Journal of Information Systems Engineering and Management
2025, 10(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Advanced Tools Used in Electric Vehicle Battery Management Systems: A Comprehensive Review

Bhushan Chavan[1], Dr. Manish Pokharna[2], Dr. Sameer Nanivadekar[3], Dr. Amol Shinde[4]
[1]*Research Scholar, Pacific Academy of Higher Education and Research University, Udaipur, Rajasthan, India*
ORC ID: 0000-0003-2871-784X
Email ID: bhushw14@gmail.com
[2]*Professor, Pacific Academy of Higher Education and Research University, Udaipur, Rajasthan, India*
Email ID: pokharna.manish@gmail.com
[3]*Associate Professor, A. P. Shah Institute of Technology, Thane, Maharashtra, India*
ORC ID: 0000-0002-7498-8336
Email ID: sameermanas@gmail.com
[4]*Assistant Professor, A. P. Shah Institute of Technology, Thane, Maharashtra, India*
ORC ID: 0000-0001-6711-8941
Email ID: asshinde@apsit.edu.in

ARTICLE INFO

Received: 18 Dec 2024

Revised: 10 Feb 2025

Accepted: 28 Feb 2025

ABSTRACT

The increasing adoption of electric vehicles (EVs) necessitates advancements in battery management systems (BMS) to enhance safety, performance, and longevity. This comprehensive review explores advanced tools and technologies integral to modern BMS, emphasising their roles in optimising EV efficiency and safety. Key areas discussed include the application of machine learning algorithms for predictive maintenance, advanced sensor integration for accurate system monitoring, and thermal management solutions to mitigate overheating risks. Additionally, the review highlights the innovative use of digital twins for real-time battery diagnostics and the integration of cloud computing for expansive data analysis. These technologies collectively improve the reliability and functionality of BMS, crucial for the broader acceptance and success of electric vehicles in the market.

Keywords: Electric Vehicle (EV), Battery Management System (BMS), Digital Twin, Machine Learning, Fault Detection.

1. INTRODUCTION

Battery management systems play a crucial role in maintaining the health and longevity of lithium-ion batteries, the primary energy source in electric vehicles.[1] The complexity of BMS lies in its multi-faceted responsibilities, including state estimation, cell balancing, thermal regulation, and safety protocols.[2] This review will discuss the cutting-edge tools currently employed and developed to address these challenges.

BMS is integral to ensuring that batteries operate within safe parameters, preventing overcharging, deep discharging, and temperature extremes that could lead to catastrophic failures.[3] In addition, BMS plays a pivotal role in maximising the efficiency and lifespan of batteries by maintaining optimal operating conditions. The continued development of advanced BMS technologies is vital for the widespread adoption of EVs, as they address key concerns such as safety, cost, and performance.

2. OVERVIEW OF BATTERY MANAGEMENT SYSTEMS (BMS)

A Battery Management System (BMS) is a crucial control system in electric vehicles (EVs) that monitors and manages battery cells.[3] It monitors parameters like SOC, SOH, voltage, current, and temperature to ensure safe operation and detect potential issues. BMS also balances battery cells to maintain uniform charge distribution and prevent cell damage. Proper thermal management ensures optimal operating temperatures and prevents overheating or thermal runaway.[4] BMS also protects against overcharging and deep discharge, preventing potential damage or safety risks.

Journal of Information Systems Engineering and Management
2025, 10(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

These functions ensure the reliability, safety, and longevity of EV batteries, making BMS an essential component in modern EVs.[3]

2.1 State-of-the-Art Battery Management System Architecture

The architecture of a modern BMS encompasses hardware and software components that operate in harmony to manage the battery's state of charge (SoC), state of health (SoH), and thermal characteristics.[5]

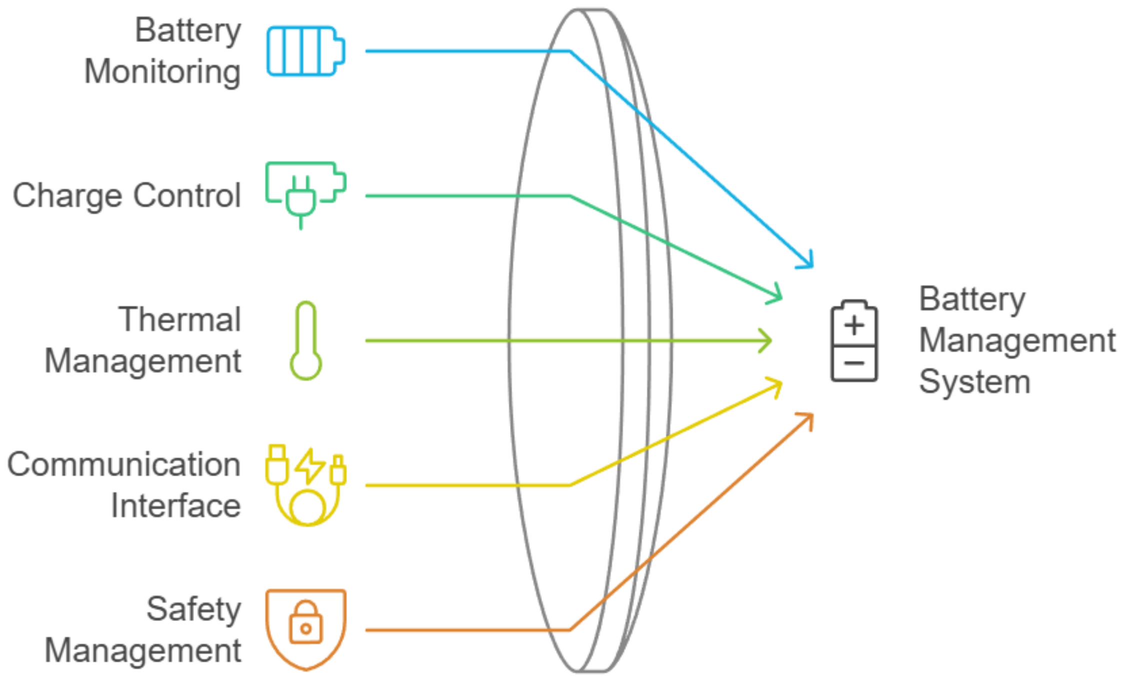

Fig. 1 State-of-the-Art Battery Management System Architecture

Microcontroller Units (MCUs) are high-performance devices that enable real-time data processing, enabling quick decision-making for safety and efficiency.[6] They often have built-in diagnostic tools for continuous monitoring of cell performance and system health. Communication protocols like CAN, LIN, and Ethernet are explored for robust data transmission, ensuring seamless data exchange between BMS components and the vehicle's ECU.[7] Power electronics, such as MOSFETs and IGBTs, are crucial for controlling electricity flow within the battery pack, facilitating efficient energy transfer and protection against short circuits. Advances in semiconductor technology have led to higher efficiency and lower thermal dissipation, as shown in figure 1.

3. ADVANCED TOOLS IN BMS

3.1 Digital Twins

The digital twin technology is a key innovation in modern battery management.[8] It creates a virtual replica of the physical battery, which interacts dynamically with the real battery and updates itself using real-time data. This approach facilitates better battery diagnostics, allows for predictive maintenance, and helps in optimizing battery usage and more parameters as shown in figure 2.

Digital twins provide a comprehensive view of battery behaviour by simulating different operating conditions and analysing their impact on the battery. This allows manufacturers and operators to optimise battery design, forecast maintenance needs, and improve overall performance. According to the literature, digital twins have been implemented to model battery behaviour, predict the remaining useful life, and control system parameters based on sensor data.[9] For example, the work by [10] on digital twins for battery packs shows how these models help optimise performance by simulating real-life operating conditions.

Journal of Information Systems Engineering and Management
2025, 10(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

The use of digital twins also enables the detection of faults before they lead to significant failures, thereby reducing downtime and improving the safety of electric vehicles. By providing a real-time representation of the battery, digital twins allow for precise monitoring and control, which is crucial for maintaining battery health.[11]

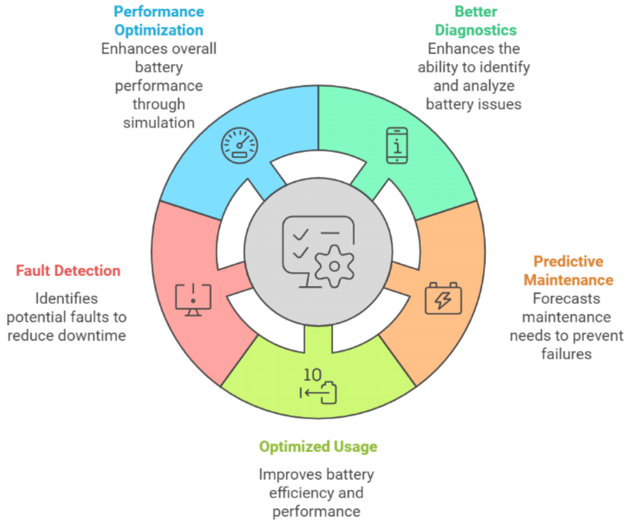

Fig. 2 Applications of Digital Twin in Battery Management

3.2 Cloud Computing for BMS

Cloud computing has significantly enhanced the computational power and storage capabilities of battery management systems. With cloud-based BMS, real-time data is collected from sensors, transmitted to the cloud, and processed using high-performance computing tools. This approach provides several advantages, such as enhanced data analysis, better storage capacity, and the ability to leverage powerful algorithms for decision-making.[12]

Bosch's cloud-based services [13] enable continuous monitoring of battery health, using machine learning algorithms to forecast battery life. The integration of cloud computing allows for remote monitoring, enabling manufacturers and users to access battery data from anywhere, thus facilitating proactive maintenance and reducing the likelihood of unexpected failures.[14]

The CHAIN framework and layered cloud architecture provide multi-scale data visualisation and enable hierarchical management of battery systems. This enhances the capability to detect faults early, predict failures, and ensure reliability. Cloud computing also supports scalability, allowing the BMS to handle increasing amounts of data as more vehicles are integrated into the system.[15]

3.3 Machine Learning in BMS

Machine learning algorithms have become an integral part of modern BMS, especially for tasks like lifetime forecasting, fault detection, and optimisation. These models leverage historical data and operating conditions to predict the degradation pattern and recommend operational strategies to extend battery life. Machine learning can identify patterns that are not apparent through traditional data analysis methods, making it a powerful tool for enhancing BMS performance.[16]

For instance, LSTM (Long Short-Term Memory) models have been used to evaluate battery performance under dynamic conditions, as explored by [17]. These models are capable of learning complex temporal dependencies, which makes them ideal for predicting the future state of batteries based on historical data. By utilising machine learning, BMS can adapt to changing conditions and optimise battery performance in real time.

Machine learning also plays a critical role in fault detection by identifying anomalies in battery behaviour. Early detection of faults can prevent catastrophic failures and extend the life of the battery. Additionally, machine learning

Journal of Information Systems Engineering and Management
2025, 10(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

models can be used to optimise charging and discharging cycles, ensuring that the battery operates efficiently and safely throughout its lifecycle.[18]

Machine learning (ML) algorithms are revolutionising the BMS landscape by enabling predictive maintenance and accurate state estimations. The integration of AI allows for more sophisticated and adaptable BMS that can respond dynamically to changing conditions.[19]

Deep learning models like recurrent neural networks and convolutional neural networks are promising for improving state estimation and energy optimisation in battery systems. These models, trained on historical data, can learn complex patterns, providing more accurate predictions than traditional methods.[20], [21] Reinforcement learning algorithms can develop adaptive strategies for cell balancing and thermal management, optimising battery performance over time for improved energy efficiency and longer battery life. Early fault detection and lifetime prediction models use machine learning techniques to predict battery cell remaining useful life and suggest maintenance schedules to prevent unexpected failures.

3.4. Advanced Sensor Integration

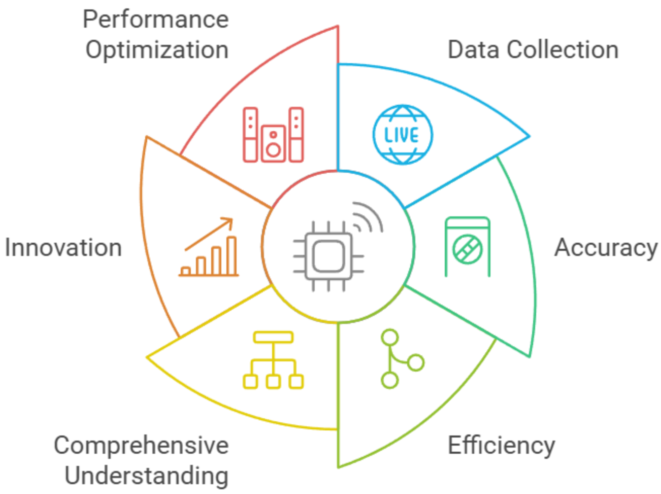

Fig. 3 Advanced Sensor Integration

Advanced sensor technologies are integral to BMS for real-time data acquisition and decision-making. These sensors provide the necessary input data for accurate monitoring and control of the battery pack as shown in figure 3.

Advanced voltage and current sensors are crucial for accurate SoC estimation, enabling real-time feedback loops to adjust charging and discharging protocols. Temperature sensors maintain optimal thermal conditions, preventing overheating and thermal runaway.[22] Modern sensors can detect minute temperature variations and trigger safety mechanisms. Impedance spectroscopy is a non-invasive monitoring technique used to detect cell degradation, providing valuable information about the internal state of the battery, helping to predict potential failures and optimize performance.[23]

3.5. Thermal Management Solutions

Thermal management is pivotal to prevent overheating, which could lead to catastrophic failures. Effective thermal management ensures that the battery operates within its optimal temperature range, improving both safety and performance.[24]

Liquid cooling systems circulate coolant through the battery pack to absorb and dissipate heat, ensuring uniform temperature across all cells and preventing hotspots. These systems also use Phase Change Materials (PCMs) in passive thermal management solutions to regulate temperature without additional energy input. Heat pipes and vapour chambers use phase change and capillary action to transfer heat away from battery cells, effectively managing high thermal loads. Active and passive hybrid cooling systems combine active cooling (liquid cooling) with passive

Journal of Information Systems Engineering and Management
2025, 10(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

cooling (PCMs) to optimise energy use while maintaining effective temperature regulation. These technologies help maintain a uniform temperature across all cells and enhance battery performance.[25]

3.6. Battery Modelling and Simulation Tools

Simulation tools are essential for designing and testing BMS solutions before real-world application. These tools help engineers understand how different strategies impact battery performance and lifespan.

MATLAB/Simulink is a widely used tool for modelling battery dynamics, including electrochemical behaviour and thermal characteristics. It allows engineers to simulate charging and discharging scenarios to evaluate battery management strategies. Analysis Fluent and COMSOL Multiphysics simulate thermal behaviours and fluid dynamics within battery packs, optimising thermal management systems. Battery Management System Simulators provide real-time simulation platforms for prototyping and testing BMS algorithms in a controlled environment, integrating with hardware-in-the-loop systems for a realistic testing experience.

4. CHALLENGES AND RESEARCH GAPS

4.1. Fault Detection and Diagnosis

Ensuring the reliability of BMS involves implementing advanced fault detection mechanisms. Detecting and diagnosing faults early can prevent costly damage and ensure the safety of both the vehicle and its occupants. Model-Based Fault Diagnosis involves creating mathematical models to represent battery system behaviour, comparing real-time data with predictions to identify potential faults. Data-Driven Approaches use machine learning models to identify faults based on sensor data patterns, offering high accuracy and adaptability. A dual-layer architecture with backup systems enhances reliability and safety, particularly in preventing system failures during critical operations. These approaches are particularly useful in detecting faults in battery systems.

4.2. Advanced Communication and Cybersecurity Measures

With increased connectivity in modern EVs, communication and cybersecurity measures are paramount. As vehicles become more integrated with the Internet of Things (IoT) and smart grids, protecting data and ensuring secure communication channels is crucial.

Over-the-Air (OTA) updates allow real-time software enhancements and bug fixes, enabling the BMS to adapt to new challenges without requiring physical access to the vehicle. Secure Communication Protocols like TLS and blockchain-based methods protect against unauthorised access and data tampering, ensuring vehicle safety. Anomaly Detection Systems analyse real-time network traffic to detect potential security breaches, using AI algorithms to quickly identify threats and initiate countermeasures.

Advanced battery management systems (BMS) face several challenges, including initial SOC and current measurement errors, network and privacy concerns, and the complexity of digital twins. Accurate estimation of SOC is crucial for safe battery operation, and errors can lead to incorrect assessments of battery health and capacity. Network speed and unstable connections can hinder cloud-based BMS performance, while data privacy is a concern. Additionally, the complexity of creating and maintaining digital twins increases as more parameters are added, making it difficult to achieve real-time synchronisation with the physical battery.

The gaps identified in the literature include the need for more robust models that can handle uncertainties, optimise resource allocation, and minimise errors during real-world operation. Addressing these challenges is critical for the widespread adoption of advanced BMS technologies in electric vehicles.

5. INTEGRATION OF MODERN TOOLS FOR ENHANCED BMS PERFORMANCE

5.1 Integration with Smart Grids

Smart grid integration offers benefits such as vehicle-to-grid (V2G) capabilities, which can enhance energy efficiency and grid stability.

EVs can serve as mobile energy storage units, supporting grid demand during peak hours and providing potential revenue for owners. They can also use AI algorithms for predictive load management, enabling more efficient charging strategies and reducing energy costs. Additionally, EV batteries can serve as distributed energy resources, supporting renewable energy integration and contributing to a more sustainable energy system by storing excess energy generated from renewable sources.

5.2 Combined Use of Digital Twins, Cloud Computing, and Machine Learning

A comprehensive approach combining digital twins, cloud computing, and machine learning is needed to fully utilise modern tools in battery management systems (BMS). This system can provide real-time monitoring and predictive maintenance, reducing downtime and improving safety. It can also optimise resource utilisation, extending battery life and reducing costs by identifying energy consumption patterns. Machine learning models can detect anomalies in the battery system, while digital twins can simulate different scenarios to understand their impact. This combination allows for comprehensive diagnostics and timely interventions to prevent failures, ultimately improving the cost-effectiveness of electric vehicles.

The integration of digital twins, cloud computing, and machine learning creates a powerful toolset for managing electric vehicle batteries, ensuring their health and efficiency over their entire lifecycle.

5.3 Case Studies and Practical Implementations

Recent studies have shown successful implementations of integrated BMS solutions:

- **Case Study 1: Bosch Cloud-Based BMS**: Bosch has demonstrated the effectiveness of cloud-based BMS in extending battery life by using machine learning algorithms to analyse charging patterns and environmental factors. This system provides a continuous window into battery health, enabling proactive maintenance (McMahan, 2019). By using cloud computing, Bosch's BMS can remotely monitor battery parameters, predict potential issues, and suggest maintenance actions, thereby extending battery life and enhancing vehicle safety.
- **Case Study 2: Digital Twin for Battery Lifecycle Management**: The use of digital twins for battery lifecycle management has been explored by Anandavel et al. (2021), where real-time data was used to update the virtual model and make informed decisions regarding battery maintenance and optimisation. The digital twin provided a dynamic representation of the battery, allowing for predictive maintenance and performance optimisation. This case study highlights the potential of digital twins to improve battery management by providing detailed insights into battery behaviour under various conditions.

6. CONCLUSION AND FUTURE DIRECTIONS

The adoption of advanced tools like digital twins, cloud computing, and machine learning has greatly improved the capabilities of EV Battery Management Systems. These technologies not only enhance real-time monitoring and diagnostics but also extend the operational life of battery systems, making electric vehicles more reliable and cost-effective.

However, further research is needed to overcome challenges related to data accuracy, network reliability, and computational complexity. Future work should focus on integrating these advanced tools into a unified system that offers a seamless, efficient, and secure BMS solution for electric vehicles. Moreover, pilot testing on real-world electric vehicle fleets can provide valuable insights into the practical challenges and benefits of these integrated solutions.

The development of robust, scalable, and secure BMS solutions will be crucial for the future of electric vehicles. By leveraging digital twins, cloud computing, and machine learning, the next generation of BMS can ensure that electric vehicles are not only efficient and cost-effective but also safe and reliable for consumers.

REFERENCES

[1] S. Bhuvaneswari, A. Mohan, and A. Sundaram, “Improved BMS: A Smart Electric Vehicle Design based on an Intelligent Battery Management System,” in *2024 International Conference on Inventive Computation Technologies (ICICT)*, IEEE, Apr. 2024, pp. 1999–2006. doi: 10.1109/ICICT60155.2024.10544810.

[2] A. Otto *et al.*, “Battery Management Network for Fully Electrical Vehicles Featuring Smart Systems at Cell and Pack Level,” in *Advanced Microsystems for Automotive Applications 2012*, Berlin, Heidelberg: Springer Berlin Heidelberg, 2012, pp. 3–14. doi: 10.1007/978-3-642-29673-4_1.

[3] Y. Zou, X. Hu, H. Ma, and S. E. Li, “Combined State of Charge and State of Health estimation over lithium-ion battery cell cycle lifespan for electric vehicles,” *J Power Sources*, vol. 273, pp. 793–803, Jan. 2015, doi: 10.1016/j.jpowsour.2014.09.146.

[4] C. C. Chan, A. Bouscayrol, and K. Chen, “Electric, hybrid, and fuel-cell vehicles: Architectures and modeling,” *IEEE Trans Veh Technol*, vol. 59, no. 2, pp. 589–598, Feb. 2010, doi: 10.1109/TVT.2009.2033605.

[5] V. Manoj, V. Guntreddi, P. Ramana, B. Vineela Rathan, M. Sasi Kowshik, and S. Pravallika, “Optimal Energy Management and Control Strategies for Electric Vehicles Considering Driving Conditions and Battery Degradation,” *E3S Web of Conferences*, vol. 547, p. 03015, Jul. 2024, doi: 10.1051/e3sconf/202454703015.

[6] S. Yayla and E. Ozdemir, “Smart Vehicle to Grid Energy Management Algorithm for Electric Vehicle Supported by Photovoltaic Energy Sources,” *Electric Power Components and Systems*, pp. 1–17, Mar. 2024, doi: 10.1080/15325008.2024.2330097.

[7] S. AMAMRA and H. KIZMAZ, “ICT-Based Vehicle-to-Grid Operation Based on the Fast Discharge Power for Economic Value,” *European Journal of Technic*, vol. 13, no. 2, pp. 94–100, Oct. 2023, doi: 10.36222/ejt.1362587.

[8] Vandana, A. Garg, and B. K. Panigrahi, “ Multi-dimensional digital twin of energy storage system for electric vehicles: A brief review ,” *Energy Storage*, vol. 3, no. 6, Dec. 2021, doi: 10.1002/est2.242.

[9] F. Naseri *et al.*, “Digital twin of electric vehicle battery systems: Comprehensive review of the use cases, requirements, and platforms,” Jun. 01, 2023, *Elsevier Ltd.* doi: 10.1016/j.rser.2023.113280.

[10] M. Tarafdar-Hagh, K. Taghizad-Tavana, M. Ghanbari-Ghalehjoughi, S. Nojavan, P. Jafari, and A. Mohammadpour Shotorbani, “Optimizing Electric Vehicle Operations for a Smart Environment: A Comprehensive Review,” *Energies (Basel)*, vol. 16, no. 11, p. 4302, May 2023, doi: 10.3390/en16114302.

[11] X. Zhao and G. Liang, “Optimizing electric vehicle charging schedules and energy management in smart grids using an integrated GA-GRU-RL approach,” *Front Energy Res*, vol. 11, Sep. 2023, doi: 10.3389/fenrg.2023.1268513.

[12] S. Gao, K. T. Chau, C. Liu, D. Wu, and C. C. Chan, “Integrated Energy Management of Plug-in Electric Vehicles in Power Grid With Renewables,” *IEEE Trans Veh Technol*, vol. 63, no. 7, pp. 3019–3027, Sep. 2014, doi: 10.1109/TVT.2014.2316153.

[13] K. Kumari.K.S, L. Chitra, J. M. Abraham, N. Joseph, and Y. K. T.K, “The Role of IOT & AI in Battery Management of Electric Vehicles,” in *2023 International Conference on Signal Processing, Computation, Electronics, Power and Telecommunication (IConSCEPT)*, IEEE, May 2023, pp. 1–7. doi: 10.1109/IConSCEPT57958.2023.10170275.

[14] G. Le Gall, N. Montavont, and G. Z. Papadopoulos, “IoT Network Management within the Electric Vehicle Battery Management System,” *J Signal Process Syst*, vol. 94, no. 1, pp. 27–44, Jan. 2022, doi: 10.1007/s11265-021-01670-2.

[15] G. Srihari, R. S. R. Krishnam Naidu, P. Falkowski-Gilski, P. Bidare Divakarachari, and R. Kiran Varma Penmatsa, “Integration of electric vehicle into smart grid: a meta heuristic algorithm for energy management between V2G and G2V,” *Front Energy Res*, vol. 12, Apr. 2024, doi: 10.3389/fenrg.2024.1357863.

[16] M. Bin Kaleem, W. He, and H. Li, “Machine learning driven digital twin model of Li-ion batteries in electric vehicles: a review,” *AI and Autonomous Systems*, May 2023, doi: 10.55092/aias20230003.

[17] Kai Zhao and Ying Liu, “Digital Twin-Supported Battery State Estimation based on TCN-LSTM Neural Networks and Transfer Learning,” *CSEE JOURNAL OF POWER AND ENERGY SYSTEMS*, pp. 1–13, 2015.

[18] M. Abdul-Hak, N. Al-Holou, and U. Mohamm, “Predictive Intelligent Battery Management System to Enhance the Performance of Electric Vehicle,” in *Electric Vehicles - Modelling and Simulations*, InTech, 2011. doi: 10.5772/17099.

[19] K. Sethi, A. Gupta, G. Gupta, and V. Jaiswal, “Comparative Analysis of Machine Learning Algorithms on Different Datasets,” 2019. [Online]. Available: www.ccsarchive.org

[20] A. Shinde, R. Kumar Swami, and S. Nanivadekar, “A Review of the Autonomous Electric Vehicles: Challenges and Future Scope,” 2025.

Journal of Information Systems Engineering and Management
2025, 10(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

[21] M. Elsisi, M. Q. Tran, K. Mahmoud, M. Lehtonen, and M. M. F. Darwish, "Deep learning-based industry 4.0 and internet of things towards effective energy management for smart buildings," *Sensors (Switzerland)*, vol. 21, no. 4, pp. 1–19, Feb. 2021, doi: 10.3390/s21041038.

[22] W. Wu, S. Wang, W. Wu, K. Chen, S. Hong, and Y. Lai, "A critical review of battery thermal performance and liquid based battery thermal management," *Energy Convers Manag*, vol. 182, pp. 262–281, Feb. 2019, doi: 10.1016/j.enconman.2018.12.051.

[23] J. Gomez, R. Nelson, E. E. Kalu, M. H. Weatherspoon, and J. P. Zheng, "Equivalent circuit model parameters of a high-power Li-ion battery: Thermal and state of charge effects," *J Power Sources*, vol. 196, no. 10, pp. 4826–4831, May 2011, doi: 10.1016/j.jpowsour.2010.12.107.

[24] T. M. Bandhauer, S. Garimella, and T. F. Fuller, "A Critical Review of Thermal Issues in Lithium-Ion Batteries," *J Electrochem Soc*, vol. 158, no. 3, p. R1, 2011, doi: 10.1149/1.3515880.

[25] F. Kennel, D. Gorges, and S. Liu, "Energy Management for Smart Grids With Electric Vehicles Based on Hierarchical MPC," *IEEE Trans Industr Inform*, vol. 9, no. 3, pp. 1528–1537, Aug. 2013, doi: 10.1109/TII.2012.2228876.