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Original Article

Integrating AI for Enhanced Battery Lifespan and Efficiency in Electric Vehicles

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Abstract: *Advancements in a variety of artificial intelligence fields have spurred technological advancements not only in power consumption and efficiency but also in battery development, influencing electric vehicle advancement. By recognizing the great importance of batteries in electric vehicles, a platform that unites genetic algorithms with finite element analysis with neural networks in AI has been developed to consider various factors that affect battery design. The results of a series of tests to validate the approach were promising and seemed to be in good agreement with experimental measurements. It was evident that with the help of AI, the current trajectory of already rapid advancements in the EV field is likely to continue, which can be expected to lead to even more efficient, cheaper, and safer electric vehicles with longer lifespans, thereby further reducing the impact on the environment and simultaneously providing global economic and social benefits. Discussions suggest AI use is a must-have factor that needs to evolve under practically unlimited performance data for EVs.*

In summary, electric vehicles rely heavily on power storage to guarantee long driving range, lightweight, low cost, and long lifespan, with these factors having a complex interrelationship and requiring system optimization. This paper addresses this issue by presenting how integrating AI has the potential to help accelerate EV advancements. The combination of GA/AN with FEA methods studied in this work enables us to optimize our battery systems for different magnet manufacturers, and reduce the unnecessary research and development costs, impairing our battery testing.

Keywords: *Enhanced Battery Lifespan and Efficiency in Electric Vehicles, Industry 4.0, Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning (ML), Smart Manufacturing (SM), Computer Science, Data Science,Vehicle, Vehicle Reliability.*

I. INTRODUCTION TO AI INTEGRATION IN ELECTRIC VEHICLES

One of the primary challenges that haunt electric vehicles is the limited mileage and battery lifespan. Most modern electric vehicles are powered by lithium-ion batteries. Generally, there are two big challenges in battery management: the uncertainty in charge/discharge cycles and the trend due to aging. Due to the fluctuations of charge/discharge cycles as well as time, the battery capacity may decay, which will directly affect the electric vehicle mileage. In recent years, advanced learning algorithms were combined with real-life data to act as a quite powerful tool for battery management including aging estimation, fault diagnosis, and remaining useful life prediction.

Battery management system (BMS) faces a great challenge, for it has to keep a real-time record of the current status of a wide variety of lithium batteries scattered over the vehicle. The monitoring workload of the traditional BMS is very heavy, so the cost is relatively high. The reinforcement learning algorithm of explanation-guided representation learning with model-based exploration (SLM) proposed in this paper can simplify the model on the premise of avoiding confusion and exploring the environment and exploring the difficulties and balance between exploration and exploitation well and has an excellent estimation of high-Q-value. Finally, the performance of the SLMQ is tested on the OpenAI Gym and shown well. The strategy performance in the development environment demonstrates the adaptability of the algorithm to the environment. These algorithms can construct optimal decision rules from a large amount of operational data and can be actively applied to battery management in electric vehicles.

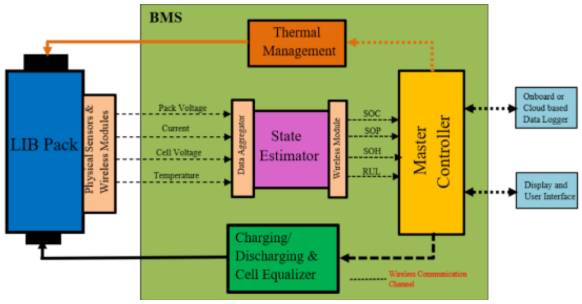

Figure 1: Schematic layout of a generic WBMS

A. Significance of Battery Efficiency in EVs

An electric vehicle (EV) is a sustainable mode of transport that converts some or all of its energy from the grid using advanced technologies. Like any automobile, the popularity of electric vehicles depends on several factors, which include vehicle cost, driving range, and fuel cost. The ownership cost of an electric vehicle is 41% lower than a plug-in hybrid electric vehicle (PHEV) over a 5-year time frame. One of the most important differences between electric cars and gasoline cars is the energy storage system. This system is called the battery system and is regarded as the most critical element of an electric vehicle. It plays a vital role in the vehicle's total performance, range, and safety. Battery performance characteristics such as state of health (SoH), state of power (SoP), state of safety (SoS), and state of charge/discharge (SoC/SoD) are important factors that need to be continuously monitored to guarantee cycling efficiency during the life of the battery.In other words, these various states depict performance, total capacity, power capability, and other properties that deliver reliable energy storage management. Reduced performance or weakened battery state can cause a decrease in performance, minimization of range capability, and an increase in charge time. Moreover, the use of batteries in the second-life market as storage systems, protection systems, and voltage stabilizers is also possible after they have reached the car's end-of-life. The battery's useful life is subject to the state of each cell, which is charged and discharged daily during vehicle operation. This causes the battery to rapidly degrade, changing its capacity over time and resulting in a lower battery lifespan. Due to fast capacity degradation, useful life numbers of cells in batteries are found near 85-90% of the obtained energy.

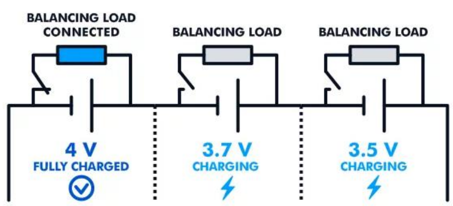

Figure 2: Cell Balancing Process

B. Fundamentals of Battery Management Systems (BMS)

Electric vehicles (EVs) are gaining a lot of importance in the fast-growing, energy-hungry world. The critical component that is responsible for the viability of an electric vehicle is the battery that powers it. To increase the range, lifetime, and efficiency of EVs, different approaches are being followed in the area of battery management systems to ensure smooth communication between the vehicle and the battery. BMS systems in EVs are sensor-based monitoring systems that ensure a vehicle's smooth performance during its life. This article explains the very basics of the battery management system, the various types of BMS, the common problems of BMS systems that occur, and methods to enhance them. Also, the relevance of implementing an artificial intelligence algorithm to solve these problems is discussed.

A Battery Management System (BMS) is a key part of an EV system. This system ensures the operation, safety, and performance of battery-powered vehicles under all conditions. The levels of this system can be scaled. In the simplest approach, the Management System (MS) at the battery level supports individual batteries. Furthermore, vehicles with higher storage devices (e.g., vehicles for material management) utilize Energy Management Systems (EMS) in which levels of Management Systems range from single cells to battery systems. The Vehicle Management System binds the battery with the vehicle in an automotive solution. The fundamental capabilities translate the fundamental performance and security requirements to the optimum level under varying car usage. With the advent of EVs, it has become the focus of BMS innovation. The BMS leadership is the bottleneck in the development of useful EVs and a comprehensive system that allows the highest possible performance and the longest usable life of the battery by continually optimizing it.

II. LITERATURE REVIEW KEY COMPONENTS AND FUNCTIONS

The HEV/EV powertrain consists of a complex series of hardware and control systems that function together as an integrated system. The Power Electronics (PE) subsystem contains electric motor drives and the higher performance power electronic converters that connect the energy sources and sinks to the electric machines. The PE subsystem is a significant and complex portion of most HEV/EV drivetrains in terms of both cost and efficiency because energy losses from the energy storage system to the wheels and back require power electronic conversion. High-speed electric traction drives are most commonly two- and three-level power converters. Different types of power converters and their specific requirements for high-heat generation influencing their lifespan are discussed in Section 2.1.2. In addition to the power electronics, a microprocessor-based inverter control logic is necessary to enable the high dynamic performance of electric traction drive that the industry demands. The power conversion section of an HEV/EV consists of multiple peripheral power electronics integrated. This section typically converts electrical energy from the electric traction or auxiliary drive motor to mechanical energy at the wheels or from the energy sources or sinks to the energy storage system. Power conversion types include multiple PWM voltage source inverter (VSI) drives that connect to three-phase AC traction motors and a buck or boost to DC-DC converters that connect to the energy storage systems.

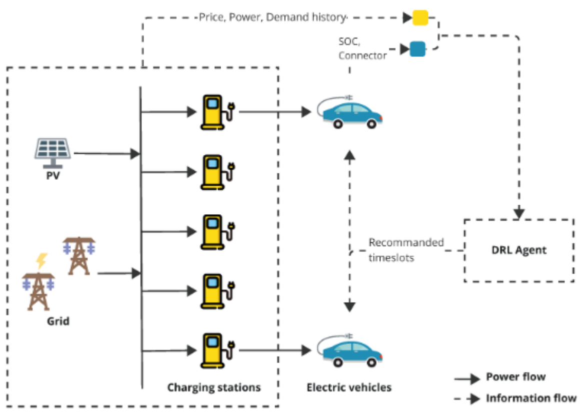

Figure 3: Charging Scheduling System Architecture

III. ROLE OF ARTIFICIAL INTELLIGENCE IN BATTERY MANAGEMENT

The existing methods for diagnosing a battery's state of health (SoH) include expert knowledge-aided model-based approaches. These methods use an electrochemical model and parameter estimation techniques under different operating conditions of the battery. In power systems for machine learning, these techniques can model the system and make predictions and decisions. Over time, the AI can improve the performance because of increases in data-driven algorithm performance and the volume of available data. AI, in the form of data-driven strategies, can analyze large datasets and recognize patterns in the battery's state, the variables that affect the battery's behavior, and how these variables are influenced in diverse environmental and operating conditions. The size and high-frequency data provided by sensors can be processed using machine learning methods for predictive event recognition, condition monitoring, and the classification of the event.AI methods allow a battery's aging process to modify the relationship between the battery's voltage and capacity. Researchers have shown the success of deep learning technologies for the SoH prognosis of a battery. Data-driven models such as the Support Vector Machine (SVM), Random Forest, k-NN, and Decision Tree have been used for good prognosis results. Data-driven models account for the relationship between SoH and an EV's secondary power source and are valuable tools for identifying and recognizing the events. Model algorithms consist of data transformations, a learning technique, and a decision-making technique. It is the responsibility of the machine learning model to understand the pattern of data so that algorithms with this understanding can make inferences and predictions. Machine learning and artificial intelligence algorithms extrapolate data to the training input data conditions.

A. Machine Learning Algorithms for Predictive Maintenance

As mentioned earlier, the paper proposes using machine learning algorithms for effective predictive maintenance of batteries in EVs. A variety of machine learning algorithms can be used for this purpose, such as artificial neural networks (ANN), decision trees (DT), support vector machines (SVM), Bayesian networks (BN), reinforcement learning, and the like. Among these, artificial neural networks (ANN) and decision trees (DT) are simple and efficient approaches that have been utilized in several studies and have been observed to yield promising results. A shallow ANN with a single layer can be used to capture a linear pattern in input-output data, whereas a deep ANN with multiple hidden layers can be utilized to define complex nonlinear functions. The prediction error of deep ANNs consisting of multiple layers is usually lesser than other conventional machine learning algorithms. It was found feasible and concluded that ANN models estimated the linear relationship between the features and output health parameters for the lithium-ion batteries. The authors have prepared the ANN network employing two inputs, voltage, and temperature, and as per the paper, the output of the ANN network was used as a feature for the battery state of the health prediction model.

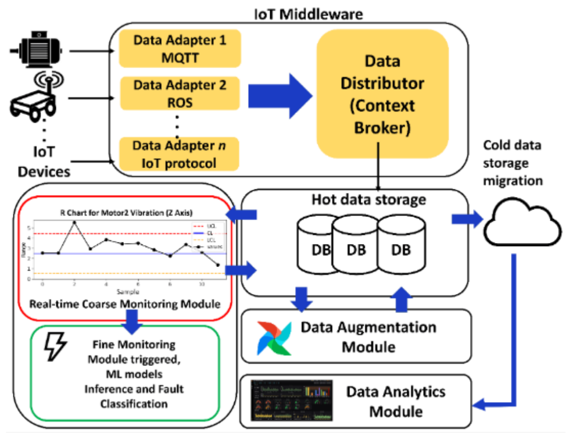

Figure 4: An overview of the implemented CPS architecture for PdM applications

IV. CASE STUDIES AND APPLICATIONS

AI-integrated manufacturing, labeling, assembly, and optimization of automation and O&M for an MPPT and distribution of charge controllers for electric vehicles via a smart battery with battery management systems to guarantee rapid energy storage in application backup of ampere-hour high-capacity electronic conversion switch stations. P2000124 with proposed AI in BMS MLP and RNN control algorithms to develop data-driven model servo deserved to be validated experimentally to guarantee the efficiency of the model and the trustworthy convergence of a specific optimal corresponding demand of model power. The online self-calibration testing and adjustment of the results maximization must be proposed and verified for artificial neurosis. Grid-friendly model. It comes with the automatic abyss buffer operation that drives backups for batteries and all isolated or nearby energy storage smooth and fails.The economic evaluation of the economic benefits presented that investment in high-capacity battery storage is worthy to be considered as a quantified improvement in backup energy supply cost efficiency, reduction of social and environmental electricity costs, shortening the economic scale of the battery backup, and the contribution to sustainable smart ampere-hour stations with positive compensation for environmental and energy policies and a reduction in the common use of the urgent capacity of fa stateful energy pumped storage. Sustainable application and focus on integrating MPPT and Battery Distribution Labeling for the smart battery technology electric vehicles in the residential and focus group identified in this area in the future. These analysis methods and techniques in the industry have already been developed and validated.

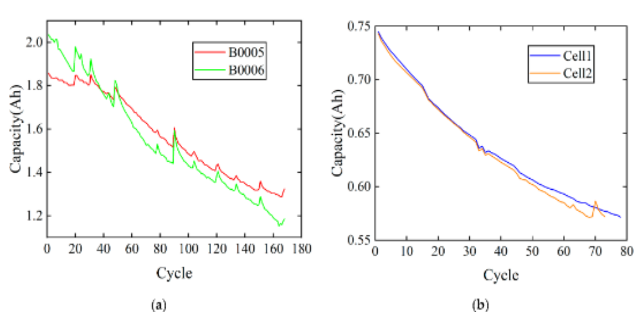

Figure 5: Battery capacity decline curve: (a) Battery B0005 and B0006 in the NASA dataset; (b) Battery Cell and Cell2 in the Oxford dataset

A. Tesla's Use of AI for Battery Optimization

Tesla has been developing AI to optimize battery charge and discharge dynamics with a very likely outcome of extending battery lifespan. The Tesla Gigafactory is described as a machine that builds machines, consisting of four fundamental parts. The Raw Material Processing Unit processes raw materials, the Foil/Winder unit manufactures the cell, and the small parts and components are made in the Module and Pack unit as the final product is tested. A fifth in-house-developed manufacturing software and AI platform connects all of those parts and functions by synchronizing and optimizing the manufacturing process. Nonetheless, the same software and machine learning structure most likely are also applied in the battery optimization process known as the Tesla S.W.A.G (State of Wei's AI Group), a multidisciplinary AI group at Tesla. The S.W.A.G originated in 2013 when Tesla's CTO Wei Lien Dang gave a proposal on how to extend electric vehicle battery life. Then, the idea was implemented along with several other suggestions in the 2014 Model S software to improve the battery life warranty. Tesla S.W.A.G is a department with the only purpose of developing software to extend the lifetime of the battery in electric vehicles.So far, Tesla is the only company in the world that has shown AI deployment in battery management during the ten following years, giving them a competitive advantage and a head start worth more than 100 billion dollars. The battery management system (BMS) is the critical battery component responsible for monitoring the battery state, controlling charge, and discharge operations, and indicating the SOC to the driver. Enhancing battery management systems to increase user battery life would be the most effective policy to attract more customers. Tesla's battery pack has 16 modules, with the BMS provided with a dedicated microcontroller. Respecting battery maintenance means that daily SOC should not exceed 20% to 80% and when the distance is very long, then 100% should not be reached in any way, especially for the country, mountain, and desert territories. Currently, the collective battery capacity can vary from 90.7 to 100 kWh, with the technique of stopping 0% charge in each module in advance having to minimize the charge and discharge velocity. The goal is to preserve electricity for a longer time by trying to smooth the number of processor clock cycles during the battery lifetime. It will help to rejuvenate the battery pack reduction of modular capacity non-linearity, detecting when one of the 450 modules is underperforming.

V. CHALLENGES AND FUTURE RESEARCH DIRECTIONS

There are several research and development directions to expand the integration of AI in battery thermal management systems and to achieve long battery life, high power capability, and efficiency, and a healthy or safe state of both batteries and TMS. Firstly, energy management with long-term planning that considers driving cycle forecasts can be incorporated into the B-TMS to minimize cycle degradation and prevent the premature failure of EV batteries. Several machine learning or advanced control methods such as RL and deep learning could be applied to reduce the complexity of long-horizon energy management strategy and then reduce the dependency on a priori high-precision future cycle information.

Secondly, the starkly different thermal states or balance between different batteries request flexible strategies to reduce needless discomforts or degradation of. This flexibility for individual differences could be the key feature that distinguishes AI-optimized thermal management from industry-standard heuristic methods. The integration of reinforcement learning could adjust the energy share of intro pack forced air cooling air to account for sudden thermal aggressions and lead to more judicious use of available electrochemical energy of the cells. Thirdly, B-TMS with AI modules can guarantee battery healthiness and then reduce thermal runaway potential during or after severe thermal excursions by predicting future demand/x-TMS thermal states and then implementing pre-cooling together with physical parameters control of cells such as SOC, LSV, and terminal voltage.

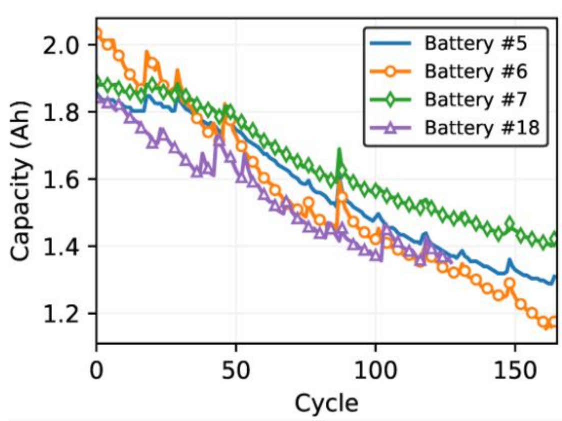

Figure 6: Lithium-Ion Battery Degradation with Respect to Number of Cycles

A. Overcoming Data Privacy Concerns in AI Integration

Data privacy is a concern that often leads to the resistance or ruling out of artificial intelligence technologies as much of the currently utilized data is both valuable and highly sensitive. User-related information was collected by vehicles or residential IoT and is often required to be analyzed to provide benefits to the user. The physical privacy concerns are still fundamentally rooted in the smart grid, which is built on a system of systems networks whose innate uncertainty can exacerbate privacy-related risks. The need for a comprehensive analysis of the laws and regulations governing data sharing and cyber and information privacy, including but also stretching beyond privacy, security, health, and economic preservation, is recognized.

The 'data supply chain' requires the strong coupling of aspects that span from data collection to data treatment or even data sales, and data leakage is not an unlikely event. The case for AI as an enabling technology for data privacy enhancement is that AI usually deals with the settlement of services against a problem space so that the user data can remain localized and secure. By implementing privacy-preserving hardware and determining the minimal amount of data, then the existing privacy frameworks such as usage and aggregation of user information, AI can provide concurrent data utility and privacy. Furthermore, AI functions concerned with various forms of random transformations can now maintain and benefit from the piecewise linearity property of certain functions or the low-rank property of matrices. Outreach is steadily growing for AI models such as an auto-encoder that implements semantically similar data manipulation that can then provide adversary non-compatible obfuscating samples. Subsequently, a collaborative AI approach was inspired by competitive learning to refine and verify the efficiency of crypto processors and information flow analysis.

VI. CONCLUSION

The incorporation of artificial intelligence (AI) systems into electric vehicle (EV) devices offers several benefits, including enhanced performance, increasing the lifespan of the battery, and efficient internal distribution of states-of-charge (SoC) within the unit cells of the lithium-ion battery. The optimization of SoC can help to effectively manage the EV energy, which thereby maximizes its performance and prolongs its lifespan.

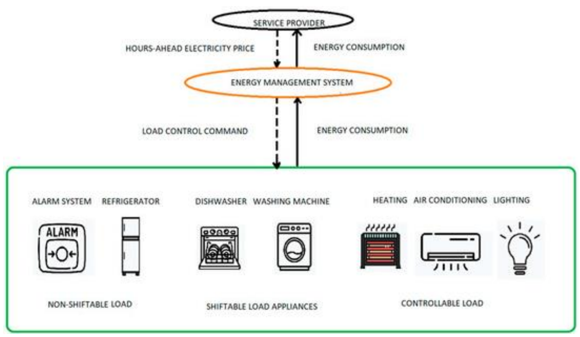

Figure 7: An Example of Home Energy Management System

The application of AI to EV thermal management systems acts as a fast-acting system response that detects the temperature within the battery cell. Rapid and effective cooling or heating processes can be achieved through effective AI systems. In tandem, the battery pack thermal architecture can be enhanced through the integration of the AI controller's findings. AI can be beneficial in terms of assisting in the control and management of the battery thermal system. Similarly, AI systems can assist in the management of the SoC, which can enable the battery pack to attain maximum efficiency and performance capabilities. AI can also assist in designing the battery thermal management system to enhance the battery operation. The incorporation of AI in thermal management results in enhanced thermal and aging modeling, optimal design planning, real-time thermal shutoff control, and vapor cooling-assisted thermal management.

A. Future Trends

The interest in extending the range of EVs is still dominant, in the effort to bring them to the cost parity of ICEVs. It is reasonable to expect a continuous improvement in battery energy density, with Ni-rich positive electrodes and a capacity of 300 Ah. These advances are feasible with the most promising technology, Li-ion (LTO anode, NMC811, Ni-rich cathode-based chemistries in safe systems), or with safer batteries like Li-metal. NMC811 and LTO are already in production and can largely be used when NMC111 and CNT/Si negative electrode-based batteries have been phased out. The consequence would be a higher battery lifetime, with LTO-based EVs easily living for 10-15 years, so new long-lasting Li-ion chemistries would only reduce the costs of used EVs, which are already affordable today.

A lateral market, dominating regional or urban EV demands, could be soon phased out by LFP-based EVs. The specific energy per volume is not drastically higher than that of the batteries for last-generation hybrids. Therefore, the specific driving range would mostly depend on the initial charge. Some OEMs partially eased the battery cost by not installing thermal management for LFP batteries, under the consideration that regional and urban EVs would not need fast charging. For keeping the range usable under any climatic condition, the battery should have >18 kWh capacity, for home charging overnight, with more than 10 kW (Europe) or 15 kW (USA) as suitable power for the most widespread plug types.

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