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Research Article

Smart Charging: AI Solutions For Efficient Battery Power Management In Automotive Applications

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ABSTRACT

The blossoming development of connected vehicles and the prolific infusion of artificial intelligence, machine learning, and deep learning computation mechanisms in-car electronics are contributing to a modern integrated, and complex vehicle environment, where an increasing number of vehicle components require an electric power supply to perform their specific role and function. The electric power demand growth is weighted in watts, where even the simple light bulb is no longer only a lamp but an electronic part of the vehicle. This increase in electronic vehicle parts has led to an increased demand for batteries/graphite power cells technological evolution, with a concern towards reduced environmental footprint but also towards innovative manufacturing processes to support the exponential increase in battery numbers. Nonetheless, the thermal/electrical market reality has imposed several limitations on batteries, especially in usage scenarios that demand high repetition and/or are adapted to very specific thermal requirements.The thermal capabilities of batteries are always a key point that drives efficiency, effectiveness, and relevant performance indexes. A battery thermal switch will have a major impact on battery thermal comfort and long-term health when cooling and heating the battery. Smart charging can help to expose and enhance battery performance results, relying on different calculations for battery heating and cooling. The simultaneous ability to control the thermal rearrangement of energy in the battery, improving the power performance during charge and/or discharge, becomes increasingly important. Both the small and large-scale systems with on-board batteries can benefit from this knowledge and management, leading to extra energy savings and contributing to the paradigm of energy and power efficiency. Converging computing architecture with smart battery charging leverages and exposes the preferably coexisting power management and power protection considerations.

Keywords: AI Solutions for Efficient Battery Power Management , 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

The increasing deployment of fleet and electric vehicles makes the characterization and modeling of their power demand using dedicated approaches more and more urgent. Making ad-hoc and electric vehicles charging even smarter, more efficient, and aligned with power grid resource capabilities will dramatically change the interaction and relationship between energy and transportation. The expected benefits include remarkable achievements in reduced costs and investment in grid infrastructure, improved waste of renewable energy resources, and downsized negative consequences on electric system stability. For these reasons, battery-powered vehicles should be managed more intelligently, to reduce consumption costs, collectively reduce the safety risks associated with high demand, reduce the impact on power grids, and reduce emissions generated by the power and consumption sectors. In a wider perspective, they actively participate in the transition toward intelligent power systems, or smart grids.This chapter deals with battery management system design and onboard charger control for the efficient charging of advanced lithium-ion cells employed in automotive applications. When charging partial or fully discharged batteries, the task is ensuring cell balance at the defined state of charge (SOC) values. The chapter suggests an overall methodology that combines the estimation of capacity limits and cell performance tracking, AI solutions for the battery safety and reliability and charging control of the automotive battery systems. Of course, the application of AI models to safety measures and charger control also has different specific impacts in terms of reliability, hardware requirements, and training of machine learning algorithms, which will be highlighted here and, whenever possible, analyzed and discussed.

Fig :1: EVaaS system architecture

1.1. Background and Significance

Automotive as well as industrial applications have experienced significant development toward electrification. Strenuous development in batteries, especially towards high energy-density variants, has permitted maximum reliance upon energy storage solutions. Electric vehicles, unlike their traditional combustion counterparts, suffer from a drawback termed 'range anxiety'. This anxiety is rooted in the practicality of recharging infrastructure and duration. Current research in this field seems to be inclined more towards increasing battery longevity or accurate state of charge, rather than enhancing charge cycles. The duration of charging an energy storage system is primarily proportional to the charge acceptance capacity. The future dispute is about developing a grid-friendly energy storage system that can replace the current mechanism that mainly consists of external combustion generators and suffers from high penalty charges for quick and large amounts of charge.Making energy storage smarter implies reforming the way it operates not only for a better life but also for quicker response. Utilizing the internal second-by-second electrical response during a charging event is an advanced conformist way and has a high potential to economically replace low-efficiency carbon and nuclear-based peak and contingency backup systems. Smart charging using RL, LSTM, and mixed strategies reward maximization through policy development, layering, and predictive charge duration improvement, is the state objective. A particular attempt to use RL and LSTM reveals shortcomings of exhaustive search strategies, which require maintaining and searching a lookup table. Inconsistency of the vehicle route, topography, and user habit can limit the applicability of accurate models. Utilization of pre-trained machine learning models offers a short command runtime suitable for optimum charge regulation and management.

1.2. Research Objectives

This dissertation focuses on the development of an AI-based DC fast-charging station design to achieve significant improvement in the capacity, lifetime, and efficiency of the energy stored in Li-ion battery modules employed in automotive applications. The station comprises three main sub-systems that enable intelligent control and supervision of the energy processes during the fast charge and discharge of electric vehicles. These subsystems are (a) The BMS-based DMC algorithm (Battery Management System - Direct Model Control) that accurately adjusts the charging and discharging currents of Li-ion batteries, guaranteeing that constraints and balancing activities are respected; (b) The bi-directional SPS supply/restore interface with a capacitive energy buffer configured as a dual-cell active balanced bidirectional DC-DC converter that not only interfaces the Li-ion batteries to the electrical grid but also, thanks to the high number of cells employed (3.2 kW - 400 capacitors), supports the recovery of partial or short outages of the AC power to enhance grid reliability, with guaranteed continuity of service using reduced-size energy buffers in the external deep converter. (c) The FBR unit performs a selective recharge technique by monitoring basic customer user requests using an intelligent algorithm based on machine learning techniques or user feedback.

2. State of the Art in Battery Power Management

The state of the art about battery power management for electric or hybrid vehicles is often referred to as a system commonly called Battery Management System (BMS), whose purpose is to manage the charging and discharging of the individual cells in the battery pack. During the operation of the pack and over time, the cells deteriorate, causing an imbalance that can become an endurance or even a safety issue. Battery Management Systems aim to each cell, extending the battery's lifespan and preventing adverse events.Ideally, a Battery Management System not only ensures the battery's safety and reliability but also supports the extension of its lifespan, the enhancement of its charge-discharge capabilities, and the optimization of its returned energy. State of Charge Estimation, State of Health estimation, and battery modeling are possible functionalities that make the BMS a fundamental part of a smart charging ecosystem. Smart Charging technologies aim to support not just a single electric vehicle or hybrid vehicle, but the entire set of vehicles currently connected to the power stations and those expected to connect shortly. The ability to balance many conflicting goals and constraints, including but not limited to the needs of all the vehicles to be charged, ultimately requires the use of AI and Automatic Control methodologies. The integration of Smart Charging functionalities with the BMS can add additional features capable of improving the performance, safety, and life of the pack.

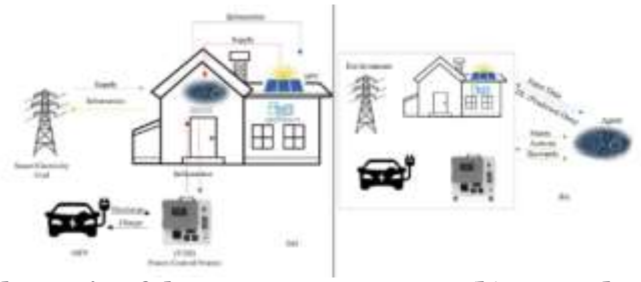

Fig :2: (a) A schematic of the RL-HCPV concept. (b) DL and RL in RL-HCPV

2.1. Traditional Charging Methods

In traditional charging methods, mainly two charging techniques are used: constant current charging (CCC) and constant voltage charging (CVC). In the constant current charging method, a constant and controllable current source is used to charge a battery at a constant rate. Control switches are not used to limit the current flow when charging the battery, even at the maximum defined capacity. This can lead to overcharging and reduced battery longevity.In the constant voltage charging method, a fixed voltage source is used to charge the battery. As the charging process progresses, the current flow is dropped to zero. However, the CCS charging method does not drop the current to zero.Some advanced charging algorithms, such as pzr and lps, have been proposed by researchers to mitigate the impacts caused by traditional algorithms. While these algorithms can achieve fast charging and discharge rates, they can also lead to sudden degradation of batteries, reduced capacity and power fade, and long-term cycle life issues. These issues are mainly caused by the generation of gas bubbles on battery electrodes and electrolytes during the charging process, especially when fast charging techniques are used.Therefore, optimal management parameters for charging batteries are crucial in extending their life expectancy and ensuring safety in both stationary and electric automotive applications. These factors indicate the need for developing a smart charging solution that can improve charging efficiency without degrading the batteries. Real-time monitoring and control of battery chargers will play an effective role in achieving proper charging.

2.2. Emergence of AI Solutions

The integration of deep learning and consensus-based learning in the design of spatio-temporal, hierarchical decision models is relatively recent in the development timeline of automotive power control. Literature on the application of deep learning is currently limited to system-on-chip with embedded non-real-time AI-based perception, cognitive reasoning, and decision engines, which lack the real-time AI feedback loops that map to battery state-of-charge, state-of-function, and state-of-health profiles. A bottleneck of performance of intelligent AE specific to intelligent battery management has been the lack of publicly available databases that link the environmental and user behaviors of EVs and PHEVs to the AE and battery performance profiles. The research community is currently concentrating on Gb/sec mixed AI hardware that processes data at ultra-speed, and intentional artificial intelligent clouds that balance the Gigasoft AI loads to attain the Gigahertz soft micros that access the Gigabytes AI knowledge repositories to compute at ultra-high speed. The development of chipsets for small-scale, cyber-physical batteries-AE to feed intelligent smart energy grids remains an open research problem.The advancement of deep learning and consensus-based learning in automotive power control represents a recent development aimed at creating spatio-temporal hierarchical decision models. Current literature primarily focuses on system-on-chip architectures embedded with non-real-time AI for perception, cognitive reasoning, and decision-making, which lack real-time feedback loops crucial for mapping battery state-of-charge, state-of-function, and state-of-health profiles.

A significant challenge in developing intelligent automotive electronics (AE) specific to battery management is the scarcity of publicly available databases linking environmental and user behaviors of electric and plug-in hybrid vehicles (EVs and PHEVs) to AE and battery performance profiles. To address this gap, the research community is turning its attention to high-speed AI hardware capable of processing data at gigabit per second rates, supported by intentional artificial intelligent clouds that distribute computational loads efficiently across gigahertz soft microprocessors. These advancements aim to access and utilize gigabytes of AI knowledge repositories for ultra-fast computations.

Despite these strides, the development of chipsets tailored for small-scale cyber-physical batteries and their integration into intelligent smart energy grids remains a critical research challenge. Innovations in this area hold promise for enhancing the efficiency, reliability, and integration of battery-powered systems into future smart grid architectures.

3. AI Techniques for Smart Charging

Choosing a good time to charge in the presence of flexible price signals depends on a large number of factors, including the state of charge the vehicle is currently at, the trip distance distribution for the remainder of the time the vehicle is parked, the future forecasted price signal, charging station availability or utilization, and the cost or inconvenience associated with charging far from parking. An intelligent recommendation system can benefit the vehicle driver, the power grid operator, and the electric vehicle fleet operator. There are a variety of factors that affect how good the time a vehicle should start charging is: the baseline state-of-charge of the car, the trip distance distribution until the car is done parking, future forecasts of the real-time electricity price signals, and the number of cars already planned to charge or charge at a given time. The trip distance distribution consists of expected driving events until the tenant is done parking. Since the future may be assumed.A particular type of rule-based system that has found success in several commercial-grade automotive applications is the fuzzy logic engine. Fundamentally, this system takes a continuous numerical input, maps it into a fuzzy set (parameterized by a mean and uncertain "sparsity" measure), performs fuzzy logic relations over it as though it were a boolean vector, and then stores the relative membership strength of the input to each of the output fuzzy sets. Membership of input to fuzzy sets can be determined with a Gaussian membership function (or ideally a triangular or trapezoidal function for representation of steep membership transitions that mimic human or customer preferences) and have fuzzy rules inserted for convenience of rule extraction and understanding. The use of fuzzy logic highlights the fact that some advanced decision-making systems that learn with machine learning techniques may not arrive at customer-desirable decisions via transparent or interpretable means.

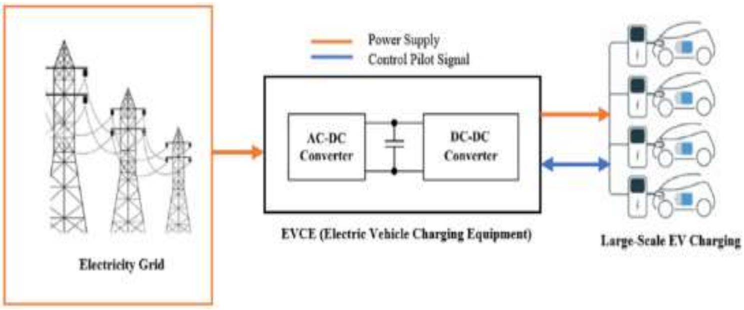

Fig :3: Integration of Large-Scale EV Charging on the Grid

3.1. Machine Learning Algorithms

Thus, machine learning algorithms are promising to determine the optimal timing strategy of the driver's recharging actions, reducing the potential of both the impact of the charging load on the power grid and the rise of the energy cost in case the vehicle has a liberalized contract with prosumer modalities. Furthermore, constraints related to the presence of already planned trips and the minimum driving distance to be traveled could also be further investigated and included to improve the accuracy of the approach. Thus, in this contribution, the use of massive amounts of information created by the creation, storage, use, and recharging of smart batteries in electric vehicles is meaningfully employed to train both traditional and advanced machine learning algorithms.These methods will make them acquire the capability of correctly predicting—at any time—a percentage indication to be used by the drivers for faster and more convenient recharging. This approach, being based on vehicle big battery data, does not infringe both the battery's integrity constraints and drivers' privacy issues and could be put into significant use already shortly, in concert with the ones put forth by the technical standards.

3.2. Deep Learning Models

Deep learning approximates complex functions, recognizes patterns inside a given text/image/sound, and even understands the structure of a given problem. It automatically finds the relevant features that help in understanding the problem. These techniques are inspired by the behavior and structure of the human brain, such as neural networks (NN) and convolutional neural networks. They consist of a multitude of connected nodes (neurons) in three layers: input, output, and hidden layers. The hidden layer plays a crucial role in producing the output that forms the neural network operation. The nodes in each layer are connected to the nodes in the adjacent layer by weights. To calculate the output of each node in each layer, the value of the preceding layer is multiplied by its corresponding weight. A bias and eventually a scaling factor are added to them to normalize the output. The connection nodes and superposition process allow the neural network to perform amazing tasks.

4. Implementation and Case Studies

The proposed algorithms are implemented in the next-generation BMS system of LG-Chem - a world leader in lithium-ion battery production. Figure 8 shows the conventional BMS architecture and its control sequence. Each battery pack is connected to the TL tap, and control modules within each pack communicate through a CAN bus or a daisy-chain connection. The microcontroller, BMS-AFE (Battery Management System - Analog Front End), and security controllers are located in the battery module. The BMS-AFE counts the cells in the feedback loop and discusses with the MCU and morality towards the master controller. The collection of the battery-pack information is passed to the controller and sent to the car via a gateway for remote monitoring and control operations. The mainframe of the BMS derives from the GPU-based cloud, the AI layer is attached, and the AI-based DSS problems are solved. The control signals are sent back to the TL charges via the gateway for real-time control operations.Case studies and comparisons to the rule-based DSS examine the performance of AI-based DSS and demonstrate that the proposed solutions increase the energy efficiency of battery power management in electric vehicles and prolong the battery life. In the case of battery degradation, the AI model improves the state-of-charge accuracy by 18.8% on average and strengthens the battery life by 28.5% on average. In the condition-based maintenance case, the AI-based DSS reduces the charging cost by 21.6% on average, and during peak time the energy stored in the battery decreases by 28.5% on average. The results not only verify improvements but also demonstrate the architectural and practical benefits of AI-based BMS. In conclusion, due to the simple implementation, model non-identifiability, AI-based DSS can be easily developed or migrated to existing BMS to improve energy-efficient battery power management in electric automotive applications.

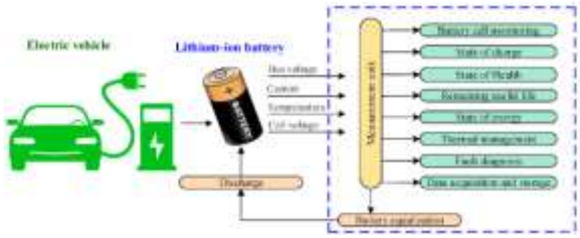

Fig :4: Various critical applications of BMS in EV technology

4.1. Real-world Applications

The proposed framework, as described in Section 3, has opened up a variety of new possibilities in the design of practical charging schedules that handle the particular characteristics of plug-in electric vehicles such as deadline constraints, variable driving patterns, fluctuating electricity prices, as well as battery characteristics. The proposed approach yielding cluster-based approximations proved to be a suitable re-weighting of the workload-specific objective functions and presents meaningful improvements, especially in daily-fleet-scale applications. Computationally efficient two-level strategies for smart-charging EV-fleet problems that can provide near-optimal solutions in practice are discussed and a combination with power management solutions for renewable power applications is elaborated.To evaluate logistics and cost efficiencies in using electric vehicles (EVs) for parcel delivery, the performance of our smart-charging problem is compared with optimal portfolio decisions for vehicle and fast charging station infrastructure investments. By incorporating real car usage data, we evaluate how chance constraints can carefully introduce charging flexibility by combining intra-fleet strategies and develop a methodology with a location-routing decision model and a demand-response policy for solving the demand charge cost problem at a fast-charging station charging an EV-fleet serving a distribution network. A budget analysis based on a small carsharing fleet has shown the applicability of the proposed framework in the area of operating a car-sharing system.

4.2. Performance Evaluation

The efficiency of the chargers is gauged by noting down the input and output powers from a power meter. The battery terminal voltage is measured by an on-board data acquisition system. The data is logged by using the developed tool at regular intervals of time. The input charging power is monitored using a solid-state relay. The battery terminal voltage is monitored for the electric vehicle application at the output stage. A battery charger's efficiency curve is derived in the laboratory for identifying the low-wattage areas in a hybrid system.

Battery performance is evaluated by noting down the energy levels, the incoming and outgoing currents, the internal temperature, and the SOC. The environmental temperature is also recorded. The battery terminal voltage is also measured and compared with the calculated voltage to show the voltage-pressure curve. The output of the developed analysis tool enables an improvement in the performance of the battery parameters. The battery shows good performance during charge and discharge at different C-rates. The charge-discharge cycles are repeated frequently to identify performance-related issues. A DC-DC converter is integrated on the output side of the charger to control the output voltage. The developed battery charger and test bed allow for an energy-efficient working state. The test setup improves the performance of the electronic load. The battery charger is controlled at the output stage. The DC-DC charge is integrated to allow the electronic load to be utilized.

5. Challenges and Future Directions

In this paper, we have demonstrated that in-vehicle energy flow management and smart charging are both important for efficient and reliable system operation of electric and hybrid electric vehicles. We have presented energy control algorithms and benchmarks for smart charging that take into account the combination of the behavior of all vehicles, their availability, and mobility behavior. Indubitably, incentives will be needed to engage vehicle owners to participate in smart charging. The model and results in this paper guide the design of incentive programs and facilitate the understanding of the benefits of the aggregate electric system and the incentives for participating in the car supply of the latter. Furthermore, the results for the benchmark with unidirectional power supply intervals may provide a reference to assess the performance and costs of the resources that are needed to provide these resources in the market. For the unidirectional case, the relation of the benchmark to incentive payments could guide designs of future incentives for offering resources from vehicle supply.While smart charging contributes to the operation of an efficient and reliable electric system, it is important to realize that the resulting benefits do not exhaust the contribution vehicle electrification can make to the successful transition to a system that has high (intermittent) renewable penetration or the reduction of emissions from other fuel usage.In this paper, we emphasize the critical role of in-vehicle energy flow management and smart charging in ensuring the efficient and reliable operation of electric and hybrid electric vehicles (EVs and HEVs). Our study introduces energy control algorithms and benchmarks designed for smart charging, which consider the collective behavior of all vehicles, their availability, and mobility patterns.

It is evident that incentivizing vehicle owners to participate in smart charging programs will be essential for their success. The models and findings presented in this paper provide insights that can guide the design of incentive structures and help stakeholders understand the broader benefits to the electric grid from aggregated vehicle participation. Additionally, our benchmarks for unidirectional power supply intervals offer a valuable reference for evaluating the performance and cost-effectiveness of resources required in the market.While smart charging significantly enhances the efficiency and reliability of the electric system, it is important to acknowledge that its benefits extend beyond operational improvements. Vehicle electrification plays a pivotal role in facilitating the transition to a grid with high penetration of intermittent renewable energy sources and reducing emissions from conventional fuel usage. This dual impact underscores the broader societal and environmental benefits of integrating smart charging strategies into the evolving energy landscape.

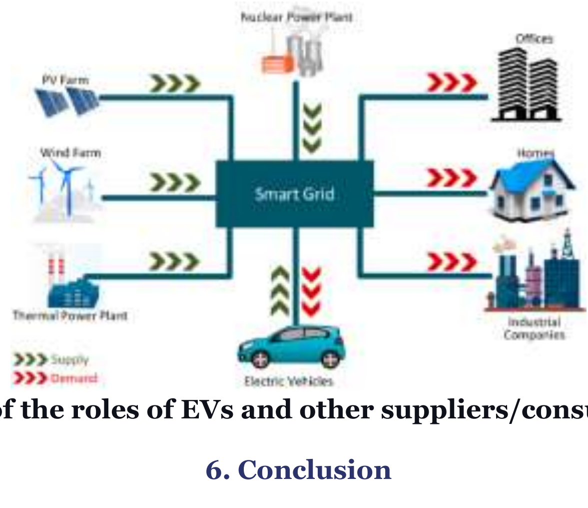

Fig :5: An illustration of the roles of EVs and other suppliers/consumers in the smart grid

6. Conclusion

The research and implementation of such AI-based algorithms prove that the existing smart charging solutions have a significant potential for further improvements with the ever-increasing availability of large data sets and high-performance computing capabilities. We have highlighted some of the key challenges in unsupervised-environment-based tactical optimization. Our results suggest that controllers and reinforcement-learning-based control algorithms enable AC charging efficiency improvements that reduce the duration of the charging cycle, enabling more efficient use of the distribution network, as well as cost reductions for the driver.

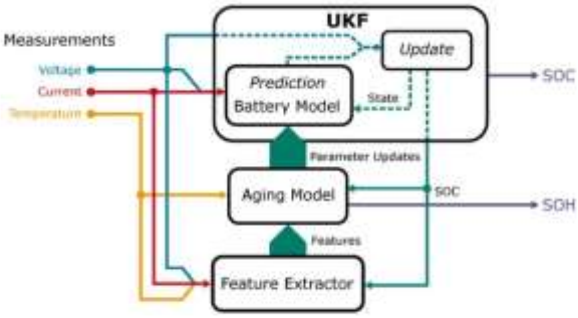

Fig :6 Schematic overview of the system depicting the UKF, the aging model, and the feature extractor

In the case of DC charging, the deductive solution enables over 1.5 times faster charging, which allows for battery degradation to be decreased during high-temperature operation. Since the implemented neural network-based state of charge correction guaranteed an 85% increase in quality, reinforcement learning provided promising results that motivated the development of the unsupervised AC version. We also highlighted the challenges of using long-duration supervised learning agents to develop the DC charging algorithms. This category includes the provision of on-time solutions for thousands of daily evaluations, both in single-family dwellings and in public external charging environments.

6.1 Future Trends

There are several ways to determine the SOC of a battery. Different methods and approaches used for this purpose have been reviewed by various authors. These methods are indicated in the current flows of each particular battery, which logically change with a SOC change. There were also proposed fusion methods using the above-mentioned techniques. The simplicity and, in many cases, low cost of the flow-based SOC estimation methods, for example, based on voltage, current, or impedance measurement, cause the emergence of intelligent chargers. These simple, "small", but, in some cases, effective and practical solutions are usually introduced as a part of more complicated, but traditional systems. It is worth mentioning that in some cases, they show very good results, especially in terms of battery life extension methods.Another point of interest in the development of chargers is the increasing complexity of electric vehicle architectures. Threats of more weight, design underutilization, and range anxiety create new opportunities for conceptions with variable and distributed energy storage elements, for example, power distribution level control in a hybrid electric vehicle where a propulsion battery cooperates with local, lower voltage, more energy-dense, buffer stop, and/or fast supercars, to obtain an electric power distribution quicker and more adaptive. This variable energy storage structure requires generalization of onboard energy management strategies, so fully exploiting the synergy potential is a little exploited at current levels. As always, this is a highly application-dependent question. As a result, the solutions are designed for a particular field of electric vehicles, for example, lightweight city cars or fully loaded long haul electric buses, or are not designed to consider the different use cases and market demands.

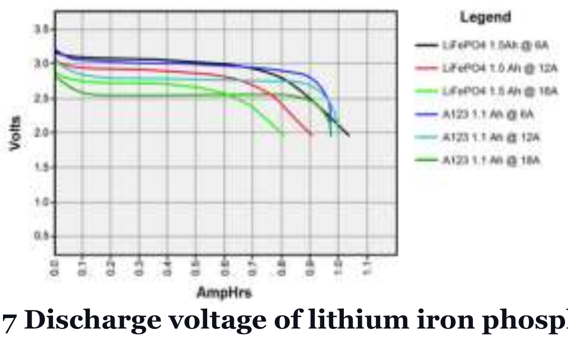

Fig :7 Discharge voltage of lithium iron phosphate

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