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BATTERY MANAGEMENT SYSTEM OF EV WITH HYBRID CHARGING USING IOT AND AI

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Abstract: Future Electrical vehicles (EV) are widely praised for their environmental benefits, superior efficiency, and enhanced driving experience compare to conventional internal combustion engine (IC) vehicles. They represent a significant stepping sustainable transportation, though they still phase challenges related to initial cost and infrastructure. BMS systems will not only extend the battery life and promote safe operation, but also incorporate two new functionalities: the capability to optimize scheduling and utilization lifetime, and the ability to detect and diagnose anomalies early to enable predictive maintenance and minimize downtime. Furthermore, BMS development and deployment for hybrid energy storage and end-of-life equipment repurposing are key enablers for achieving the broad adoption of electric vehicles and the accelerated integration of renewable energy into the electrical grid.

Keywords Battery Management System, Electric Vehicles, Hybrid Charging, Artificial Intelligence, Internet of Things, Machine Learning, Datasets.

I. INTRODUCTION

The path toward achieving the desired goal is outlined, showing how Relational Model Theory, Internet-of-Things (IoT) technology, and Artificial Intelligence can be employed to integrate Hybrid Charging Capabilities into Advanced Battery Management Systems [1]. The overview of these contributions explains how artificial intelligence supports real-time data-driven diagnostics, predictive state estimation, optimization of charging protocols, and anomaly detection. Internet of Things technologies enable real-time monitoring, distributed intelligence, and secure communication for battery management systems. The work proceeds to articulate the special system-level considerations that result from integrating artificial intelligence and the Internet of Things at runtime [2]. Next, it details thermal management optimization, improvement of state of charge and state of health estimations, and redundancy-enhanced reliability and availability, before addressing hazards and compliance with established standards. Finally, it examines how to test and validate battery management systems enhanced with artificial intelligence and the Internet of Things [3].

Artificial intelligence plays an important role in the four areas of real-time data-driven diagnostics, predictive state estimation, charging-protocol optimization, and anomaly detection [4]. Data-driven diagnostics provide a flexible framework for capturing and interpreting a wide range of symptoms onset of an overvoltage condition, triggered airbag, or even road hazard with data collected from sensors or a combination of sensors and historical database models.

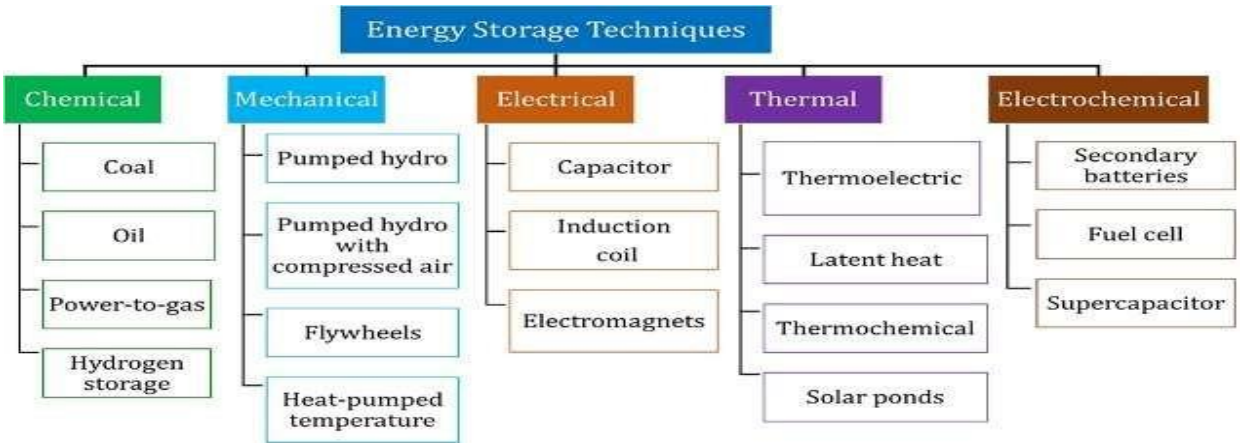

Fig 1: Types of Electrochemical Energy storage source

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Battery management systems (BMS) perform analysis and supervisory control in battery-based energy storage systems by fulfilling four core functions: accurate battery state estimation; monitoring and detecting operational anomalies; optimizing charging/discharging strategies for given policy objectives; and facilitating safe operation [5]. A BMS consists of a set of Battery Management Units (BMUs) connected to a Battery Management Controller (BMC), with hierarchical, modular, or even completely distributed Automation solutions being used in practical deployments [6].

With global battery production expected to increase significantly, safety-enhancing functionalities are becoming an ever more important part of BMS operation. Pure EV produce no exhaust emission, which significantly reduce local area pollution and help improve urban air quality. This can lead to reduction in respiratory illness [7]. A diagram illustrates the integrated battery management system, with the primary battery management system and data communication with partner systems (cloud computing and IoT) at the top. The support systems include hybrid charging, predictive maintenance, and thermal zone management. Solid arrows indicate the principal data communication pathways, while dotted arrows denote secondary information interchanges. The business rationale for the entire configuration encompasses the need for an always-available battery [8].

The system comprises several distinct stakeholders. Vehicle battery management systems must ensure long service life by closely monitoring the battery's state of charge and state of health, including temperature conditions that relate to internal resistance [9]. Industrial and grid-scale applications require similar monitoring and modelling of the state of charge and state of health, supplemented by data from sensors that support thermal zone management and predictive maintenance; these functions must be operational throughout the battery life. IoT-edge devices such as small sensors, cameras, door locks, and lighting systems can reduce their battery capacity and lifetime budget by battery management system cooperation, including thermal zone support for battery drains. These tasks must all be resolved for any proposed solution to be commercially viable. [10].

Key performance indicators for the proposed integrated battery management system are efficiency, longevity, and availability. Efficiency reduces the direct cost of energy from the battery through optimal charging, long-life scheduling, avoidance of heavy battery self-heating, and proper signaling to guarantee sufficient charge/discharge rates. Longevity reduces both direct battery cost and indirect global pollutant levels (e.g., CO2, elemental lithium) through optimal state-of-health maintenance and predictive maintenance scheduling. Availability ensures that the local battery is charged and ready to absorb power at any anticipated point in future operation whenever such charging is physically possible. [11].

II. LITERATURE REVIEW

The representativeness of battery-cell datasets and the efficacy of the underlying models remain open questions. In addition, support for the rapid inference and long-term analysis needed for IoT deployment is often overlooked.
Research on BMS data utilization is abundant, especially for state-of-charge estimation. The widely adopted Kalman-filtering approach has evolved to accommodate battery-cell nonlinearity, component mismatch, model uncertainty, and the multi-physics nature of aging phenomena [12]. Remaining-useful-life indicators for different chemistries have been proposed, along with specific degradation models and associated fault signatures. Nevertheless, the integration of anomaly detection and model-update mechanisms has received insufficient attention. Furthermore, the emerging area of BMS IoT deployment has attracted less focus, particularly for the definition of edge and cloud workloads, data orchestration, blueprint–dashboard coupling, data governance, security and privacy, and compliance with relevant standards.

III. METHODOLOGY

The hardware platform includes numerous sensors connected to a real-time controller board and an industrial microprocessor running an edge computing stack [13]. Fault tolerance is achieved by redundant components, supervision of critical systems, and an automated power-management subsystem. In the software stack, the data pipeline manages information flows to training and inference models, governed by a middleware layer that automates the use of pretrained models deployed on the edge node [14]. Data orchestration and storage are handled by a cloud component that supports standard telemetry dashboards and long-term analysis, addressing privacy and data-governance requirements. The data-acquisition setup specifies data types and sampling rates for critical parameters, outlines preprocessing steps, synchronizes and transmits signals, and detects unexpected correlations, enabling confidence in subsequent metadata analyses [14].

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IV. PROPOSED METHOD

Recent years have seen considerable research into Battery Management Systems (BMS) for Electric Vehicles (EV) considering battery life, safety, availability, and performance [15]. However, full safety, reliability, and performance requirements are not being met, even for conventional BMS, when additional tools such as Internet of Things (IoT) integration and Artificial Intelligence (AI) are incorporated. Performance, safety, and reliability requirements of BMS operation in both conventional and hybrid charging scenarios must be defined and met. To provide a real benefit, such requirements must also be validated during field operations by the three main classes of BMS stakeholders: BMS developers, vehicle manufacturers and fleet operators [16].

During the last decade, a wide variety of BMS tools and functionality have been proposed or incorporated, and continue to be developed. Even the small number of tools listed here demonstrate that a complete BMS solution is far from being available, even in a specific EV application [17].

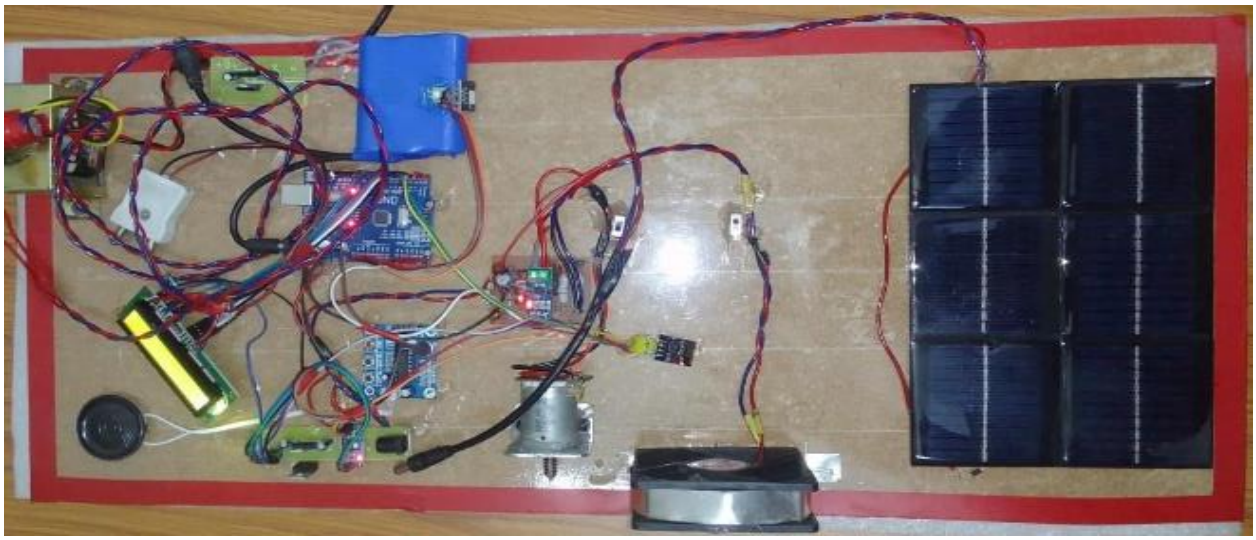

Fig 2: Model of BMS

The proposed BMS integrates three layers to manage the battery efficiently. The bottom layer consists of multiple battery packs each fitted with a data acquisition system that collects information from various sensors and monitors the charging or discharging process at the cell/module level [18]. The second layer handles hybrid charging by coordinating grid-integrated, wireless, and plug-in charging interfaces and exploring energy harvesting opportunities (e.g., photovoltaic surfaces or wind turbines) to supplement batteries. The third layer comprises edge and cloud functionality: the edge performs safety-critical processing, while the cloud supports data-intensive procedures involving real-time optimization and machine learning. Data flows among the three layers are defined, and the architecture is generalized to accommodate high-power systems, such as those used in large EV fleets or market-driven rapid charging stations [19].

The BMS design responds to three major requirements. First, the performance of SOC and SOH estimates must be accurate enough to support reliable predictions of battery durability and operational safety. Second, the system should be capable of thermal control at cell/module levels, to enable optimal EV dimensioning, to reduce battery degradation, and to enhance safety by preventing over-temperature conditions not detected by other diagnostic functions. Third, the BMS needs to provide effective diagnostics and safety protection, especially through the detection of hard faults such as internal short circuits, whose physical basis is well understood. In view of these objectives, SOC estimation uses a combination of Kalman filtering and a reduced-order detailed electrochemical model. With regard to thermal management, a hierarchical strategy regulates the ambient temperature of modules and batteries through reversible thermal networks, while also supporting optimal system dimensioning [20].

Prediction accuracy affects usability: dynamics increase with fast-changing demands but decrease with shorter trips. SOC estimation is generally well-understood, with a mix of data-driven and model-based approaches [21].

SOH estimates facilitate maintenance, enable health-aware functions, reduce lifecycle costs, and impact product design choices. Understanding degenerative pathways and measuring related variables such as interparticle distance or sulphation state support RUL prediction [22]. SHM combines algorithmic inspection and monitoring with reduced-cost scheduling of manual check-upshot sensitiveness, and should not be calculated in-flight, Environmental monitoring is simplest with estimated SOC exogenous, Observability under uncertainty is a key issue when cooling is predictive. Causal models are emerging that predict cell thermal behaviour given past and present cooling operations, quantising State of Thermal Runaway [23].

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Thermal modelling facilitates the design of optimal cooling strategies for BESS operation. Real-time estimation of thermal runaway risk, combined with assessment of battery pack composition and relevant monitored parameters, enables timely alerts and activation of safety mechanisms, such as circuit breaker or cooling fans.

Battery thermal management is crucial for performance, lifetime, and safety. Energy-storage systems operate under varying load and environmental conditions affecting temperature distribution. The thermal model predicts temperature as a function of heating/cooling powers and thermal resistances, enabling optimization of the eighth battery heat-dissipation capacity and cooling fan. The prediction of thermal runaway risk informs the design of manufacturer and system-level safety measures.

Large-scale battery packs are essential for the transition to zero-carbon transportation and economy, yet risk thermal runaway. Such events are extremely dangerous, and their anticipation is a priority. Sensor data streams may therefore be inspected to minimize risk. Without training data for the condition to be predicted, methods based on imbalanced classification are employed to detect thermal-runaway conditions. Sensory redundancies are used for cross-validating the conditional prediction of thermal runaway. Such predictive monitoring cannot replace safety protocols implemented at battery-pack level; however, it can guarantee the integrity of more vulnerable battery packs in products offered or services provided.

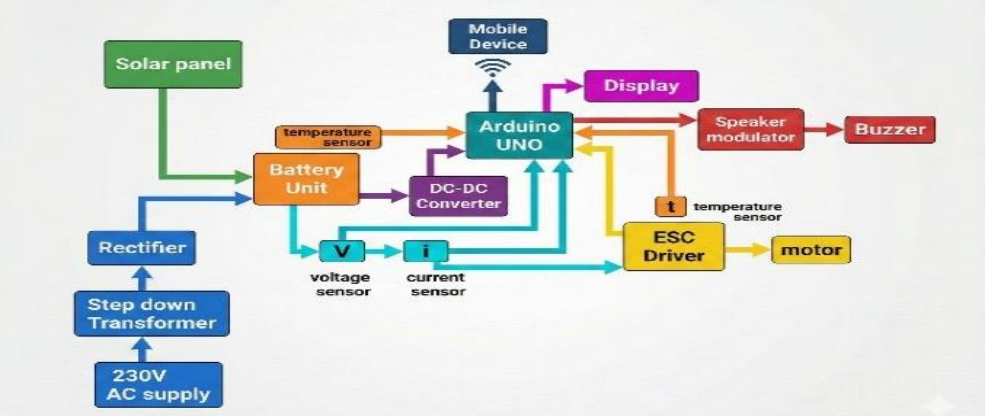

Fig.3: Flow chart of data acquisition in battery monitoring

V. RESULTS AND DISCUSSION

A Several future trends are expected to shape the future development of BMS incorporating IoT and AI. Notably, the complexity and volume of data originating from the sensing subsystem warrant a shift towards a data-centric paradigm. The premise of IoT is the availability of data from different sources with varying timeframes that can be leveraged by third-party AI systems. This creates a strong pressure for BMS designers to invest time and effort in exposing the right set of events, alerts, and data flows with the right level of latency tolerances. Consequently, several research directions remain open, especially regarding the definition of adequate event-driven data flows. A comprehensive overview of standardization is provided, with an emphasis on the standards that concern health, safety, and performance. Such standards nally allow assurance of compliance with homologue regulations and reduce their cost.

Graph 1: Output of Current VS. Time

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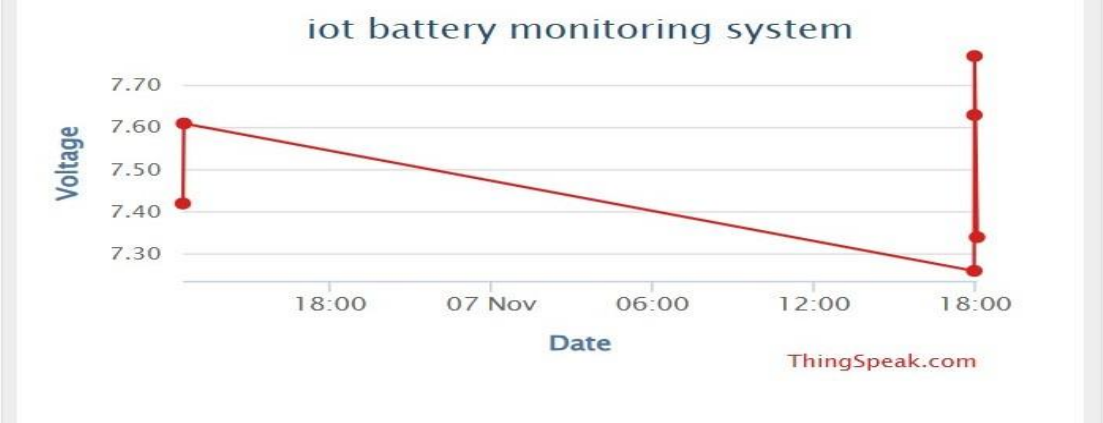
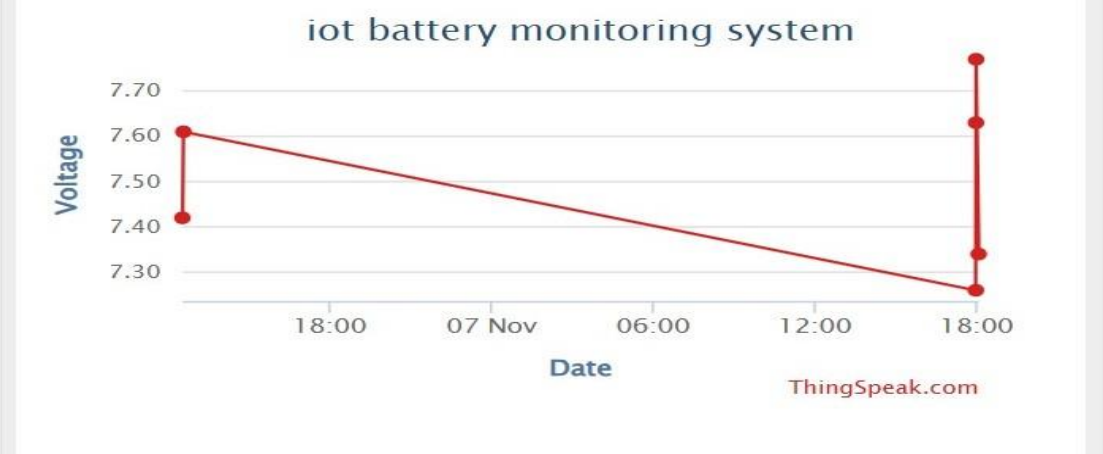


Graph 2: Output of Voltage VS. Time



Graph 3: Output of Temperature VS. Time

IoT architecture for BMS relies on sensors, which must meet accuracy, working range, surrounding environment, preservation need, and operational lifetime constraints, among others. A substantial number of sensors are required, and their calibration may introduce a non-negligible cost. Combining several functions in one sensor has to be investigated, especially for safety-critical data such as temperature and gas detection.

BMS data can owes not just from the sensor suite to the Internet but also from the cloud continuously to edge gateways (in a centralized manner) or from edge devices to the cloud (in a more decentralized manner). The communication protocols governing data owes should cover the entire data life cycle, including data collection, storage, and analysis. The edge-cloud interplay must be subject to specie rules governing which hierarchical level is in charge of computing which task multiple layers real-time requirements for the adoption of the Internet of Things for BMS are also demanding, since the system should guarantee the continuous acquisition of interest data and/or of boundary values of the monitored parameters, enabling an event-driven approach.

Multiple event-driven paths are feasible, both for sensor data-modelling and control-decisions: sensors can directly feed action triggering events on actuators (notably fans) or can be continuously monitored by an underlying model that simulates the BMS along with the underlying (battery) dynamics. The second solution enables the introduction of short delays in the action triggering events, thus relaxing the need for ultra-fast sensors.

VI. CONCLUSION

The work presents an advanced battery management system integrating artificial intelligence and the Internet of Things to enhance performance and safety. Computerized data pipelines for state-of-charge estimation, state-of-health assessment, and remaining-useful-life prediction are implemented in the battery management system. An edge-cloud architecture supports real-time inference, telemetry, and long-term data analytics. Supporting data acquisition hardware is developed to acquire all relevant battery data and facilitate data-sharing via well-defined protocols.

The hardware and software systems are validated using a real-time electric vehicle charging and discharging scenario. An extensive dataset is collected to quantify accuracy, latency, reliability, energy efficiency, and robustness.

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VII. FUTURE SCOPE

The underlying principle of electricity is that it is created, transmitted, and stored as required. The management of electricity consumption in buildings is theoretically capable of following the real-time supply-drought-and-surge curves, by electrical and thermal batteries being able to follow the supply of non-controllable renewable energy from heat and light. A successful battery management system (BMS) in buildings needs to give meaning to storage and consumption by sharing with the inventory's electrical energy market the independently controlled battery physical and operational features of charge and discharge, operation range of charging and discharging power, operation range of stacking, with these operations being also the result of BMS-data-enhanced forecasts of the electricity market price. The enhanced forecasts also allow the BMS of the building to initiate on its own transactions with the market.

Lesser-importance, non-centralised battery storages can use their charging power to help balance compressively and, by the charged structural battery, release and charge the electrically and thermally externally non-controllable sources of electricity from the wind and the sun. In the same way, they can charge to supply the associated electrical consumer from the grid's structural battery. To avoid overheating arisen by over slab and reused energy from recharging on the non-controllable source of energy, the associated thermally controlled environment needs to also embark slabs but more thickly rechargeable that is replenished electrical and thermal charges not burning and replenishable dumps and the microgrid in the process.

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