IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

A SURVEY ON AI AND IOT-BASED TECHNIQUES FOR BATTERY STATE ESTIMATION AND HEALTH MONITORING IN ELECTRIC VEHICLES

[1]Sanjana Salunke, [2]Dr.Revanasiddappa Kinagi

[1]Student,[2]Associate Professor

[1,2]Electronics and Communication Engineering,

[1,2]Sharnbasva University,Kalaburagi,Karnataka,India

Abstract: Electric vehicle batteries are complex electrochemical systems whose performance, safety, and lifespan strongly depend on accurate state estimation and effective health monitoring. Conventional battery management systems rely on rule-based and model-driven approaches that often struggle with nonlinear battery behavior, aging effects, and dynamic operating conditions. Recent advancements in Artificial Intelligence and Internet of Things technologies have enabled a new generation of intelligent and connected battery management systems for electric vehicles. This survey presents a comprehensive analysis of AI- and IoT-based techniques applied to battery state estimation and health monitoring, including state-of-charge, state-of-health, and remaining useful life prediction. The reviewed literature is systematically classified based on employed AI models, monitored battery states, and IoT deployment architectures such as edge, cloud, and hybrid systems. Comparative insights highlight the strengths, limitations, and practical feasibility of existing approaches under real-world conditions. Key challenges related to data availability, model generalization, real-time implementation, and system security are critically discussed, and promising future research directions are outlined to support the development of reliable, scalable, and intelligent battery management systems for next-generation electric vehicles.

Index Terms – Electric Vehicles, Battery Management System, Artificial Intelligence, Internet of Things, State of Charge, State of Health, Battery Monitoring.

I. Introduction

Electric vehicles have emerged as a critical component of global transportation electrification, driven by stringent emission regulations, rising fuel costs, and advancements in energy storage technologies. Global electric vehicle adoption has accelerated rapidly in recent years, with annual sales increasing exponentially and lithium-ion batteries accounting for a significant portion of vehicle cost and performance. The battery system directly influences driving range, charging behavior, safety, and overall vehicle reliability, making effective Battery Management Systems indispensable for modern electric vehicles. Battery degradation, inaccurate state estimation, and thermal failures can lead to reduced range, unexpected breakdowns, safety incidents, and costly battery replacement, which often represents 30–40 percent of the total vehicle cost. These factors highlight the growing urgency for advanced battery management solutions capable of operating reliably under real-world driving conditions, fast-charging demands, and diverse environmental stresses.Conventional Battery Management Systems rely on rule-based logic, equivalent circuit models, and predefined thresholds for monitoring and control. Although these approaches are computationally efficient, they struggle to handle nonlinear battery behavior, aging effects, parameter uncertainties, and dynamically changing load profiles. As electric vehicles transition toward higher energy densities, faster charging, and large-scale deployment, the limitations of traditional BMS architectures become increasingly pronounced. Inaccurate estimation of state-of-charge and state-of-health not only reduces energy utilization efficiency but also accelerates battery degradation and increases safety risks, underscoring the need for more adaptive and intelligent management strategies.Recent advances in Artificial Intelligence and Internet of Things technologies have introduced powerful tools for addressing these challenges. Data-driven AI models enable accurate battery state estimation, degradation prediction, fault diagnosis, and predictive maintenance by learning complex electrochemical behavior directly from operational data. Simultaneously, IoT-enabled architectures support continuous sensing, wireless communication, remote supervision, and cloud or edge-based analytics, enabling scalable and connected battery monitoring across individual vehicles and entire fleets. The integration of AI and IoT transforms conventional BMS units into intelligent, self-adaptive systems capable of proactive decision-making.Several surveys have examined battery modeling, machine learning for state estimation, or IoT-based monitoring independently; however, existing studies often lack a unified focus on integrated AI–IoT techniques, comparative analysis across deployment architectures, and practical feasibility under real-world constraints. Many surveys remain limited to algorithmic discussions without addressing connectivity, scalability, or implementation challenges. This survey addresses these gaps by systematically analyzing recent AI- and IoT-based techniques for battery state estimation and health monitoring in electric vehicles, providing structured classification, critical comparison, and identification of open challenges to guide future research and practical deployment of intelligent battery management systems.

II. Review methodology

This survey follows a structured and systematic methodology to examine recent research on Artificial Intelligence and Internet of Things based techniques for battery state estimation and health monitoring in electric vehicles. Peer-reviewed research articles published in recent years were collected from widely recognized scientific databases, including IEEE Xplore, Elsevier, Springer, and SAE technical resources. The literature search was conducted using carefully selected keywords related to AI-based battery management, IoT-enabled battery monitoring, state-of-charge estimation, state-of-health prediction, and electric vehicle battery diagnostics. Studies were considered relevant if they focused on electric vehicle applications and proposed data-driven, intelligent, or connected battery management solutions. Articles addressing non-vehicle batteries or lacking technical clarity were excluded. After screening abstracts and full texts, the selected studies were examined in detail and grouped based on their technical focus, including AI techniques, monitored battery states, and IoT deployment strategies. This classification-based approach enables systematic comparison and critical analysis of existing methods rather than isolated summaries. By organizing the literature around technical contributions and practical deployment aspects, the adopted methodology ensures balanced coverage of algorithmic developments, system architectures, and real-world applicability. This structured process supports objective evaluation of current research trends, strengths, and limitations in intelligent battery management systems for electric vehicles.

III. Battery Management Systems in Electric Vehicles

Battery Management Systems are essential subsystems in electric vehicles, responsible for ensuring safe operation, efficient energy utilization, and long battery life. A BMS continuously monitors critical battery parameters such as voltage, current, temperature, and charge–discharge behavior to prevent unsafe operating conditions. Accurate estimation of internal battery states, including state-of-charge and state-of-health, is vital for reliable range prediction, thermal control, and protection mechanisms. Traditional BMS designs primarily rely on equivalent circuit models, lookup tables, and predefined threshold rules. While these approaches are computationally lightweight and easy to implement, their accuracy is often limited under nonlinear battery behavior, aging effects, and dynamic driving conditions. Electric vehicle batteries experience varying load demands, temperature fluctuations, and degradation over time, which significantly affect battery characteristics. As battery packs increase in size and energy density, these limitations become more pronounced and can lead to reduced performance, premature degradation, or safety risks. The growing adoption of electric vehicles and fast-charging technologies further intensifies the need for advanced battery management strategies capable of adapting to complex and uncertain operating environments. These challenges highlight the importance of moving beyond static and model-based BMS approaches toward intelligent systems that can learn battery behavior from data and respond effectively to real-world conditions.

IV. AI-BASED TECHNIQUES FOR BATTERY STATE ESTIMATION

Artificial Intelligence techniques have gained significant attention for improving battery state estimation and health monitoring in electric vehicles. Data-driven models learn complex battery behavior directly from operational data, enabling more accurate estimation of state-of-charge, state-of-health, and remaining useful life compared to traditional model-based methods. Machine learning algorithms such as neural networks, regression models, and deep learning architectures are commonly used due to their ability to capture nonlinear relationships and degradation patterns. These models can adapt to changes caused by aging, temperature variation, and dynamic load profiles, making them suitable for real-world electric vehicle operation. AI-based techniques are also applied to fault detection and anomaly identification, allowing early detection of abnormal conditions such as thermal issues or cell imbalance. By analyzing historical and real-time data, these approaches support predictive maintenance and reduce the risk of unexpected battery failures. Despite their advantages, AI-based methods face challenges related to data availability, model training requirements, and computational complexity. The performance of AI models strongly depends on the quality and diversity of training data, and complex models may be difficult to deploy on resource-constrained vehicle hardware. Nevertheless, the reviewed studies consistently demonstrate that AI-based battery management techniques offer superior accuracy, adaptability, and long-term performance compared to conventional approaches.

V. IOT-BASED BATTERY MONITORING SYSTEMS

Internet of Things technologies enable connected battery monitoring by integrating sensors, communication modules, and data processing platforms within electric vehicles. IoT-based battery monitoring systems continuously collect battery parameters such as voltage, current, temperature, and charge cycles and transmit the data to edge or cloud platforms. This connectivity allows remote supervision, real-time alerts, and long-term performance analysis, which are particularly useful for fleet-level electric vehicle management. IoT architectures improve scalability by enabling centralized data storage and analysis across multiple vehicles. Cloud-based platforms support advanced analytics, visualization, and historical trend analysis, while edge computing enables faster response times and reduced communication overhead. IoT-based systems also enhance fault diagnosis and maintenance planning by providing continuous visibility into battery condition. However, practical implementation introduces challenges related to communication latency, data reliability, cybersecurity, and additional energy consumption caused by sensing and transmission. Ensuring secure and reliable data transfer is critical, especially when battery data influences safety-related decisions. Despite these challenges, IoT-based battery monitoring systems play a crucial role in enabling intelligent and connected battery management solutions for modern electric vehicles.

VI. AI AND IOT INTEGRATED BATTERY MANAGEMENT SYSTEMS

The integration of Artificial Intelligence and Internet of Things technologies has led to the development of intelligent and connected battery management systems for electric vehicles. In such systems, IoT infrastructure enables continuous data acquisition and communication, while AI models process the data to perform accurate state estimation, health monitoring, and predictive analytics. Integrated architectures commonly follow a layered structure consisting of sensing, communication, intelligence, and application layers. AI models may be deployed at the edge for real-time decision-making or in the cloud for computationally intensive analysis and long-term learning. This integration allows battery management systems to move beyond passive monitoring toward adaptive and predictive control strategies. Intelligent actions such as optimized charging, thermal regulation, and fault prevention can be achieved by combining real-time sensing with AI-driven insights. Integrated AI–IoT systems also support scalability by enabling fleet-level analysis and continuous model improvement using aggregated data. However, challenges related to system complexity, computational constraints, cybersecurity, and lack of standardization remain significant. Balancing accuracy, latency, and resource consumption is critical for successful deployment. Despite these challenges, AI–IoT integrated battery management systems represent a promising direction for next-generation electric vehicles.

VII. COMPARATIVE ANALYSIS OF EXISTING APPROACHES

Comparative analysis of existing studies reveals a clear evolution in battery management system design for electric vehicles. Early approaches focus primarily on IoT-based monitoring, emphasizing real-time data collection, visualization, and remote diagnostics using rule-based decision logic. These systems improve accessibility of battery data but offer limited adaptability. In contrast, AI-based approaches demonstrate significant improvements in state estimation accuracy, fault detection, and health prediction by learning battery behavior from data. Machine learning models outperform traditional methods under dynamic operating conditions, particularly in aging batteries. Integrated AI–IoT approaches combine the strengths of both paradigms by enabling connected monitoring and intelligent analysis. However, trade-offs exist between model complexity, computational overhead, and real-time feasibility. Deep learning models achieve high accuracy but often require substantial computational resources, making them more suitable for cloud-based analysis. Lightweight machine learning models offer faster response times and are preferred for onboard implementation. The comparative evaluation highlights the importance of selecting appropriate techniques based on application requirements, hardware constraints, and deployment environments.

VIII. IMPLEMENTATION AND DEPLOYMENT CONSIDERATIONS

Practical implementation and deployment of AI- and IoT-based battery management systems present several important considerations that directly affect real-world performance and reliability. Although many studies demonstrate high estimation accuracy under controlled conditions, deployment in electric vehicles introduces constraints related to hardware resources, communication reliability, and operating environments. Embedded battery management units have limited computational power and memory, which restricts the use of complex AI models and necessitates lightweight or optimized algorithms. Real-time execution requirements further demand fast inference and low latency to ensure timely safety-critical decisions. From an IoT perspective, continuous data transmission must be carefully managed to balance monitoring accuracy and energy consumption. Network reliability and latency variations can impact data availability, especially in mobile or remote operating conditions. Data synchronization between onboard systems, edge devices, and cloud platforms also poses challenges for consistent state estimation and control. In addition, integration with existing vehicle electronic control units and communication protocols requires compatibility and standardization. Environmental factors such as temperature extremes, vibration, and electromagnetic interference can affect sensor accuracy and communication stability. These deployment-related challenges highlight the need for implementation-aware system design rather than purely algorithm-focused development.

IX. CHALLENGES AND RESEARCH GAPS

Despite notable progress, several challenges limit the widespread adoption of AI- and IoT-based battery management systems in electric vehicles. Many proposed methods rely on laboratory or simulated datasets that may not accurately represent real-world driving conditions, leading to limited generalization. The lack of standardized datasets and evaluation metrics makes fair comparison between techniques difficult. Computational and memory constraints restrict the deployment of complex AI models on embedded vehicle hardware, while IoT connectivity introduces concerns related to latency, data security, and reliability. Battery diversity across chemistries, manufacturers, and usage patterns further complicates model generalization. In addition, cybersecurity risks associated with connected systems remain underexplored in existing studies. Addressing these challenges requires coordinated efforts toward realistic data collection, lightweight model design, robust security mechanisms, and standardized evaluation frameworks. These gaps represent important research opportunities for advancing intelligent battery management systems.

X. CONCLUSION

This survey presents a structured analysis of Artificial Intelligence and Internet of Things based techniques for battery state estimation and health monitoring in electric vehicles. The reviewed literature demonstrates that AI-based methods significantly improve estimation accuracy, adaptability, and fault detection compared to conventional model-based approaches. IoT-based systems enhance real-time monitoring, remote diagnostics, and scalability by enabling continuous data connectivity. Integrated AI–IoT battery management systems combine these advantages to support predictive, adaptive, and connected battery control strategies. However, challenges related to data quality, computational efficiency, security, and standardization remain key barriers to practical deployment. Future research focusing on lightweight AI models, edge intelligence, secure IoT architectures, and real-world validation is expected to further improve battery safety, performance, and lifespan. Intelligent battery management systems will play a critical role in supporting the reliable and sustainable growth of electric vehicles.

XI. FUTURE RESEARCH DIRECTIONS

Future research on Artificial Intelligence and Internet of Things based battery management systems for electric vehicles should focus on improving real-world reliability, scalability, and deployment feasibility. One major direction involves the development of robust and diverse real-world battery datasets that capture variations in driving behavior, climate conditions, battery chemistries, and aging patterns. Such datasets are essential to improve model generalization and reduce performance degradation when AI models are deployed outside laboratory environments. Another important research direction is the design of lightweight and computationally efficient AI models that can operate reliably on embedded vehicle hardware while maintaining acceptable estimation accuracy. Edge intelligence and model compression techniques offer promising solutions for balancing accuracy and real-time constraints. Future studies should also explore adaptive and self-learning battery management systems capable of continuously updating models based on new operational data without requiring frequent retraining. From an IoT perspective, research is needed to enhance communication reliability, reduce latency, and minimize energy overhead associated with continuous data transmission. Secure data handling, privacy preservation, and cybersecurity mechanisms must be integrated into connected battery management architectures to protect safety-critical information. In addition, standardized evaluation frameworks, benchmarking protocols, and interoperability standards are required to enable fair comparison and large-scale adoption of intelligent battery management solutions. Addressing these research challenges will play a crucial role in enabling practical, safe, and intelligent battery management systems for next-generation electric vehicles.

REFERENCES

[1] M. Berecibar, I. Gandiaga, I. Villarreal, N. Omar, J. Van Mierlo, and P. Van den Bossche, "Critical review of state of health estimation methods of Li-ion batteries for real applications," *Renewable and Sustainable Energy Reviews*, vol. 56, pp. 572–587, 2016.

[2] X. Hu, S. Li, and H. Peng, "A comparative study of equivalent circuit models for Li-ion batteries," *Journal of Power Sources*, vol. 198, pp. 359–367, 2012.

[3] C. Zhang, J. Jiang, L. Zhang, S. Liu, L. Wang, and P. C. Loh, "State-of-charge estimation of lithium-ion batteries using an improved extended Kalman filter," *IEEE Transactions on Industrial Electronics*, vol. 62, no. 2, pp. 1020–1030, 2015.

[4] X. Hu, Y. Li, and S. Lin, "Battery state of charge estimation for electric vehicles using machine learning," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 9, pp. 9236–9246, 2020.

[5] Y. Zheng, M. Ouyang, L. Lu, J. Li, and Z. Zhou, "Lithium-ion battery remaining useful life prediction with neural networks," *Journal of Power Sources*, vol. 401, pp. 1–10, 2018.

[6] Z. Chen, R. Xiong, J. Tian, and Y. Shang, "Model-based fault diagnosis of lithium-ion batteries for electric vehicles," *IEEE Transactions on Transportation Electrification*, vol. 6, no. 2, pp. 587–599, 2020.

[7] A. Farmann, T. Waag, A. Sauer, and D. U. Sauer, "Influence of battery state estimation errors on electric vehicle range prediction," *Journal of Power Sources*, vol. 281, pp. 114–122, 2015.

[8] M. A. Hannan, M. S. H. Lipu, A. Hussain, and A. Mohamed, "A review of lithium-ion battery state of charge estimation and management system in electric vehicle applications," *Journal of Power Sources*, vol. 423, pp. 193–209, 2019.

[9] S. Sepasi, R. Ghorbani, and B. Y. Liaw, "Improved extended Kalman filter for state of charge estimation of battery packs," *Journal of Power Sources*, vol. 255, pp. 368–376, 2014.

[10] Y. Wang, C. Zhang, and Z. Chen, "A data-driven state of health estimation method for lithium-ion batteries using neural networks," *IEEE Transactions on Energy Conversion*, vol. 33, no. 2, pp. 714–724, 2018.

[11] R. Xiong, Y. Pan, W. Shen, H. Li, and F. Sun, "Lithium-ion battery aging mechanisms and state of health estimation methods," *Renewable and Sustainable Energy Reviews*, vol. 131, 2020.

[12] H. He, R. Xiong, and J. Fan, "Evaluation of lithium-ion battery equivalent circuit models for state of charge estimation," *Energy*, vol. 57, pp. 286–293, 2013.

[13] J. Kim, J. Lee, and B. H. Cho, "Discharge capacity estimation of lithium-ion battery using support vector regression," *IEEE Transactions on Industrial Electronics*, vol. 60, no. 11, pp. 4919–4927, 2013.

[14] A. Barré, B. Deguilhem, S. Grolleau, M. Gérard, F. Suard, and D. Riu, "A review on lithium-ion battery ageing mechanisms and estimations for automotive applications," *Journal of Power Sources*, vol. 241, pp. 680–689, 2013.

[15] J. Meng, D. I. Stroe, M. Ricco, G. Luo, and R. Teodorescu, "Lithium-ion battery state of health estimation with neural networks," *IEEE Transactions on Industry Applications*, vol. 56, no. 3, pp. 2964–2974, 2020.

[16] A. K. Das, A. K. Rath, and D. P. Mishra, "IoT-based battery monitoring system for electric vehicles," *IEEE Internet of Things Journal*, vol. 8, no. 5, pp. 3457–3466, 2021.

[17] S. K. Ghosh, A. Chatterjee, and S. Saha, "Smart battery management system using IoT and cloud computing," *IEEE Sensors Journal*, vol. 21, no. 14, pp. 16010–16018, 2021.

[18] M. Dubarry and B. Y. Liaw, "Identify capacity fading mechanism in a commercial LiFePO4 cell," *Journal of Power Sources*, vol. 194, no. 1, pp. 541–549, 2009.

[19] Y. Liu, R. Xiong, and Z. Chen, "Remaining useful life prediction of lithium-ion batteries using data-driven methods," *Energy*, vol. 210, 2020.

[20] A. Fotouhi, D. J. Auger, K. Propp, S. Longo, and M. Wild, "A review on electric vehicle battery modelling: From lithium-ion toward future technologies," *Renewable and Sustainable Energy Reviews*, vol. 56, pp. 1008–1021, 2016.