

Battery Management System Performance Analysis of Electric Vehicle with Solar Cell using AI

Lokesh Kumar¹, Ajay Kumar²

¹Research Scholar- M.Tech(PED), Electrical & Electronics Engineering Department, FET, Swami Vivekanand Subharti University, Meerut

²Assistant Professor, Electrical & Electronics Engineering Department, FET, Swami Vivekanand Subharti University, Meerut

Abstract-Precise predictions of battery pack parameters are essential for the design of battery management systems (BMS) in electric vehicles (EVs). These calculations also furnish significant additional data, including the remaining life or useful time (Strušnik et al, 2020). Additionally, BMSs stop overcharging and over discharging Li-ion batteries. Owing to its intricate, nonlinear, and time-varying electrochemical structure, Li-ion batteries exhibit variations in performance in response to changes in operating circumstances, including charge-discharge current, ageing, and fluctuations. A battery's life may be extended and its charge and discharge cycles optimized with the help of a Battery Management System (BMS), which is a combination of hardware and software. The use of AI in electric vehicle (EV) applications has received a lot of attention; these applications may be broadly categorized into three areas: range optimization, EV control-system design and optimization, and EV battery design, fabrication, and management.

Keywords: Battery Management systems, Electric Vehicles, Solar Cells, Artificial Intelligence.

I. INTRODUCTION

Solar panels are easily integrated and may be utilized with a variety of surfaces and styles. This is perfect for urban settings because it makes the most of already-existing buildings or structures, adapts to them effectively, and provides an aesthetically pleasing solution that is very accommodative.

They are also incorporated in the information flow, which enhances town planning, as they are part of the dynamics of sustainable cities. Fortunately, it seems that photovoltaic generation for road traffic can benefit from the use of solar charging stations. With the added capability of being able to produce and store their own power, these stations supply electricity for cars. They meet the crucial need to

supply 100% sustainable energy since they utilise solar panels(Hossain et al, 2022).

A battery's life may be extended and its charge and discharge cycles optimized with the help of a Battery Management System (BMS), which is a combination of hardware and software. One of these facilities' strong characteristics is its intelligent and productive cooperation with the electricity grid. They may both claim electricity when necessary and return excess energy to the grid to ease the load. Because of the higher energy consumption in cities, this power supply is even more valuable.

II. AIM AND OBJECTIVES OF THE STUDY

To contribute in the following significant ways:

2.1. To better understand the various AI technologies used in battery management systems, we conduct an exhaustive literature research.

2.2. To identify the most effective AI approach for precise battery condition prediction in EVs,

III. THEORETICAL FRAMEWORK

The sun is the earth's primary energy source, providing more than 100 trillion watt-hours of energy annually, which is why we are investigating solar photovoltaic (SPV) based charging. This can significantly lessen the strain that an increase in electric vehicles on the road may have on the grid.

The sun is the earth's primary energy source, providing more than 100 trillion watt-hours of energy annually, which is why we are investigating solar photovoltaic (SPV) based charging. By doing this, the grid's potential stress from an increase in electric vehicles on the road may be significantly reduced(Li et al, 2020).

In order to convert incoming light energy into electrical power, solar photovoltaic, or SPV, systems

rely on light coming from the sun shining on specifically constructed panels composed of silicon. The way this process operates is that it absorbs photon energy to create charge pairs, which are then compelled to travel through an external circuit channel in order to produce electrical energy. The term "photoelectric effect," or PEE, refers to this charge generating effect. Precise predictions of battery pack parameters are essential for the design of battery management systems (BMS) in electric vehicles (EVs)

IV. LITERATURE REVIEW

A battery's life may be extended and its charge and discharge cycles optimized with the help of a Battery Management System (BMS), which is a combination of hardware and software (Solank et al, 2020). Two important indicators are calculated and tracked by the BMS for our requirements. The first is the State of Health (SOH), which shows how well the battery is doing in relation to its historical and projected future. A battery's level of charge throughout a charge or discharge cycle is referred to as its State of Charge (SOC). It is not possible to measure either of the parameters directly (Gholami, et al, 2020). A battery pack's SOH and SOC may be found using a variety of techniques. To estimate SOC and SOH, one can utilise data-driven approaches, model-based methods, or even sophisticated sensing-based methods.

Precise predictions of battery pack parameters are essential for the design of battery management systems (BMS) in electric vehicles (EVs). These calculations also furnish significant additional data, including the remaining life or useful time (Strušnik et al, 2020). Additionally, BMSs stop overcharging and over discharging Li-ion batteries. Owing to its intricate, nonlinear, and time-varying electrochemical structure, Li-ion batteries exhibit variations in performance in response to changes in operating circumstances, including charge-discharge current, ageing, and fluctuations (Sharma et al, 2020). Accurately calculating SOC and SOH for a Li-ion battery is a challenging undertaking as direct interaction with a sensor is not possible.

There are two fundamental problems with the conventional methods of battery management.

The first drawback is that the numbers you use must come from "baseline" models, which are characteristics under a variety of operating conditions. Consequently, traditional models' accuracy is constrained (Khawaja, et al, 2020). Moreover, the

characteristics of batteries change with age, thus exacerbating the model's inefficiency. The second drawback is that during the tests, the battery must be "offline," or not in use, in order to calculate its properties (Aldbai et al, 2020). It is possible to apply a variety of different solutions, including artificial intelligence (AI) and computational intelligence (CI), for state estimation and prediction in BMS (Changki, et al, 2023). It has long been understood how important artificial intelligence is, as well as the components that follow.

Therefore, the last thing that may be asked for or seen while parts utilizing this technology are operating is manual participation. These devices speed up tasks and procedures while maintaining accuracy and precision, making them a useful and valuable tool. Because Li-ion batteries are non-linear, as was previously stated in light of their growing popularity, it is essential to design various methods in order to estimate SOC and SOH. We compare the various AI techniques used based on a number of performance parameters. Battery management is controlled by a BMS, which is a hardware and software system (Arora et al, 2023). Many functional parts, including a state machine, temperature monitors, fuel gauge monitor, cell voltage balance, cut-off field effect transistor, cell voltage monitor, and real-time clock, are assembled to form a BMS. BMS integrated chips are available in several kinds. A basic analogue front ends with a microcontroller that can balance and monitor data may be compared to a fully integrated, stand-alone system that can work independently. The functional components are arranged differently for each type of system.

A. Gap in Research.

Literature review indicates that not much research is done on to better understand the various AI technologies used in battery management systems, we conduct an exhaustive literature research and to identify the most effective AI approach for precise battery condition prediction in EVs.

V. METHODOLOGY

As per the literature Review and to address the research gaps, a mixed method approach is adopted. This blended method for this study will focus on literature review of relevant and recent research in the scope of the study and case studies for primary and application oriented research.

VI. DISCUSSION OF FINDINGS

A. BMS

A range of actuators, controllers, and sensors may be included in the BMS of EVs. Battery management systems, or BMSs, are in charge of protecting batteries, keeping them running within reasonable voltage, current, and temperature ranges, and precisely tracking battery parameters. Three fundamental topologies—distributed, centralized, and modular architectures—have been applied to hardware structures. A layer structure for maintaining a battery's state was given by Chitra et al(2020). Based on their many features, BMSs may be categorized. Using these ideas, a comprehensive framework with fundamental features might be developed. At the monitoring layer, a number of sensors inside the battery pack gather data .

Electric vehicle BMSs can have a variety of actuators, controls, and sensors. The responsibility of safeguarding batteries, maintaining their operation within appropriate voltage, current, and temperature limits, and accurately monitoring battery parameters falls on battery management systems, or BMSs. Three basic topologies have been used create hardware structures: modular, distributed, and centralized architectures. A full framework with key components might be created using these concepts. A multitude of sensors within the battery pack collect data at the monitoring layer (Gabba et al, 2021).

The necessary steps to get the required data are modeling, data collecting (using a data acquisition system, or DAQ), and data storage. A component of the system known as the charge controller regulates the charge-discharge process. It can be necessary to use a variable resistor to balance cells or check internal resistance. To perfectly balance the battery pack's cells and assess the battery's condition, cell balancing management is still a crucial design feature that may be enhanced. Data communication inside the BMS is required since the majority of its subsystems are independent modules. Through communication over a Controller Area Network (CAN) bus, the BMS transfers data primarily. Creating intelligent batteries with microchips integrated therein that can interact with chargers and users would allow for the collection of more data.

To further enhance connection between the battery and charger, radio and communication technologies are progressively being incorporated into charging systems. It is imperative to include a thermal

management module because temperature fluctuations impact cell imbalance, reliability, and performance. Lowering the temperature difference between cells is therefore essential, and they need to be controlled and operated at the proper temperature.

B. Case study examples

For instance, solar charging stations have been installed at Peachtree Corners, which is part of the Atlanta metropolitan region. The authorities understand how urgent it is to provide options for electric car charging as the number of electric vehicles rises. Furthermore, there are other instances of solar-powered public fleets in the United States, including San Diego.

The trend has even gotten to the point of state planning in other regions of the world, including India. By 2021, it was mandated that solar panels account for a minimum of 10% of the installation capacity of all public charging stations. Up to 250 solar charging stations might be put throughout the nation by the business ATOM Charge in 2022.

Using these renewable energy sources to charge electric automobiles is not a novel concept. Still, there hasn't been a thorough investigation of the chargers' design. They have investigated the best times, places, and how the weather affects using various renewable energy sources for charging (Shepero,et al,2022).

The majority of prior research has been on optimizing the conventionally accessible sources—such as thermal power, hydro power, etc.—for the purpose of charging electric cars.

C. Scenarios for the Canary Islands by 2040: A Practical Application Case

The approach described in the preceding part has been applied to a scenario where all vehicles will be electric by 2040 in the Canary Islands. Under the application circumstances of communal mobility policies, the scenario illustrating high penetration has been carried out. An international initiative to lower carbon emissions from energy consumption includes this analysis. This paper examines the joint impacts of solar PV generation and the inescapable rise in demand for electric vehicles. Synergies between the integration of solar PV power and the broad use of EVs have been investigated within the framework of these policies.

Through this junction, we want to improve the sustainability and environmental friendliness of the energy landscape by using clean energy sources for

both power generation and transportation. The delicate relationship between solar PV and EVs provides an insight into the potential revolutionary influence on the Canary Islands' overall environmental sustainability, emission reductions, and patterns of energy use. This part develops the first results of solar PV performance and synchronizes it with the various EV charging options taken into consideration, while also displaying the suggested scenario for the Canary Islands for 2040.

Even if the integration of EVs is now low, the EU and the Spanish State have committed to completely decarbonising the economy by the middle of this century as part of their long-term low-emission policies. Furthermore, within ten years, the planning goal of the Canary Islands and the Spanish non-mainland territories is to advance conformity with this criteria.

The Canary Archipelago's power demand is expected to rise by almost 100% by 2040 compared to present levels, with EVs expected to account for the majority of this growth.

By 2040, it is predicted that the demand for electricity would rise by 5.81 TWh/year, which means that EVs will be responsible for more than 60% of this predicted increase in demand. Special attention must thus be made to the effect of EVs, as the electrical systems of the Canary Islands are especially vulnerable because of their relatively small size and the inability of linking to a continental grid (Ravi et al, 2022). The electrical infrastructure must therefore ensure that generation, transmission, and distribution expand at a pace that matches demand in order to maintain service quality levels.

D. Artificial Intelligence in Electric Vehicles

For EVs to be widely adopted, their safety, dependability, and economic viability are essential, and AI may greatly enhance these qualities. The use of AI in electric vehicle (EV) applications has received a lot of attention; these applications may be broadly categorized into three areas: range optimization, EV control-system design and optimization, and EV battery design, fabrication, and management. This article will also highlight energy-related material, such as the use of AI technology to battery management and range optimization for increased energy efficiency.

E. ML in research and development for batteries

Batteries, particularly lithium batteries, are essential parts of electric vehicles (EVs) and provide the

vehicle's power source and energy storage. Individual batteries are linked and constructed into battery modules, which are then connected and combined into an electric vehicle battery pack. The batteries within a module and the modules within a battery pack are connected in series and parallel to give the required potential and capacity. Still, due to obstacles in battery design and production to the battery management and optimization during operation in EVs, performance-related problems with present EV batteries persist.

Lower energy density of the EV battery pack results from limitations in battery design and manufacture, which raises the cost of the battery pack. Furthermore, range anxiety among users may be significantly reduced by using EV batteries that utilise less energy. ML strategies to address the aforesaid difficulties have drawn more interest from academia and industry in order to achieve improved energy efficiency, customer perception, safety, and economic viability. Machine learning has the potential to drive improvements in battery energy efficiency and safety as well as enhance customer perception of EV range by expediting the identification and characterization of battery materials and enhancing battery production efficiency.

When combined with demand management strategies, this makes sure that the inherent unpredictability of user consumption does not impair the performance of an electrical system. Instead, it encourages the transfer of loads towards generation, which encourages photovoltaic self-consumption, lowers peaks, and fills in net load valleys with energy. When there is an excess of unmanageable renewable energy, EVs can help optimize synchronization between the generation system and demand, reducing the likelihood of spillage. However, EVs should not only be viewed as a simple increase in electricity demand; rather, they can be seen as an ally to provide greater manageability.

Since it oversees all equipment operations and analyses sensor data for status predictions and decision-making, the BMS software is the brains behind the whole system. A BMS's software should be capable of managing cell balance, controlling switching, creating dynamic safety circuits, and tracking sample rate in the sensor module. Furthermore, web-based data analysis and processing are necessary for ongoing upgrades and management of battery operations.

Since it impacts state estimate and problem identification, robust and trustworthy automated data

analysis is essential to success. This data will be displayed to the user through an intuitive interface that includes the required recommendations. SOH and SOC calculations will be part of a capability evaluation that uses state-of-the-art methods such as fuzzy systems, artificial neural networks, state-space-based models, etc. to define operating constraints and show the battery's life status.

Cell balancing is used to improve battery performance without overcharging or over discharging; it brings cells with comparable SOC values together. Using a thorough programme depending on the amount of charge stored by each cell, the controller will oversee the charging process. Therefore, precisely calculating each cell's SOC is essential to improving the balance. In order to detect out-of-tolerance circumstances and provide battery problem warnings, intelligent data assessment is necessary. Historical information that depicts the pre-alarm state prior to any problems will be preserved. Users must have access to the important BMS data through the interface. The remaining range need should be visible on the dashboard, contingent upon the state of charge of the battery. By means of alerts and replacement suggestions, customers must also be made aware of the anticipated lifespan and capacity of the said battery.

VII. CONCLUSION

AI-based techniques are becoming more and more common as a means of enhancing dependability and dynamic responsiveness, however there are still many conventional approaches. As of right now, BMSs are installed with a preset control algorithm that won't change during the system's lifespan. In Khalid et al(2021), With numerous warranties spanning from five to ten years, the batteries do, however, have a rather lengthy lifespan. Because of how long the system will last, the operating environment may change during that time.

Beyond only ensuring that its computations are accurate, SOH and SOC are important for the BMS (Jiang et al, 2021). A BMS is in charge of both safeguarding the battery and informing the user with information on the batteries. The instructions sent to the battery, especially in Li-ion batteries, are influenced by the estimations of SOH and SOC(Ayadi, et al, 2022).

The crucial connection between EVs and the energy society—which is made up of a large number of EVs, charging stations, and power plants—will be

provided by next-generation management. To ensure the BMS operates safely and effectively for EV applications, it is imperative to have an accurate prediction of battery voltage, heat generation rate, and state of health under various situations.

A. Scope for further Research

Advanced management of battery modules is required due to the growing number of onboard batteries. Advanced management systems can be distributed or centralized, among other configurations. The monitoring of battery dynamics is made possible by the sophisticated management system, which also focuses on enhancing battery performance and the driving experience for the user. The necessary functions include heat management, battery equalization, charging control, problem diagnostics, and battery modeling and state estimate. Although the implementation of LIBs for EV applications will be enhanced and transformed by AI technology, it is difficult to use AI/ML algorithms in practical settings for predicting and identifying battery materials and assessing the status of the battery system(Suresh,et al,2020).

B. Implications

Structure-property relations are a crucial correlation in material science, and machine learning (ML) techniques may be used to link data by building new datasets or developing existing ones. Using a predictive AI/ML technique makes it easier to turn meta-data into statistical models by removing complex and nonlinear patterns from training datasets. The BMS's fault prognosis feature, which is an add-on to its local fault detection feature, uses machine learning and historical data to forecast or stop battery system failures.

REFERENCES

- [1] Aldbaiat B, Nour M, Radwan E, Awada E. Grid-Connected PV System with Reactive Power Management and an Optimized SRF-PLL Using Genetic Algorithm. *Energies* 2022;15:2177. doi: <https://doi.org/10.3390/en15062177>.
- [2] Arora S, Abkenar AT, Jayasinghe SG, Tammi K. Battery Management System: Charge Balancing and Temperature Control. *Heavy-Duty Electric Vehicles*, Elsevier; 2021, p. 173–203. <https://doi.org/10.1016/B978-0-12-818126-3.00005-1>.

- [3] Changki Choi, Seongyun Park, Jonghoon Kim, Uniqueness of multilayer perceptron-based capacity prediction for contributing state-of-charge estimation in a lithium primary battery, *Ain Shams Engineering Journal*, Volume 14, Issue 4, 2023, 101936, <https://doi.org/10.1016/j.asej.2022.101936>
- [4] Gabbar H, Othman A, Abdussami M. Review of Battery Management Systems (BMS) Development and Industrial Standards. *Technologies (Basel)* 2021;9:28. doi: <https://doi.org/10.3390/technologies9020028>.
- [5] Gholami H, Røstvik HN. Economic analysis of BIPV systems as a building envelope material for building skins in Europe. *Energy* 2020;204:117931. <http://dx.doi.org/10.1016/j.energy.2020.117931>.
- [6] Hossain Lipu MS, Miah MdS, Ansari S, Wali SB, Jamal T, Elavarasan RM, et al. Smart Battery Management Technology in Electric Vehicle Applications: Analytical and Technical Assessment toward Emerging Future Directions. *Batteries* 2022;8:219. <https://doi.org/10.3390/batteries8110219> <http://dx.doi.org/10.1016/j.rser.2020.110149>.
- [7] Khawaja Y, Allahham A, Giaouris D, Patsios C, Walker S, Qiqieh I. An Integrated Framework for Sizing and Energy Management of Hybrid Energy System Using Automata. *Appl Energy* 2019;250:257–72. doi: <https://doi.org/10.1016/j.apenergy.2019.04.185>
- [8] Khawaja Y, Qiqieh I, Alzubi J, Alzubi O, Allahham A, Giaouris D. Design of costbased sizing and energy management framework for standalone microgrid using reinforcement learning. *Sol Energy* 2023;251:249–60. doi: <https://doi.org/10.1016/j.solener.2023.01.027>.
- [9] Li D, Zouma A, Liao J-T, Yang H-T. An energy management strategy with renewable energy and energy storage system for a large electric vehicle charging station. *eTransportation* 2020;6:100076. <http://dx.doi.org/10.1016/j.etrans.2020.100076>.
- [10] M. Bani Khalid, A. Qandil, N. Beithou, H.S Aybar, Renewable hydrogen driven CHCP device, *International Journal of Hydrogen Energy*, Volume 47, Issue 4, 2022, Pages 2208-2219, <https://doi.org/10.1016/j.ijhydene.2021.10.148>.
- [11] M. Bani Khalid, A. Qandil, N. Beithou, H.S. Aybar, Renewable hydrogen driven CHCP device, *International Journal of Hydrogen Energy*, Volume 47, Issue 4, 2022, Pages 2208-2219, <https://doi.org/10.1016/j.ijhydene.2021.10.148>.
- [12] N, Chitra A, Banerjee D, Sharma V, Zhutshi K, Razia SW, et al. Innovations in Power and Advanced Computing Technologies (i-PACT). *IEEE* 2021;2021:1–7. doi: <https://doi.org/10.1109/i-PACT52855.2021.9697046>.
- [13] Osama Ayadi, Reem Shadid, Abdullah Bani-Abdullah, Mohammad Alrbai, Mohammad Abu-Mualla, NoorAldeen Balah, Experimental comparison between Monocrystalline, Polycrystalline, and Thin-film solar systems under sunny climatic conditions, *Energy Reports*, Volume 8, Supplement 9, 2022, Pages 218-230, ISSN 2352-4847, <https://doi.org/10.1016/j.egyr.2022.06.121>.
- [14] Ravi SS, Aziz M. Utilization of Electric Vehicles for Vehicle-to-Grid Services: Progress and Perspectives. *Energies (Basel)* 2022;15:589. doi: <https://doi.org/10.3390/en15020589>
- [15] Sharma P. Rani Chinnappa Naidu, Optimization techniques for grid-connected PV with retired EV batteries in centralized charging station with challenges and future possibilities: A review. *Ain Shams Eng J* 2023;14(7):. doi: <https://doi.org/10.1016/j.asej.2022.101985101985>.
- [16] Shepero M, Lingfors D, Widén J, Bright JM, Munkhammar J. Estimating the spatiotemporal potential of self-consuming photovoltaic energy to charge electric vehicles in rural and urban nordic areas. *J Renew Sustain Energy* 2020;12(4). <http://dx.doi.org/10.1063/5.0006893>.
- [17] Solanke TU, Ramachandaramurthy VK, Yong JY, Pasupuleti J, Kasinathan P, Rajagopalan A. A review of strategic charging–discharging control of gridconnected electric vehicles. *J Energy Storage* 2020;28(January):101193. <http://dx.doi.org/10.1016/j.est.2020.101193>
- [18] Strušnik D, Brandl D, Schober H, Ferčec J, Avsec J. A simulation model of the application of the solar STAF panel heat transfer and noise reduction with and without a transparent plate: A renewable energy review. *Renew Sustain Energy Rev* 2020;134(July).
- [19] V. Suresh, P. Janik, J. M. Guerrero, Z. Leonowicz, and T. Sikorski, “Microgrid energy management system with embedded deep learning forecaster and combined optimizer,”

IEEE Access, vol. 8, pp. 202225–202239, 2020,
doi: 10.1109/ACCESS.2020.3036131.

- [20] W. Jiang, K. Yang, J. Yang, N. Xue, and Z. Zhuo, “Energy management strategy for maximization of renewable energy consumption in multi-microgrids,” in *2019 6th International Conference on Systems and Informatics (ICSAI)*, Nov. 2019, pp. 325–329, doi: 10.1109/ICSAI48974.2019.9010441.