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Research Article

Optimizing Electric Vehicle Performance With AI-Driven Battery Management Systems

Karthikeyan Palanichamy[1*], Jatin Soni[2]

[1*]Product Owner, Karthikeyanpalanicham@Yahoo.Com
[2]Software Developer, Jatinsonii@Yahoo.Com

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ABSTRACT

Decreasing battery functionality is the primary roadblock to the widespread adoption of electric vehicles (EVs). Hence, solutions are required to optimize the safety, performance, and cycle life of lithium-ion batteries. To address this issue, we present the first AI-driven battery management system (BMS) capable of model-free prediction of state-of-charge, state-of-health, and likely failure dynamics in EV batteries. We utilize industrial X-ray computed tomography to inspect the internal electrodes and separator quality and state-of-charge, and electrochemical impedance spectroscopy to quantify cell state-of-health. Our model-free approach tackled both experimental and industrial EV-relevant data; we demonstrated ground-breaking prediction accuracy and showed neither calibration nor any commercial tool assistance was required. The approach offers a qualitatively fundamentally novel perspective on battery performance that will enable its ultimate understanding and optimized design. Our approach directly supports sustainability and the low-cost driving of electric vehicles.The increasing pace of vehicle electrification and hybridization necessitates accelerating advances in lithium-ion battery performance and safety, which are mainly reliant on sophisticated embedded battery management systems. Specifically, lifelong accurate tracking of the state-of-charge (SoC) and state-of-health (SoH) of the individual cells is of cardinal importance. The influence of underperformance in these capabilities will cause, amongst others, EVs to be stranded at the side of the highway, downtime of large-scale electricity energy buffers, reduced overall EV battery pack use, and early frequent costly degradation and replacement. Decreased reliability affects not only the promise for hardware-in-the-loop research but is a direct consequence of EV industry proliferation. Numerous problems can arise with battery characteristics alone, and the consensus is that the issues will only become more severe. To strongly reduce this risk and accommodate the electrification evolution, battery service life needs to be prolonged by pursuing advanced machine learning algorithms focusing on battery monitoring, modeling, and management.

Keywords: Optimizing Electric Vehicle Performance, Electric Vehicles (EVs), Battery Management Systems (BMS), AI (Artificial Intelligence), Performance Optimization, Energy Efficiency, Machine Learning, Battery State of Charge (SOC),Battery State of Health (SOH)

1. Introduction

Electric vehicles are introducing a paradigm shift in the automotive market, driven by notable reductions in pollution and noise levels, and the availability of a diversified set of tried and tested battery technology for traction. Current marketing and legislative postures are getting aligned to boost the implementation of this technology novel, which requires accounting for battery aging and growing environmental concerns. A sustainable electric vehicle society is where the vehicle operating costs are significantly trimmed, i.e., enhanced battery life, which, in turn, implies a more efficient use of their stored energy budget.Battery efficiency can be improved under predictive Battery Management Systems (BMS). Obtaining a full Electrochemical Impedance Spectroscopy (EIS) on the battery is expensive in terms of sensor, post-processing time, and signal processing complexity (the test consists of sinusoidal voltage and current generation and measurement) and cannot be applied outside lab conditions. In-vehicle monitoring is excellent for both, feeding a supervising AI and imposing linear and physical rules (fast limit conditions, disconnection, and information powerline availability). We focus on deep learning EIS sensing, inverting specially designed artificial neural networks used in a different way along the research field, adapting its design and exploitation to embedded applications. We shake the battery with current and voltage harmonics between uses, and as long as we detect phonon vibrations via a tuning fork generator, we will work on more consistent connected time signals. If we first distribute a known amount of harmonic vibration and identify their exact position and their associated transfer functions, battery EIS information contents are greatly ennobled via some signal scanned and ungated complex phase Fourier transformations. These are usually applied using very frequent local approximations proportional to the phase scanning shifts. Our question is: Are we transforming the signal, integrating? What are the exact bilinear integration characteristics? Properly applying integration as a linear filter reduces considerably the data sorting effort for ANNs while improving the location linear definition. Upon transforming, we can better calibrate a defined signal branch in signal dispersion. We save the scanning phasing coefficients as Signal Data Arrays, then distribute them in the form of interconnected MetaDatabanks for DAS inceptor and distributor retrieval. DAS inceptor retrieves a Signal Data Array which is identified via the shift integral, while the distributor provides the filter design, and signal-dependent hyperplane reconstruction matrices for the Classification and Regression of different goals. DataBanks are connected via steganographic arrays, focused on inhibiting data altering and repeat.

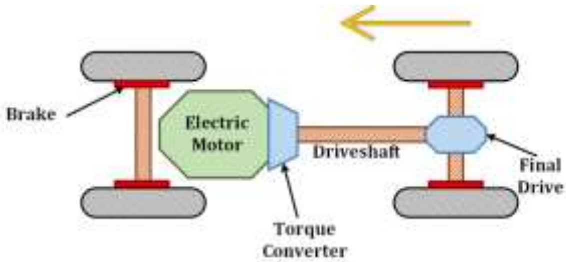

Fig : 1: Electric Vehicle

1.1. Background and Significance

The development of distributed and vehicle-integrated (or "edge") machine-learning models for predicting battery health, range, and mitigation strategies for improving battery life is both a critical accelerator for electric vehicle fleet penetration and a high-dimensional challenge for researchers. In the short term, fleets and individual electric vehicle owners face persistent range anxiety, as none will take a chance of becoming stranded without a viable fueling infrastructure. The concern is grounded in battery and vehicle control model complexity and a lack of context for the environment and cell conditions being unpredicted operations. In the medium term, automotive manufacturers stand to lose millions in warranty claims if widespread usage patterns are not identified and root causes are mitigated before electric vehicle components begin to fail in the wild. Without information on the distribution, charging profile, and thermal environment of electric vehicle operations, useful inferences cannot be made on battery wear mechanisms or vehicle-level power delivery.Both stakeholders and researchers in the field of electric vehicle grid integration need new insights into operations at the edges of the vehicle and its battery. Analysis of large-scale data sets for insights that will pay off must begin while the transgressor distributions still contain many signals. Using a Bayesian Probabilistic Matrix Factorization model trained on inductive charging data with specific battery chemistry, we detected differences in charging patterns attributable to an upcoming battery fault. In contrast to many models developed for these purposes, our model features a negative control, i.e., occupants who are unlikely to know the underlying cell conditions, but frequently subject the vehicle to charging experiments as its primary use case.

1.2. Research Objectives

The main objective of the proposed research is to develop an AI-driven BMS for electric vehicles to optimize EV performance through AI-based data fusion and decision-making at the system, pack, and cell levels. This will be achieved through the following research objectives:- To create a novel multiple model estimation framework integrating functionality, state, and fault estimation into cohesive processes to robustly estimate the state of charge and state of health of EV battery cells. The approach will have the capability to quantify the state of life and predict the remaining useful life of the cells. - To develop a hierarchical and physics-aware state of charge and state of health estimation scheme for the EV battery pack to perform the task efficiently using multiple data sources. - To integrate the proposed cell level and pack level estimation framework within an iterative data integration and decision-making process to optimize the EV battery performance and achieve the desired trade-offs between different objectives such as robustness, accuracy, computational overhead, and interpretability. - To design an AI-driven BMS framework suitable for safe and reliable operation in both the nominal and off-nominal scenarios with the lowest cost and highest rewards.

2. Electric Vehicle Battery Management Systems

Electric vehicle (EV) battery management systems are in charge and of paramount importance to plan and realize tools supporting all challenges associated with the EV market growth: maximizing energy density, recovering state-of-health (SoH) losses, and safely acting under fast-charging and difficult climatic conditions. Fully unleashing benefits from increased energy density is vital to electric vehicles to enhance the hobbled driving ranges that EVs currently offer. Energy recovery procedures are important since battery operating windows have a limited number of cycles (roughly 500 cycles for renewable energy scenarios) and the cost of the pack is high for the ice age and is of critical importance to make EV production costs competitive with those of traditional internal combustion engines.Increases in battery energy density are associated with the use of NMC-811 ($LiNi_{0.8}Mn_{0.1}Co_{0.1}O_2$) - a material that is used among new electric vehicles launched by Tesla, Porsche, and other suppliers. However, the increase in energy density with NMC-811 challenges us when warming up the cell. The problem is one of the design of the cooling circuit with too high SoC of NMC-811 in a short time acting on a low-temperature level of the cooling plates. The lifetime of a battery pack is greatly affected by the number of charging/discharging operations of the battery cells. Besides the cost of the pack, energy recovery procedures are really important since battery operating windows have a limited number of cycles (roughly 500 cycles for renewable energy scenarios), and the cost of the pack is high for EVs. EV isn't considered the only market sector and their durability during long-term use cases is even more challenging to plan, compared to stationary systems.

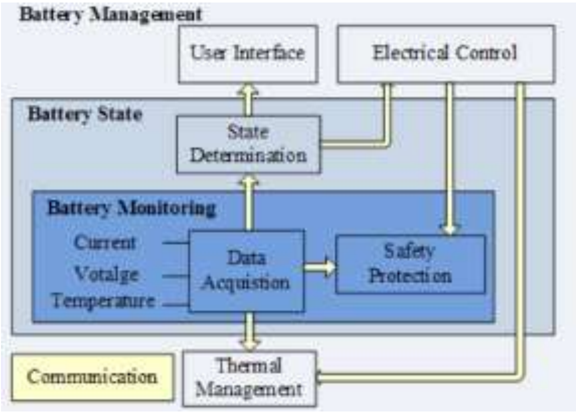

Fig :2: Illustration of a battery management system.

2.1. Overview of Battery Management Systems (BMS)

Batteries are the main energy storage solution for modern electric vehicles (EVs). A battery management system (BMS) is an active control system that is essential for operating lithium-ion (Li-ion) batteries safely and effectively. The autonomous performance capabilities of BMS should provide real-time information allowing for optimization of charging and discharging rates and thereby enabling more accurate and efficient use of battery capacity. In addition, this advanced information can be used to quickly detect and respond to any system faults to protect both the battery and the vehicle. The traditional BMS high computing demand limits system performance, making a smarter BMS computer software solution desirable. This review discusses the recent advancements in BMS computer software development as well as ongoing research and industrial activities. Machine learning and artificial intelligence-based BMS (ML and AI BMS) are discussed in detail, with the current issues identified and areas requiring further development summarized. Finally, the potential future directions for performance improvement are presented.

2.2. Challenges in Battery Management for Electric Vehicles

Current battery management systems for electric vehicles, such as the IGBT-based converters with standard control algorithms, have shortcomings. These systems do not provide feedback on the current profile of the cells or the state of charge (SOC) of the cells. They are also prone to suffering from many issues. They are inefficient and contribute to energy loss, are costly, and are not able to identify weak cells, resulting in suboptimal performance of the battery and reduced vehicle range.

The earlier method to measure the SOC was to pick the voltage of the cell and divide it by the voltage when it is fully charged, which was stored in the memory. Other methods measure internal temperature, and the voltage also tends to vary with mechanical and thermal stress, aging, and mismatched cells.

As they do not measure cell voltage directly, they are prone to mistakenly measure the energy in the battery. The current cell monitoring IC is a 16-bit ADC, which misses any voltage fluctuations that could aid in the sudden stranding of the vehicle without any indication. The current-voltage monitoring method only updates the SOC when the key is in. The lithium-ion battery is sensitive to overcharging and discharging, which leads to a temperature increase.

3. Artificial Intelligence in Battery Management

Many automotive manufacturers are working on using AI to help manage the energy in a vehicle's battery. The battery isn't a single device. It is a combination of many individual battery cells. To get longer battery life, you would like the individual cells to have the same electrical characteristics. However, battery manufacturing isn't perfect, and cells can have different internal resistances, different self-discharge characteristics, and in some cases even different capacities. What we want is a battery that looks more like one of those self-contained battery modules. With a module, you have multiple cells that perform similarly surrounded by protective systems. Ideally, the battery management system (BMS) software would know all the internal details of the cells and control everything so that the battery as a whole gets the most performance and life. The problem is, that there are so many factors that even making the BMS optimal during manufacturing doesn't make sense since people don't all use their cars the same way.Big automakers like GM and Ford with their battery technologies could gain a big advantage in performance and lifetime by optimizing their power systems to take advantage of those special BMS features. And of course, any company that builds next-generation battery systems could also gain an equally large advantage. Artificial Intelligence appears to be a very effective and cost-effective approach for improving battery usage efficiency. The Communicator is one of the few firms that have transitioned from basic research to a commercial BMS. Their commercial system uses multiple levels of coordination and reporting many times a second to control the battery. At the top, there's an AI that controls a smaller AI that sends each of the vehicle's control systems messages on how to use the battery. Each of those control systems will control some portion of the vehicle. The idea is that without controlling the whole vehicle, a large part of the battery's use looks like a typical profile of how a car battery is used. At the lowest level, the battery cells themselves are communicating with a smaller AI that figures out how best to balance the individual cell.

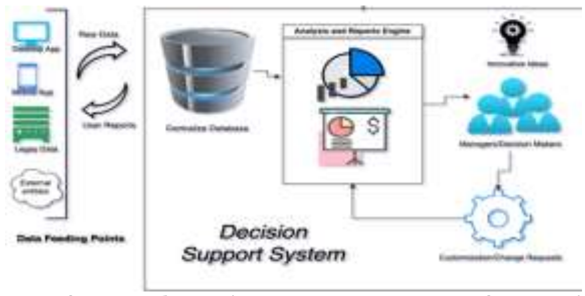

Fig :3: Impact of AI and ML in Management Information Systems

3.1. Machine Learning Algorithms for BMS Optimization

With the extended driving range and enhanced characteristics increasingly promised by new battery technology advances, accurate and fast state evaluation is an easier task. The Electric Distribution over Intelligence (EDISON) approach is taking advantage of advancements in AI and machine learning. EDISON uses a variety of sensing and monitoring solutions based on artificial intelligence, big data analytics, and edge-cloud interaction to optimize every phase of the battery life cycle: cost, performance, and safety, to mitigate the anxiety of EV driving range. The EDISON Platform allows the predictive maintenance for multi-chemistry traction batteries and the development and deployment of a multi-technology high-power density sub-pack, including a software layer for electro-thermal management, thus reducing the cost per kWh.The sensors are utilized to create empirical models. It may seem complicated to have an empirical model that is challenging to explain the behavior of the non-linear end-of-charge capacity measurement for various techno-economic limits, but artificial intelligence can help define a target tolerance as a percentage, maximum errors, and standard deviation, and split the device into learning, validation, and testing portions. The results showed that Neural Networks outperform some other traditional classifiers such as Decision Trees, Random Forest, ExTrees, and others. Using simple features allowed us to obtain satisfactory performance with Neural Networks. Handling all cells as independent units is very challenging as cells with the same $LiCoO_2$ cathode are characterized by different electrochemical responses and cycling paths.

3.2. Deep Learning Applications in Battery Health Monitoring

As of 2021, the emphasis on health and state of charge (SoC) predictions of LiBs has shifted from conventional methods that use fundamental electrochemistry principles to those that leverage deep learning methods using input-output data. The functions and tasks that can be trained and executed with deep learning methods are diverse. The hierarchical, multi-layer design of deep learning models allows for manifestly complex functions to be learned, such as the relationship between cell potential, state of health (SoH), and cell temperatures, to enable improved parameter estimation. Deep learning models are potent universal function approximators, and certain designs can theoretically emulate any kind of given relationship between different input and output data. In the investigation of battery SoH, deep learning methods have demonstrated promising capabilities and advantages in addressing the issues caused by battery nonlinearity and complex coupled temperature-electrochemistry degradation mechanisms.Numerous battery health-related studies have been carried out. These works can be generally categorized into three groups. The first investigates the detection of internal short-circuiting and other SoH estimating using in-situ and ex-situ battery analysis methods. Researchers have previously applied deep learning to LiB experiment results to estimate battery internal resistance, training models on cycle data, and the measurements of impedance data. The second group focuses on health prediction and deep learning-based RUL estimation, where long short-term memory (LSTM) networks have been shown to perform well when making battery discharge predictions for widely spread, noisy voltages, current, and temperature data. The third group involves label gap implementation. Scene simulations could be conducted to obtain SOC deviation histogram (SDH) data and trained to predict cell failure rate based on remaining useful life (RUL) data, with a causal degradation modeling method having previously been established as well. These studies of battery health prediction and RUL estimation verify various deep learning efficiency and predictive prowess in elaborative battery health research tasks, further ensuring the reliability and flexibility of applied methods for real-world data application. The rapid expansion of efficient and precise deep learning-based degradation estimation further verifies the rising significance and value of AI technologies such as these to the progression of energy storage interviews.

4. Case Studies and Applications

If you manage a public or commercial fleet, your top priority is keeping your vehicles on the road. That means maximizing the life of your all-important battery pack. Grepow's new monitoring system can let you know if you're about to lose a $10,000 pack so you can eliminate risk early while you can still run out more transportation than your competitors. And it knows more than just voltage and temperature—it can give you insights into your fleet's performance and what kind of terrain and speeds each system sees. Using machine learning, you get more value from existing data. Predictions for failing cells that had decent accuracy for a lithium-ion pack needed between 35 and 50,000 pairs of two weeks' stock of Canyon head Canyon tests with several thousand parts. For predictions on tens of cells with decent classification rates, we needed another 25,000 pairs.

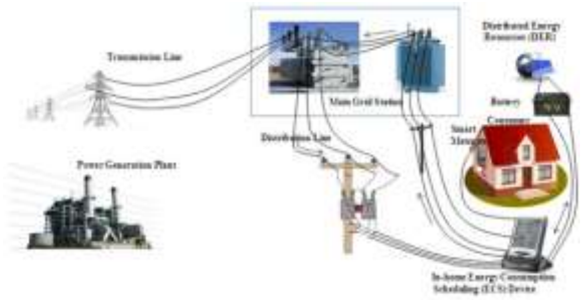

Fig 4: General layout of the smart grid's architecture.

Grepow's machine learning-driven battery management system monitors each cell instead of the whole pack like existing products. It can detect when individual cells are worn out with approximately 92 percent accuracy before they cause pack failure. It's also simple enough to implement that it should be economical for moderate-volume commercial vehicles and some high-end consumer products. Finally, since the system generates a lot of data on a vehicle's range, number of cycles, and what ranges are allowed with different temperatures and road types, we can use it to create custom packs that are less expensive while providing better performance—the system learns a lot about individual cell performance under different circumstances!Grepow's innovative machine learning-driven battery management system represents a significant advancement over existing products by monitoring individual cells rather than entire packs. This approach allows for early detection of cell wear-out with impressive accuracy of approximately 92%, effectively preventing pack failures. Moreover, its implementation is straightforward, making it economically viable for moderate-volume commercial vehicles and select high-end consumer products.The system generates extensive data on various parameters such as vehicle range, cycle counts, and optimal ranges under different environmental conditions and road types. This wealth of data enables the creation of custom battery packs that offer improved performance at a reduced cost. By learning from the individual cell performance across diverse operating conditions, Grepow's system optimizes battery management, enhancing both reliability and efficiency in electric vehicles and other applications.

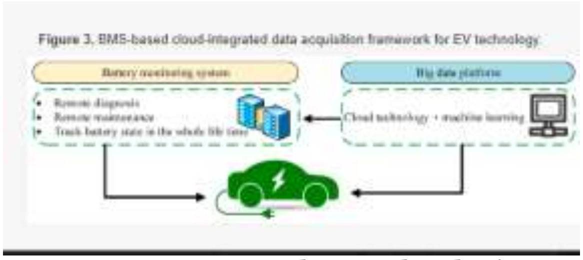

Fig 5: Battery Management key Technologies Methods

4.1. Real-World Implementations of AI-Driven BMS

In current implementations, the data processing performed by AI-driven BMSs takes place in microcontrollers and microprocessors inside the BMS. This includes preprocessing the data that is fed into the AI model to make sure that the model is presented with information that is usable for making predictions. The preprocessing phase comes before the inference phase, where the AI model has been trained and is used for the task it has been trained for, typically either classification or prediction. The results of the AI model inference are also post-processed. These approaches and techniques are common in many other domains, including autonomous driving, and much of the existing AI hardware and software technology is used as is or modified for use in BMSs.We should also mention that some parts of the AI processing can be distributed into the battery pack or vehicle controller. For example, in the edge computing approach, instead of feeding the raw data from the sensor node to the cloud for processing, preprocessing might be done locally by local AI inference nodes closer to the sensors. Some AI-driven BMS-related work presents concepts and prototypes with edge computing functionality. Some distributed systems also include parts of the AI model in a signal processing chain after the raw data has been acquired with low spatial or temporal resolution. Overall, the distributed systems we have found do not push the envelope on the type of AI models or types of AI processing that can be run. We have not yet found any work on AI-driven BMSs that focuses on real-time processing of high-resolution spatiotemporally dense raw data.

5. Future Directions and Implications

The goal of the proposed text is to provide a concise yet coherent concept paper review that will be grounded in data, introduce a contemporary battery management system for electric vehicles, and propose recommendations for future directions and implications of the work. Creating intelligent battery management systems with AI/ML-based strategies exhibits immense research potential and wider implications in the electric vehicle sector. Although AI/ML holds promise for battery state identification that provides performance optimization under challenging battery operations, current approaches exhibit low adaptability, high computational cost, and large energy consumption. Using upscalable, parallel, multidimensional, limited input sensor data to provide fast optimal battery management information can permit current electric vehicle adoption and implementation to proceed until more challenging plans address longer-term issues.This may improve both the operation of developed battery management system strategies and inform additional desirable battery-related electric vehicle and infrastructure requirements such as fast-charging, fuel cell range extenders, supercapacitor augmenters, V2G, and charging systems designs. These systems solutions applicable to level buses, trucks, industrial, military, and aerospace applications. Additionally, fast-response intelligent artificial intelligence-based battery management system practices can contribute essential and transformative batteries to electric vehicle scenarios. Proposing optimized strategies that are designed to function effectively regardless of battery type, electrode, operating parameters, power or capacity are also key research considerations. Researchers should identify how to build solutions that avoid popular limitations concerning size, cost, computational capability, and successful one-size-fits-all strategy practices.

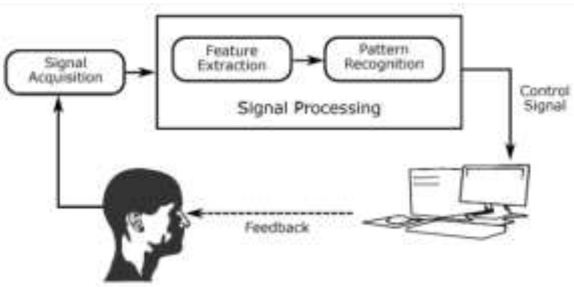

Fig 6: Teaching the Basics of Motor Imagery Classification

5.1. Potential Innovations in AI-Driven BMS

Some faults and tests could be innovated with increased AI capabilities in the battery management system. The architecture mentioned in the above section could be created as mentioned – or "sub-modules" as we could refer to them, could be created in this architecture encompassing testing and detection techniques. Some of these sub-modules could be automated to specifically detect only battery models and manufacturer-specific behavior. These sub-modules could encompass battery collision tests, aging, and temperature-specific testing. Innovations should be introduced at the specific string level, which can analyze the routing histories "through automation". This can be done in detail for the cells of the battery whether they are in various states of a temperature of charge state (SOC), during which power or energy-specific routing histories need to be detected to optimize the performance of the battery during frequent regeneration tests. This restructuring and reorganization of the routing histories could be matched to the battery model and manufacturer specifics, with improved performance ready to be delivered in the field.The focus should also be on detecting charge insertion drag (IRDR according to charge-based resistance), the internal temperature of the battery, and detecting subsurface convection currents in the battery. As we can see in the last few paragraphs, testing and various levels of fault detection could be innovated in this specific domain, with potential improvements in general system design, performance, and corner mode capabilities. Several other innovations specific to this particular case of battery testing, including routing history determinations or storage time, battery temperatures, or measuring data for display diagnostics, should also be implemented. The discussion section below treats these topics in more extensive detail.

6. Conclusion

In this work, we present a novel notion of an AI-driven BMS capable of extracting the full potential of EV batteries. With comprehensive sensors and robustly engineered booster circuits, TessBMS is capable of fine-grained battery model training within the real onboard operating context. Coupled with powerful hardware for AI model deployment, the AI-driven BMS can provide high performance and robust system performance to monitor, protect, and actively manage every cell in the battery pack. In contrast to traditional BMSs, which only execute passive SOC & SOH tracking, the TessBMS allows active command by the controller to the BMS – such as optimizing SOC, creating a voltage headroom or even managing the battery to reduce heat for safety. Hence, the results are evident in a perfect balance between power and thermal management, ensuring safety, higher performance, and a longer lifespan. Hosted at the EVE platform, TessBMS can transform EV automotive safety and durability while maintaining or even enhancing performance.Our failure analysis suggests that BMS without the TessBMS capabilities can detect only major shorts to protect cells and also severely limit power output in the event of field failures. This operational strategy leaves the system with energy or power remaining under abnormal conditions, which can quickly escalate to an out-of-control thermal runaway. In algorithmic sensitivity tests, our analysis suggests that a standard safety strategy can allow serious faults to progress and result in catastrophic failure of the entire battery pack. With our TessBMS, considering thermal management as an integrated feature of the BMS, combining Safety-in-Control and controlling the battery temperature even before extensive thermal runaway and flame propagation, our system completely avoids battery-pack failure and mitigates thermal hazards effectively.

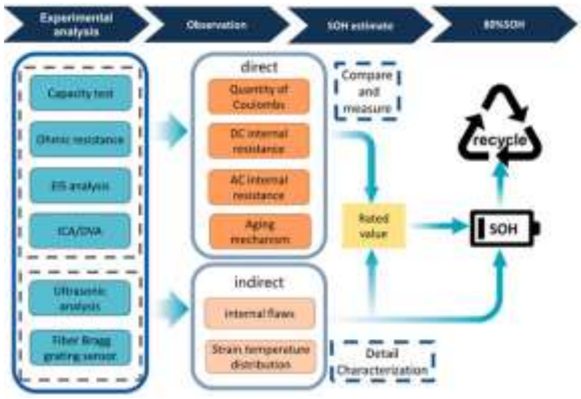

Fig 7: Different experimental analysis methods for SOH estimation.

6.1 Future Trends

As previously mentioned in this paper, the immersive employment of AI in EV BMS is expected to meet the stringent requirements of high-performance EVs. Remotely high safety, reliability, flexibility, energy efficiency, and long cycle life of EV BMS will be achieved by refactoring the prevalent charging scheme, state-of-health, and state-of-life estimation techniques and application of shared big data deriving from AI to the forefront of EV BMS design. Then, what does this trend look like and how far is it from us?The most challenging fact, charging, in EV BMS is considered here first. Remote electric charging has gradually evolved from an individual phenomenon to a widely applied behavior of a group. Shortly, it may be more appropriate to say that it is an online big data storage, retrieval, and sharing platform. In this platform, a transient charging mechanism design representing AI for distributed EV wireless smart charging will be a desirable feature to expedite mutual performance enhancement. For a passive wireless charging system, the current approach is to use resonators to increase the range and overcome the perpendicularity requirements. This approach has limitations, as the resonator requirements imply a large system size, which is impractical. The proposed alternative relies on a self-regulation method for the receiver's direct current (DC) voltage on the frequency control stage, thus establishing a robust charging system. Promising gains in wireless charging link robustness and efficiency have been demonstrated through simulation, as well as through two practical implementations, one with a momentum transfer function for electrifying wedge-tail eagles (Aquila audax), and the other with an inductive-like resonance charging condition for charging an electric power-assist bicycle (e-scooter) during motion.

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