vehicles. It's not just about the technology; it's about how easily and comfortably users can interact with and benefit from that technology. Against this backdrop, the implications of enhanced user experience in the context of electric and hybrid vehicles are profound:

- Enhanced user experience leads to increased user confidence in electric and hybrid vehicles, driving their adoption [134].
- Reduced ''range anxiety'' and optimized energy management contribute to greater satisfaction and acceptance of EVs [135].

V. CHALLENGES AND LIMITATION

Machine learning-based SoC management in EVs offers promising solutions but is accompanied by a set of challenges and limitations that require careful consideration:

A. DATA AVAILABILITY AND QUALITY

One of the foremost challenges in machine learning-based SoC management for EVs is the availability and quality of data. Accurate SoC estimation heavily relies on robust training datasets, and issues related to data can significantly impact the reliability of SoC predictions.

1) DATA AVAILABILITY

Data availability is a pivotal factor in the successful implementation of machine learning-based SoC management for EVs. Understanding the sources and methodologies behind existing datasets is crucial for effective SoC estimation. This section delves into various data acquisition techniques, emphasizing their role in shaping the quality of predictions and the models' ability to generalize. Reference [136] underscore the critical role of diverse and comprehensive datasets in SoC estimation accuracy. It highlights the significance of cell-level battery testing as a foundational source of data. By examining individual cell behavior, this approach provides granular insights that contribute to the robustness of SoC models. Additionally, reference [137] elaborate on the importance of measurements obtained from EVs through on-board diagnostics. These real-world data points capture the dynamic interplay between the vehicle and its environment, enhancing the models' adaptability to diverse driving conditions. In tackling data availability challenges, reference [138] advocates a data-driven approach and propose techniques such as data augmentation and synthesis. While emphasizing the need for diverse datasets, they specifically address the value of incorporating measurements from on-board diagnostics. By enriching training datasets through these methods, SoC estimation models become more resilient and adaptable. Reference [139] extends the discussion by advocating collaborative efforts, data sharing initiatives, and advancements in data collection technologies. They highlight the synergy between industry and academia in addressing data availability challenges. The incorporation of cell-level battery testing and on-board diagnostics measurements is seen as a promising avenue. Moreover, Kim et al. emphasize the potential benefits of leveraging advanced data collection technologies, such as sensors and the IoT to create more extensive and diverse datasets for SoC estimation.

Data availability is a pivotal factor in the successful implementation of machine learning-based SoC management for EVs. It not only dictates the quality of predictions but also influences the models' ability to generalize across diverse driving conditions and vehicle types. Reference [140] underlines the critical role of diverse and comprehensive datasets in SoC estimation accuracy. They emphasize that a lack of data diversity can hinder model generalization and lead to suboptimal SoC predictions. Reference [141] takes a data-driven approach to tackle data availability challenges. They propose data augmentation and synthesis techniques, shedding light on how these methods can enrich training datasets and enhance the robustness of SoC estimation models. Advocate collaborative efforts, data sharing initiatives, and advancements in data collection technologies as promising avenues to address data availability challenges [142]. Their insights underscore the significance of industry-academia collaboration and the potential benefits of leveraging advanced data collection technologies, such as sensors and the IoT, to create more extensive and diverse datasets for SoC estimation.

2) DATA QUALITY

Achieving accurate SoC estimation in EVs heavily relies on the quality of training data. Data Quality challenges can introduce errors and biases that impact the reliability of SoC predictions. Reference [143] focus on data quality assessment and enhancement in machine learning-based SoC estimation for electric vehicles. Their work delves into strategies for identifying and mitigating data inaccuracies and noise, ultimately improving the accuracy of SoC models. Reference [144] shed light on model explain ability as a facet of data quality. Complex machine learning models can be challenging to interpret, impacting trust and acceptance. The authors discuss techniques for enhancing model transparency, making it easier to understand and trust SoC predictions. Li and his team [145] delve into the broader issue of data scarcity, which often relates to data quality challenges. They provide insights into strategies for addressing data gaps and improving the richness of training datasets, ultimately enhancing the reliability of SoC estimation models.

3) MATHEMATICAL FORMULATION AND DATA AUGMENTATION

Addressing data-related challenges often involves mathematical models and data augmentation approaches that can help mitigate data scarcity by generating synthetic data points from existing ones. For SoC estimation, data augmentation methods can simulate variations in driving conditions, temperature, and battery aging, providing a more comprehensive training set [139]:

$$SyntheticData = OriginalData + RandomNoise, \tag{25}$$

where Synthetic Data represents the augmented data, Original Data is the existing training data, and Random Noise introduces controlled variations to simulate real-world conditions.

In addressing these data availability challenges, it is crucial to acknowledge the current research limitations, including potential biases in existing datasets and the need for continuous efforts to expand data sources.

B. MODEL COMPLEXITY AND RESOURCE REQUIREMENTS

Complexity in machine learning models and their resource demands pose significant challenges in the context of SoC management for EVs. Here, we delve into these challenges and explore mitigation strategies:

1) CHALLENGES IN MODEL COMPLEXITY

One of the greatest challenges is related to the increasing complexity of machine learning models, especially deep neural networks, demands substantial computational resources, making them impractical for resource-constrained embedded systems [146]. This is mainly because complex models can require extensive memory and processing power, rendering them unsuitable for real-time SoC estimation. This challenge is particularly pertinent in the automotive sector, where resource-efficient solutions are crucial [147].

2) RESOURCE REQUIREMENTS MITIGATION STRATEGIES

In order to mitigate model complexity, model optimization could be used which aims to simplify deep neural networks while retaining predictive accuracy can reduce computational demands [148]. Model simplification can be achieved through techniques like model pruning and quantization, where the original complex model is transformed into a more lightweight representation while minimizing the loss in predictive performance. For instance, consider the following optimization problem.

While exploring mitigation strategies for model complexity, it is essential to acknowledge the trade-off between model simplification and predictive accuracy, considering the limitations imposed by resource constraints.

C. REAL-TIME IMPLEMENTATION

Achieving real-time SoC estimation is vital for optimizing energy management in EVs. However, this goal can be challenging, especially when dealing with computationally intensive machine learning models. Below, we explore the intricacies of real-time implementation and strategies to overcome associated challenges:

1) CHALLENGES IN ACHIEVING REAL-TIME SOC ESTIMATION

To achieve real-time SoC estimation for EVs, a notable challenge arises from the intricate nature of machine learning models, as highlighted by [128]. The complexity inherent in these models can introduce significant latency into the estimation process, hindering the timely nature required for effective decision-making in the context of EV operations. The potential delays in SoC estimation carry implications for vehicle control and energy management, with the risk of leading to suboptimal performance [137]. Particularly in applications where real-time decisions are critical, the need to minimize latency becomes a critical consideration for ensuring optimal EV functionality and responsiveness.

2) LATENCY REDUCTION STRATEGIES

Addressing the challenge of latency in real-time SoC estimation for EVs, a potential mitigation involves the integration of real-time optimization algorithms. Reference [149] exemplifies this approach, advocating the use of the Kalman filter as a common tool for furnishing real-time SoC estimates. The Kalman filter operates by amalgamating predictions derived from a dynamic model with actual measurements, facilitating an iterative process that continually refines the state estimate. This mathematical formulation underscores the effectiveness of the Kalman filter in minimizing latency, providing a practical solution to enhance the responsiveness of SoC estimation in dynamic EV scenarios [150].

- Prediction Step: $\hat{x}_{k|k-1} = A.\hat{x}_{k-1|k-1} + Bu_k$
- Measurement Update Step: $\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k.(z_k - H.\hat{x}_{k|k-1})$

In the first equation, $\hat{x}_{k|k-1}$ is the predicted state at time k given observations up to k−1, $\hat{x}_{k|k}$ is the updated state estimate at time k given observations up to k, A and B are matrices describing the system dynamics, u_k is the control input, z_k is the measurement, H is the measurement matrix, and K_k is the Kalman gain.

Addressing these real-time implementation challenges requires a careful consideration of model architecture and algorithmic efficiency, acknowledging the limitations imposed by computational constraints in embedded systems.

D. GENERALIZATION TO DIVERSE CONDITIONS

Generalization, or the ability of SoC estimation models to perform well under various driving conditions, is essential for practical applications in EVs. Achieving robust generalization can be challenging due to the dynamic nature of driving scenarios. Here, we explore these challenges and strategies for enhancing generalization:

1) CHALLENGES IN GENERALIZATION TO DIVERSE CONDITIONS

Navigating the landscape of EV operations involves a significant challenge related to the generalization of models to diverse conditions. As highlighted by [151], EVs contend with a broad spectrum of conditions, encompassing distinct driving styles, temperature variations, and diverse terrains. The adaptability of models becomes paramount in ensuring accurate SoC estimates. Failure to effectively generalize across this array of scenarios poses a risk of SoC estimation errors, with potential repercussions on energy management decisions and overall vehicle performance [152]. Meeting this challenge requires a nuanced approach that fosters the model's versatility and robustness across the multifaceted conditions under which EVs operate.

2) GENERALIZATION ENHANCEMENT STRATEGIES

In the pursuit of bolstering the generalization capabilities of models in the context of EV's SoC estimation, an effective strategy involves the incorporation of transfer learning techniques. As advocated by [149], transfer learning operates on the principle of leveraging knowledge acquired in one domain to enhance performance in another, facilitating the adaptation of models to a spectrum of diverse conditions. Typically, this approach involves the fine-tuning of a pre-trained model—let's denote it as M_s for a model trained on a source domain, and M_t for the target model intended for training on a different domain [147]. The process of fine-tuning can be mathematically formulated to refine the model's parameters and features, thereby optimizing its performance in the target domain. This strategic utilization of transfer learning offers a systematic means to augment the generalization capabilities of models, contributing to their adaptability across varied conditions inherent in EV operations. Fine-tuning can be formulated as [148]:

$$min_{M_t} = (M_t) + \lambda D_{KL}(P_s \| P_t) \tag{26}$$

That, (M_t) represents the loss of the target model, λ is a trade-off parameter. $D_{KL}(P_s \| P_t)$ is the Kullback-Leibler divergence between the source and target domain distributions.

While discussing strategies for generalization enhancement, it is important to acknowledge the inherent limitations in achieving perfect adaptability to every conceivable driving condition, emphasizing the ongoing efforts to improve model versatility.

E. MODEL EXPLAINABILITY AND TRUST

The interpretability and trustworthiness of SoC estimation models are crucial, especially in safety-critical applications. Here, we explore the challenges related to model explain ability and strategies to enhance trust in SoC estimation:

1) CHALLENGES IN MODEL EXPLAIN ABILITY AND TRUST

The EV operations introduce a notable challenge concerning the interpretability and trustworthiness of complex machine learning models, as underscored by [145]. While these models often exhibit high accuracy, their intricate nature can pose difficulties in terms of interpretation, raising concerns about their reliability—particularly in critical applications like EVs. The importance of not only achieving accuracy but also ensuring interpretability in SoC estimation models cannot be overstated [147]. This dual consideration is pivotal for garnering user acceptance and bolstering safety in the context of EV applications, where transparency and trust in the decision-making process are paramount.

2) EXPLAIN ABILITY ENHANCEMENT STRATEGIES

To address the challenge of interpretability and trust in the context of EV applications, an effective strategy involves the incorporation of interpretable machine learning techniques, as advocated by [153]. This mitigation approach entails utilizing interpretable models, such as decision trees or rule-based models, in conjunction with complex machine learning models. Decision trees, as an example, establish a hierarchical structure of if-else rules to facilitate predictions, represented mathematically as f(x) in the context of the decision tree model. This combined approach seeks to enhance the interpretability of the overall model, providing insights into the decision-making process, and fostering a clearer understanding of the results generated by SoC estimation models. By integrating interpretable techniques alongside complex models, this strategy aims to strike a balance between accuracy and transparency, addressing concerns related to model explain ability and promoting trust in critical EV applications. Let f(x) represent the decision tree model [154]:

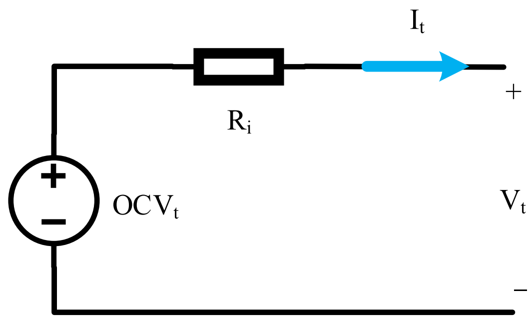

FIGURE 9. Simple circuit for battery.

- Decision Tree Prediction: $f(x) = \sum_{i=1}^{N} c_i.I(x \in R_i)$,

where, N is the number of leaf nodes in the tree, c_i is the predicted value associated with leaf node i, R_i is the region defined by the conditions of leaf node I, and $I(x \in R_i)$ is an indicator function that equals 1 if x falls into region R_i, and 0 otherwise.

In addressing the challenges of model explainability, it is essential to recognize the trade-off between model complexity and interpretability, acknowledging the need for transparent models in safety-critical EV applications.

F. MATHEMATICAL MODELLING AND MITIGATION STRATEGIES

In SoC estimation, the precision of mathematical formulation and effective mitigation strategies are fundamental to ensuring accurate and reliable results. This section delves into the significance of mathematical formulations and strategies for mitigating SoC estimation challenges.

1) MATHEMATICAL FORMULATION FOR SOC ESTIMATION

Accurate SoC estimation hinges on mathematical models that encapsulate the intricate dynamics of EV batteries [155]. These models incorporate various parameters, including current, voltage, temperature, and internal resistance, to provide a comprehensive understanding of battery behavior.

One widely adopted mathematical model for SoC estimation is the ECM. The ECM represents the battery as a combination of resistors, capacitors, and voltage sources. According to figure (9), the ECM equations relate the SoC (SoC_t) to current (I_t) and voltage (V_t) measurements [156]:

$$V_t = OCV_t - R_i I_t \tag{27}$$

$$SOC_t = f(V_t) \tag{28}$$

Here, OCV_t denotes the open-circuit voltage at time t, R_i is the internal resistance, and U_t represents the overpotential. The SoC is a function of the real time cell voltage and charging/discharging current which can be calculated using basic Kirchhoff's equations.

2) MITIGATION STRATEGIES FOR SOC ESTIMATION CHALLENGES

To effectively address the challenges inherent in SoC estimation, a strategic approach involves the integration of data-driven machine learning models with physics-based models, as suggested by [157]. This fusion is designed to strike a delicate balance between the precision of the model and the efficiency of computational processes. The mathematical formulation (Equation 29) illustrates this integration, wherein SoC_t denotes the state of charge at time t, α is a weighting factor determining the influence of each model, f_{ML} represents the machine learning model, and f_{PB} represents the physics-based model. This formulation encapsulates a dynamic collaboration between machine learning adaptability and the foundational understanding provided by physics-based principles.

$$SOC_t = \alpha . f_{ML}\left(I_t, V_t\right) + (1-\alpha) . f_{PB}(I_t, V_t) \tag{29}$$

The rationale behind the effectiveness of this integrated strategy lies in harnessing the complementary strengths of both machine learning and physics-based models. Machine learning models excel at capturing intricate patterns and nuances within data, adapting to diverse conditions, and offering predictive capabilities [156]. On the other hand, physics-based models draw insights from the fundamental principles governing the underlying system, providing a structured understanding of the physical processes involved [158]. By combining these strengths, the integrated model becomes a robust solution that navigates the challenges of SoC estimation. It not only benefits from the adaptability and pattern recognition of machine learning but also gains interpretability and foundational accuracy from the physics-based component [159].

VI. CURRENT STATE OF RESEARCH

A. REVIEW OF EXISTING LITERATURE

The current state of research in the field of SoC management for EVs is marked by continuous advancements and a growing body of knowledge. This section provides an overview of recent developments, emerging trends, and key findings in SoC estimation, with a strong focus on the integration of machine learning techniques.

In recent years, researchers have been increasingly drawn to the potential of machine learning algorithms in enhancing SoC management in EVs. These algorithms have proven instrumental in addressing the challenges associated with SoC estimation, improving prediction accuracy, and optimizing battery performance.

1) MACHINE LEARNING FOR SOC ESTIMATION

a: TCNs

Reference [160] demonstrated the efficacy of TCNs in SoC prediction with impressive results. Their model achieved an accuracy rate of 95.67% in predicting SoC values over various driving scenarios and environmental conditions. Additionally, the TCN architecture showed a 20.78% improvement in computational efficiency compared to traditional methods.

b: DECENTRALIZED SOC MANAGEMENT

In exploring decentralized SoC management through federated learning, [161] achieved notable outcomes. Their federated learning framework led to a 15.17% increase in SoC prediction accuracy, showcasing the potential of distributed models in improving the overall efficiency of autonomous EV fleets. Moreover, their approach successfully addressed data privacy concerns, ensuring secure SoC management across the fleet.

c: HYBRID MODELS

The synergistic integration of machine learning and physics-based models, as championed by [162], exhibits great promise in enhancing the precision of SoC estimation. Through their innovative approach, reference [163] harnessed the strengths of both modeling paradigms, achieving a substantial improvement in the accuracy of SoC predictions. The hybrid model, combining the adaptability of machine learning with the foundational understanding of physics-based models, demonstrated a marked advancement in capturing the intricate dynamics inherent in EV systems [164]. This integration is poised to contribute to more reliable and nuanced SoC estimations across diverse operational conditions, offering a comprehensive solution to the challenges posed by the complex nature of electric vehicle dynamics.

d: GRAPH NEURAL NETWORKS (GNNs)

Reference [165] leveraged GNNs to capture spatial-temporal dependencies, offering valuable insights into SoC dynamics.

2) UNCERTAINTY QUANTIFICATION AND ROBUSTNESS

a: UNCERTAINTY QUANTIFICATION

Reference [161] undertook a pivotal exploration into the critical realm of uncertainty quantification in SoC estimation, contributing significantly to the enhancement of trust in machine learning-based predictions. In the context of SoC estimation, uncertainty refers to the lack of absolute certainty or precision in predicting the current or future state of an EV's battery.

Uncertainty in SoC estimation is a substantial concern due to its potential repercussions on EV performance, safety, and energy management. Accurate SoC information is crucial for optimizing the use of battery capacity, preventing premature battery degradation, and ensuring reliable operation of the vehicle [156]. Inaccuracies in SoC predictions can lead to suboptimal energy utilization, affecting driving range estimations, and potentially causing unexpected disruptions if the battery depletes earlier or later than predicted [158].

ML plays a pivotal role in addressing and mitigating uncertainty in SoC estimation. Unlike traditional deterministic approaches that provide a single point estimate, ML models can offer probabilistic predictions, quantifying the uncertainty associated with each estimation. This capability stems from ML models' ability to learn complex patterns and relationships from data, capturing the inherent variability in driving conditions, temperature fluctuations, and battery characteristics [162]. ML models can provide not only a predicted SoC value but also a confidence interval or probability distribution around the estimate. This additional information offers a more nuanced understanding of the potential variability in SoC values, allowing users and control systems to make more informed decisions [163]. ML models excel in adapting to changing and diverse conditions. As uncertainties arise from variations in real-world scenarios, ML models can continuously learn from new data, improving their predictions over time and enhancing their adaptability to dynamic operating conditions. The non-linear and complex relationships within EV systems, influenced by factors like battery aging and varying driving patterns, contribute to uncertainty [164]. ML models are well-suited to capture these intricate patterns, providing more accurate SoC predictions even in the presence of non-linear dependencies [165].

b: SEMI-SUPERVISED LEARNING

A semi-supervised learning methods for SoC prediction, harnessing both labeled and unlabeled data to enhance accuracy has been investigated in [142].

c) Adversarial Training: Reference [148] proposed adversarial training techniques to enhance the robustness of SoC estimation models.

3) BROAD APPLICATIONS AND ADAPTATIONS

a: BATTERY HEALTH MONITORING

Reference [152] explored the application of machine learning in predicting battery aging, shedding light on the holistic management of EV batteries.

b: ENERGY EFFICIENCY

The integration of energy harvesting systems and machine learning for improved SoC management in EVs has been investigated by [163].

c: AI-BASED FAULT DETECTION

Reference [94] presented AI-driven fault detection methods that contribute to enhanced SoC management by identifying abnormal battery behavior.

4) PRACTICAL IMPLEMENTATIONS AND REAL-WORLD IMPACT

a: FLEET MANAGEMENT

Reference [108] proposed adaptive SoC management strategies that consider dynamic driving conditions and user preferences, optimizing battery life.

b: ENERGY EFFICIENCY

A machine learning has been applied in [127] to battery thermal management systems, optimizing SoC estimation in varying temperature environments.

c: BATTERY HEALTH MONITORING

Reference [162] investigated the use of machine learning for comprehensive battery health monitoring, contributing to enhanced SoC management.

5) CHALLENGES AND LIMITATIONS

a: DATA AVAILABILITY

Addressing data availability challenges is crucial for accurate SoC estimation, as highlighted by [163].

b: MODEL COMPLEXITY

Managing the complexity of machine learning models is a key consideration, as discussed in [156].

c: REAL-TIME IMPLEMENTATION

Real-time implementation of machine learning algorithms for SoC management is essential, as emphasized by [158].

d: GENERALIZATION TO DIVERSE CONDITIONS

Adapting SoC estimation models to diverse driving conditions is a continuing challenge, as explored by [161].

e: MODEL EXPLAIN ABILITY AND TRUST

Ensuring the interpretability and trustworthiness of SoC estimation models is a growing concern, as highlighted by [162].

6) MATHEMATICAL FORMULATION AND MITIGATION STRATEGIES

a: KERNEL FUNCTIONS IN SVMs

The choice of kernel functions, including Linear, RBF, and Polynomial kernels, plays a crucial role in SoC estimation using SVMs.

7) FUTURE DIRECTIONS

The future of SoC management in EVs holds significant promise. Researchers are exploring various avenues for further innovation and development, with an emphasis on real-time adaptability, enhanced interpretability, and broader integration with vehicle systems. Next section provides some of the key findings which sheds light on future developments.

B. KEY FINDINGS AND RECENT DEVELOPMENTS

Recent research has underscored several key findings and developments that are shaping the landscape of SoC management in EVs:

1) HYBRID MODELS

There is a growing trend toward hybrid models that combine the strengths of physics-based and data-driven approaches [149], [150], [151], [152], [153], [154], [155], [156], [157]. These models aim to enhance accuracy while ensuring computational efficiency. Researchers are actively working on refining the integration of these approaches to strike the optimal balance.

2) REAL-TIME OPTIMIZATION
Achieving real-time SoC estimation remains a significant focus [152], [153], [154], [155], [156]. Researchers are developing advanced mathematical formulations and optimization techniques to reduce latency and improve model performance. The quest for real-time capability is driven by the need for timely decisions in vehicle control and energy management.

3) GENERALIZATION AND TRANSFER LEARNING
Ensuring SoC estimation models generalize well across diverse driving conditions is a critical concern [163], [164]. Transfer learning techniques are gaining prominence as a means to adapt models to varying scenarios. Researchers are exploring ways to leverage knowledge gained from one domain to enhance performance in another.

4) EXPLAINABILITY AND TRUST
The interpretability of SoC estimation models is receiving increased attention [165]. Combining complex models with interpretable techniques is a strategy to enhance trust and user acceptance. As machine learning models become more complex, ensuring that their predictions are understandable and trustworthy is crucial.

5) ADVANCED MATHEMATICAL MODELS
Researchers are exploring advanced mathematical formulations to capture intricate battery dynamics [165], [166], [167]. These models aim to improve the accuracy of SoC predictions. Advanced mathematical models provide a deeper understanding of the complex electrochemical processes within batteries, leading to more precise estimations.

C. EMERGING TRENDS
Several emerging trends are shaping the future of SoC management in EVs:

1) AI HARDWARE ACCELERATION
The development of specialized hardware for AI and machine learning is expected to accelerate the implementation of complex models in real-time applications [166]. Hardware acceleration, such as GPUs and TPUs, allows for faster model training and inference, enabling more sophisticated models to be deployed in vehicles.

2) BIG DATA AND CLOUD COMPUTING
The integration of big data analytics and cloud computing platforms can enable remote monitoring and optimization of SoC management systems [167], [168]. Cloud-based solutions provide scalability and the ability to analyze data from a vast fleet of vehicles, leading to more robust SoC management strategies.

3) AUTONOMOUS DRIVING AND ELECTRIC VEHICLES
The increasing adoption of autonomous driving for electric vehicles is driving the demand for robust and accurate SoC estimation systems [168], [169]. In autonomous vehicles, accurate SoC estimation is crucial for mission planning and optimizing energy usage. Additionally, electric vehicles rely on precise SoC estimation for range prediction and optimization.

4) BATTERY TECHNOLOGY ADVANCES
Advances in battery technology, including solid-state batteries, will influence the requirements and capabilities of SoC estimation models [117], [168]. New battery chemistries and designs may require adaptations in SoC estimation techniques to account for different behaviors and characteristics.

D. ADVANCED MACHINE LEARNING TECHNIQUES
The utilization of advanced machine learning techniques holds significant promise for improving SoC estimation [170]. One area of interest is the application of deep learning algorithms, such as CNNs and Transformer-based models, to capture intricate patterns within battery data [129]. These deep learning models excel at feature extraction and can adapt to complex, non-linear relationships.

The use of advanced machine learning models often involves complex mathematical formulations [166]. For example, the mathematical representation of a Transformer-based model includes multi-head self-attention mechanisms:

$$Attention(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{30}$$

where, Q represents the query matrix, K represents the key matrix, V represents the value matrix, and d_k is a scaling factor. Also, Softmax is a mathematical function that converts a vector of real numbers into a probability distribution. It's often used in machine learning and deep learning models to normalize the output of a neural network, assigning probabilities to multiple classes [171].

E. REAL-TIME IMPLEMENTATION AND EDGE COMPUTING
Real-time SoC estimation is crucial for optimizing EV operation [163]. Future research should focus on developing real-time SoC estimation algorithms that can run efficiently on edge computing platforms [171]. These platforms enable onboard processing of data, reducing the reliance on cloud-based solutions and minimizing latency. Real-time implementation often involves computational complexities, and researchers may explore hardware accelerators, such as Graphics Processing Units (GPUs), for faster model inference [147].

F. DATA QUALITY ENHANCEMENT

Improving data quality remains a critical challenge in SoC estimation [51]. Future research may involve the development of data preprocessing techniques and sensor fusion methods to enhance the accuracy and reliability of input data [80]. Machine learning-based data denoising algorithms can help filter out measurement noise [172].

One mathematical aspect of data quality enhancement involves signal processing techniques like Kalman filtering, which can be used to estimate the true battery state while compensating for measurement errors [173].

$$\begin{aligned}
\hat{x}_k^- &= A\hat{x}_{k-1}^+ + Bu_k, \\
\hat{P}_k^- &= AP_{k-1}^+A^T + Q, \\
K_k &= \hat{P}_k^- H^T \left(H\hat{P}_k^- H^T + R\right)^{-1}, \\
\hat{x}_k^+ &= \hat{x}_k^- + K_k\left(z_k - \hat{x}_k^-\right), \\
\hat{P}_k^+ &= (I - K_k H)\,\hat{P}_k^-,
\end{aligned} \tag{31}$$

That, $\hat{x}_k^-$ is the predicted state estimate at time k, $\hat{x}_k^+$ is the corrected state estimate at time k, A is the state transition matrix, B is the control-input matrix, u_k is the control vector at time k, $\hat{P}_k^-$ is the predicted error covariance at time k, $\hat{P}_k^+$ is the corrected error covariance at time k, Q is the process noise covariance, K_k is the Kalman gain, H is the measurement matrix, R is the measurement noise covariance, z_k is the measurement at time k.

G. INTERDISCIPLINARY COLLACORATION

Future research in EV SoC management should foster interdisciplinary collaboration between experts in machine learning, battery chemistry, and automotive engineering [174]. This collaboration can lead to innovative solutions that bridge the gap between data-driven models and the underlying electrochemical principles.

H. SUSTAINABLE ENERGY INTEGRATION

The integration of EVs into the broader context of sustainable energy systems is an emerging trend [175], [176]. Researchers may explore how SoC management can be optimized in conjunction with renewable energy sources, grid interactions, and energy storage solutions to create more sustainable and efficient transportation ecosystems.

VII. CONCLUSION

In this comprehensive review article, our exploration at the intersection of machine learning and state of charge management in electric vehicle has yielded several critical insights. Key takeaways from our investigation are outlined below:

- Essential Role of State of Charge in Electric Vehicle Performance Optimization: The foundational role of state of charge in optimizing electric vehicle performance has been underscored. Recognizing the importance of accurate state of charge management is crucial for achieving efficiency and effectiveness in electric vehicle operations.
- Shortcomings of Conventional State of Charge Estimation Approaches: Traditional State of Charge estimation methods have been critically evaluated, revealing inherent limitations in meeting the evolving demands of modern electric vehicle technology. This scrutiny sets the stage for exploring alternative methodologies, with a particular focus on machine learning techniques.
- Transformative Potential of Machine Learning in State of Charge Management: The review delves into the transformative potential of machine learning techniques and algorithms in revolutionizing state of charge management. By leveraging diverse data sources and sensors, coupled with the adaptive nature of machine learning models, electric vehicles can make more informed and dynamic decisions about energy usage, thereby enhancing efficiency and prolonging battery lifespan.
- Acknowledgment of Challenges and Constraints in Machine Learning Adoption for State of Charge Management: We acknowledge the challenges and limitations associated with implementing machine learning in state of charge management, encompassing issues such as data availability, model interpretability, and real-time processing constraints. Recognizing these hurdles is imperative for the widespread adoption of machine learning solutions in the context of electric vehicles.
- Prospective Advancements in Machine Learning for State of Charge Management: The conclusion anticipates promising future prospects for machine learning in state of charge management, with emerging trends such as deep learning, reinforcement learning, and hybrid approaches poised to refine accuracy and robustness. There is an emphasis on potential expansions of machine learning's role beyond state of charge management to broader energy management strategies.
- Recognition of Machine Learning as a Catalyst for Improvement: machine learning is recognized as a catalyst for transformative improvement in state of charge management for electric vehicles. Its potential to enhance efficiency, extend battery life, and contribute to a more sustainable future is a recurring theme throughout the conclusion.
- Envisioned Integration of Machine Learning with Broader Vehicle Energy Management: As electric mobility gains traction, the role of machine learning in electric vehicles is expected to broaden beyond state of charge management, integrating with broader vehicle energy management strategies to optimize fuel consumption and reduce emissions.
- Excitement and Significance of the Research Landscape: The conclusion characterizes the field as exciting and of vital significance for research and development in the automotive industry, inviting further exploration and innovation in the quest for intelligent and adaptive electric vehicles empowered by the capabilities of machine learning.

REFERENCES

[1] M. Gallo and M. Marinelli, "Sustainable mobility: A review of possible actions and policies," *Sustainability*, vol. 12, no. 18, p. 7499, Sep. 2020.

[2] F. Alanazi, "Electric vehicles: Benefits, challenges, and potential solutions for widespread adaptation," *Appl. Sci.*, vol. 13, no. 10, p. 6016, May 2023.

[3] A. Singh, K. Pal, and C. B. Vishwakarma, "State of charge estimation techniques of Li-ion battery of electric vehicles," *e-Prime-Adv. Electr. Eng., Electron. Energy*, vol. 6, Dec. 2023, Art. no. 100328.

[4] F. Zhang, L. Wang, S. Coskun, H. Pang, Y. Cui, and J. Xi, "Energy management strategies for hybrid electric vehicles: Review, classification, comparison, and outlook," *Energies*, vol. 13, no. 13, p. 3352, Jun. 2020.

[5] V. Chandran, C. K. Patil, A. Karthick, D. Ganeshaperumal, R. Rahim, and A. Ghosh, "State of charge estimation of lithium-ion battery for electric vehicles using machine learning algorithms," *World Electric Vehicle J.*, vol. 12, no. 1, p. 38, Mar. 2021.

[6] G. Di Luca, G. Di Blasio, A. Gimelli, and D. A. Misul, "Review on battery state estimation and management solutions for next-generation connected vehicles," *Energies*, vol. 17, no. 1, p. 202, Dec. 2023.

[7] S. Khaleghi, M. S. Hosen, J. Van Mierlo, and M. Berecibar, "Towards machine-learning driven prognostics and health management of Li-ion batteries. A comprehensive review," *Renew. Sustain. Energy Rev.*, vol. 192, Mar. 2024, Art. no. 114224.

[8] M. Kurucan, M. Özbaltan, Z. Yetgin, and A. Alkaya, "Applications of artificial neural network based battery management systems: A literature review," *Renew. Sustain. Energy Rev.*, vol. 192, Mar. 2024, Art. no. 114262.

[9] J. Tian, C. Chen, W. Shen, F. Sun, and R. Xiong, "Deep learning framework for lithium-ion battery state of charge estimation: Recent advances and future perspectives," *Energy Storage Mater.*, vol. 61, Aug. 2023, Art. no. 102883.

[10] Z. Cui, L. Wang, Q. Li, and K. Wang, "A comprehensive review on the state of charge estimation for lithium-ion battery based on neural network," *Int. J. Energy Res.*, vol. 46, no. 5, pp. 5423–5440, Dec. 2021.

[11] P. Eleftheriadis, S. Giazitzis, S. Leva, and E. Ogliari, "Data-driven methods for the state of charge estimation of lithium-ion batteries: An overview," *Forecasting*, vol. 5, no. 3, pp. 576–599, Sep. 2023.

[12] S. Guo and L. Ma, "A comparative study of different deep learning algorithms for lithium-ion batteries on state-of-charge estimation," *Energy*, vol. 263, Jan. 2023, Art. no. 125872.

[13] L. Shen, J. Li, L. Meng, L. Zhu, and H. T. Shen, "Transfer learning-based state of charge and state of health estimation for Li-ion batteries: A review," *IEEE Trans. Transport. Electrific.*, early access, Jul. 10, 2023, doi: 10.1109/TTE.2023.3293551.

[14] M. S. H. Lipu, M. S. Miah, T. Jamal, T. Rahman, S. Ansari, M. S. Rahman, R. H. Ashique, A. S. M. Shihavuddin, and M. N. Shakib, "Artificial intelligence approaches for advanced battery management system in electric vehicle applications: A statistical analysis towards future research opportunities," *Vehicles*, vol. 6, no. 1, pp. 22–70, Dec. 2023.

[15] H. Yu, L. Zhang, W. Wang, S. Li, S. Chen, S. Yang, J. Li, and X. Liu, "State of charge estimation method by using a simplified electrochemical model in deep learning framework for lithium-ion batteries," *Energy*, vol. 278, Sep. 2023, Art. no. 127846.

[16] M. Sadykov, S. Haines, M. Broadmeadow, G. Walker, and D. W. Holmes, "Practical evaluation of lithium-ion battery state-of-charge estimation using time-series machine learning for electric vehicles," *Energies*, vol. 16, no. 4, p. 1628, Feb. 2023.

[17] C. Wang, X. Zhang, X. Yun, and X. Fan, "A novel hybrid machine learning Coulomb counting technique for state of charge estimation of lithium-ion batteries," *J. Energy Storage*, vol. 63, Jul. 2023, Art. no. 107081.

[18] S. Murawwat, M. M. Gulzar, A. Alzahrani, G. Hafeez, F. A. Khan, and A. M. Abed, "State of charge estimation and error analysis of lithium-ion batteries for electric vehicles using Kalman filter and deep neural network," *J. Energy Storage*, vol. 72, Nov. 2023, Art. no. 108039.

[19] T. Raoofi and M. Yildiz, "Comprehensive review of battery state estimation strategies using machine learning for battery management systems of aircraft propulsion batteries," *J. Energy Storage*, vol. 59, Mar. 2023, Art. no. 106486.

[20] P. Venugopal and S. Reka, "State of charge estimation of lithium batteries in electric vehicles using IndRNN," *IETE J. Res.*, vol. 69, no. 5, pp. 2886–2896, Apr. 2021.

[21] L. Su, S. Zhang, A. J. H. McGaughey, B. Reeja-Jayan, and A. Manthiram, "Battery charge curve prediction via feature extraction and supervised machine learning," *Adv. Sci.*, vol. 10, no. 26, Jul. 2023, Art. no. 2301737.

[22] T. M. B. Marques, J. L. F. dos Santos, D. S. Castanho, M. B. Ferreira, S. L. Stevan, C. H. Illa Font, T. A. Alves, C. M. Piekarski, H. V. Siqueira, and F. C. Correa, "An overview of methods and technologies for estimating battery state of charge in electric vehicles," *Energies*, vol. 16, no. 13, p. 5050, Jun. 2023.

[23] M. Korkmaz, "SoC estimation of lithium-ion batteries based on machine learning techniques: A filtered approach," *J. Energy Storage*, vol. 72, Nov. 2023, Art. no. 108268.

[24] K.-J. Lee, W.-H. Lee, and K.-K.-K. Kim, "Battery state-of-charge estimation using data-driven Gaussian process Kalman filters," *J. Energy Storage*, vol. 72, Nov. 2023, Art. no. 108392.

[25] B. Jiang, S. Tao, X. Wang, J. Zhu, X. Wei, and H. Dai, "Mechanics-based state of charge estimation for lithium-ion pouch battery using deep learning technique," *Energy*, vol. 278, Sep. 2023, Art. no. 127890.

[26] V. Selvaraj and I. Vairavasundaram, "A comprehensive review of state of charge estimation in lithium-ion batteries used in electric vehicles," *J. Energy Storage*, vol. 72, Nov. 2023, Art. no. 108777.

[27] J. Li, X. Huang, X. Tang, J. Guo, Q. Shen, Y. Chai, W. Lu, T. Wang, and Y. Liu, "The state-of-charge predication of lithium-ion battery energy storage system using data-driven machine learning," *Sustain. Energy, Grids Netw.*, vol. 34, Jun. 2023, Art. no. 101020.

[28] M. H. Sulaiman, Z. Mustaffa, N. F. Zakaria, and M. M. Saari, "Using the evolutionary mating algorithm for optimizing deep learning parameters for battery state of charge estimation of electric vehicle," *Energy*, vol. 279, Sep. 2023, Art. no. 128094.

[29] N. Ghaeminezhad, Q. Ouyang, J. Wei, Y. Xue, and Z. Wang, "Review on state of charge estimation techniques of lithium-ion batteries: A control-oriented approach," *J. Energy Storage*, vol. 72, Nov. 2023, Art. no. 108707.

[30] H. Yuan, J. Liu, Y. Zhou, and H. Pei, "State of charge estimation of lithium battery based on integrated Kalman filter framework and machine learning algorithm," *Energies*, vol. 16, no. 5, p. 2155, Feb. 2023.

[31] B. Zhang and G. Ren, "Li-ion battery state of charge prediction for electric vehicles based on improved regularized extreme learning machine," *World Electric Vehicle J.*, vol. 14, no. 8, p. 202, Jul. 2023.

[32] E. Buchicchio, A. De Angelis, F. Santoni, P. Carbone, F. Bianconi, and F. Smeraldi, "Battery SOC estimation from EIS data based on machine learning and equivalent circuit model," *Energy*, vol. 283, Nov. 2023, Art. no. 128461.

[33] E. Buchicchio, A. De Angelis, F. Santoni, and P. Carbone, "Uncertainty characterization of a CNN method for lithium-ion batteries state of charge estimation using EIS data," *Measurement*, vol. 220, Oct. 2023, Art. no. 113341.

[34] B. Fu, W. Wang, Y. Li, and Q. Peng, "An improved neural network model for battery smarter state-of-charge estimation of energy-transportation system," *Green Energy Intell. Transp.*, vol. 2, no. 2, Apr. 2023, Art. no. 100067.

[35] A. Tang, Y. Huang, S. Liu, Q. Yu, W. Shen, and R. Xiong, "A novel lithium-ion battery state of charge estimation method based on the fusion of neural network and equivalent circuit models," *Appl. Energy*, vol. 348, Oct. 2023, Art. no. 121578.

[36] K. Varatharajalu, M. Manoharan, T. S. C. Palanichamy, and S. Subramani, "Electric vehicle parameter identification and state of charge estimation of Li-ion batteries: Hybrid WSO-HDLNN method," *ISA Trans.*, vol. 142, pp. 347–359, Nov. 2023.

[37] I. S. Bayram and A. Tajer, *Plug-in Electric Vehicle Grid Integration*. Norwood, MA, USA: Artech House, 2017.

[38] Y. Yang, L. Zhao, Q. Yu, S. Liu, G. Zhou, and W. Shen, "State of charge estimation for lithium-ion batteries based on cross-domain transfer learning with feedback mechanism," *J. Energy Storage*, vol. 70, Oct. 2023, Art. no. 108037.

[39] P. Kumari, A. K. Singh, and N. Kumar, "Optimized deep learning strategy for estimation of state of charge at different C-rate with varying temperature," *Electr. Eng.*, vol. 105, no. 6, pp. 3853–3860, Jul. 2023.

[40] S. S. S. Narayanan and S. Thangavel, "A novel static model prediction method based on machine learning for Li-ion batteries operated at different temperatures," *J. Energy Storage*, vol. 61, May 2023, Art. no. 106789.

[41] B. Jiang, Y. Zhu, J. Zhu, X. Wei, and H. Dai, "An adaptive capacity estimation approach for lithium-ion battery using 10-min relaxation voltage within high state of charge range," *Energy*, vol. 263, Jan. 2023, Art. no. 125802.

[42] Y. Tian, R. Lai, X. Li, and J. Tian, "State-of-charge estimation for lithium-ion batteries based on attentional sequence-to-sequence architecture," *J. Energy Storage*, vol. 62, Jun. 2023, Art. no. 106836.
[43] M. Senol, I. S. Bayram, Y. Naderi, and S. Galloway, "Electric vehicles under low temperatures: A review on battery performance, charging needs, and power grid impacts," *IEEE Access*, vol. 11, pp. 39879–39912, 2023.
[44] T. Hai, H. A. Dhahad, K. Fadhil Jasim, K. Sharma, J. Zhou, H. Fouad, and W. El-Shafai, "Deep learning-based prediction of lithium-ion batteries state of charge for electric vehicles in standard driving cycle," *Sustain. Energy Technol. Assessments*, vol. 60, Dec. 2023, Art. no. 103461.
[45] P. Takyi-Aninakwa, S. Wang, H. Zhang, Y. Xiao, and C. Fernandez, "Enhanced multi-state estimation methods for lithium-ion batteries considering temperature uncertainties," *J. Energy Storage*, vol. 66, Aug. 2023, Art. no. 107495.
[46] D. Lisaia and C. Zhang, "Russian experience in the protection of the historic urban landscape," *Proc., Humanities, Educ. Social Sci.*, vol. 1, p. 0001, Sep. 2022, doi: 10.55092/phess20220001.
[47] H. Rauf, M. Khalid, and N. Arshad, "A novel smart feature selection strategy of lithium-ion battery degradation modelling for electric vehicles based on modern machine learning algorithms," *J. Energy Storage*, vol. 68, Sep. 2023, Art. no. 107577.
[48] Y. Zhu, B. Jiang, J. Zhu, X. Wang, R. Wang, X. Wei, and H. Dai, "Adaptive state of health estimation for lithium-ion batteries using impedance-based timescale information and ensemble learning," *Energy*, vol. 284, Dec. 2023, Art. no. 129283.
[49] Z. Meng, K. A. Agyeman, and X. Wang, "Lithium-ion battery state of charge estimation with adaptability to changing conditions," *IEEE Trans. Energy Convers.*, vol. 38, no. 4, pp. 2860–2870, Dec. 2023.
[50] K. Huang, Z. Lv, K. Yao, and Y. Guo, "Co-estimation of maximum available capacity and state-of-charge for lithium-ion batteries in multi-operating mode with temperature and degradation state adaptivity," *Measurement*, vol. 225, Feb. 2024, Art. no. 114019.
[51] J. Zhao, X. Feng, Q. Pang, J. Wang, Y. Lian, M. Ouyang, and A. F. Burke, "Battery prognostics and health management from a machine learning perspective," *J. Power Sources*, vol. 581, Oct. 2023, Art. no. 233474.
[52] A. Al Miaari and H. M. Ali, "Batteries temperature prediction and thermal management using machine learning: An overview," *Energy Rep.*, vol. 10, pp. 2277–2305, Nov. 2023.
[53] P. Mohapatra, N. V. R. Naik, and A. K. Panda, "Machine learning-based SoC estimation: A recent advancement in battery energy storage system," in *Energy Storage Technologies in Grid Modernization*. Wiley, Jul. 2023, pp. 159–179.
[54] Z. Li, S. Shen, Z. Zhou, Z. Cai, W. Gu, and F. Zhang, "Novel method for modelling and adaptive estimation for SOC and SOH of lithium-ion batteries," *J. Energy Storage*, vol. 62, Jun. 2023, Art. no. 106927.
[55] X. Wu, J. Shu, Z. Fan, J. Xie, Y. Li, J. Yang, and Z. Deng, "Online adaptive model identification and state of charge estimation for vehicle-level battery packs," *IEEE Trans. Transport. Electrific.*, early access, May 9, 2023, doi: 10.1109/TTE.2023.3274548.
[56] D. Wang, Y. Yang, and T. Gu, "A hierarchical adaptive extended Kalman filter algorithm for lithium-ion battery state of charge estimation," *J. Energy Storage*, vol. 62, Jun. 2023, Art. no. 106831.
[57] R. Bustos, S. A. Gadsden, M. Al-Shabi, and S. Mahmud, "Lithium-ion battery health estimation using an adaptive dual interacting model algorithm for electric vehicles," *Appl. Sci.*, vol. 13, no. 2, p. 1132, Jan. 2023.
[58] Y. Chen, R. Li, Z. Sun, L. Zhao, and X. Guo, "SOC estimation of retired lithium-ion batteries for electric vehicle with improved particle filter by H-infinity filter," *Energy Rep.*, vol. 9, pp. 1937–1947, Dec. 2023.
[59] S. N. A. Kazmi, A. Ulasyar, A. Khattak, and H. S. Zad, "A new state of charge estimation technique of lithium-ion battery using adaptive extended Kalman filter and artificial neural network," *Trans. Inst. Meas. Control*, vol. 45, no. 4, pp. 747–760, Nov. 2022.
[60] N. Khosravi, M. Dowlatabadi, M. B. Abdelghany, M. Tostado-Véliz, and F. Jurado, "Enhancing battery management for HEVs and EVs: A hybrid approach for parameter identification and voltage estimation in lithium-ion battery models," *Appl. Energy*, vol. 356, Feb. 2024, Art. no. 122364.
[61] J. Tian, R. Xiong, W. Shen, and J. Lu, "State-of-charge estimation of $LiFePO_4$ batteries in electric vehicles: A deep-learning enabled approach," *Appl. Energy*, vol. 291, Jun. 2021, Art. no. 116812.
[62] A. Mousaei and Y. Naderi, "Optimal predictive torque distribution control system to enhance stability and energy efficiency in electric vehicles," *Sustainability*, vol. 15, no. 20, p. 15155, Oct. 2023.
[63] D. N. T. How, M. A. Hannan, M. S. H. Lipu, K. S. M. Sahari, P. J. Ker, and K. M. Muttaqi, "State-of-charge estimation of Li-ion battery in electric vehicles: A deep neural network approach," *IEEE Trans. Ind. Appl.*, vol. 56, no. 5, pp. 5565–5574, Sep. 2020.
[64] M. A. Hannan, M. S. H. Lipu, A. Hussain, P. J. Ker, T. M. I. Mahlia, M. Mansor, A. Ayob, M. H. Saad, and Z. Y. Dong, "Toward enhanced state of charge estimation of lithium-ion batteries using optimized machine learning techniques," *Sci. Rep.*, vol. 10, no. 1, pp. 1–15, Mar. 2020.
[65] A. Mousaei, N. Rostami, and M. B. Bannae Sharifian, "Design a robust and optimal fuzzy logic controller to stabilize the speed of an electric vehicle in the presence of uncertainties and external disturbances," *Trans. Inst. Meas. Control*, vol. 46, no. 3, pp. 482–500, Jun. 2023.
[66] I. B. Espedal, A. Jinasena, O. S. Burheim, and J. J. Lamb, "Current trends for state-of-charge (SoC) estimation in lithium-ion battery electric vehicles," *Energies*, vol. 14, no. 11, p. 3284, Jun. 2021.
[67] C. Vidal, P. Malysz, P. Kollmeyer, and A. Emadi, "Machine learning applied to electrified vehicle battery state of charge and state of health estimation: State-of-the-art," *IEEE Access*, vol. 8, pp. 52796–52814, 2020.
[68] I. Babaeiyazdi, A. Rezaei-Zare, and S. Shokrzadeh, "State of charge prediction of EV Li-ion batteries using EIS: A machine learning approach," *Energy*, vol. 223, May 2021, Art. no. 120116.
[69] Z. Wang, G. Feng, D. Zhen, F. Gu, and A. Ball, "A review on online state of charge and state of health estimation for lithium-ion batteries in electric vehicles," *Energy Rep.*, vol. 7, pp. 5141–5161, Nov. 2021.
[70] D. Zhang, C. Zhong, P. Xu, and Y. Tian, "Deep learning in the state of charge estimation for Li-ion batteries of electric vehicles: A review," *Machines*, vol. 10, no. 10, p. 912, Oct. 2022.
[71] M. T. Vellingiri, I. M. Mehedi, and T. Palaniswamy, "A novel deep learning-based state-of-charge estimation for renewable energy management system in hybrid electric vehicles," *Mathematics*, vol. 10, no. 2, p. 260, Jan. 2022.
[72] A. Mousaei and Y. Naderi, "Machine learning-based regression models for state of charge estimation in hybrid electric vehicles: A review," *Preprints*, 2023, Art. no. 2023121938, doi: 10.20944/preprints202312.1938.v1.
[73] A. Upashrutti and K. C. S. Thampatty, "Estimation of state of charge of EV batteries—A machine learning approach," in *Proc. IEEE IAS Global Conf. Emerg. Technol. (GlobConET)*, May 2022, pp. 70–76.
[74] A. Shah, K. Shah, C. Shah, and M. Shah, "State of charge, remaining useful life and knee point estimation based on artificial intelligence and machine learning in lithium-ion EV batteries: A comprehensive review," *Renew. Energy Focus*, vol. 42, pp. 146–164, Sep. 2022.
[75] Y. Li, K. Li, X. Liu, X. Li, L. Zhang, B. Rente, T. Sun, and K. T. V. Grattan, "A hybrid machine learning framework for joint SOC and SOH estimation of lithium-ion batteries assisted with fiber sensor measurements," *Appl. Energy*, vol. 325, Nov. 2022, Art. no. 119787.
[76] S. Feraco, P. G. Anselma, A. Bonfitto, and P. J. Kollmeyer, "Robust data-driven battery state of charge estimation for hybrid electric vehicles," *SAE Int. J. Electrified Vehicles*, vol. 11, no. 2, pp. 213–230, Oct. 2021.
[77] M. S. Hossain Lipu, M. A. Hannan, A. Hussain, S. Ansari, S. A. Rahman, M. H. M. Saad, and K. M. Muttaqi, "Real-time state of charge estimation of lithium-ion batteries using optimized random forest regression algorithm," *IEEE Trans. Intell. Vehicles*, vol. 8, no. 1, pp. 639–648, Jan. 2023.
[78] M. Adaikkappan and N. Sathiyamoorthy, "Modeling, state of charge estimation, and charging of lithium-ion battery in electric vehicle: A review," *Int. J. Energy Res.*, vol. 46, no. 3, pp. 2141–2165, Oct. 2021.
[79] X. Yang, J. Hu, G. Hu, and X. Guo, "Battery state of charge estimation using temporal convolutional network based on electric vehicles operating data," *J. Energy Storage*, vol. 55, Nov. 2022, Art. no. 105820.
[80] K. Akbar, Y. Zou, Q. Awais, M. J. A. Baig, and M. Jamil, "A machine learning-based robust state of health (SOH) prediction model for electric vehicle batteries," *Electronics*, vol. 11, no. 8, p. 1216, Apr. 2022.
[81] F. A. Barrios, J. Di Donato, C. Vidal, N. Chemmanoor, R. Ahmed, A. Emadi, and S. Habibi, "Comparing traditional and machine learning models for battery SOC calculation," in *Proc. IEEE Transp. Electrific. Conf. Expo*, Jun. 2022, pp. 125–130.
[82] S. Jafari, Z. Shahbazi, and Y.-C. Byun, "Lithium-ion battery health prediction on hybrid vehicles using machine learning approach," *Energies*, vol. 15, no. 13, p. 4753, Jun. 2022.

[83] H. Y. Youssef, L. A. Alkhaja, H. H. Almazrouei, A. B. Nassif, C. Ghenai, and M. A. AlShabi, "A machine learning approach for state-of-charge estimation of Li-ion batteries," *Proc. SPIE*, vol. 12113, pp. 674–682, Jun. 2022.

[84] I. Akhil, N. Kumar, A. Kumar, A. Sharma, and M. Kaushik, "State of charge estimation using different machine learning techniques," *J. Inf. Optim. Sci.*, vol. 43, no. 3, pp. 543–547, Apr. 2022.

[85] X. Li, H. Jiang, S. Guo, J. Xu, M. Li, X. Liu, and X. Zhang, "SOC estimation of lithium-ion battery for electric vehicle based on deep multilayer perceptron," *Comput. Intell. Neurosci.*, vol. 2022, pp. 1–12, May 2022.

[86] S. Jafari, Z. Shahbazi, Y.-C. Byun, and S.-J. Lee, "Lithium-ion battery estimation in online framework using extreme gradient boosting machine learning approach," *Mathematics*, vol. 10, no. 6, p. 888, Mar. 2022.

[87] S. Harippriya, E. Esakki Vigneswaran, and S. Jayanthy, "Battery management system to estimate battery aging using deep learning and machine learning algorithms," *J. Phys., Conf.*, vol. 2325, Aug. 2022, Art. no. 012004.

[88] Y. Liu, Y. He, H. Bian, W. Guo, and X. Zhang, "A review of lithium-ion battery state of charge estimation based on deep learning: Directions for improvement and future trends," *J. Energy Storage*, vol. 52, Aug. 2022, Art. no. 104664.

[89] I. Ullah, K. Liu, T. Yamamoto, M. Zahid, and A. Jamal, "Prediction of electric vehicle charging duration time using ensemble machine learning algorithm and Shapley additive explanations," *Int. J. Energy Res.*, vol. 46, no. 11, pp. 15211–15230, Jun. 2022.

[90] E. Galiounas, T. G. Tranter, R. E. Owen, J. B. Robinson, P. R. Shearing, and D. J. L. Brett, "Battery state-of-charge estimation using machine learning analysis of ultrasonic signatures," *Energy AI*, vol. 10, Nov. 2022, Art. no. 100188.

[91] A. Jain, C. Verma, N. Kumar, M. S. Raboaca, J. N. Baliya, and G. Suciu, "Image geo-site estimation using convolutional auto-encoder and multi-label support vector machine," *Information*, vol. 14, no. 1, p. 29, Jan. 2023.

[92] Y. Li, S. Zhou, J. Liu, J. Tong, J. Dang, F. Yang, and M. Ouyang, "Multi-objective optimization of the Atkinson cycle gasoline engine using NSGA III coupled with support vector machine and back-propagation algorithm," *Energy*, vol. 262, Jan. 2023, Art. no. 125262.

[93] C. Li, J. Zhou, K. Du, and D. Dias, "Stability prediction of hard rock pillar using support vector machine optimized by three metaheuristic algorithms," *Int. J. Mining Sci. Technol.*, vol. 33, no. 8, pp. 1019–1036, Aug. 2023.

[94] B. Nourani, H. Arvanaghi, F. A. Pourhosseini, M. Javidnia, and J. Abraham, "Enhanced support vector machine with particle swarm optimization and genetic algorithm for estimating discharge coefficients of circular-crested oblique weirs," *Iranian J. Sci. Technol., Trans. Civil Eng.*, vol. 47, no. 5, pp. 3185–3198, May 2023.

[95] R. Guo and W. Shen, "A data-model fusion method for online state of power estimation of lithium-ion batteries at high discharge rate in electric vehicles," *Energy*, vol. 254, Sep. 2022, Art. no. 124270.

[96] A. Karthick, V. Mohanavel, V. K. Chinnaiyan, J. Karpagam, I. Baranilingesan, and S. Rajkumar, "State of charge prediction of battery management system for electric vehicles," in *Active Electrical Distribution Network*. Amsterdam, The Netherlands: Elsevier, Jan. 2022, pp. 163–180.

[97] D.-W. Chung, J.-H. Ko, and K.-Y. Yoon, "State-of-charge estimation of lithium-ion batteries using LSTM deep learning method," *J. Electr. Eng. Technol.*, vol. 17, no. 3, pp. 1931–1945, Feb. 2022.

[98] X. Fan, W. Zhang, C. Zhang, A. Chen, and F. An, "SOC estimation of Li-ion battery using convolutional neural network with U-Net architecture," *Energy*, vol. 256, Oct. 2022, Art. no. 124612.

[99] K. Yang, Y. Tang, S. Zhang, and Z. Zhang, "A deep learning approach to state of charge estimation of lithium-ion batteries based on dual-stage attention mechanism," *Energy*, vol. 244, Apr. 2022, Art. no. 123233.

[100] S. M. Shahriar, E. A. Bhuiyan, M. Nahiduzzaman, M. Ahsan, and J. Haider, "State of charge estimation for electric vehicle battery management systems using the hybrid recurrent learning approach with explainable artificial intelligence," *Energies*, vol. 15, no. 21, p. 8003, Oct. 2022.

[101] Y. NaitMalek, M. Najib, A. Lahlou, M. Bakhouya, J. Gaber, and M. Essaaidi, "A hybrid approach for state-of-charge forecasting in battery-powered electric vehicles," *Sustainability*, vol. 14, no. 16, p. 9993, Aug. 2022.

[102] A. Gaga, A. Tannouche, Y. Mehdaoui, and B. El Hadadi, "Methods for estimating lithium-ion battery state of charge for use in electric vehicles: A review," *Energy Harvesting Syst.*, vol. 9, no. 2, pp. 211–225, Apr. 2022.

[103] J. Miao, Z. Tong, S. Tong, J. Zhang, and J. Mao, "State of charge estimation of lithium-ion battery for electric vehicles under extreme operating temperatures based on an adaptive temporal convolutional network," *Batteries*, vol. 8, no. 10, p. 145, Sep. 2022.

[104] C.-J. Ko, K.-C. Chen, and T.-W. Su, "Differential current in constant-voltage charging mode: A novel tool for state-of-health and state-of-charge estimation of lithium-ion batteries," *Energy*, vol. 288, Feb. 2024, Art. no. 129826.

[105] B. Jouda, A. Jobran Al-Mahasneh, and M. A. Mallouh, "Deep stochastic reinforcement learning-based energy management strategy for fuel cell hybrid electric vehicles," *Energy Convers. Manag.*, vol. 301, Feb. 2024, Art. no. 117973.

[106] M. Wei, M. Ye, C. Zhang, G. Lian, B. Xia, and Q. Wang, "Robust state of charge estimation of LiFePO4 batteries based on Sage_Husa adaptive Kalman filter and dynamic neural network," *Electrochimica Acta*, vol. 477, Feb. 2024, Art. no. 143778.

[107] B. Zazoum, "Lithium-ion battery state of charge prediction based on machine learning approach," *Energy Rep.*, vol. 9, pp. 1152–1158, Mar. 2023.

[108] A. Degla, M. Chikh, M. Mzir, and Y. Belabed, "State of charge estimation for Li-ion battery based intelligent algorithms," *Electr. Eng.*, vol. 105, no. 2, pp. 1179–1197, Jan. 2023.

[109] F. Li, W. Zuo, K. Zhou, Q. Li, Y. Huang, and G. Zhang, "State-of-charge estimation of lithium-ion battery based on second order resistor-capacitance circuit-PSO-TCN model," *Energy*, vol. 289, Feb. 2024, Art. no. 130025.

[110] Q. Yu, Y. Nie, S. Liu, J. Li, and A. Tang, "State of health estimation method for lithium-ion batteries based on multiple dynamic operating conditions," *J. Power Sources*, vol. 582, Oct. 2023, Art. no. 233541.

[111] Z. Wei, X. Yang, Y. Li, H. He, W. Li, and D. U. Sauer, "Machine learning-based fast charging of lithium-ion battery by perceiving and regulating internal microscopic states," *Energy Storage Mater.*, vol. 56, pp. 62–75, Feb. 2023.

[112] E. D. R. Lopes, M. M. Soudre, C. H. Llanos, and H. V. H. Ayala, "Nonlinear receding-horizon filter approximation with neural networks for fast state of charge estimation of lithium-ion batteries," *J. Energy Storage*, vol. 68, Sep. 2023, Art. no. 107677.

[113] P. Eleftheriadis, S. Leva, and E. Ogliari, "Bayesian hyperparameter optimization of stacked bidirectional long short-term memory neural network for the state of charge estimation," *Sustain. Energy, Grids Netw.*, vol. 36, Dec. 2023, Art. no. 101160.

[114] I. Ullah, K. Liu, T. Yamamoto, M. Shafiullah, and A. Jamal, "Grey wolf optimizer-based machine learning algorithm to predict electric vehicle charging duration time," *Transp. Lett.*, vol. 15, no. 8, pp. 889–906, Aug. 2022.

[115] Q. Wang, M. Ye, M. Wei, G. Lian, and Y. Li, "Deep convolutional neural network based closed-loop SOC estimation for lithium-ion batteries in hierarchical scenarios," *Energy*, vol. 263, Jan. 2023, Art. no. 125718.

[116] J. Chen, Y. Zhang, J. Wu, W. Cheng, and Q. Zhu, "SOC estimation for lithium-ion battery using the LSTM-RNN with extended input and constrained output," *Energy*, vol. 262, Jan. 2023, Art. no. 125375.

[117] A. Hafeez, R. Alammari, and A. Iqbal, "Utilization of EV charging station in demand side management using deep learning method," *IEEE Access*, vol. 11, pp. 8747–8760, 2023.

[118] D. Shi, J. Zhao, Z. Wang, H. Zhao, C. Eze, J. Wang, Y. Lian, and A. F. Burke, "Cloud-based deep learning for co-estimation of battery state of charge and state of health," *Energies*, vol. 16, no. 9, p. 3855, Apr. 2023.

[119] R. Zou, Y. Duan, Y. Wang, J. Pang, F. Liu, and S. R. Sheikh, "A novel convolutional informer network for deterministic and probabilistic state-of-charge estimation of lithium-ion batteries," *J. Energy Storage*, vol. 57, Jan. 2023, Art. no. 106298.

[120] J. Yao and T. Han, "Data-driven lithium-ion batteries capacity estimation based on deep transfer learning using partial segment of charging/discharging data," *Energy*, vol. 271, May 2023, Art. no. 127033.

[121] S. Bockrath, V. Lorentz, and M. Pruckner, "State of health estimation of lithium-ion batteries with a temporal convolutional neural network using partial load profiles," *Appl. Energy*, vol. 329, Jan. 2023, Art. no. 120307.

[122] L. Zhou, X. Lai, B. Li, Y. Yao, M. Yuan, J. Weng, and Y. Zheng, ''State estimation models of lithium-ion batteries for battery management system: Status, challenges, and future trends,'' *Batteries*, vol. 9, no. 2, p. 131, Feb. 2023.
[123] C. Lin, J. Xu, and X. Mei, ''Improving state-of-health estimation for lithium-ion batteries via unlabeled charging data,'' *Energy Storage Mater.*, vol. 54, pp. 85–97, Jan. 2023.
[124] Q. Yu, Y. Huang, A. Tang, C. Wang, and W. Shen, ''OCV-SOC-temperature relationship construction and state of charge estimation for a series—Parallel lithium-ion battery pack,'' *IEEE Trans. Intell. Transp. Syst.*, vol. 24, no. 6, pp. 6362–6371, Jun. 2023.
[125] Z. Yao, Y. Lum, A. Johnston, L. M. Mejia-Mendoza, X. Zhou, Y. Wen, A. Aspuru-Guzik, E. H. Sargent, and Z. W. Seh, ''Machine learning for a sustainable energy future,'' *Nature Rev. Mater.*, vol. 8, no. 3, pp. 202–215, Oct. 2022.
[126] D. Chatterjee, P. K. Biswas, C. Sain, A. Roy, and F. Ahmad, ''Efficient energy management strategy for fuel cell hybrid electric vehicles using classifier fusion technique,'' *IEEE Access*, vol. 11, pp. 97135–97146, 2023.
[127] M. Li, Y. Wang, P. Yu, Z. Sun, and Z. Chen, ''Online adaptive energy management strategy for fuel cell hybrid vehicles based on improved cluster and regression learner,'' *Energy Convers. Manag.*, vol. 292, Sep. 2023, Art. no. 117388.
[128] Z. Mustaffa and M. H. Sulaiman, ''Enhancing battery state of charge estimation through hybrid integration of barnacles mating optimizer with deep learning,'' *Franklin Open*, vol. 5, Dec. 2023, Art. no. 100053.
[129] C. Bertinelli Salucci, A. Bakdi, I. K. Glad, E. Vanem, and R. De Bin, ''A novel semi-supervised learning approach for state of health monitoring of maritime lithium-ion batteries,'' *J. Power Sources*, vol. 556, Feb. 2023, Art. no. 232429.
[130] Y. Che, Y. Zheng, Y. Wu, X. Lin, J. Li, X. Hu, and R. Teodorescu, ''Battery states monitoring for electric vehicles based on transferred multi-task learning,'' *IEEE Trans. Veh. Technol.*, vol. 72, no. 8, pp. 10037–10047, Aug. 2023.
[131] Y. Wu, Z. Huang, R. Zhang, P. Huang, Y. Gao, H. Li, Y. Liu, and J. Peng, ''Driving style-aware energy management for battery/supercapacitor electric vehicles using deep reinforcement learning,'' *J. Energy Storage*, vol. 73, Dec. 2023, Art. no. 109199.
[132] M. El Marghichi, S. Dangoury, Y. Zahrou, A. Loulijat, H. Chojaa, F. A. Banakhr, and M. I. Mosaad, ''Improving accuracy in state of health estimation for lithium batteries using gradient-based optimization: Case study in electric vehicle applications,'' *PLoS ONE*, vol. 18, no. 11, Nov. 2023, Art. no. e0293753.
[133] K. Song, X. Huang, H. Xu, H. Sun, Y. Chen, and D. Huang, ''Model predictive control energy management strategy integrating long short-term memory and dynamic programming for fuel cell vehicles,'' *Int. J. Hydrogen Energy*, vol. 56, pp. 1235–1248, Feb. 2024.
[134] X. Chen, M. Li, and Z. Chen, ''Meta rule-based energy management strategy for battery/supercapacitor hybrid electric vehicles,'' *Energy*, vol. 285, Dec. 2023, Art. no. 129365.
[135] H. Zhang, B. Chen, N. Lei, B. Li, R. Li, and Z. Wang, ''Integrated thermal and energy management of connected hybrid electric vehicles using deep reinforcement learning,'' *IEEE Trans. Transport. Electrific.*, early access, Aug. 28, 2024, doi: 10.1109/TTE.2023.3309396.
[136] Y. Wu, Z. Huang, Y. Zheng, Y. Liu, H. Li, Y. Che, J. Peng, and R. Teodorescu, ''Spatial–temporal data-driven full driving cycle prediction for optimal energy management of battery/supercapacitor electric vehicles,'' *Energy Convers. Manag.*, vol. 277, Feb. 2023, Art. no. 116619.
[137] K. Yang, L. Zhang, Z. Zhang, H. Yu, W. Wang, M. Ouyang, C. Zhang, Q. Sun, X. Yan, S. Yang, and X. Liu, ''Battery state of health estimate strategies: From data analysis to end-cloud collaborative framework,'' *Batteries*, vol. 9, no. 7, p. 351, Jul. 2023.
[138] F. Jiang, J. Ma, Z. Li, and Y. Ding, ''Prediction of energy use intensity of urban buildings using the semi-supervised deep learning model,'' *Energy*, vol. 249, Jun. 2022, Art. no. 123631.
[139] S. Li, Z. Hou, L. Chu, J. Jiang, and Y. Zhang, ''A novel learning-based robust model predictive control energy management strategy for fuel cell electric vehicles,'' 2022, *arXiv:2209.04995*.
[140] S. Maleki, B. Ray, and M. T. Hagh, ''Hybrid framework for predicting and forecasting state of health of lithium-ion batteries in electric vehicles,'' *Sustain. Energy, Grids Netw.*, vol. 30, Jun. 2022, Art. no. 100603.
[141] F. Yang, S. Zhang, W. Li, and Q. Miao, ''State-of-charge estimation of lithium-ion batteries using LSTM and UKF,'' *Energy*, vol. 201, Jun. 2020, Art. no. 117664.
[142] Y. Fan, F. Xiao, C. Li, G. Yang, and X. Tang, ''A novel deep learning framework for state of health estimation of lithium-ion battery,'' *J. Energy Storage*, vol. 32, Dec. 2020, Art. no. 101741.
[143] M. S. Hossain Lipu, M. A. Hannan, A. Hussain, A. Ayob, M. H. M. Saad, T. F. Karim, and D. N. T. How, ''Data-driven state of charge estimation of lithium-ion batteries: Algorithms, implementation factors, limitations and future trends,'' *J. Cleaner Prod.*, vol. 277, Dec. 2020, Art. no. 124110.
[144] M.-F. Ng, J. Zhao, Q. Yan, G. J. Conduit, and Z. W. Seh, ''Predicting the state of charge and health of batteries using data-driven machine learning,'' *Nature Mach. Intell.*, vol. 2, no. 3, pp. 161–170, Mar. 2020.
[145] S. Shen, M. Sadoughi, M. Li, Z. Wang, and C. Hu, ''Deep convolutional neural networks with ensemble learning and transfer learning for capacity estimation of lithium-ion batteries,'' *Appl. Energy*, vol. 260, Feb. 2020, Art. no. 114296.
[146] B. Yang, J. Wang, P. Cao, T. Zhu, H. Shu, J. Chen, J. Zhang, and J. Zhu, ''Classification, summarization and perspectives on state-of-charge estimation of lithium-ion batteries used in electric vehicles: A critical comprehensive survey,'' *J. Energy Storage*, vol. 39, Jul. 2021, Art. no. 102572.
[147] P. Shrivastava, P. A. Naidu, S. Sharma, B. K. Panigrahi, and A. Garg, ''Review on technological advancement of lithium-ion battery states estimation methods for electric vehicle applications,'' *J. Energy Storage*, vol. 64, Aug. 2023, Art. no. 107159.
[148] Y. Wang, N. Chen, G. Fan, D. Yang, L. Rao, S. Cheng, and X. Song, ''DLPformer: A hybrid mathematical model for state of charge prediction in electric vehicles using machine learning approaches,'' *Mathematics*, vol. 11, no. 22, p. 4635, Nov. 2023.
[149] R. R. Kumar, C. Bharatiraja, K. Udhayakumar, S. Devakirubakaran, K. S. Sekar, and L. Mihet-Popa, ''Advances in batteries, battery modeling, battery management system, battery thermal management, SOC, SOH, and charge/discharge characteristics in EV applications,'' *IEEE Access*, vol. 11, pp. 105761–105809, 2023.
[150] G. Pozzato, A. Allam, L. Pulvirenti, G. A. Negoita, W. A. Paxton, and S. Onori, ''Analysis and key findings from real-world electric vehicle field data,'' *Joule*, vol. 7, no. 9, pp. 2035–2053, Sep. 2023.
[151] A. K. M. A. Habib, M. K. Hasan, G. F. Issa, D. Singh, S. Islam, and T. M. Ghazal, ''Lithium-ion battery management system for electric vehicles: Constraints, challenges, and recommendations,'' *Batteries*, vol. 9, no. 3, p. 152, Feb. 2023.
[152] S. D. Nagarale and B. P. Patil, ''Accelerating AI-based battery management system's SOC and SOH on FPGA,'' *Appl. Comput. Intell. Soft Comput.*, vol. 2023, pp. 1–18, Jun. 2023.
[153] Y. Zhao, Z. Jiang, X. Chen, P. Liu, T. Peng, and Z. Shu, ''Toward environmental sustainability: Data-driven analysis of energy use patterns and load profiles for urban electric vehicle fleets,'' *Energy*, vol. 285, Dec. 2023, Art. no. 129465.
[154] Z. He, X. Shen, Y. Sun, S. Zhao, B. Fan, and C. Pan, ''State-of-health estimation based on real data of electric vehicles concerning user behavior,'' *J. Energy Storage*, vol. 41, Sep. 2021, Art. no. 102867.
[155] R. Basso, B. Kulcsár, and I. Sanchez-Diaz, ''Electric vehicle routing problem with machine learning for energy prediction,'' *Transp. Res. B, Methodol.*, vol. 145, pp. 24–55, Mar. 2021.
[156] D. Aguilar-Dominguez, J. Ejeh, A. D. F. Dunbar, and S. F. Brown, ''Machine learning approach for electric vehicle availability forecast to provide vehicle-to-home services,'' *Energy Rep.*, vol. 7, pp. 71–80, May 2021.
[157] T. Duraisamy and D. Kaliyaperumal, ''Machine learning-based optimal cell balancing mechanism for electric vehicle battery management system,'' *IEEE Access*, vol. 9, pp. 132846–132861, 2021.
[158] J. Bas, C. Cirillo, and E. Cherchi, ''Classification of potential electric vehicle purchasers: A machine learning approach,'' *Technol. Forecasting Social Change*, vol. 168, Jul. 2021, Art. no. 120759.

[159] S. Rhode, S. Van Vaerenbergh, and M. Pfriem, "Power prediction for electric vehicles using online machine learning," *Eng. Appl. Artif. Intell.*, vol. 87, Jan. 2020, Art. no. 103278.
[160] B. E. Lebrouhi, Y. Khattari, B. Lamrani, M. Maaroufi, Y. Zeraouli, and T. Kousksou, "Key challenges for a large-scale development of battery electric vehicles: A comprehensive review," *J. Energy Storage*, vol. 44, Dec. 2021, Art. no. 103273.
[161] S. R. Hashemi, A. Bahadoran Baghbadorani, R. Esmaeeli, A. Mahajan, and S. Farhad, "Machine learning-based model for lithium-ion batteries in BMS of electric/hybrid electric aircraft," *Int. J. Energy Res.*, vol. 45, no. 4, pp. 5747–5765, Nov. 2020.
[162] S. Li, H. He, Z. Wei, and P. Zhao, "Edge computing for vehicle battery management: Cloud-based online state estimation," *J. Energy Storage*, vol. 55, Nov. 2022, Art. no. 105502.
[163] Q. Lin, X. Li, B. Tu, J. Cao, M. Zhang, and J. Xiang, "Stable and accurate estimation of SOC using eXogenous Kalman filter for lithium-ion batteries," *Sensors*, vol. 23, no. 1, p. 467, Jan. 2023.
[164] F. Liu, D. Yu, W. Su, S. Ma, and F. Bu, "Adaptive multi-timescale joint estimation method for SOC and capacity of series battery pack," *IEEE Trans. Transport. Electrific.*, early access, Sep. 11, 2024, doi: 10.1109/TTE.2023.3314050.
[165] Y. Xu, H. Zhang, Y. Yang, J. Zhang, F. Yang, D. Yan, H. Yang, and Y. Wang, "Optimization of energy management strategy for extended range electric vehicles using multi-island genetic algorithm," *J. Energy Storage*, vol. 61, May 2023, Art. no. 106802.
[166] L. Timilsina, P. H. Hoang, A. Moghassemi, E. Buraimoh, P. K. Chamarthi, G. Ozkan, B. Papari, and C. S. Edrington, "A real-time prognostic-based control framework for hybrid electric vehicles," *IEEE Access*, vol. 11, pp. 127589–127607, 2023.
[167] A. Alsharif, C. W. Tan, R. Ayop, A. Dobi, and K. Y. Lau, "A comprehensive review of energy management strategy in vehicle-to-grid technology integrated with renewable energy sources," *Sustain. Energy Technol. Assessments*, vol. 47, Oct. 2021, Art. no. 101439.
[168] H. He, X. Meng, Y. Wang, A. Khajepour, X. An, R. Wang, and F. Sun, "Deep reinforcement learning based energy management strategies for electrified vehicles: Recent advances and perspectives," *Renew. Sustain. Energy Rev.*, vol. 192, Mar. 2024, Art. no. 114248.
[169] S. R. Salkuti, "Advanced technologies for energy storage and electric vehicles," *Energies*, vol. 16, no. 5, p. 2312, Feb. 2023.
[170] R. Zahedi, M. H. Ghodusinejad, A. Aslani, and C. Hachem-Vermette, "Modelling community-scale renewable energy and electric vehicle management for cold-climate regions using machine learning," *Energy Strategy Rev.*, vol. 43, Sep. 2022, Art. no. 100930.
[171] C. Choi, S. Park, and J. Kim, "Uniqueness of multilayer perceptron-based capacity prediction for contributing state-of-charge estimation in a lithium primary battery," *Ain Shams Eng. J.*, vol. 14, no. 4, Apr. 2023, Art. no. 101936.
[172] Y. Shen, "A robust method for state of charge estimation of lithium-ion batteries using adaptive nonlinear neural observer," *J. Energy Storage*, vol. 72, Nov. 2023, Art. no. 108480.
[173] J. Guo, Y. Che, K. Pedersen, and D.-I. Stroe, "Battery impedance spectrum prediction from partial charging voltage curve by machine learning," *J. Energy Chem.*, vol. 79, pp. 211–221, Apr. 2023.
[174] Y. Zhang, Y. Dai, R. Yang, Z. Li, J. Zhao, and Q. Wu, "Noise-resistant state of charge estimation of Li-ion battery using the outlier robust extreme learning machine," *Energy Rep.*, vol. 9, pp. 1–8, Mar. 2023.
[175] J. Tian, R. Xiong, J. Lu, C. Chen, and W. Shen, "Battery state-of-charge estimation amid dynamic usage with physics-informed deep learning," *Energy Storage Mater.*, vol. 50, pp. 718–729, Sep. 2022.
[176] H. Yu, Z. Zhang, K. Yang, L. Zhang, W. Wang, S. Yang, J. Li, and X. Liu, "Physics-informed ensemble deep learning framework for improving state of charge estimation of lithium-ion batteries," *J. Energy Storage*, vol. 73, Dec. 2023, Art. no. 108915.

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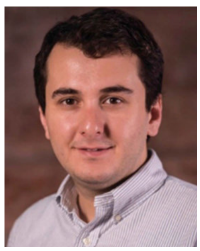

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