© December 2025 | IJIRT | Volume 12 Issue 7 | ISSN: 2349-6002

A Comprehensive Review of Solar Power Assisted Battery Balancing Using Machine Learning for Enhanced Performance of Electric Vehicles

Miss.Madina Shahajahan Tamboli[1], Dr. Dineshkumar U. Adokar[2]
[1,2]Mansarovar Global Universit, Sehore (Madhya Pradesh)

***Abstract*—Electric vehicles (EVs) rely heavily on advanced battery management systems (BMS) to maintain performance, safety, and operational lifespan. A primary limitation within EV battery packs is cell imbalance, which leads to reduced capacity, increased degradation, and safety hazards. Traditional balancing methods, such as passive and active balancing, suffer from energy inefficiency or circuit complexity. In parallel, integrating renewable energy, particularly solar photovoltaic (PV), presents an opportunity for sustainable auxiliary energy support. Machine Learning (ML)–based estimation and control methods have advanced predictive battery health assessment and intelligent balancing, enabling adaptive balancing strategies. This survey paper presents a comprehensive review of research on EV batteries, solar-assisted charging, cell balancing techniques, ML-based BMS algorithms, intelligent control architectures, and reinforcement learning (RL) approaches for balancing. Research gaps, challenges, and future opportunities for developing integrated solar–ML-driven BMS architectures are also discussed.**

***Index Terms*—Electric vehicles, Battery management system, Solar PV, Machine learning, Balancing circuits, SOC estimation, Reinforcement learning, Vehicle-integrated photovoltaics.**

I. INTRODUCTION

Electric Vehicles (EVs) have emerged as a pivotal technology in the global transition toward sustainable transportation. With increasing concerns about greenhouse gas emissions, rising fossil-fuel costs, and stringent environmental regulations, EV adoption has accelerated across passenger, commercial, and industrial sectors. The performance, safety, and cost-effectiveness of these vehicles, however, are fundamentally governed by the design and management of their battery systems. Lithium-ion batteries, the dominant choice for modern EVs, exhibit complex electrochemical behavior that requires intelligent monitoring, accurate control, and efficient energy management throughout their lifecycle. One of the major challenges within large battery packs is cell imbalance, where individual cells experience non-uniform State of Charge (SOC), State of Health (SOH), temperature, internal resistance, and aging rates. Even small variations among cells lead to under-utilization of battery capacity, increased thermal stress, accelerated degradation, reduced driving range, and potential safety hazards. Traditional Battery Management Systems (BMS) employ passive or active balancing techniques to mitigate these issues. Passive balancing dissipates excess energy as heat, making it inefficient and unsuitable for high-energy EV packs. Active balancing improves energy transfer efficiency but introduces complexity, converter losses, and control challenges, especially under dynamic driving conditions.

At the same time, vehicle-integrated photovoltaics (VIPV) and solar-assisted charging are gaining global interest as EV manufacturers attempt to reduce external grid dependency and utilize clean renewable sources. Although onboard solar panels cannot fully charge the traction battery, they can significantly support auxiliary systems, improve range in favorable conditions, and serve as an additional energy input for cell-level balancing. Integrating solar energy into the balancing mechanism not only enhances system energy efficiency but also reduces wasted heat from conventional passive balancing. This concept of solar-assisted battery balancing represents a promising pathway to make EV energy systems more self-sustaining and environmentally friendly.However, controlling such a hybrid system becomes highly complex due to fluctuating solar irradiance, varying road and driving conditions, battery non-linearity, and the need for real-time decision-making. Conventional rule-based or fixed-parameter balancing algorithms often fail to adapt to dynamic conditions. This gap highlights the need for advanced intelligent algorithms, particularly Machine Learning (ML), which can learn patterns, predict behavior, and optimize decision-making in uncertain environments.

Machine learning has shown remarkable potential in battery SOC estimation, SOH prediction, Remaining Useful Life (RUL) forecasting, fault detection, and performance optimization. Techniques such as neural networks, LSTM models, random forests, and reinforcement learning can capture non-linear patterns and provide precise predictions where conventional mathematical models struggle. When applied to balancing control, machine learning can determine when, how long, and which cells to balance, especially when solar energy availability fluctuates. Reinforcement Learning (RL) methods can intelligently switch between multiple operating modes such as solar-balancing mode, energy-storage mode, and conventional balancing mode, thus maximizing energy utilization and minimizing losses.Integrating solar PV modules, MPPT control, energy converters, and ML-driven balancing algorithms into a unified BMS architecture establishes a transformative solution for next-generation EVs. Such a system can reduce stress on the main battery, extend battery lifespan, improve SOC uniformity, enhance driving range, and promote efficient use of renewable energy. Moreover, by reducing the dependence on grid-charging and minimizing thermal losses from passive balancing, the proposed approach supports global sustainability goals and lowers operational costs.Despite significant advancements in BMS technology, research combining solar-assisted energy harvesting, active balancing, and machine learning control is still in its early stages. Prior studies have explored these domains independently, but an integrated, real-time, intelligent framework suitable for EV-scale battery packs has not been thoroughly developed. Therefore, this research aims to design, simulate, and experimentally validate a solar-assisted ML-based battery balancing system, offering a novel contribution to EV battery management.In summary, the topic addresses three critical challenges battery imbalance, limited renewable energy utilisation, and the need for intelligent decision-making and integrates them into a comprehensive solution. This introduction establishes the importance of the work and sets the foundation for detailed investigation into system design, ML algorithms, power electronics, and real-world performance evaluation.

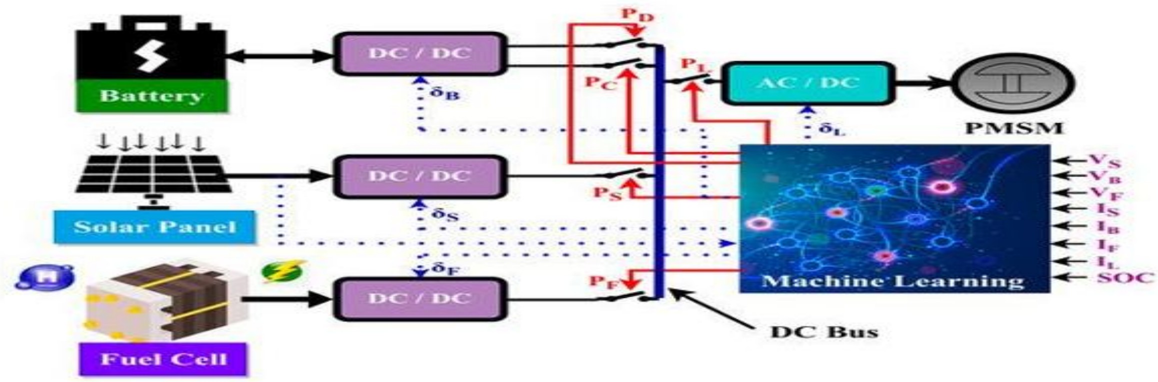

Fig.1.Block diagram of machine learning control for EV

II. BACKGROUND & MOTIVATION

The accelerating global shift toward clean mobility has positioned Electric Vehicles (EVs) as a central solution for reducing greenhouse gas emissions, minimizing fossil-fuel dependence, and achieving long-term sustainability in the transportation sector. Governments, industries, and research institutions worldwide have been investing heavily in EV technology, especially in advancing battery systems, which represent both the heart and the costliest component of modern electric vehicles. Yet, even with rapid technological progress, several bottlenecks continue to hinder the efficiency, reliability, and adoption of EVs chief among them is the challenge of ensuring healthy, balanced, and long-lasting battery packs.

2.1 Complexity and Limitations of EV Battery Packs

EV battery packs consist of hundreds or thousands of lithium-ion cells connected in series-parallel configurations. Ideally, these cells should operate uniformly. However, real-world conditions such as manufacturing inconsistencies, temperature gradients, non-uniform aging, and varied charge–discharge cycles gradually create cell imbalances. This results in:

- Non-uniform State of Charge (SOC) levels
- Divergence in State of Health (SOH)
- Increased internal resistance differences
- Thermal hotspots
- Reduced usable capacity and shorter driving range
- Accelerated degradation and safety risks

Even a single weaker cell can dictate the performance of the entire pack, leading the Battery Management System (BMS) to prematurely end charging/discharging to protect the weakest cell. This becomes a major barrier to achieving high performance and extended battery life.

2.2 Rising Global Interest in Solar-Assisted EV Systems

Vehicle-Integrated Photovoltaic (VIPV) and solar-assisted charging are gaining momentum as a way to reduce dependence on grid power and utilize clean, renewable energy. EVs offer a large surface area-roof, bonnet, doors-where thin-film or high-efficiency PV panels can be installed. Although the solar energy harvested on a vehicle is insufficient to fully charge the main traction battery, it is highly suitable for:

- Powering auxiliary loads
- Charging an intermediate buffer storage (supercapacitor or small battery)
- Supporting cell balancing operations
- Reducing net balancing energy drawn from the main battery

Thus, solar energy becomes an intelligent secondary input, reducing energy waste and increasing sustainability. Integrating PV energy into the balancing mechanism introduces a new paradigm: renewable-energy-assisted balancing, which significantly improves overall system efficiency.

2.3 Challenges of Integrating Solar with Battery Balancing

Despite its potential, combining solar power with EV battery balancing is challenging due to:

- Intermittent and unpredictable solar irradiance
- Real-time MPPT requirements
- Efficient routing of harvested solar energy
- Complex decision-making on when and how to inject solar power into the balancing topology
- Balancing the trade-off between load demand, battery health, and solar input

This creates a strong need for smart, data-driven, adaptive control strategies that can respond to continuously changing environmental and operational conditions.

2.4 The Growing Role of Machine Learning in Battery Management

Machine Learning (ML) has emerged as a transformative tool in modern BMS for:

- SOC estimation
- SOH monitoring
- Remaining Useful Life (RUL) prediction
- Fault detection and anomaly identification
- Thermal and degradation modeling
- Optimized balancing control

Unlike traditional mathematical models, ML can learn from real data, adapt to aging effects, account for temperature variations, and predict future states with high accuracy. ML especially excels when the system exhibits nonlinear, dynamic behavior—conditions under which conventional rule-based algorithms fail.

2.5 Motivation for Integrating Solar Energy with ML-Based Balancing

The intersection of solar-assisted balancing and machine-learning-based adaptive control creates a novel research direction with strong justification:

Energy Efficiency Motivation

Solar energy provides "free" renewable energy that can supplement or fully drive the balancing process, reducing energy drawn from the main battery and enhancing overall efficiency.

Battery Longevity Motivation

More intelligent balancing ensures healthier cells, uniform SOC levels, and reduced stress, directly translating into longer battery life and delayed degradation.

Predictive Maintenance Motivation

ML prediction models can forecast imbalance trends, allowing the system to balance cells before issues escalate.

Sustainability Motivation

Using renewable solar energy for internal battery management supports green transportation goals and reduces CO_2 emissions associated with electricity generation.

Adaptive Real-Time Control Motivation

Reinforcement Learning (RL) and other ML methods enable real-time decision-making under uncertainties such as:

- Solar variability
- Driving load changes
- Temperature fluctuations
- Battery aging characteristics

III. CELL BALANCING TECHNIQUES

Below is a deep-dive into cell balancing methods, organized by conceptual families, with strengths, weaknesses, typical topologies, control considerations. Objective: make cell voltages / SOC converge so the pack's usable energy and safety margin increase.

- Metrics to measure balancing quality: SOC standard deviation across cells, voltage spread (mV), balancing time to converge to threshold, energy lost during balancing, and overall impact on cycle life.

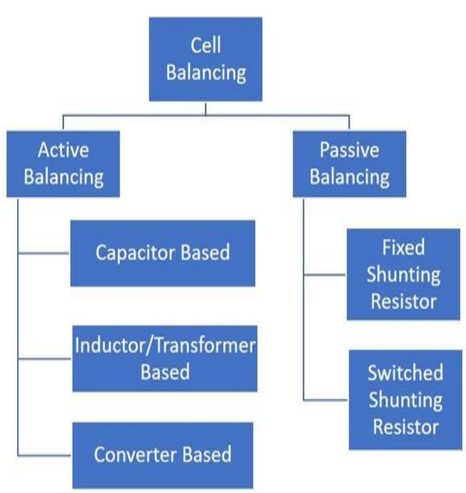

Fig.chart of the basic cell-balancing topologies

3.1 Passive Balancing (Resistive/Shunt)

Passive balancing is the simplest and most widely used method of cell balancing in Battery Management Systems (BMS), especially in electric vehicles, energy-storage systems, and consumer electronics. The goal of passive balancing is to equalize the State of Charge (SOC) of all cells in a battery pack by removing excess charge from the cells that are more charged than the others.

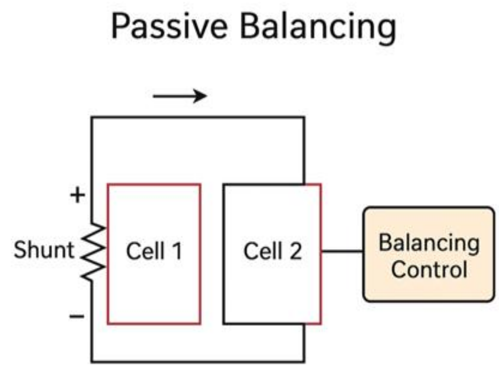

Fig.2.Block diagram of Passive Balancing

3.2 Active Balancing

Active balancing moves charge from higher-SOC cells to lower-SOC cells instead of wasting it. This can be done with different energy-transfer elements and topologies. Active balancing is an advanced battery cell equalization technique used in Battery Management Systems (BMS) to maintain uniform State of Charge (SOC) among all cells in a battery pack. Unlike passive balancing which simply burns excess energy as heat through resistors active balancing transfers energy from higher-charged cells to lower-charged cells. This makes the process far more efficient, especially for high-capacity Electric Vehicle (EV) battery packs.

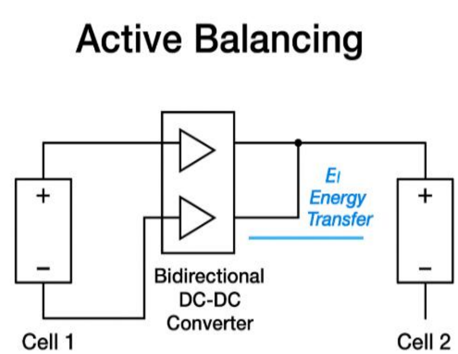

Fig.3.Block diagram of Active Balancing

Broad families:
- Switched-capacitor (charge shuttle)
- Switched-inductor
- Converter-based (bidirectional DC-DC)
- Centralized vs. distributed (modular) architectures

3.3 Switched-Capacitor Balancing (Charge Shuttle)
A capacitor is cyclically connected between cells (or cell groups) using switches, transferring charge from a higher-voltage cell to a lower-voltage one.
Topology & operation
- A common flying capacitor plus switching network that re-routes the capacitor between pairs (or sequences) of cells.
- Alternating charge/discharge cycles shift energy.
- No continuous power electronics stage; can be efficient for short hops.
- Moderate cost and simpler than full converters.

3.4 Converter-Based Balancing (Bidirectional DC–DC)
Use power converters to actively shuttle energy between cells or between cell groups and a common bus or buffer (supercap/bulk capacitor or auxiliary battery). Converter-based balancing is an active balancing technique in which energy is efficiently transferred from a higher-charged cell to a lower-charged cell using a bidirectional DC–DC converter. Unlike passive balancing which wastes excess energy as heat this method moves energy intelligently, improving efficiency and extending battery life.A bidirectional DC–DC converter allows power to flow in both directions, depending on which cell needs to be charged or discharged. Because of this, converter-based balancing works effectively even with large battery packs such as those used in Electric Vehicles (EVs), energy storage systems, and hybrid vehicles.
Topologies
- Per-cell converters: each cell has its own bi-directional DC-DC converter enabling direct regulated transfers.
- Centralized converter: single converter connects to a selected cell or module via multiplexing switches.
- Multi-port converters: converters with multiple isolated ports for several cells.
- MPPT and power electronics must be coordinated with balancing controllers to decide when PV energy should be used for balancing versus charging the main pack.

3.5 Control Strategies: Rule-based vs. Optimization vs. ML
Rule-based
- Threshold-based (bleed when voltage > Vth), cell-pair selection heuristics.
- Simple and interpretable, but rigid and non-optimal with fluctuating inputs (PV, driving load).

Optimization-based
- Model Predictive Control (MPC) or heuristic optimizers that minimize energy loss and balancing time subject to constraints.
- Require model fidelity and computation; can be heavy for embedded ECUs.

ML-driven
- Supervised models: for accurate SOC/SOH estimation used as inputs to controllers.
- Reinforcement Learning (RL): learns balancing policies to maximize long-term reward (e.g., minimising cumulative degradation, energy loss).
- Hybrid: physics-informed ML or ML that augments MPC to reduce computational burden.

Practical considerations for ML in BMS
- Need robust training data across temperatures, aging states, and driving profiles.
- Safety & interpretability: must include fallback safe controllers and verifiable constraints.
- Computation and memory constraints of automotive microcontrollers — lightweight architectures or edge-hardware acceleration may be necessary.

IV. VEHICLE-INTEGRATED PHOTOVOLTAICS (VIPV) & SOLAR EV SYSTEMS

Vehicle-Integrated Photovoltaics (VIPV) refers to the integration of solar photovoltaic modules directly onto the surface of an Electric Vehicle (EV) to generate supplemental clean energy while the vehicle is parked or in motion. Over the last decade, VIPV systems have gained major research interest due to their potential to reduce grid-charging dependence, extend driving range, support auxiliary loads, and improve overall EV energy efficiency. As battery-electric vehicles become more widespread, the need to harness renewable, decentralized energy sources inside the vehicle itself has become significant.

VIPV systems incorporate lightweight solar modules into EV surfaces such as roofs, hoods, and trunks. Benefits include:

- Reduced grid dependency
- Increased EV range (5–12 km/day under favorable irradiance)
- Support for auxiliary systems

V. MACHINE LEARNING IN BMS: SOC/SOH/RUL & INTELLIGENT CONTROL

5.1 SOC/SOH/RUL estimation

ML models (LSTM, CNN, RF, gradient-boost, and hybrid physics-informed networks) have outperformed classical estimators under noisy, non-linear dynamics (examples: Choi et al. 2019; Shen et al. 2018; Lipu et al. 2018). They improve estimation accuracy and enable prognostics (RUL). However, they demand careful preprocessing, robust feature extraction and strategies to counter limited labelled data (synthetic augmentation, coupled NN approaches).

5.2 ML for balancing control

Recent exploratory works (e.g., Rao 2025) investigate ML-driven active balancing: supervised ML for anomaly detection/prediction, and reinforcement learning (RL) for policy learning to decide when/which cells to balance. RL approaches (DQN/AQN/actor-critic variants) are promising for sequential decision problems like dynamic balancing under variable solar input. The synopsis advocates supervised estimators for SOC/SOH and RL for mode/policy decisions.

5.3 Data challenges & hybridization

Data scarcity and domain shift (aging, temperature) are recurring issues. Papers propose synthetic data augmentation, coupled networks and hybrid physics + ML models (physics-informed NN, P-BiLSTM) to improve generalizability suggested in the synopsis as part of model design.

VI. SYSTEM INTEGRATION: POWER ELECTRONICS, MPPT, APM, AND EMBEDDED MACHINE LEARNING

Integrating solar power into an Electric Vehicle (EV) Battery Management System (BMS) is not a simple "add-on." It requires a coordinated architecture involving power electronics, energy routing, buffer management, real-time monitoring, and intelligent decision-making algorithms. This section provides a complete, technical description of how these components come together to support solar-assisted battery balancing using Machine Learning (ML).

VII. CONCLUSION

The review of existing literature clearly demonstrates that significant opportunities exist in improving electric vehicle battery performance through the combined use of solar-assisted charging and advanced active cell balancing. Although solar energy has been explored as a supplementary source for EVs, most research treats it only as an auxiliary power input, without deeply integrating it into the internal energy management mechanisms of the battery pack. Similarly, active balancing methods have matured in terms of converter topologies and energy-transfer techniques, but they continue to rely on static or rule-based control strategies that fail to adapt to rapidly changing driving conditions, battery aging behavior, and fluctuating environmental factors such as irradiance. Machine learning introduces a transformative capability in this domain, offering predictive intelligence, real-time adaptability, and the ability to manage complex nonlinear system interactions that conventional algorithms cannot handle effectively.

REFERENCES

[1] Ren, Z., Liu, S., Yu, X., & Dong, X. (2023). A review of machine learning state-of-charge and state-of-health estimation methods for lithium-ion batteries. — Review article summarizing ML algorithms (LSTM, RF, gradient boosting) for SOC/SOH. ScienceDirect

[2] Araki, K. (2025). Testing and rating of vehicle-integrated photovoltaics. — Paper addressing

VIPV testing standards, performance and reliability. ScienceDirect

[3] Samadi, H., et al. (2025). Evaluating the Role of Vehicle-Integrated Photovoltaic (VIPV). MDPI — Case studies and energy contribution analyses for VIPV in vehicles. MDPI

[4] Pochont, N. R., et al. (2023). Recent trends in photovoltaic technologies for sustainable applications (including VIPV). — Survey of PV tech and implications for VIPV. ScienceDirect

[5] Ashraf, A., et al. (2024). Review of cell-balancing schemes for electric vehicle battery packs. Energies (2024) — comprehensive review of passive vs active balancing and performance trade-offs. MDPI

[6] Zhao, F., Guo, Y. & Chen, B. (2024). A review of lithium-ion battery SOC estimation methods based on machine learning. World Electric Vehicle Journal / review (2024). MDPI

[7] Heinrich, M., et al. (2020). Potential and challenges of vehicle-integrated photovoltaics (VIPV). — Early VIPV overview discussing benefits, costs, and integration issues. Fraunhofer ISE

[8] Sovetkin, E., et al. (2023). Vehicle-Integrated Photovoltaics — Irradiation modelling for VIPV applications. Solar R&D paper — modelling partial shading and curved-surface effects. Wiley Online Library

[9] Krishnamoorthy, U., et al. (2023). Investigation of active cell balancing performance for series-connected packs using buck converters. IET / PEL conference paper — converter-based balancing experimental study. IET Research Journals

[10] Macías, J., et al. (2024). On the optimization of the interconnection of photovoltaic systems for vehicle integration. — Examines PV interconnection strategies and energy flow optimisation for onboard PV. PMC

[11] Chen, Z., et al. (2021). State-of-charge estimation of lithium-ion batteries based on machine-learning approaches. Journal article (2021) — summarizes FNN, RBF, ensemble ML for SOC. ScienceDirect

[12] Omariba, Z. B. (2019). Review of battery cell balancing methodologies for optimizing battery pack performance in electric vehicles. IEEE/Conference review (2019) — early systematic review (2019). ADS

[13] Ooi, C. A., et al. (2025). A novel active lithium-ion cell balancing method based on DSoP/CSoP criteria. (2025, open access). — New active balancing algorithm & evaluation. PMC

[14] Karoui, F., et al. (2023). Integrated photovoltaics potential for passenger cars: energy and feasibility study. Preprint / conference (2023). — practical VIPV potential estimates and case studies. Preprints

[15] Tang, P., et al. (2024). Prediction of lithium-ion battery SOC based on IGA-GRU and multi-head attention (2024). Energy Informatics — advanced RNN/attention SOC predictor. SpringerOpen

[16] Oluwalana, O. J., et al. (2025). Solar-Powered Electric Vehicles: Comprehensive Review. Energies (2025) — SEV and VIPV survey up to 2025. MDPI

[17] Tang, K. (2025). The state of health (SOH) estimation of lithium-ion batteries: methods and trends. MDPI (2025) — SOH review emphasizing ML & physics-informed approaches. MDPI

[18] Safari, A., et al. (2025). State-of-the-art review on battery cell balancing strategies. Springer / journal (2025) — comparative analysis of DC–DC topologies and tradeoffs. SpringerLink

[19] Ren, X., Liu, S., Yu, X. & Dong, X. (2023). Review: ML techniques for SOC/SOH (additional detailed review). — supports ML choices for BMS design. ScienceDirect

[20] Zilali, A., et al. (2025). Machine learning-based SOC estimation for Li-ion under variable temperature conditions. (2025). — robustness-focused ML SOC study. ScienceDirect

[21] Hannan, M. A., Lipu, M. S. H., Hussain, A., et al. (2020). Toward enhanced state-of-charge estimation of lithium-ion batteries using optimized machine learning techniques. Scientific Reports (2020) — widely-cited ML-SOC benchmark study. Nature

[22] Karoui / Pohlmann group (2023–2024). Practical VIPV case studies & energy-yield estimations (multiple conference/preprint studies summarised). Preprints+1