Electric Vehicle Battery Management System: A Comprehensive Review

Gowri Sankar P. A.[1], Shanmuga Priya S. R.[2], Karthikumar K.[3] and Suba S.[4]
[1]Department of Electrical and Electronics Engineering, Knowledge Institute of Technology, Salem, Tamil Nadu, India
[2]Department of Embedded System Technology, Knowledge Institute of Technology, Salem, Tamil Nadu, India
[3]Department of Electrical and Electronics Engineering, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Chennai, Tamil Nadu, India
[4]Mahendra Engineering College, Namakkal, Tamil Nadu, India

Keywords: Electric Vehicle, Battery Management System, Battery Charging, Batter Technology, Battery Mechanism.

Abstract: The Battery Management System (BMS) plays a critical role in enhancing the performance, safety, and longevity of Electric Vehicles (EVs). The BMS continuously monitors various parameters such as current, temperature, and overall battery health, ensuring that the battery operates within optimal conditions. The BMS collects real-time data from sensors embedded within the EV, providing insights into battery status, charge levels, and temperature fluctuations. By tracking these parameters, the BMS prevents overcharging, overheating, and deep discharging, all of which can negatively impact battery life and performance. In this article, we present an extensive literature review about the recent three year what are the advantages, techniques, mechanism, AI/ML algorithm used for the Battery Management System (BMS) is presented. This review paper plays a vital role for the research who pursuing his research especially in the BMS for advancing sustainable transportation.

1 INTRODUCTION

Electric vehicles offer significant advantages to the environment, cheaper to run, and offer a smoother, quieter ride. Electric vehicles are eco-friendly, cost-effective, and provide a smoother, quieter driving experience. Recent EV trends include rapid sales growth, tech innovations, and a focus on sustainability. Electric vehicle sales increased by 27% in 2024 relative to the previous year. Battery aging significantly impacts fuel economy, drivability, and electric range (Anselma, P. G, et, al 2022) Demonstrated effectiveness through simulations and experiments, showing improved fuel cell durability and reduced hydrogen consumption across various driving conditions (Yuan, H,et, al, 2022) Develop a comprehensive methodology for estimating the duration of lithium battery packs of electric vehicles (EVs) (Ceraolo, M, et, al, 2024)Energy management strategy using model-based reinforcement learning (MBRL) and fuel cell electric vehicles (FCEVs) Lee, H., & Cha, S. W. (2021). Efficient energy use, battery life reduction due to charge cycles, and cybersecurity threats. Novel taxonomy for battery optimization, demand-side management, revenue maximization, and machine learning applications (Colucci, R, et, al, 2024) Rolling resistance increases significantly with speed. Aerodynamic drag is influenced by gradient. Proposed a hybrid Pneumatic-Liquid Thermal Management System to battery temperature control (Agrawal, A, et, al, 2023) Classifies EMS methodologies into rule-based, dynamic optimization-based, and learning-based strategies. Emphasizes lifetime optimization of fuel cell systems and batteries (Rudolf, T, et, al, 2021)

Examines the critical role of the Battery Management Systems (BMS) in battery-powered UAVs. Identifies nine key areas categorized into: Charging and discharging strategies, Battery state estimation (SOC, SOH, RUL), System components and safety issues (Jiao, S, et, al, 2023) Developing the Model Predictive Control (MPC) based Energy Management System (EMS) for series hybrid electric agricultural tractor. Achieved 7.2% fuel reduction, improved battery state of health (SoH), and better thermal management relative to the conventional rule-based EMS (Curiel-Olivares, G, et, al, 2023). Historical safety concerns with Li-ion batteries across

A., G. S. P., R., S. P. S., K., K. and S., S.
Electric Vehicle Battery Management System: A Comprehensive Review.
DOI: 10.5220/0013914000004919

In *Proceedings of the 1st International Conference on Research and Development in Information, Communication, and Computing Technologies (ICRDICCT'25 2025) - Volume 4*, pages 402-412
ISBN: 978-989-758-777-1

various applications. Lack of customer safety consideration; corrective actions insufficient to address root causes. Suggestions for improved safety measures in future EV battery implementations (Aalund, R, et, al 2021). The article explores the electrification of road freight in India, focusing on battery-electric trucks (BETs) and their potential to address health, ecological and energy security issues related to conventional transportation. It presents the usage of energy simulation study tailored to Indian conditions, analysing key components such as powertrain systems, battery technologies, and charging infrastructure. The findings aim to inform future research on the feasibility and practicality of BETs in India, ultimately supporting the transition towards sustainable transportation solutions (Madichetty, S, et, al, 2022)

Utilizes LSTM for real-time velocity prediction and a neural network-optimized rule-based energy management strategy. Prolonged battery lifespan by 26.85%. Reduced total energy losses by 22.25%. Improved efficiency and energy throughput for supercapacitors (Udeogu, C. U, et, al, 2022). The proposed system significantly reduces peak load demand and operational costs in real distribution networks. Utilizes real load patterns, various EV types, and financial analysis to validate performance against prediction-based techniques (Das, N, et, al, 2023). Utilizes MATLAB/Simulink for system configuration and Mixed Integer Programming (MIP) for cost calculations. Two test cases demonstrate the model's effectiveness in both regulated and deregulated environments. Findings indicate notable economic savings and efficient battery state of charge (SOC) management. The framework is applicable to various operational environments, enhancing the feasibility of OLEV systems (Nisar, F, et, al, 2021). Developed a battery model using real-world data; integrated into an optimization scheme. Advanced thermal models are crucial in charging power > 7 Kw. Ignoring battery aging can underestimate operating costs by up to 30%. Effective Vehicle-to-Grid (V2G) services require consideration of battery aging costs and dynamic electricity tariffs (Schwenk, K, et, al, 2021). Figure 1 shows Battery Management System (BMS) for electric vehicles, where sensors attached to the battery module measure current, voltage, and temperature. This data is then processed by the BMS, which calculates and communicates state of charge (SOC), state of health (SOH), thermal management, and power optimization to a display unit, ensuring the safety and optimal performance of the battery pack.

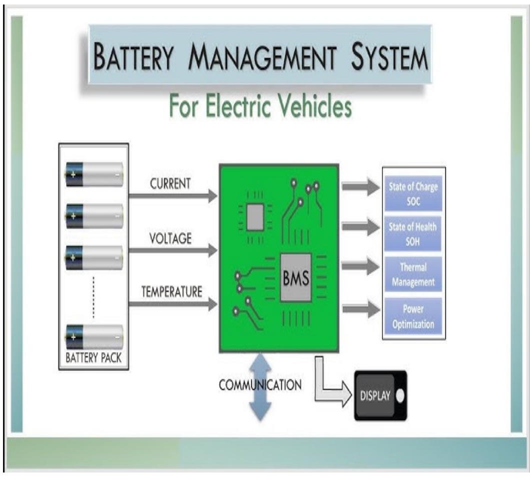

Figure 1: Battery management system (BMS).

2 BATTERY MANAGEMENT SYSTEM

2.1 Literature Review

Research on the electric vehicle charging safety warning system (Diao, X, et, al, 2023). This paper discusses the model predicts voltage changes during charging, dynamically adjusts warning thresholds, and effectively identifies abnormal charging data, enhancing safety and reducing risks of fire incidents. In this paper, the limitations of the study regarding data acquisition for EV charging, is founded upon the limitations in data acquisition concerning the State of Health (SOH) of the battery cell and the lack of complete life cycle EV charging data. Additionally, the collected charging information lacked any fault data, which could affect the robustness of the early warning model. Further research is suggested to explore these areas in greater depth.

Machine learning-based on the battery management system for the electric vehicle (Duraisamy, T, 2021). This paper focuses on improving battery management systems (BMS) for electric vehicles through an optimal cell balancing mechanism. It employs machine learning algorithms to select balancing resistors based on factors such as cell imbalance, balancing time, and temperature, resulting in enhanced balancing speed, reduced power loss, and better thermal management compared to traditional methods. The effectiveness of the suggested mechanism is evaluated using BPNN, RBNN, and LSTM models, showcasing superior accuracy and efficiency. The main categories of the machine learning methods used in battery management system applications are categorized into supervised learning, unsupervised learning, semi-supervised learning and reinforcement learning.

Review of cloud-based lithium-ion battery management systems for the electric vehicle (Ismail, M., & Ahmed, R. 2024). The Cloud computing enhances BMS efficiency and reliability. Identified research gaps include online learning, connectivity, and security. Future work should integrate recent cloud advancements to improve BMS functionality. Battery Management Systems (BMS) face challenges such as limited onboard computational resources, which restrict the use of accurate state estimation techniques and lead to energy inefficiencies. Additionally, BMS cannot be updated remotely, making it difficult to adapt to changes in battery behaviour due to aging and preventing manufacturers from offering new features. These limitations hinder the overall performance and reliability of BMS in electric vehicles.

Energy management in hybrid electric and hybrid energy storage system vehicles (Maghfiroh, H, 2024). This paper emphasizes the environmental benefits of HEVs and HESS EVs while discussing various types of FLC and their practical applications. Additionally, the review analyses the advantages and challenges associated with FLC EMS and outlines future research directions in this field. The benefits of using Fuzzy Logic Controllers in managing energy consumption in hybrid vehicles, Fuzzy Logic Controllers (FLC) in effective energy management in hybrid vehicles brings numerous advantages, such as enhanced adaptability to varying driving conditions, leading to enhanced fuel efficiency and reduced power consumption. They outperform traditional control methods, such as Proportional-Integral (PI) and Sliding Mode Control (SMC), in areas like voltage regulation and energy management. Additionally, FLCs can be combined with other methods to address limitations and optimize performance, contributing to more efficient and sustainable transportation solutions.

Development of fuzzy logic and ANFIS control for the energy management in electric vehicle (Suhail, M., et, al, 2024) This study centres on the development of the fuzzy logic and Adaptive Neuro-Fuzzy Inference System (ANFIS) controllers for managing energy consumption in hybrid electric vehicles (HEVs). The primary goal is to improve the state of charge (SOC) of battery to enhance vehicle autonomy and efficiency. Results indicate that the ANFIS controller outperforms the fuzzy logic controller in maintaining higher SOC levels, suggesting better energy management strategies for HEVs. The ANFIS controller improves the SOC profile of hybrid electric vehicles by utilizing precise fuzzy modelling and real-time data to adaptively control the battery charging process. It analyses input variables such as state of charge (SOC) and engine speed to adjust the forward gain, optimizing the quantity of generated torque utilized for the battery charging. This leads to a smoother SOC curve and an increased SOC levels by the conclusion of the drive cycle, enhancing overall energy efficiency and performance.

Prediction of the battery state using the digital twin framework (Jafari, S, et, al, 2022). The methodology employs Extreme Gradient Boost (XGBoost) and Extended Kalman Filter (EKF) to achieve accurate battery state estimation. The findings indicate that the DT model significantly improves the reliability, optimization, and accuracy of battery management, ultimately extending battery life through effective monitoring and predictive maintenance. The main types of battery cell models discussed in the paper are Equivalent Circuit Models (ECM), electrochemical models, and machine learning models. Each model boasts unique strengths and limitations, playing different roles in the battery system digital twin. ECMs are particularly used for accurately monitoring the battery cell, state of charge (SOC), and state of health (SOH).

Online data-driven efficient energy management of the hybrid electric vehicle (Lee, H, et, al, 2020): The proposed framework is designed to learn driving conditions and adapt control policies in real-time, resulting in simulation outcomes that demonstrate near-optimal fuel economy, surpassing conventional rule-based strategies. This work enhances the understanding of HEV control and offers a robust, explainable approach to energy management, with future efforts aimed at experimental validation and balancing computational efficiency with fuel economy performance. The proposed Q-learning algorithm enhances fuel economy in hybrid electric vehicles by utilizing a model-based approach that learns from real-time driving data to optimize control policies. It effectively separates the internal powertrain dynamics from external driving conditions, allowing for a more tailored and efficient energy management strategy. Furthermore, the algorithm's ability to update the vehicle state approximation model through interactions helps refine decision-making, leading to improved fuel efficiency over time.

Battery management techniques for an electric vehicle traction system (Abdelaal, A. S, et, al, 2022): This paper focuses on the implementation of Battery

Energy Management (BEM) techniques in electric vehicle (EV) traction systems, specifically utilizing conventional Fuzzy Logic Controller (FLC) and the Model Predictive Control (MPC) alongside a Cascaded FLC (CSFLC) to enhance battery longevity and minimize current fluctuations. The findings suggest that the CSFLC technique improved battery lifetime by 5.6% during the New European Driving Cycle (NEDC) & 6.1% during the US06 cycle, while also demonstrating lower battery current consumption compared to the traditional FLC approach. Overall, the study highlights the efficiency of advanced control strategies in optimizing energy use for EV traction systems. The Fuzzy MPC (FMPC) technique contributes to battery energy management in EVs by generating a reference current signal for motor speed regulation while dynamically adjusting the input weight in the MPC depending on the battery's state of charge (SOC) and its variations. This approach minimizes battery energy consumption and degradation by optimizing the current signal in real-time, leading to extended battery runtime and lifetime. Additionally, FMPC exhibits lower computational effort compared to traditional methods, enhancing overall system efficiency.

Energy management system for hybrid renewable energy (Karmaker, A, et, al, 2023). The document discusses the operation and maintenance costs (Co&m) associated using Electric Vehicle Charging Stations (EVCS) and highlights the payback period (PBP) for charging station owners, which is relatively short, indicating profitability. It emphasizes the use of a SIMULINK model to optimize power generation and charging costs, resulting in a 74.67% reduction in energy costs compared to flat rate tariffs. Additionally, the integration of hybrid renewable resources significantly lowers greenhouse gas emissions. The integration of renewable resources in EV charging stations leads to a significant reduction in charging costs, especially during off-peak hours, with savings of up to 74.67% compared to conventional rates. Additionally, it results in a CO2 emission reduction of up to 54.86% when 84% of the energy is sourced from renewables, thereby enhancing environmental sustainability. Overall, increased renewable utilization decreases both charging costs and greenhouse gas emissions.

Development of optimal power-distribution-management algorithm (Lee, H, et, al, 2021): This research is dedicated to developing an ideal allocation of power control algorithm for the 4WD electric vehicles to enhance improving battery efficiency and driving range. Simulations demonstrated improvements in battery efficiency improved by 0.2% under the specified conditions urban driving and 2.52% on highways compared to a comparison model, with increased driving efficiency at high-speed and high-torque ranges. Future efforts will aim to refine the power allocation ratio contingent on actual driving behaviour and environmental factors to further improve the performance of the 4WD electric vehicles. The study employed urban and simulations of highway driving based on EPA standards for analysing battery performance. It utilized dynamic programming and Pontryagin's minimum principle for optimizing power distribution, and MATLAB/Simulink for modelling the vehicle's dynamic characteristics. Performance comparisons were conducted between the proposed optimal power distribution algorithm and a comparison model to assess battery efficiency and power consumption.

Energy management of the hybrid electric vehicles by sequential programming (Ghandriz, T, et, al, 2021): The document discusses a sequential programming and gear optimization algorithm for hybrid powertrains, focusing on minimizing energy consumption by selecting optimal gears based on vehicle speed and force. It outlines the constraints and equations governing the system, including power balance among various components like internal combustion engine (ICE) and electric motor (EM). Additionally, it highlights the importance of preventing frequent gear shifts to enhance fuel efficiency and overall performance. The study utilized sequential linear programming (SLP) and compared it with sequential quadratic programming (SQP) to address the predictive control problem. It also mentioned the application of dynamic programming (DP) and Pontryagin's minimum principle (PMP) as model-based solution methods for optimal control. These methods were employed to address the challenges of real-time predictive energy management for the hybrid electric vehicles.

Driving cycle recognition for the hybrid electric vehicles (Chen, D, et, al, 2022): This paper focuses on developing an adaptive equivalent consumption minimization strategy (A-ECMS) for the hybrid electric vehicles (HEVs) by employing driving cycle recognition. The authors utilize a learning vector quantization (LVQ) neural network, achieving a recognition accuracy of 98%. The results demonstrate that A-ECMS enhances fuel economy by 3.8% in the New European Driving Cycle (NEDC) and 3.6% in the China Heavy-duty Truck Cycle (CHTC-LT) compared to traditional logic-based energy management strategies. The primary goal of the study on A-ECMS for hybrid electric vehicles (HEVs) is to create an adaptive equivalent consumption minimization strategy that optimizes fuel consumption by recognizing driving cycles, thereby improving energy management and overall fuel economy.

Comparative performance of the machine learning algorithm for predicting electric vehicles energy consumption (Ullah, I, et, al, 2022): The research assesses a range of machine learning (ML) frameworks for forecasting electric vehicle (EV) energy usage, utilizing data derived from 38,362 trips in Aichi Prefecture, Japan. Advanced ML models, specifically XGBOOST and Light GBM, demonstrated superior prediction accuracy compared to conventional frameworks such as multiple linear regression (MLR) and artificial neural networks (ANN). Key factors impacting energy consumption include trip distance, heater and A/C usage, and road gradient, with Light GBM achieving the best performance, reflected by an R^2 of 0.98, highlighting its effectiveness in this domain. The dataset was split into two sections: 80% for training and 20% for testing. This division is crucial for evaluating the efficacy of the proposed machine learning algorithms. Additionally, a 10-fold cross-validation method was utilized to improve the robustness and efficacy of the prediction models.

A real-time energy management strategy for the hybrid electric vehicles (Lee, W, et, al, 2021) It highlights the potential of HEVs to enhance fuel efficiency significantly while addressing the challenges of transitioning to zero-emission vehicles. The suggested approach showcases enhanced performance compared to existing adaptive Energy Consumption Management Strategies (ECMS), achieving fuel efficiency improvements of 0.5% to 1.5% across different driving cycles. Future driving information is crucial in the proposed control strategy as it allows the intelligent control part to estimate the optimal costate in real-time, enhancing decision-making for energy management. By predicting factors such as vehicle power demand, speed, and acceleration, the strategy can adjust the costate to optimize the distribution of energy between fuel and electricity, leading to improved fuel efficiency. This predictive capability enables the vehicle to proactively manage its energy resources, ensuring better performance under varying driving conditions.

Battery management system of electric vehicle using an artificial neural network (Afzal, M, et, al, 2024) This paper presents an innovative Battery Management System (BMS) that combines artificial neural networks (ANN) and fuzzy logic. This new system features decentralized control and communication-free operation, leading to improved reliability, a 15% increase in energy efficiency, and a 20% enhancement in battery life. The BMS was validated through simulations and experimental prototypes utilizing a 100kWh lithium-ion battery pack, representing a substantial advancement in electric vehicle battery management. The key innovations in the new Battery Management System (BMS) for electric vehicles include the application of artificial neural networks (ANN) and fuzzy logic for decentralized control and communication-free operation. It features adaptive virtual admittance for even load sharing, leading to improved reliability, a 15% increase in energy efficiency, and a 20% enhancement in battery life.

Energy modelling for the electric vehicles building on real driving cycles Mądziel, M. (2024). The study analyses real driving cycles across varying temperatures, yielding a summer model with an R^2 of 0.86 and MSE of 1.4, and a winter model with an R^2 of 0.89 and MSE of 2.8. The findings are intended to assist city planners in optimizing charging infrastructure and enhancing the understanding of EV energy behaviour in different environmental conditions. The neural network method performs comparably to gradient boosting in predicting energy values for electric vehicles, with superior validation results, particularly for the test set. While the random forest technique shows slightly better performance, the neural network method is recognized as the best due to its lower error rates and effective predictions. Overall, the neural network method is favoured for its simplicity and satisfactory results in energy consumption modelling.

AI models for energy efficiency in hybrid and electric vehicles Mądziel, M., & Campisi, T. (2024). The model demonstrates high accuracy in forecasting energy usage based on vehicle velocity and acceleration, which can significantly aid in optimizing charging infrastructure and energy management. The findings support sustainable transport policies and provide valuable insights for decision-making among EV users. This study contributes to intelligent optimizing energy usage in electric vehicles (EVs) by accurately predicting energy consumption based on driving conditions, such as velocity and acceleration. This anticipatory feature enables better strategic planning regarding the deployment of charging stations and the incorporation of renewable energy sources into the grid. Additionally, it enhances the understanding of vehicle operation for users, ultimately supporting environmental protection and optimizing energy use goals.

Role of generative artificial intelligence in internet of the electric vehicles (Zhang, H, et, al, 2024): The paper explores GAN-based methods, especially WGAN-GP, for addressing uncertainties in EV charging load analysis using data from 32 stations in Zhejiang. It highlights the limited comparative studies with other Generative AI methods and introduces CopulaGAN for generating diverse vehicle types. These approaches aim to improve EV charging behaviour generation and data augmentation for better scheduling. The purpose of the WGAN-GP approach in EV charging load analysis is to tackle spatial-temporal uncertainty by generating realistic EV charging scenarios without relying on uniform probability assumptions across charging stations. It aims to explore load dynamics and improve the accuracy of load forecasting at various nodes in the distribution network. This method enhances the understanding of EV charging behaviours and their impact on the power grid.

Artificial intelligence for the electric vehicle energy systems integration (Hua, W, et, al, 2023): The paper discusses the incorporation of electric vehicles (EVs) into energy systems through the application of artificial intelligence (AI). It highlights challenges such as battery production, charging infrastructure, and grid demand, while reviewing AI's role in optimizing EV integration, including range prediction and load management. Additionally, it identifies limitations like gaps in real-world validation and consumer trust, and suggests future research directions focusing on advancements in AI algorithms, explainability, and peer-to-peer energy trading. The main technical challenges faced by electric vehicles (EVs) include battery technology issues such as capacity, range, charging efficiency, lifespan, and cost. Additionally, developing sufficient charging infrastructure and decarbonizing the battery supply chain are significant hurdles. Public opinion and high costs also impact EV adoption.

Recent AI applications in electrical vehicles for sustainability (Reddy, K, et, al, 2024): The paper discusses the function of artificial intelligence (AI) in electric vehicles (EVs) to enhance sustainability by improving vehicle control, energy management, and battery design. It notes significant reductions in greenhouse gas emissions but highlights challenges like data security and regulatory issues. The authors emphasize the necessity for future research to tackle these challenges and improve infrastructure for AI in EVs. AI contributes the energy management of the electric vehicles (EVs) by optimizing charging schedules, predicting energy usage, and enhancing battery management systems. It utilizes algorithms for range prediction, smart charging, and grid integration, which help reduce peak grid loads and improve overall efficiency. Additionally, AI enables real-time monitoring and control of energy consumption, ultimately maximizing driving range and minimizing operating costs. Table 1 show the Authors, Features, Mechanism Used, Advantages and Disadvantages.

Table 1: Authors, features, mechanism used, advantages and disadvantages.

Reference Paper	Year	Features	Control Technique	Advantages	Disadvantages
Xiaohong Diao, et. al.	2023	- Early warning system for EV charging safety - Prediction of voltage changes	Adaptive Long Short-Term Memory (A-LSTM) algorithm	- Accurate prediction of voltage changes - Dynamic adjustment of warning thresholds - Real-time warnings	- Requires extensive historical charging data - Potential for false alarms if data is not accurate
Thiruvonasundari et. al.	2021	- Optimal cell balancing for EV batteries - Improved balancing time and power loss management	Machine Learning (ML) algorithms (BPNN, RBNN, LSTM)	- Enhanced battery run time and lifespan - Optimized power loss management	- Requires accurate data for effective balancing - Implementation complexity

Mohanad Ismail, et. al.	2024	- Integration with cloud computing - Enhanced data analysis and monitoring - Real-time battery management	Cloud-based data processing and analytics	- Improved battery performance and lifespan - Enhanced predictive maintenance - Better resource utilization	- Dependency on internet connectivity - Potential data privacy concerns - Implementation complexity
Hari Maghfiroh, et. al.	2024	- Efficient energy utilization in hybrid electric and hybrid energy storage system vehicles - Fuzzy logic controller (FLC)	Fuzzy Logic Controller (FLC)	- Efficient energy storage and power flow regulation - Improved performance and stability	- Complexity in designing and modelling - Requires accurate rule definition
Mohammad Suhail, et. al.	2021	- Progressive fuzzy logic - Adaptive Neuro-Fuzzy Inference System (ANFIS) - Efficient energy utilization for plug-in hybrid electric vehicles	Fuzzy Logic Controller (FLC) and ANFIS	- Improved battery performance - Enhanced energy management - Better fuel efficiency	- Complexity in designing and modelling - Requires accurate rule definition
Sadiqa Jafari, et. al.	2022	- Digital Twin framework - State of Health (SOH) & State of Charge (SOC) prediction	Extreme Gradient Boost (XGBoost) and Extended Kalman Filter (EKF)	- Enhanced situational awareness - Accurate SOH and SOC estimation - Improved battery maintenance	- Requires accurate data for effective predictions - Complexity in implementation
Heeyun Lee, et. al.	2020	- Online data-driven energy management - Model-based Q-learning	Model-Based Q-Learning	- Adaptive to driving environment - Near optimal control solution - Improved fuel economy	- Requires accurate model of vehicle dynamics - Complexity in implementation
Ahmed Sayed Abdelaal, et. al.	2022	- Two battery energy management (BEM) techniques - Indirect field-oriented (IFO) induction motor (IM) drive system	- Cascaded Fuzzy Logic Controllers (CSFLC) - Fuzzy Tuned Model Predictive Control (FMPC)	- Regulates motor speed - Minimizes battery pack state of charge (SOC) reduction and state of health (SOH) degradation	- Requires accurate battery information - Higher computational burden for CSFLC compared to FMPC

				- Prolongs battery runtime and lifetime	
Ashish Kumar Karmaker, et. al.	2023	- Hybrid solar and biogas-based EV charging station - Fuzzy inference system	Fuzzy Logic Controller (FLC)	- Optimizes real-time charging costs - Enhances renewable energy utilization - Reduces greenhouse gas emissions	- Requires accurate data for effective management - Dependency on renewable energy sources
Hae-Sol Lee, et. al	2021	- Optimal power distribution for 4WD EVs - Improved battery efficiency	Power-distribution-management optimization algorithm	- Increased vehicle battery range - Reduced power loss - Enhanced driving energy efficiency	- Requires accurate vehicle driving condition data - Complexity in implementation
Toheed Ghandriz, et. al.	2021	- Real-time predictive energy management - Optimal control strategy - Sequential linear programming	Model Predictive Control (MPC) and Sequential Linear Programming	- Reduced fuel consumption - Optimal power split between vehicle power sources and brakes - Enhanced vehicle performance	- Requires high-fidelity vehicle model for accurate predictions - Complexity in real-time implementation
Dongdong Chen, Tie Wang, et. al.	2022	- Adaptive Equivalent Consumption Minimization Strategy (ECMS) - Driving cycle recognition	Neural networks and optimization algorithms	- Improved fuel economy - Enhanced adaptability to driving conditions - Better energy management	- Requires accurate driving cycle data - Complexity in implementation
Irfan Ullah et. al.	2022	- Comparative performance of ML algorithms - Prediction of EV energy consumption	Extreme Gradient Boosting (XGBoost) and Light Gradient Boosting Machine (LightGBM)	- Higher accuracy in prediction - Better performance compared to traditional models - Enhanced sustainability	- Necessitates substantial data for training purposes - Complexity in implementation
Woong Lee, et. al.	2021	- Real-time intelligent energy management - Reinforcement	Deep Q-Networks (DQN)	- Improved energy efficiency - Optimal control parameter determination	- Requires extensive training data - Complexity in implementation

		learning (Deep Q-Networks)		- Enhanced vehicle performance	
Muhammad Zeshan Afzal, et. al.	2023	- ANN-based adaptive droop control theory - Improved load distribution - Enhanced battery performance	Artificial Neural Network (ANN) and Fuzzy Logic	- Decentralized control architecture - Communication-free capability - Improved reliability and efficiency	- Requires accurate SOC data - Complexity in implementation
Maksymilian Mądziel et. al.	2024	- AI-based energy modelling - Real driving cycles - Microscale analysis	Neural Networks	- High precision in energy consumption prediction - Rapid generation of results - Creation of energy maps	- Necessitates substantial data for training purposes - Complexity in implementation
Maksymilian Mądziel, et. al.	2024	- AI-based energy efficiency models - Real driving cycles - Microscale analysis	Deep Neural Network (DNN)	- High accuracy in energy consumption prediction - Versatility in application - Useful for transport policy planning	- Necessitates substantial data for training purposes - Complexity in implementation
Hanwen Zhang, Dusit Niyato, et. al.	2024	- Generative AI in IoEV - Applications across multiple layers	Generative AI techniques	- Enhanced charging management - Improved cyber-attack prevention - Versatile applications across different layers	- Requires extensive data for training - Complexity in implementation
Weiqi Hua, Daniel Mullen, et. al.	2024	- AI for EV energy systems integration - Addressing integration challenges	Various AI techniques	- Enhanced integration of EVs into energy systems - Improved energy management - Support for global Net Zero transition	- Necessitates substantial data for training purposes - Complexity in implementation
K. Balaji Nanda, et. al.	2024	- AI applications in EVs Sustainable transportation solutions	Various AI techniques	- Improved vehicle control - Enhanced energy management - Reduced greenhouse gas emissions	- Requires extensive data for training - Complexity in implementation

3 CONCLUSIONS

This paper's primary goal is to provide an in-depth analysis of the battery management systems that are already in use for different types of electric vehicles. The review article summarizes the various methods, algorithm proposed for the BMS and provide a clear knowledge for the unconfiguring researchers and methods for the new BMS. One of the fundamental components of electrical energy storage systems is the BMS. The components, topology, operation, and functionality of BMS for energy storage systems are all covered in detail in this study. Although the BMS can have a variety of configurations depending on the application, its fundamental operating objective and safety feature never change. The research offers BMS suggestions for the present market and battery technologies.

REFERENCES

Aalund, R., Diao, W., Kong, L., & Pecht, M. (2021). Understanding the non-collision related battery safety risks in electric vehicles a case study in electric vehicle recalls and the LG chem battery. IEEE Access, 9, 89527-89532.

Abdelaal, A. S., Mukhopadhyay, S., & Rehman, H. (2022). Battery energy management techniques for an electric vehicle traction system. IEEE Access, 10, 84015-84037.

Afzal, M. Z., Aurangzeb, M., Iqbal, S., Pushkarna, M., Rehman, A. U., Kotb, H., ... & Bereznychenko, V. (2023). A Novel Electric Vehicle Battery Management System Using an Artificial Neural Network-Based Adaptive Droop Control Theory. International Journal of Energy Research, 2023(1), 2581729.

Agrawal, A., Singh, R., Kumar, N., Singh, V. P., Alotaibi, M. A., Malik, H., ... & Hossaini, M. A. (2023). Mathematical Modeling of Driving Forces of an Electric Vehicle for Sustainable Operation. IEEE Access, 11, 95278-95294.

Anselma, P. G., Kollmeyer, P. J., Feraco, S., Bonfitto, A., Belingardi, G., Emadi, A., ... & Tonoli, A. (2022). Economic Payback Time of Battery Pack Replacement for Hybrid and Plug-In Hybrid Electric Vehicles. IEEE Transactions on Transportation Electrification, 9(1), 1021-1033.

Ceraolo, M., Fioriti, D., Lutzemberger, G., Quilici, F. G., Scarpelli, C., & Bianchi, F. (2024). Electro-Thermal Modeling and aging evaluation of Lithium Battery Packs for Electric Vehicles. IEEE Access.

Chen, D., Wang, T., Qiao, T., Yang, T., & Ji, Z. (2022). Driving cycle recognition based adaptive equivalent consumption minimization strategy for hybrid electric vehicles. IEEE Access, 10, 77732-77743.

Colucci, R., Mahgoub, I., Yousefizadeh, H., & Al-Najada, H. (2024). Survey of strategies to optimize battery operation to minimize the electricity cost in a microgrid with renewable energy sources and electric vehicles. IEEE Access.

Curiel-Olivares, G., Johnson, S., Escobar, G., & Schacht-Rodríguez, R. (2023). Model Predictive Control-Based Energy Management System for a Hybrid Electric Agricultural Tractor. IEEE Access, 11, 118801-118811.

Das, N., Haque, A., Zaman, H., Morsalin, S., & Islam, S. (2023). Domestic load management with coordinated photovoltaics, battery storage and electric vehicle operation. IEEE Access, 11, 12075-12087.

Diao, X., Jiang, L., Gao, T., Zhang, L., Zhang, J., Wang, L., & Wu, Q. (2023). Research on Electric Vehicle Charging Safety Warning Based on A-LSTM Algorithm. IEEE Access, 11, 55081-55093.

Duraisamy, T., & Kaliyaperumal, D. (2021). Machine learning-based optimal cell balancing mechanism for electric vehicle battery management system. IEEE Access, 9, 132846-132861.

Ghandriz, T., Jacobson, B., Murgovski, N., Nilsson, P., & Laine, L. (2021). Real-time predictive energy management of hybrid electric heavy vehicles by sequential programming. IEEE Transactions on Vehicular Technology, 70(5), 4113-4128.

Hua, W., Mullen, D., Wahid, A., Sitabkhan, K., & Mason, K. (2023, September). An overview of artificial intelligence for electric vehicle energy systems integration. In European Conference on Artificial Intelligence (pp. 178-186). Cham: Springer Nature Switzerland.

Ismail, M., & Ahmed, R. (2024). A Comprehensive Review of Cloud-Based Lithium-Ion Battery Management Systems for Electric Vehicle Applications. IEEE Access.

Jafari, S., & Byun, Y. C. (2022). Prediction of the battery state using the digital twin framework based on the battery management system. IEEE Access, 10, 124685-124696.

Jiao, S., Zhang, G., Zhou, M., & Li, G. (2023). A Comprehensive Review of Research Hotspots on Battery Management Systems for UAVs. IEEE Access.

Karmaker, A. K., Hossain, M. A., Pota, H. R., Onen, A., & Jung, J. (2023). Energy management system for hybrid renewable energy-based electric vehicle charging station. IEEE Access, 11, 27793-27805.

Lee, H., Kang, C., Park, Y. I., Kim, N., & Cha, S. W. (2020). Online data-driven energy management of a hybrid electric vehicle using model-based Q-learning. IEEE Access, 8, 84444-84454.

Lee, H. S., Hwang, M. H., & Cha, H. R. (2021). Development of an optimal power-distribution-management algorithm for four-wheel-drive electric vehicles. IEEE Access, 9, 99731-99741.

Lee, H., & Cha, S. W. (2021). Energy management strategy of fuel cell electric vehicles using model-based reinforcement learning with data-driven model update. IEEE Access, 9, 59244-59254.

Lee, W., Jeoung, H., Park, D., Kim, T., Lee, H., & Kim, N. (2021). A real-time intelligent energy management strategy for hybrid electric vehicles using reinforcement learning. IEEE Access, 9, 72759-72768.

Madichetty, S., Neroth, A. J., Mishra, S., & Babu, B. C. (2022). Route towards road freight electrification in India: examining battery electric truck powertrain and energy consumption. Chinese Journal of Electrical Engineering, 8(3), 57-75.

Mądziel, M., & Campisi, T. (2024). Predictive AI Models for Energy Efficiency in Hybrid and Electric Vehicles: Analysis for Enna, Sicily.

Mądziel, M. (2024). Energy Modeling for Electric Vehicles Based on Real Driving Cycles: An Artificial Intelligence Approach for Microscale Analyses. Energies, 17(5), 1148.

Maghfiroh, H., Wahyunggoro, O., & Cahyadi, A. I. (2024). Energy Management in Hybrid Electric and Hybrid Energy Storage System Vehicles: A Fuzzy Logic Controller Review. IEEE Access.

Nisar, F., Haider, S., Alam, I., Waqar, A., Ahmed, T., & Usman, M. (2021). Parametic Model for Optimization of Battery Capacity and Power Transmitters of On-line Electric Vehicles in Closed/Open Environments. CSEE Journal of Power and Energy Systems, 9(1), 185-196.

Reddy, K. B. N. K., Pratyusha, D., Sravanthi, B., & Reddy, E. J. Recent AI Applications in Electrical Vehicles for Sustainability, International Journal of Mechanical Engineering, Volume 11 Issue 3, Year of Publication: 2024.

Rudolf, T., Schürmann, T., Schwab, S., & Hohmann, S. (2021). Toward holistic energy management strategies for fuel cell hybrid electric vehicles in heavy-duty applications. Proceedings of the IEEE, 109(6), 1094-1114.

Schwenk, K., Meisenbacher, S., Briegel, B., Harr, T., Hagenmeyer, V., & Mikut, R. (2021). Integrating battery aging in the optimization for bidirectional charging of electric vehicles. IEEE Transactions on Smart Grid, 12(6), 5135-5145.

Suhail, M., Akhtar, I., Kirmani, S., & Jameel, M. (2021). Development of progressive fuzzy logic and ANFIS control for energy management of plug-in hybrid electric vehicle. Ieee Access, 9, 62219-62231.

Udeogu, C. U., & Lim, W. (2022). Improved deep learning-based energy management strategy for battery-supercapacitor hybrid electric vehicle with adaptive velocity prediction. IEEE Access, 10, 133789-133802.

Ullah, I., Liu, K., Yamamoto, T., Al Mamlook, R. E., & Jamal, A. (2022). A comparative performance of machine learning algorithm to predict electric vehicles energy consumption: A path towards sustainability. Energy & Environment, 33(8), 1583-1612.

Yuan, H. B., Zou, W. J., Jung, S., & Kim, Y. B. (2022). A real-time rule-based energy management strategy with multi-objective optimization for a fuel cell hybrid electric vehicle. IEEE Access, 10, 102618-102628.

Zhang, H., Niyato, D., Zhang, W., Zhao, C., Du, H., Jamalipour, A., ... & Pei, Y. (2024). The roles of generative artificial intelligence in internet of electric vehicles. arXiv preprint arXiv:2409.15750.