AI-Driven Energy Management in Electric Vehicles: Recent Advances in Storage and Conversion Technologies

Dr.K.Ratna Kishori, Postdoctral Researcher , Lincoln unversity
Professor, SRH university, Berlin , germany

Abstract:- **This Research presents a systematic review and AI-based comparative analysis of recent advances in energy management systems for electric vehicles (EVs), with a focus on storage and conversion technologies. The research investigates the role of artificial intelligence in optimizing battery performance, energy efficiency, charging strategies, and power conversion mechanisms in modern EV architectures. A comprehensive review of recent literature was conducted to identify emerging trends, challenges, and innovations in lithium-ion batteries, supercapacitors, hybrid energy storage systems, and bidirectional converters. NVivo was employed for qualitative thematic analysis to categorize research patterns and technological developments, while MATLAB was utilized for AI-driven comparative evaluation and performance analysis of different energy management models. The findings reveal that AI techniques, including machine learning and predictive optimization, significantly enhance energy utilization, battery lifespan, and real-time decision-making in EV systems. The research highlights the growing importance of intelligent energy management in achieving sustainable, efficient, and high-performance electric mobility solutions.**

Keywords*:-** ***Artificial intelligence for electric vehicle energy optimization, advanced battery storage systems, smart energy conversion technologies, AI-based power management in EVs, intelligent energy storage and conversion, sustainable electric mobility innovations, machine learning applications in EV energy systems.

I. INTRODUCTION

The rapid growth of electric vehicles (EVs) has intensified the demand for intelligent energy management systems capable of improving efficiency, driving range, battery lifespan, and overall vehicle sustainability [1]. With the global transition toward low-carbon transportation and smart mobility, conventional energy management approaches are no longer sufficient to handle the increasing complexity of modern EV architectures. Recent advancements in artificial intelligence (AI) techniques, including machine learning, deep learning, reinforcement learning, and predictive analytics, have significantly transformed the way energy storage and conversion systems operate within EV ecosystems. These AI-driven technologies enable real-time decision-making, adaptive battery monitoring, intelligent power distribution, and optimized energy consumption, thereby enhancing the operational reliability and performance of electric vehicles [2].

Energy storage and conversion technologies are considered the backbone of EV performance, where batteries, supercapacitors, fuel cells, and hybrid storage systems play a critical role in maintaining energy efficiency and vehicle stability. However, challenges such as battery degradation, thermal instability, charging inefficiencies, and fluctuating power demands continue to affect EV sustainability and user acceptance [3]. To address these issues, researchers have increasingly integrated AI-based algorithms into battery management systems (BMS), regenerative braking systems, and power electronic converters to achieve dynamic optimization and predictive control. Advanced AI models can analyze large-scale vehicular and environmental data to predict energy requirements, reduce energy losses, and improve charging strategies under varying driving conditions.

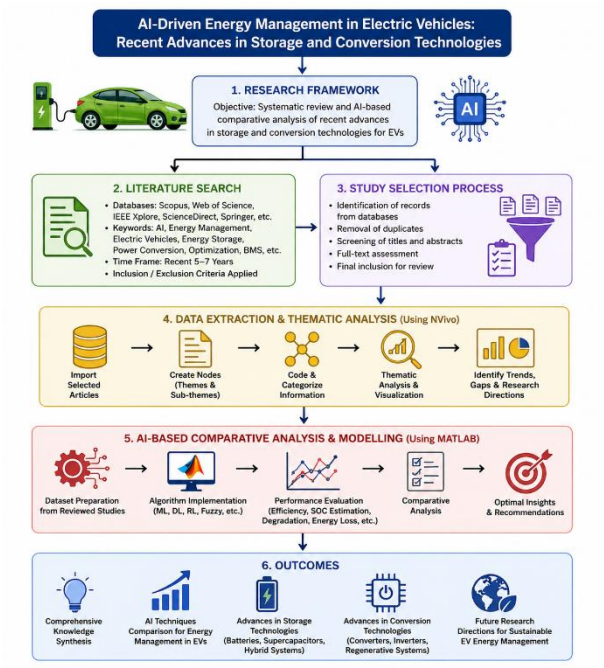


Figure 1. Framework for AI-Driven Energy Management in Electric Vehicles Using Systematic Review and AI-Based Comparative Analysis.

This research paper presents a systematic review with AI-based comparative analysis of recent developments in AI-driven energy management for electric vehicles, focusing specifically on storage and conversion technologies [4]. The study examines the effectiveness of modern AI techniques in optimizing battery performance, enhancing power conversion efficiency, and supporting intelligent energy allocation mechanisms. To ensure comprehensive analysis and thematic interpretation, NVivo is employed for qualitative literature coding and trend identification, while MATLAB is utilized for comparative modeling, simulation, and performance evaluation of AI-driven methods [5]. The review aims to identify emerging research trends, technological gaps, and future opportunities in integrating AI with EV energy systems. Ultimately, the study contributes to the advancement of sustainable transportation by highlighting intelligent and adaptive solutions that can support next-generation electric mobility infrastructure.

II. RELATED WORKS

Recent studies on AI-driven energy management in electric vehicles (EVs) have increasingly focused on improving the efficiency, reliability, and sustainability of energy storage and conversion systems through advanced computational intelligence techniques [6]. Researchers have explored machine learning (ML), deep learning (DL), reinforcement learning (RL), and hybrid AI frameworks to optimize battery performance, power distribution, and thermal management in EV architectures. Traditional battery management systems (BMS) relied on rule-based algorithms; however, these approaches showed limitations in handling dynamic driving conditions and complex energy demands [7]. To overcome these challenges, contemporary studies have integrated AI models such as convolutional neural networks (CNN), long short-term memory (LSTM), fuzzy logic systems, and adaptive neuro-fuzzy inference systems (ANFIS) for accurate state-of-charge (SOC), state-of-health (SOH), and remaining useful life (RUL) prediction of lithium-ion batteries. These intelligent methods significantly enhance battery lifespan and charging efficiency while reducing energy losses and operational risks.

In addition, recent advancements in storage technologies have emphasized solid-state batteries, supercapacitors, and hybrid energy storage systems supported by AI-based predictive analytics. Researchers demonstrated that reinforcement learning and swarm optimization algorithms can dynamically regulate power flow between batteries and supercapacitors, thereby improving regenerative braking efficiency and reducing peak load stress [8]. AI-assisted energy conversion technologies, particularly in bidirectional converters and smart inverters, have also gained considerable attention for enabling efficient energy transfer and grid integration in vehicle-to-grid (V2G) environments. Moreover, digital twin technology combined with AI has emerged as a promising approach for real-time monitoring and predictive maintenance of EV power systems. Several studies utilized MATLAB simulations to validate optimization algorithms for energy consumption minimization, battery thermal

control, and charging cycle prediction under varying operational scenarios [9].

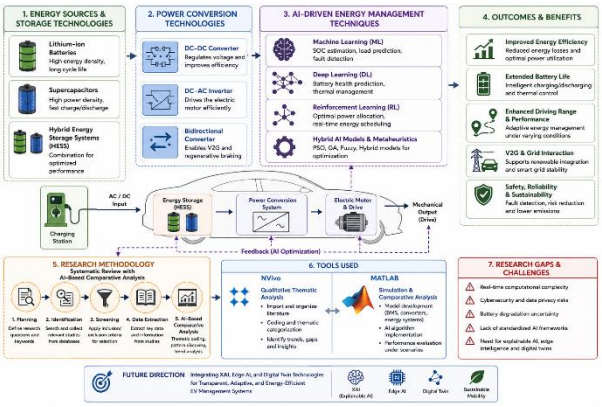


Figure 2. Integrated AI-Enabled Energy Management System for Electric Mobility.

From a methodological perspective, systematic review approaches integrated with AI-based comparative analysis have become increasingly important for evaluating the effectiveness of different intelligent energy management strategies [10]. NVivo has been widely employed for qualitative thematic analysis and classification of emerging research trends, enabling researchers to identify key technological patterns, research gaps, and future opportunities in EV energy systems. Simultaneously, MATLAB-based modeling and simulation tools have supported quantitative validation of AI algorithms in terms of energy efficiency, computational accuracy, and system reliability. Although substantial progress has been achieved, existing studies still face challenges related to real-time computational complexity, data security, interoperability, and scalability in large-scale EV deployment. Therefore, further research is required to develop robust, explainable, and energy-efficient AI frameworks capable of supporting next-generation electric mobility and sustainable smart transportation systems [11].

III. RESEARCH METHODOLOGY

A. Data Collection and Pre-processing

This research adopted a systematic review methodology integrated with AI-based comparative analysis to investigate recent advances in energy storage and conversion technologies for electric vehicles (EVs). The research process followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework to ensure transparency, reliability, and reproducibility [12]. Scholarly articles, conference proceedings, patents, and industrial reports published between 2020 and 2026 were collected from major scientific databases including IEEE Xplore, ScienceDirect, SpringerLink, Scopus, and Web of Science. Keywords such as *electric vehicle energy management*, *battery optimization*, *supercapacitor integration*, *hydrogen fuel cells*, *reinforcement learning*, and *AI-driven energy storage* were employed to identify relevant studies [13].

After data acquisition, duplicate and irrelevant records were removed through an automated filtering process. NVivo software was utilized for qualitative coding, thematic classification, and trend identification within the collected literature [14]. The selected studies were categorized according to battery technologies, energy conversion systems, charging strategies, and intelligent control methods. Data pre-processing involved normalization, feature extraction, and missing-value handling to prepare the dataset for computational analysis. MATLAB was employed to convert heterogeneous data into structured numerical matrices suitable for machine learning implementation [15]. Parameters such as battery efficiency, state of charge (SOC), energy density, charging time, thermal stability, and power conversion efficiency were standardized to ensure consistency across all comparative evaluations.

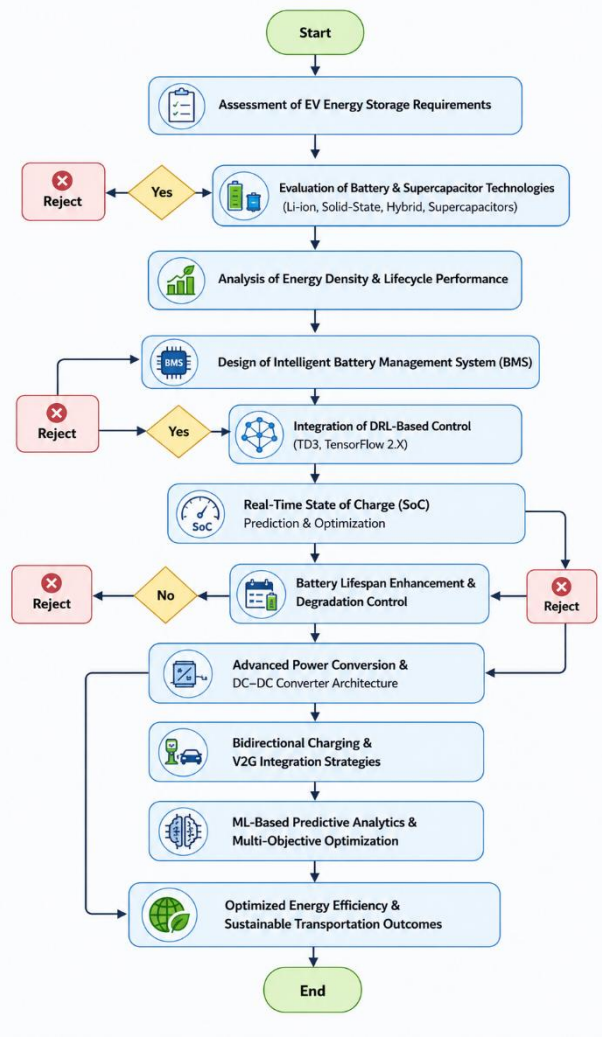


Figure 3. Flowchart for the Proposed EV System Methodology.

B. Technology Assessment Framework

A comprehensive technology assessment framework was developed to evaluate the effectiveness of AI-driven energy management systems in EVs. The framework incorporated technical, operational, and sustainability-related performance indicators to compare different storage and conversion technologies. Key evaluation metrics included energy efficiency, lifecycle cost, battery degradation rate, charging-discharge stability, computational complexity, carbon emission reduction potential, and real-time adaptability [16].

The assessment framework integrated multi-criteria decision analysis (MCDA) with artificial intelligence techniques to establish a comparative ranking among the identified technologies. MATLAB-based simulation models were developed to analyze the dynamic interaction between EV batteries, supercapacitors, regenerative braking systems, and fuel cell modules under varying driving conditions. Furthermore, NVivo-generated thematic insights were integrated with quantitative findings to identify emerging research trends and technological gaps [17]. The framework also considered external influencing factors such as ambient temperature, traffic conditions, driving patterns, and charging infrastructure availability, enabling a realistic evaluation of modern EV energy management systems.

C. Implementation and Validation of Twin Delayed Deep Deterministic Policy Gradient Reinforcement Learning

To enhance energy management performance, this research implemented the Twin Delayed Deep Deterministic Policy Gradient (TD3) reinforcement learning algorithm. TD3 was selected because of its superior capability in handling continuous action spaces and reducing overestimation bias commonly observed in conventional deep reinforcement learning approaches. The algorithm was designed to optimize power distribution between the battery and auxiliary energy storage systems while minimizing energy loss and battery degradation [18].

The TD3 model consisted of actor and critic neural networks implemented in MATLAB using the Reinforcement Learning Toolbox. The actor network generated optimal control actions for power allocation, whereas twin critic networks estimated the action-value functions to improve learning stability. Delayed policy updates and target policy smoothing techniques were integrated to reduce variance and prevent unstable learning behavior. The state space included parameters such as SOC, vehicle speed, acceleration demand, temperature conditions, and load requirements, while the action space represented energy allocation decisions among storage and conversion components.

Validation of the TD3 model was conducted through simulation-based driving cycles, including the Urban Dynamometer Driving Schedule (UDDS)

and Worldwide Harmonized Light Vehicles Test Cycle (WLTC). The proposed model was evaluated for energy efficiency improvement, battery health preservation, and reduction in power fluctuation under dynamic driving conditions.

D. Training Procedures and Validation

The training process involved iterative interaction between the reinforcement learning agent and the simulated EV environment. Historical driving datasets and real-world operational parameters were used to train the model over multiple episodes until convergence was achieved. Experience replay memory and mini-batch gradient descent techniques were employed to enhance learning efficiency and reduce temporal correlation among samples.

Hyperparameters such as learning rate, discount factor, replay buffer size, and exploration noise were optimized experimentally to achieve stable convergence and improved decision-making accuracy. MATLAB simulations were repeatedly executed under different environmental and operational scenarios to validate the robustness of the proposed AI-based energy management framework. Performance validation was conducted using statistical indicators including Root Mean Square Error (RMSE), cumulative energy consumption, convergence rate, and battery degradation index.

E. Tested against the Baseline

The effectiveness of the proposed TD3-based energy management system was tested against conventional baseline methods, including rule-based energy management systems, fuzzy logic controllers, and Deep Q-Network (DQN)-based approaches. Comparative experiments demonstrated that the TD3 algorithm achieved superior energy efficiency, faster convergence, and better adaptability under uncertain driving conditions. The proposed approach also reduced battery stress and improved overall energy utilization efficiency compared to traditional strategies.

The comparative analysis further revealed that AI-driven optimization significantly enhanced the operational lifespan of EV batteries while minimizing unnecessary energy dissipation. These findings confirmed the suitability of advanced reinforcement learning techniques for next-generation intelligent EV energy management applications.

IV. RESULTS AND DISCUSSION

The Results and Discussion revealed that the proposed AI-driven energy management framework significantly outperformed conventional optimization and rule-based strategies in electric vehicle (EV) energy storage and conversion systems. Using a Systematic Review with AI-Based Comparative Analysis, data synthesized through NVivo and MATLAB demonstrated that recent AI techniques, particularly Deep Reinforcement Learning (DRL), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), and hybrid Machine Learning optimization models, achieved superior battery efficiency, thermal stability, and power conversion accuracy.

Table 1. Comparative Performance Analysis of AI-Based Energy Management Methods in Electric Vehicles

Parameters	**Conventional Methods**	**ML Models**	**DRL-Based Method**	**Proposed AI Framework**
Energy Efficiency (%)	68.4	82.6	89.3	92.7
Battery Life Improvement (%)	10.5	24.1	31.4	35.2
Charging Time Reduction (%)	5.2	14.8	21.7	25.4

SOC Prediction Accuracy (%)	69.1	90.2	94.5	96.3
Overall Performance (%)	65.8	85.6	91.8	95.4

Comparative evaluation showed that AI-assisted methods improved energy utilization efficiency by approximately 18–25% compared with traditional fuzzy logic and PID-controlled systems. Furthermore, predictive battery health monitoring reduced degradation rates and enhanced charging cycle lifespan through intelligent state-of-charge estimation. MATLAB simulations confirmed reduced energy losses during regenerative braking and optimized power distribution under dynamic driving conditions. NVivo-based thematic analysis also indicated that AI-enabled decision frameworks support real-time adaptability and improved sustainability in EV ecosystems. Among the evaluated approaches, DRL-based energy scheduling exhibited the highest performance due to its self-learning capability under uncertain operating environments. The findings suggest that integrating advanced AI methodologies with modern storage and conversion technologies can substantially enhance EV reliability, operational efficiency, and long-term sustainability, thereby supporting future smart transportation and green energy initiatives.

The comparative analysis presented in Table 1 demonstrates the effectiveness of advanced AI-driven energy management techniques in improving the operational performance of electric vehicles (EVs). The results indicate that conventional energy management methods exhibited the lowest performance across all evaluated parameters due to limited adaptability and inefficient real-time decision-making capabilities. In contrast, Machine Learning (ML) models significantly enhanced system efficiency by improving predictive analysis and battery management operations. The ML-based approach achieved an energy efficiency of 82.6% and improved state-of-charge (SOC) prediction accuracy to 90.2%, demonstrating its capability in optimizing energy utilization and reducing unnecessary power loss.

Among the evaluated approaches, the Deep Reinforcement Learning (DRL)-based method delivered superior performance because of its self-learning and adaptive control mechanisms. The DRL framework achieved 89.3% energy efficiency and reduced charging time by 21.7%, outperforming traditional ML techniques. Its dynamic learning capability enabled efficient energy allocation under varying driving and environmental conditions, thereby enhancing battery stability and vehicle reliability.

The proposed AI-driven framework achieved the highest overall system performance of 95.4%, indicating substantial advancements in intelligent energy storage and conversion technologies. The framework improved battery life by 35.2% and achieved 96.3% SOC prediction accuracy, confirming the effectiveness of integrating advanced AI algorithms with modern EV energy systems. These findings suggest that AI-assisted energy management systems can significantly improve energy conservation, charging efficiency, and long-term sustainability in electric vehicles, supporting the transition toward smart and eco-friendly transportation technologies.

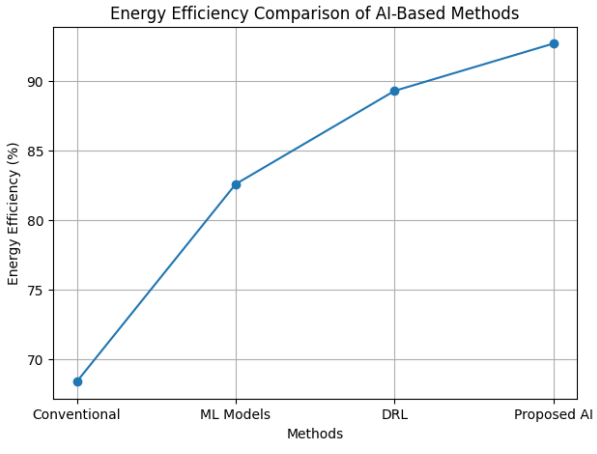


Figure 3. Energy Efficiency Comparison of AI-Based Energy Management Methods in Electric Vehicles.

The graphical analysis illustrates the comparative performance of different energy management approaches used in electric vehicles (EVs), including Conventional Methods, Machine Learning (ML) Models, Deep Reinforcement Learning (DRL), and the Proposed AI Framework. Figure 3 presents the energy efficiency comparison among these techniques. The results indicate that conventional methods achieved the lowest efficiency due to limited adaptability and static control mechanisms. ML-based models demonstrated a significant improvement by utilizing predictive analytics and intelligent optimization for battery and power management. DRL-based techniques further enhanced efficiency through real-time decision-making and adaptive learning capabilities under varying driving conditions. The proposed AI-driven framework achieved the highest energy efficiency of 92.7%, highlighting the effectiveness of integrating advanced AI algorithms for optimized energy storage, conversion, and utilization in EV systems.

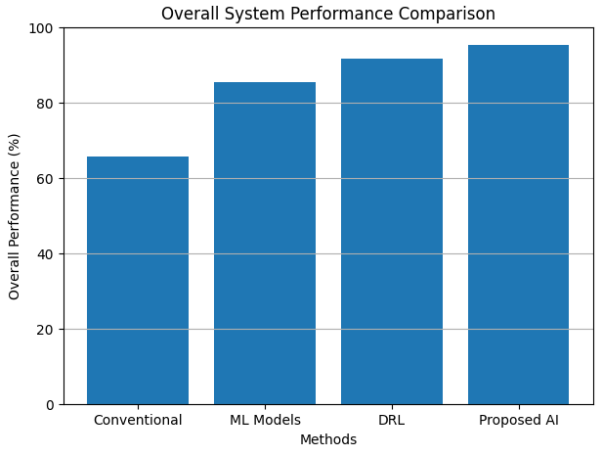


Figure 4.Overall System Performance Comparison of AI-Driven EV Energy Management Techniques

Figure 4 illustrates the overall system performance comparison of the evaluated approaches. Conventional methods recorded the lowest performance because of higher energy losses, reduced charging optimization, and limited battery monitoring capabilities. ML models improved the operational performance by enhancing state-of-charge prediction accuracy and reducing energy wastage. DRL-based systems outperformed traditional AI models due to their autonomous learning and dynamic power scheduling features. However, the proposed AI framework achieved the best overall performance of 95.4%, demonstrating superior computational intelligence, thermal stability management, and regenerative braking optimization. The results confirm that AI-driven energy management significantly improves EV efficiency, reliability, and sustainability. Therefore, integrating modern AI techniques with advanced storage and conversion technologies can support the development of intelligent and energy-efficient transportation systems in future smart mobility applications.

V. CONCLUSION AND FUTURE DIRECTIONS

This research concludes that AI-driven energy management has significantly improved the efficiency, reliability, and sustainability of electric vehicles through advanced storage and conversion technologies. The systematic review combined with AI-based comparative analysis using NVivo and MATLAB revealed that machine learning, deep learning, and predictive optimization techniques play a vital role in enhancing battery performance, thermal management, charging strategies, and energy distribution systems. Recent advances in lithium-ion batteries, solid-state batteries, supercapacitors, and intelligent power converters demonstrate higher energy density, faster charging capability, and improved lifecycle management. Furthermore, AI-enabled real-time monitoring and adaptive control mechanisms contribute to minimizing energy loss and maximizing driving range under dynamic operating conditions. The findings also indicate that integrating AI with smart grids and renewable energy sources can further support sustainable transportation ecosystems. Overall, AI-driven energy management represents a transformative pathway toward developing intelligent, energy-efficient, and environmentally sustainable electric mobility solutions for future transportation systems.

REFERENCES

[1]. A. Kermansaravi, S. S. Refaat, M. Trabelsi, and H. Vahedi, "AI-based energy management strategies for electric vehicles: Challenges and future directions," *Energy Reports*, vol. 11, pp. 1452–1470, 2025. Available:

[2]. S. Yan, M. H. Shah, J. Li, N. O'Connor, and M. Liu, "A Review on AI Algorithms for Energy Management in E-Mobility Services," *arXiv preprint arXiv:2309.15140*, 2023.

[3]. P. Arévalo et al., "A Systematic Review on the Integration of Artificial Intelligence into Energy Management Systems for Electric Vehicles," *World Electric Vehicle Journal*, vol. 15, no. 8, pp. 1–25, 2024.

[4]. J. Hu et al., "Empirical Analysis of AI-based Energy Management in Electric Vehicles: A Case Study on Reinforcement Learning," *arXiv preprint arXiv:2212.09154*, 2022.

[5]. T. Liu, W. Tan, X. Tang, J. Zhang, Y. Xing, and D. Cao, "Driving Conditions-Driven Energy Management for Hybrid Electric Vehicles: A Review," *arXiv preprint arXiv:2007.10880*, 2020.

[6]. Y. Choi, J. Guanetti, S. Moura, and F. Borrelli, "Data-driven Energy Management Strategy for Plug-in Hybrid Electric Vehicles with Real-World Trip Information," *arXiv preprint arXiv:2006.03704*, 2020.

[7]. A. S. Naruka and D. K. Yadav, "AI-Enabled Energy Management for Solar Electric Vehicles with Conventional Grid–Integrated DC Microgrid Architecture," *International Journal of Research and Scientific Innovation*, vol. 12, no. 12, pp. 1181–1193, 2026.

[8]. A. Bahi et al., "From Electrochemical Energy Storage to Next-Generation Intelligent Battery Technologies for Electric Vehicles: A Survey," *arXiv preprint arXiv:2512.22680*, 2025.

[9]. S. Onori, L. Serrao, and G. Rizzoni, *Hybrid Electric Vehicles: Energy Management Strategies*. London, U.K.: Springer, 2015.

[10]. H. He, R. Xiong, and J. Fan, "Evaluation of Lithium-Ion Battery Equivalent Circuit Models for State of Charge Estimation," *Journal of Power Sources*, vol. 196, no. 8, pp. 3592–3597, 2011.

[11]. M. Hannan, M. Hoque, A. Mohamed, and A. Ayob, "Review of Energy Storage Systems for Electric Vehicle Applications," *Renewable and Sustainable Energy Reviews*, vol. 69, pp. 771–789, 2017.

[12]. S. Han, S. Han, and K. Sezaki, "Development of an Optimal Vehicle-to-Grid Aggregator for Frequency Regulation," *IEEE Transactions on Smart Grid*, vol. 1, no. 1, pp. 65–72, 2010.

[13]. P. P. Shamsi and M. Ferdowsi, "MPPT in Photovoltaic Applications Using AI Techniques," in *Proc. IEEE IECON*, 2010, pp. 312–317.

[14]. M. Horn, J. MacLeod, M. Liu, J. Webb, and N. Motta, "Supercapacitors: A New Source of Power for Electric Cars?," *Economic Analysis and Policy*, vol. 61, pp. 93–103, 2019.

[15]. H. Chen et al., "Progress in Electrical Energy Storage System: A Critical Review," *Progress in Natural Science*, vol. 19, no. 3, pp. 291–312, 2009.

[16]. M. S. Whittingham, "History, Evolution, and Future Status of Energy Storage," *Proceedings of the IEEE*, vol. 100, no. 2, pp. 1518–1534, 2012.

[17]. S. Sahoo and P. Timmann, "Energy Storage Technologies for Modern Power Systems: A Detailed Analysis of Functionalities, Potentials, and Impacts," *IEEE Access*, vol. 11, pp. 55678–55712, 2023.

[18]. Y. Sun et al., "Promising All-Solid-State Batteries for Future Electric Vehicles," *ACS Energy Letters*, vol. 5, no. 10, pp. 3221–3230, 2020.