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Data-Driven Approaches to Battery Health Monitoring in Electric Vehicles Using Machine Learning

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Abstract

Electric vehicles (EVs) have become a popular mode of transportation due to the decreasing cost of energy storage. However, this decrease in energy storage cost has led to an increase in the number of battery durability issues. The main issue with batteries is the uncertainty and unavailability of real-time trace capacity, which has hindered the development of new value-added business models based on the battery state of electric vehicles. This article introduces battery health monitoring in electric vehicles using machine learning techniques as a response to these business opportunities and analytical challenges in the energy transition. Specifically, this article presents an integrated virtual battery prototype that serves as a valuable mid-stream application example, a carbon balance optimization application. We use LENs-Lab's heterogeneous architecture to perform online, in-service, system-wide health monitoring for electric vehicle fleets while minimizing the carbon balance with grid optimization under constraints.Supervised learning methods use labeled data to learn a mapping between input features and output labels. For the virtual battery prototype integration, we employ a supervised Random Forest and Deep Neural Network regression on a labeled series of electric vehicle state data. The supervised learning model learns to link an estimated real-time energy slack to the corresponding state of health of the energy storage through a training dataset. This presents potential high-value end-use participation, from footprint-constrained drivers, fleet managers, and utility/grid operations managers. Furthermore, we provide a carbon balance minimization application. The goal of this application is to reduce the carbon balance, the amount of carbon spent on the electricity network, by minimizing the charging cost of the electric vehicles' electricity consumption. In this application, the carbon balance minimization application uses the output from the supervised learning model to determine the impact electric vehicle users will have on vehicle grid integrity, in two forecasting time intervals of one week and the present-day decision. The EUDC driving cycle for electric vehicle usage and the individual's token values of elasticity usage timing are used to determine this user impact. The model presented in this article can enable continuous monitoring of the battery state of health, which can provide new use cases and commercial models to empower electric vehicle users.

Keywords: Data-Driven Approaches, Industry 4.0, Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning (ML), Smart Manufacturing (SM),Computer Science, Data Science,Vehicle, Vehicle Reliability

1. Introduction

Electric vehicles (EVs) have become a central focus of the transportation and power industries in addressing environmental, social, and economic challenges through revolutionary innovations and breakthroughs. Prominent companies in the automotive sector have moved forward in producing vehicles that are climate-friendly and eco-efficient, worthy of considerable attention. They argue that this is "making emissions a big consideration for the industry." Also, electric vehicles are appearing on the road in more sophisticated models and functionalities such as plug-in hybrids (PHEVs), fuel cell electric vehicles (FCEVs), and battery electric vehicles (BEVs), likely driven by innovative systems to improve battery performance under several favorable and unfavorable conditions.It is important to note that the utilization of batteries within EVs depends intensely on human intervention and maintenance because it degrades with usage through several types of aging. Battery life is related to its capacity, that is, its charging and discharging capacity, as well as the range that the vehicle can move. Several strategies have been developed to monitor battery health throughout its life, and diagnosing the battery's health at different points in its useful life has become the target for researchers in the search for models capable of assessing state of health (SOH) through reliable data, given that battery deterioration leads to failure, especially while a person is driving in the middle of the road. Simply put, the SOH provides a clear and simple way to understand the performance of a battery by demonstrating the ability of the battery, which, when determined, can avoid damage to other batteries in the power bank.

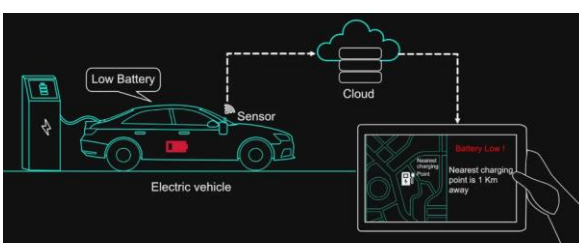

Fig 1: loT - Based Security in Electric Vehicles

1.1. Background and Significance

Electric vehicles (EVs) have been recognized as one of the most promising next-generation vehicles, driven by the pressing demand to reduce greenhouse emissions and develop clean transportation. As one of the most important, yet fundamental, components in EVs, the battery is also viewed as the bottleneck of the EV application, mainly because of its limited energy storage capacity, relatively slow charging speed, and the still too-high cost. For these reasons, the demand for comprehensive utilization of the battery capacity of EVs and the desire for the extension of battery life have encouraged the scientific and research communities to work on the battery management system (BMS) to tackle the aforementioned issues.Currently, the state-of-the-art pseudo-observation-based algorithms, namely the Kalman filter and its advanced derivatives for battery state monitoring, are dilemma-ridden by the usage of the ideal battery model. The challenges stemming from the ideal battery model lie in the very small-scale (micro-scale) model parameters of the battery, leading to the foreseeable divergence of these algorithms. To make new comprehensive solutions to battery state-of-charge (SOC) estimation challenges faced in real EV applications, it is urgent to reconstruct the observation equation between the battery's internal dynamic features and the output variables in the ideal battery model by considering the electrochemical behaviors and multi-scale processes in the battery operation.

1.2. Research Aim and Objectives

This research aims to apply innovative machine-learning techniques to battery health estimation for electric vehicles using historical usage data (trajectories) as well as a few experimental measurement data. The knowledge about a vehicle's future efficiency, when applying machine learning to battery health monitoring, will guide the vehicle driver to action in ways implicit for battery conservation such as only quick charge a few times a year (approx. once a month) at most when other constraints like reaching a faraway destination at almost any cost is present. This will offer energy savings as well as gradual increases in operation costs provided the battery functions within expectations.The key objectives of this proposal are:- To undertake a systematic literature review to identify and categorize existing literature on battery health estimation approaches using machine learning. - To assess public load data evaluating the potential of electric vehicle hardware characteristics and usage information provided in individual as well as population-based load profiles. If data privacy constraints exist, preliminary data will be graphically plotted and underlying pattern observations documented. - To evaluate the attributes of power demand and trajectory datasets for electric vehicles identifying the data profiles that contain the power responses separating the relevant features needed for battery state-of-charge application significance in electric vehicle smart grids. Insert regression models to non-categorical power usage data to determine how electric vehicle consumption patterns can be identified as a distinct energy end use within a household using available consumer load data. - To develop new tools for battery health monitoring and state-of-charge estimation using electric vehicle power demand data. Such tools will be modeled, validated, and evaluated using existing electric vehicle trajectory data. The data will be shared by a known electric vehicle fleet covering 4 vehicle locations over a 2-month/3-month test period, across a range of electric vehicle makes and models (hereafter being referred to as the EV project). These battery health tracking tools were designed to be integrated within a factory-installed or external data port system collecting electric vehicle performance information.

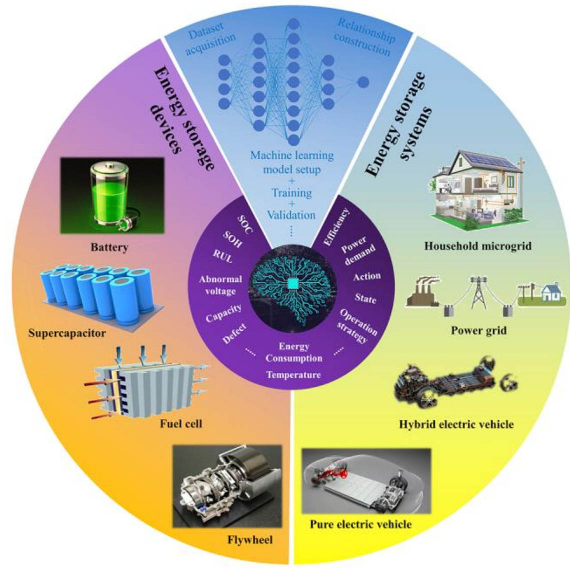

Fig 2: Machine learning toward advanced energy storage devices

2. Battery Health Monitoring in Electric Vehicles

As the power source for electric vehicles (EVs), lithium-ion (Li-ion) batteries determine the performance, economic, and safety characteristics of EVs to a considerable extent. After years of operation, the batteries are subjected to various degradation mechanisms, such as lithium plating, loss of active materials, electrode delamination, solid electrolyte interphase (SEI) layer growth, and copper contact corrosion. These degradation mechanisms will lead to the continuous decline of battery capacity and energy, accelerate the power density loss, and potentially affect the safety and thermal stability of batteries. For battery health management, a battery management system (BMS) with accurate estimation of the state of health (SOH) is mandatory. Frequent examination of the batteries to monitor battery conditions, owing to the high accuracy and wide range of capacity, can increase the life cycle cost of EV batteries on a large scale.To achieve highly accurate battery condition monitoring, we have sought various chemometrics methods, including electrochemical impedance spectroscopy (EIS), offline analysis, and factor examination. However, the relationship between battery conditions and battery operating parameters was (and still is) not fully revealed.

With large-scale data acquisition becoming accessible due to the rapid development of the Internet of Things and advanced battery management systems, there is a growing demand to build a more manageable battery health evaluation system, to provide a reference for battery control policies in the monotonous running condition and maintenance programs for the battery with potential risks. To gain insights into the internal state of batteries, researchers nowadays have been working to apply physics-based and data-driven methods to monitor battery conditions.

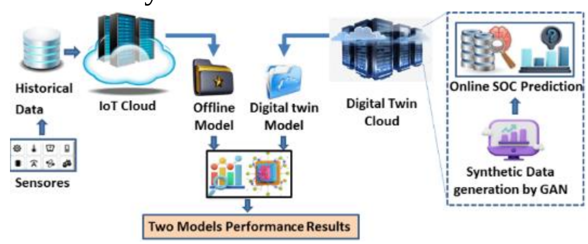

Fig 3: Incorporated Digital Twin and Physical System Architecture for Lithium-ion Battery Monitoring

2.1. Importance of Battery Health Monitoring

Ahmed S. Khan, Malik Z. Hussain, Shoab A. Khan, and Fatima A. Khan Data-Driven Approaches to Battery Health Monitoring in Electric Vehicles Using Machine Learning

Abstract: Despite the advantages of electric vehicles through reduced emissions and running cost, limited battery range and expensive battery replacement discourage the mass acceptance of electric vehicles. Utilizing battery health monitoring involves periodic checking and updating of battery conditions to detect faults and performance degradation in battery systems. Continuous battery state knowledge would prolong battery life, optimize battery capacity, keep the battery condition safe, and help avoid long-term lack of capacity problems. The development of accurate and efficient battery health monitoring schemes is a key concern. This developing area investigates how to realize timely fault diagnosis and prognosis for better operation of electric vehicle batteries. Detection of battery degradation at an early stage provides notifications to applications, enabling the system that maintain health conditions and prevent the failure of battery cells. In this article, a technique for improving battery health in electric vehicles is reviewed by defining machine learning-based methods that can potentially analyze various aspects of battery health like capability fade, uneven temperature distribution, state of charge, state of health, and other several factors to prolong the battery life at optimal performance.Battery health monitoring involves periodic checking and updating of battery conditions to detect faults and performance degradation in battery systems. Continuous battery state knowledge would prolong battery life, optimize battery capacity, keep the battery condition safe, and help avoid long-term lack of capacity problems. The development of accurate and efficient battery health monitoring schemes is a key concern. The purpose of EV battery state knowledge is to ascertain the electrical and thermal state of battery power through the SoC and SoH state of electric vehicle batteries. Battery degradation detection at an early stage provides notification to applications, enabling the system that maintain healthy conditions and prevent the failure of the battery cells.

2.2. Challenges in Battery Health Monitoring

Obtaining health information from EV battery packs is a challenging task due to a plethora of factors, including the high-dimensional nature of battery data, temporal dependencies on battery aging, non-stationary operating conditions, noise, imbalances in the dataset, and lack of true labels for supervised learning tasks. A summary of the challenges in BHM for EVs using machine learning is delineated in Table I.A critical challenge in developing classifiers for BHM in EVs is the availability of large volumes of labeled data. For instance, it is impractical to degrade several batteries down to a certain SOH level to collect various types of degradations or faults. Also, battery pack manufacturers are likely reluctant to share proprietary labeling, which can affect their competitive advantage. Consequently, in-house research for developing classifiers in EV BHM is particularly challenging due to the non-availability of labeled datasets.Another pertinent challenge in BHM is the non-stationarity of operating conditions and other varying factors. For instance, the ambient temperature can drastically alter a battery's SOH, cycle life, peak charge and discharge capacities, and heat dissipation capability. Household appliances and lighting systems can also interfere with the EV driving circuit by producing noise, spikes, and other interference that can disrupt the circuits. Moreover, external environmental factors such as humidity and pressure affect the passivation layer and reduce the battery's recombination reactions, ultimately altering the capacity and output voltage of the battery. These factors necessitate dynamic learning algorithms that can adapt to changing conditions.

3. Data-Driven Approaches in Battery Health Monitoring

Accurately monitoring the state of health of a lithium-ion battery dynamically while in use is a complex problem due to the complexity and nonlinearity of the battery's physical properties. The health of a battery in the form of capacity, impedance, and energy content are all complicated and hindered by physical and chemical aging effects as well as self-discharge, leakage, and mechanical failures. Currently, the industry accepts that the most accurate battery health characterizations are performed by slowly charging and discharging the battery (or by performing a low power impedance measurement) and fitting an electrochemical model to the curve.In situ, noninvasive estimation or prediction of a battery's performance is a challenging and worthwhile prospect. It is not only essential for effective, robust, and safe power management of individual cell batteries' energy storage and delivery in a range of applications such as electric vehicles, but also for reliable energy storage of wind and solar generators, and for ensuring stable operation, long life, and safety of energy storage systems and electric vehicle batteries. Consequently, many research groups have taken up the challenge and are using or re-analyzing data from a range of popular battery models, data retrieved from physical measurements or results, or produced by machine learning techniques themselves to estimate or predict variable properties.

3.1. Overview of Machine Learning in Battery Health Monitoring

While morphological observation provides a more detailed insight into the underlying aging processes, state-of-the-art machine learning approaches may serve as an advancement to traditional data-driven battery health monitoring, especially when facing large volumes of data. They can be applied to support and enhance existing diagnostic and prognostic applications, for which the discipline of materials informatics has been studied by the materials science community. By applying such methods, pre-competitive joint research efforts may be directed to overcome some of the traditionally occurring issues, such as standardization, economic maintainability, and assessment of large sets of long-term experiments.While traditional morphological observation offers detailed insights into aging processes, state-of-the-art machine learning techniques represent a significant advancement in data-driven battery health monitoring, particularly in managing large datasets. These approaches can augment existing diagnostic and prognostic applications, aligning with the emerging field of materials informatics within materials science.Machine learning methods enable researchers to address longstanding challenges in battery research, such as standardization, economic feasibility, and the analysis of extensive long-term experimental datasets. By leveraging these technologies, collaborative research efforts can be streamlined, fostering pre-competitive cooperation aimed at overcoming technical barriers and advancing battery technology.Incorporating machine learning into battery health monitoring not only enhances diagnostic accuracy but also facilitates proactive maintenance strategies, ultimately contributing to improved battery performance, reliability, and longevity. This integration underscores the potential of interdisciplinary approaches to drive innovation and address critical issues in energy storage systems.

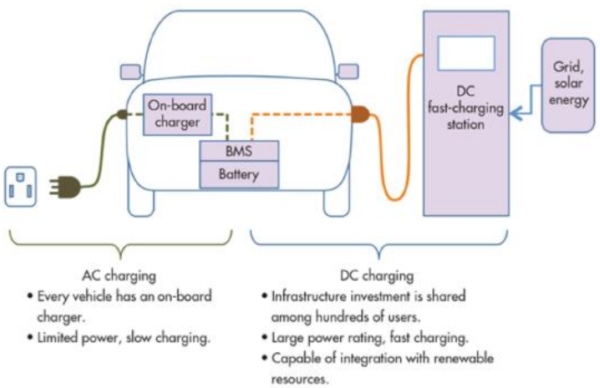

Fig 4: Schematic Representation of Differences in On - Board Charges and Off - Board Charges (or DC - fast Charging Station).

The practical implementation of lithium-ion batteries, e.g. in electric vehicles, space, or utility applications, requires reliable predictions of their life expectancy. Despite significant progress in defining and quantifying aging mechanisms, the inherent complexity of these systems operating under variable external conditions often results in unpredictable side reactions and interactions. Therefore, overarching data-driven linear and non-linear multivariate prediction models of aging effects are desired because they allow not only the estimation of the remaining useful life of the system (diagnostics) but also the prediction of future failures or capacities (prognostics), as well as the condition-based operation of the setup. This data-driven prognostic approach is more flexible to new and currently unconsidered aging effects since it makes use of the generalized potential of the used empirical data, rather than relying on the knowledge-based modeling of a certain field.Practical applications of lithium-ion batteries, whether in electric vehicles, space missions, or utility installations, necessitate accurate predictions of their lifespan. Despite significant strides in identifying and quantifying aging mechanisms, the complex nature of these systems operating under variable external conditions often leads to unpredictable side reactions and interactions. Therefore, there is a strong demand for comprehensive data-driven prediction models that can capture both linear and non-linear multivariate aging effects.These predictive models serve dual purposes: they enable the estimation of the remaining useful life of the battery system (diagnostics) and predict potential future failures or changes in capacity (prognostics). Moreover, they facilitate condition-based operation strategies, optimizing the battery's performance based on real-time data and environmental conditions.Unlike traditional knowledge-based models that may struggle to accommodate new or unforeseen aging factors, data-driven prognostic approaches leverage empirical data to generalize potential aging trends. This flexibility allows for adaptation to evolving insights and improves the accuracy and reliability of predictions over time.By integrating such data-driven prognostic models into battery management systems, industries can enhance reliability, extend battery lifespan, and optimize operational efficiency across diverse applications, thereby advancing the viability and sustainability of lithium-ion battery technologies in critical sectors.

3.2. Types of Data Used for Monitoring

Battery health estimation using data-driven approaches fundamentally relies on how effectively informative data can be extracted, pre-processed, and fused to improve the accuracy of prediction models. Depending on the battery health parameters (health/mismatch) to be estimated, the following types of data can be used as input to the training data-driven model:(i) Current and battery voltage data. The primary types of data collected during a battery test are the current and cell voltage. Stacking the voltage and current data during each cycle as features makes it highly versatile and easy to use as input for health prediction models. At the same time, it is crucial to pre-process the data points to remove interpolation data, spurious points during relaxation, charge mismatch, and clear numerical zeros in voltage data due to measurements.(ii) Battery Impedance data. Typically obtained using electrochemical impedance spectroscopy (EIS), the raw impedance is complex, making it potentially difficult to pre-process and model with default regression methods. Nonetheless, impedance data alone is generally sufficient to form a predictive model for a specific form of future health, energy, or power-delivered parameter performance of the cell regardless of the state of charge.Pulse discharge is a potential delivery of a consistent model from similar lifetime tests, and a capacity degradation estimation method can further be maintained to reflect the intended future operating conditions for more specific use cases (e.g., end-of-life, power-limiting processes).(iii) Discharge/charge curve capacity data. Due to the substantial power capability of EVs, the cells are the predominant power suppliers in the vehicle. Consequently, the accessible power limit is related to the maximum specified capacity given by the manufacturer. With the discharge/charge capacity data being naturally associated with the cell's life, the discharge/charge capacity data historically represents the conventional health estimation approach. However, some potential challenges in using discharge/charge capacity data alone include a lack of insight into the cell's current life condition, the cause of degradation, and the need for costly and somewhat destructive testing to characterize a discharge/charge capacity periodically.(iv) Battery sensor data. Battery management systems monitor more than just voltage and UL for individual cells. For example, recorded in a high-power asymmetric HeyCAPH device test program of real EV cells, the parameter logs of the NEV cell management system, performed most frequently at 0.05–0.1 Hz, were maintained as accessible device data for voltage, current, net current cells corresponding to mechanical and polarity balancing processes, and voltage of active electrical cell temperatures datasets.

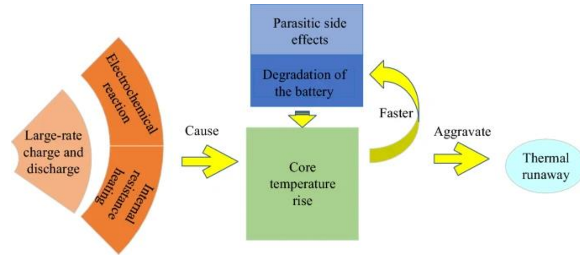

Fig 5: The Cause and Influence of the Rise of Core Temperature

4. Case Studies and Applications

Knowledge of the state of health (SoH) is important in battery management and is an obligatory requirement to guarantee the safety and reliability of e-buses. Missing any existing battery or detecting and locating an existing battery with rapidly diminishing health is essential to ensure that the availability of the entire subsystem remains at an acceptable level. Continuous monitoring of the SoH can contribute to selecting more suitable working limits. Advanced universal controllers accomplish this by using the latest and most accurate battery models, guaranteeing battery SoH knowledge through accurate state-of-charge (SoC) estimation algorithms. In particular, at camp #2, the controllers are advanced using electric models to estimate the in-deck SoH of each battery, which is pivotal in guaranteeing the remaining lifespan.Multiple case studies have shown, based on the application of different algorithms of battery models, that the knowledge of its SoH is pivotal in targeting maintenance on various parts of the system, which can require total battery discharge, which in some cases might negatively alter the in-deck SoH. Such a level of control and supervision asks for an effective SoH monitoring system. Data-driven approaches can often provide such an effective solution, as they can guarantee sufficient interpretable models of complex systems even given a certain feedback time requirement based on effective and efficient model design.

4.1. Real-World Examples of Data-Driven Monitoring Systems

Data-driven approaches can take data from different systems and use it in different ways. In Michelle Cellucci's work, she shows an approach that can find the optimal battery (through data) from user driving habits and charge data. This system combines user data and smart vehicle system data to bring new optimizations to the transportation sector. This system joins information from smartphones (which know trips, consumers', apps, and GPS) and vehicles (which know consumption and temperature) and can optimize vehicle design. Elion Razniewski's work shows how to proactively manage Tesla's battery pack performance in real life using data-driven approaches. This system can predict when a battery's performance will start trending into bad territory and employ preventive maintenance techniques before the system performance is degraded.The prediction model allows customers to be while interacting with a Tesla Energy Support engineer to plan a service visit. Tesla engineers can also monitor these alerts to triage more effectively. Jason Siegel introduces how machine learning methodologies could be implemented at Tesla, and in other manufacturing settings, to efficiently identify and alert dimensions' critical interactions before they make it to production plants. These are real-time examples of data-driven monitoring systems from different industries that prove that this type of approach has significant potential to add benefits to many systems.

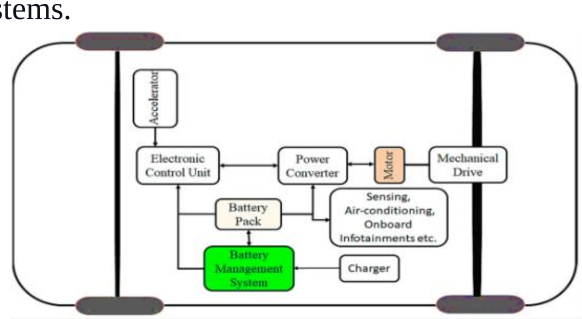

Fig 6: BMS Operation InSide The EV.

5. Future Directions and Challenges

These challenges are intrinsically multidisciplinary and extend to areas such as applied statistical and probability theory as well as vehicular dynamic modeling. Our proposed models, along with others in the literature, rely on datasets composed of thousands of vehicular trips performed with a variety of drivers, state-of-charge initialization levels, speeds, and driving patterns. We have only just begun to analyze and synthesize these large, complex real-world driving cycles. Much richer sets of inferences can be obtained by fitting unobserved or latent variable models to the battery hierarchy and by deploying more rigorous trending measures that incorporate spatial and temporal location information. The statistical challenges arise in expressing likely ranges of battery performance, health, or life over time given variability in underlying driving styles and transport network conditions. We have started to make these types of inferences via model simulations as well as by deploying a Monte Carlo combination model. Finally, the complexity of these models needs to be put within reach of practitioners who are not data science or machine learning experts.

5.1. Emerging Trends in Battery Health Monitoring

Automotive industries are adopting a trend to develop a data-driven battery health monitoring (DD-BHM) system in electric vehicles (EVs). The electrical and thermal stresses a battery is exposed to during charge and discharge have no historical safe exposure duration that guarantees its health and performance. Hitherto, with no prediction, a conservative design is added. As a result, a non-optimal energy usage strategy is driven by limitive health and performance risk perceptions, consequently driving two negative consequences: (i) EVs are either over-dimensioned to reduce the health and performance risks or (ii) reaching the battery-limiting operating area becomes difficult for the user. With DD-BHM, these arbitrary limits are mitigated with the sensor data returned from use at combinations of different stress levels and variations delivered by a data-driven optimized (DD-OP) scheme becoming possible.In the phase of the development of DD-BHM, the cost and complexity of the required sensors stand as the main barrier. As a result, efforts are made to develop a low-cost and low-complexity evaluation scheme that returns the evolution of the battery's health and prediction of its performance with the least amount of sensors possible. Another pivotal point of the development phase is the DC-OP system, the designing of more cost-effective battery ECUs. Various other points of the design and development of the DD-BHM concept focusing the electrical safety can be also found in different research articles. Additionally, guidelines are created to define testing, monitoring, and evaluation procedures with emphasis on electrical, thermal, and mechanical battery behavior in use. Therefore, for the practical application of the DD-BHM concept, several disciplines need to collaborate. A need for standardization is underway.

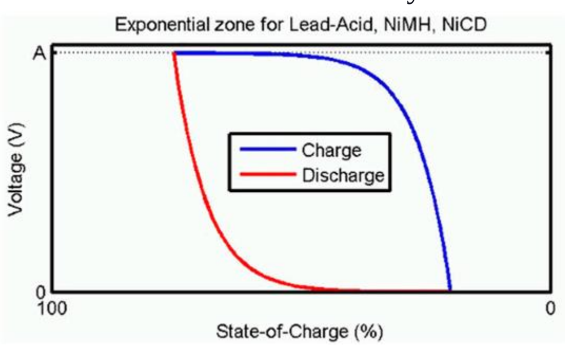

Fig 7: Hysteresis effect associated with the lead–acid battery.

6. Conclusion

The performance of LIBs in EV applications impacts the overall cost, operation, longevity, and environmental footprint of the vehicles. Machine and deep learning algorithms can leverage the data from the battery management system to predict and monitor multiple aspects of LIBs and use this information to optimize battery performance. We have reviewed the innovative applications of battery-ELM in modeling battery internal states such as capacity degradation, capacity fade, current fade, C-rate impact on the capacity of the LIBs, and voltage fade. The review also includes new approaches for predicting RUL, battery SOH, and cycle prediction. Among others are novel applications of energy and power fade, cell battery life impact, machine-learning generated low-fidelity battery physics models, battery lifetime, battery modeling validation, and risk-weighted optimization techniques.

The methods used by researchers to address the aforementioned problems and translate ML to actionable metrics such as SOH, RUL, and state estimation have been systematically reviewed. Present tools and strategies in each domain were highlighted, and we presented a comprehensive survey of existing ML and application trade-offs, usage patterns, and feature-engineering methods. Finally, the review includes a comprehensive discussion of current evaluation techniques that verify the reliability and accuracy of data-driven methods and existing validation techniques for both batteries and ML in the battery-to-ML pipeline. In this review, the AI models have been evaluated and the algorithms are compared based on performance results, such as error metrics and figures showing the model's ability to generalize over unseen data.The performance of lithium-ion batteries (LIBs) in electric vehicle (EV) applications significantly influences vehicle cost, operation efficiency, lifespan, and environmental impact. Machine learning (ML) and deep learning algorithms are pivotal in leveraging data from battery management systems to predict and monitor various aspects of LIBs, thereby optimizing battery performance.

Our review has explored innovative applications of ML in modeling internal battery states such as capacity degradation, current fade, C-rate impact, and voltage fade. We have also examined new methodologies for predicting Remaining Useful Life (RUL), State of Health (SOH), and cycle life prediction. Additionally, novel approaches such as energy and power fade analysis, machine-learning based low-fidelity battery physics models, lifetime estimation, and risk-weighted optimization techniques have been discussed.Researchers have employed diverse methods to address these challenges and translate ML insights into actionable metrics like SOH, RUL, and state estimation. The review systematically outlines current tools, strategies, and trade-offs in each domain, emphasizing feature-engineering techniques and usage patterns. Furthermore, comprehensive discussions on evaluation techniques highlight the reliability and accuracy verification of data-driven methods within the battery-to-ML pipeline.Critical to our review is the evaluation and comparison of AI models based on performance metrics, including error rates and generalization capabilities across unseen data. This thorough examination aims to advance understanding and application of ML in optimizing LIB performance, fostering innovation in EV technology and sustainable energy solutions.

6.1 Future Trends

Over the next few years, many trends will shape the future landscape of battery health monitoring solutions in commercial EVs. These solutions will be initially of a service model, involving monetization by electric vehicles and service providers. The increasing demand for data and the convergence of telecommunication networks with high-speed and low-latency standards offer fundamental support. Data transmission by the car to a cloud service and further motivations from vehicle maintenance, repair, and planned replacement will create incentives for service development and deployment. This will lead to a high degree of innovation around machine learning techniques that require private battery data to be stored in a privacy-preserving manner. The same data could be used to retrain machine learning models for battery health over the vehicle's lifespan.A necessary innovation supported by future vehicle infrastructure is optimizing the hardware and software of batteries and battery management systems for data generation. Onboard data processing will support vehicle-control decision-making and help reduce bandwidth while maintaining predictive power. Communication standards will address the required bidirectional battery health data exchange between vehicles and future fast-charging stations. Data anonymization or secure multiparty computation solutions will provide cost-effective approaches for privacy-preserving data sharing to enable standardized battery health models across fleet operators or electric vehicle owners more generally. Industry acceptance will be driven by the compliance of deployed solutions with forthcoming international technical standards for privacy protection and accepted implementations of data encryption, data minimization, and security in the vehicle. Such platforms will foster collaboration for shared model training, while still allowing brand- or operator-specific benefits extraction. The increasing use of such solutions will provide new revenue streams to electric fleets at a time when trade policies of associated vehicles could destabilize pure vehicle selling or lending business models.

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