

Hybrid and Low-Power AI Techniques for Battery Management Systems in Electric Scooters: A Literature Review

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Abstract - The rapid adoption of electric scooters has increased the demand for reliable and efficient battery management systems (BMSs) capable of ensuring battery safety, performance, and longevity. Accurate estimation of battery parameters such as State of Charge (SOC), State of Health (SOH), and Remaining Useful Life (RUL) remains a fundamental challenge due to the nonlinear and dynamic behavior of lithium-ion batteries. Over the years, researchers have explored a wide range of approaches, beginning with traditional estimation techniques and gradually moving toward machine learning and deep learning-based solutions. More recently, hybrid models that combine the strengths of multiple algorithms have demonstrated improved estimation accuracy, while low-power approaches have emerged to address the computational limitations of embedded BMS hardware. This paper presents a focused review of battery management techniques with particular emphasis on hybrid and low-power intelligent approaches. Existing methods are categorized into traditional, machine learning, deep learning, hybrid, and low-power techniques, followed by a discussion of their advantages and limitations. The review highlights recent developments in hybrid architectures and resource-efficient implementations such as TinyML and quantized neural networks. Finally, key research gaps and future opportunities are identified to support the development of accurate and deployable battery management solutions for next-generation electric scooters.

Key Words: Battery Management System (BMS), Electric Scooters, Hybrid approaches, Low power approaches, State of Charge (SOC).

1. INTRODUCTION

The growing adoption of electric vehicles (EVs) has placed battery technology at the center of modern transportation systems. Among the various EV categories, electric scooters have emerged as a practical solution for urban mobility due to their affordability, compact size, and lower operating costs. As the battery pack represents one of the most critical and expensive components of an electric scooter, ensuring its safe and efficient operation is essential. Battery Management Systems (BMSs) play a key role in achieving this objective by continuously monitoring battery conditions, protecting cells from unsafe operating states, and improving overall battery performance and lifespan [1].

A typical BMS is responsible for estimating several important battery parameters, including State of Charge (SOC), State of

Health (SOH), and Remaining Useful Life (RUL). Accurate estimation of these parameters enables efficient energy utilization, prevents premature battery degradation, and enhances operational safety. However, lithium-ion batteries exhibit complex nonlinear behavior that is influenced by temperature variations, charging and discharging patterns, aging mechanisms, and environmental conditions. As a result, developing accurate battery state estimation techniques remains an active area of research [2], [3].

Traditional battery state estimation methods such as Open Circuit Voltage (OCV), Coulomb Counting, Equivalent Circuit Models (ECMs), and Kalman Filter-based techniques have been widely adopted due to their simplicity and relatively low computational requirements. These approaches have demonstrated satisfactory performance under controlled conditions and remain popular in commercial battery management systems. Nevertheless, their estimation accuracy can deteriorate when batteries operate under dynamic loads, varying temperatures, and aging conditions, motivating the search for more adaptive and data-driven solutions [4] – [7].

Recent advances in artificial intelligence have introduced new opportunities for battery management. Machine learning techniques such as Support Vector Machines, Decision Trees, Random Forests, and Gradient Boosting methods have shown promising results by learning complex relationships directly from battery data. Similarly, deep learning architectures including Artificial Neural Networks (ANNs), Long Short-Term Memory (LSTM) networks, Autoencoders, and Transformer-based models have further improved estimation accuracy by capturing nonlinear and temporal battery characteristics. Despite these advantages, many of these approaches require significant computational resources and memory, which can limit their deployment on resource-constrained BMS hardware commonly used in electric scooters [8], [9].

To address these challenges, recent research has increasingly focused on hybrid and low-power intelligent battery management approaches. Hybrid techniques combine multiple estimation methods to leverage their individual strengths and improve robustness, accuracy, and generalization capability. Examples include CNN-LSTM, CNN-Transformer, Transformer-LSTM, Physics-Informed Neural Networks (PINNs), and Attention-based architectures. At the same time, low-power solutions such as TinyML and quantized neural networks are being explored to enable efficient deployment of intelligent algorithms on embedded platforms with limited computational resources [10]–[14].

This paper presents a focused literature review of battery management approaches with particular emphasis on emerging hybrid and low-power techniques. Existing studies are categorized into traditional, machine learning, deep learning, hybrid, and low-power approaches to provide a structured overview of current developments in the field. In addition, the strengths and limitations of these approaches are discussed, and key research gaps are identified to highlight future directions for the development of accurate, efficient, and deployable battery management systems for electric scooter applications.

2. Classification of Battery Management Approaches

The evolution of battery management systems has been driven by the increasing demand for accurate, reliable, and efficient battery state estimation. Over the years, researchers have proposed a wide range of approaches for estimating key battery parameters such as State of Charge (SOC), State of Health (SOH), and Remaining Useful Life (RUL). These approaches have gradually progressed from conventional physics-based techniques to advanced artificial intelligence-driven solutions capable of handling the nonlinear and dynamic behavior of lithium-ion batteries [1], [2].

Traditional approaches form the foundation of modern battery management systems and include direct measurement methods, book-keeping methods, model-based methods, and adaptive filter-based techniques. Methods such as Open Circuit Voltage (OCV), Coulomb Counting, Equivalent Circuit Models (ECMs), and Kalman Filter variants have been widely adopted due to their simplicity and relatively low computational requirements. However, their performance can be affected by parameter variations, battery aging, and changing operating conditions [4] – [6].

To address these limitations, data-driven techniques based on machine learning and deep learning have gained significant

attention. Machine learning approaches, including regression models, Support Vector Machines (SVMs), Decision Tree-based methods, and Fuzzy Logic systems, have demonstrated improved predictive capabilities by learning complex relationships directly from battery data. Similarly, deep learning architectures such as Artificial Neural Networks (ANNs), Long Short-Term Memory (LSTM) networks, Autoencoders, and Transformer-based models have shown superior performance in capturing nonlinear battery dynamics and long-term temporal dependencies [8], [9], [11].

More recently, researchers have focused on hybrid approaches that combine multiple algorithms to leverage their complementary strengths. Hybrid models such as CNN--LSTM, CNN--Transformer, Transformer--LSTM, EKF--LSTM, and Physics-Informed Neural Networks (PINNs) have demonstrated improved estimation accuracy and robustness compared to standalone methods. At the same time, the growing need for deploying intelligent battery management algorithms on embedded hardware has led to the emergence of low-power approaches. Techniques such as TinyML and quantized neural networks aim to reduce computational complexity, memory consumption, and energy requirements while maintaining acceptable estimation performance [10], [12] – [14].

Based on the reviewed literature, the approaches considered in this study are classified into five major categories: Traditional Approaches, Machine Learning Approaches, Deep Learning Approaches, Hybrid Approaches, and Low-Power Approaches, as illustrated in Fig. 1. This classification provides a structured framework for understanding the progression of battery management techniques and highlights the growing shift toward hybrid intelligence and resource-efficient deployment strategies for electric scooter applications.

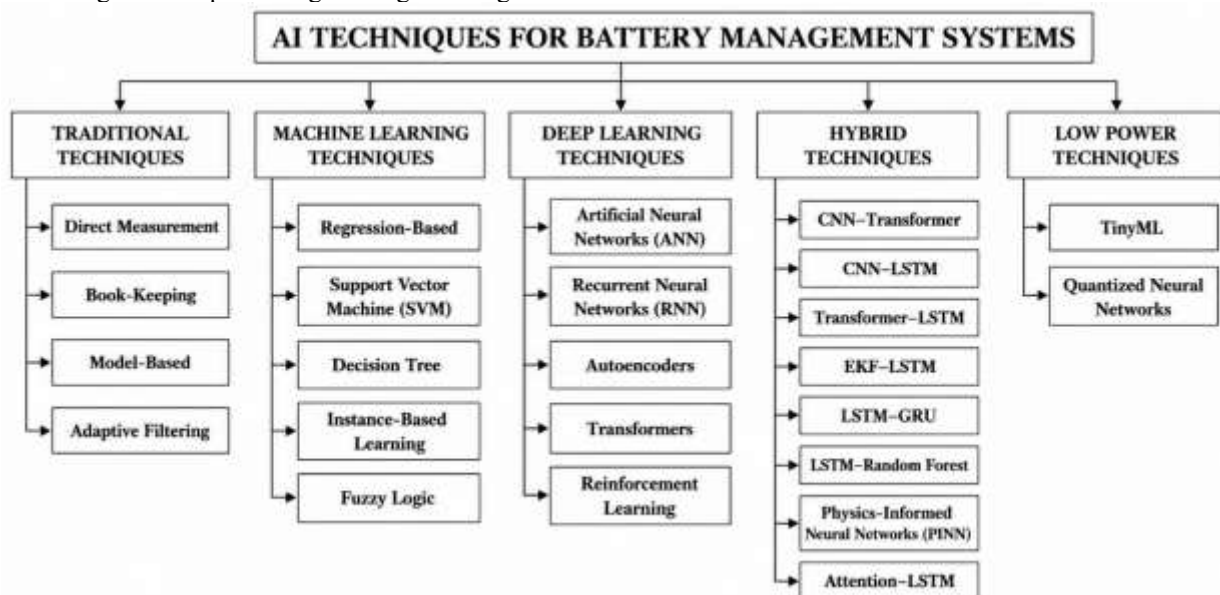


Fig -1: Taxonomy of battery management approaches discussed in this review.

3. Traditional Approaches

Traditional battery management techniques rely on electrical measurements, mathematical models, and filtering algorithms to estimate battery states such as SOC and SOH. Common methods include Open Circuit Voltage (OCV), Coulomb Counting, Equivalent Circuit Models (ECMs), and Kalman Filter-based techniques. These approaches are computationally efficient and remain widely adopted in commercial battery management systems due to their simplicity and ease of implementation. However, their estimation performance often deteriorates under dynamic operating conditions, battery aging, parameter variations, and temperature fluctuations, motivating the development of more adaptive data-driven approaches [4] – [7], [15].

4. Machine Learning Approaches

Machine learning methods improve battery state estimation by learning nonlinear relationships directly from battery data without requiring explicit electrochemical modeling. Commonly used techniques include regression models, Support Vector Machines (SVMs), Decision Trees, Random Forests, and other ensemble learning methods. These approaches generally outperform traditional methods in handling battery degradation patterns and nonlinear operating behavior while maintaining moderate computational requirements. Nevertheless, their performance often depends on effective feature engineering and the availability of representative training datasets [8], [16] – [18].

5. Deep Learning Approaches

Deep learning approaches further improve battery state estimation by automatically extracting hierarchical features from battery measurements such as voltage, current, and temperature. Architectures including Artificial Neural Networks (ANNs), Long Short-Term Memory (LSTM) networks, Gated Recurrent Units (GRUs), Autoencoders, Transformers, and Reinforcement Learning frameworks have been successfully applied to SOC, SOH, and RUL prediction tasks. Their ability to model complex nonlinear and temporal battery behavior has resulted in significant improvements in estimation accuracy compared with conventional machine learning methods. However, high computational and memory requirements remain major challenges for deployment on resource-constrained battery management hardware [9], [11], [19] – [24].

6. Hybrid Approaches

Although machine learning and deep learning techniques have significantly improved battery state estimation, individual models often face challenges related to generalization, robustness, and computational efficiency. To address these limitations, recent research has increasingly focused on hybrid approaches that combine multiple algorithms to exploit their complementary strengths. By integrating feature extraction, temporal learning, filtering techniques, and physical battery knowledge, hybrid models have demonstrated improved estimation accuracy and reliability compared with standalone methods.

6.1. CNN--Transformer Hybrid Models

CNN--Transformer architectures combine the local feature extraction capability of Convolutional Neural Networks (CNNs) with the global dependency modeling ability of Transformer networks. In the reviewed study, the proposed model was evaluated on the NASA battery dataset for SOH estimation and achieved an MAE of 0.0048 and RMSE of 0.0072, outperforming standalone CNN, LSTM, and Transformer models [11]. The CNN component effectively extracts local degradation characteristics from battery measurements, while the Transformer captures long-range dependencies through self-attention mechanisms. This combination enables accurate modeling of battery aging behavior and demonstrates strong potential for battery health prediction applications.

6.2. CNN--LSTM Hybrid Models

CNN--LSTM models integrate convolutional feature extraction with temporal sequence learning. CNN layers automatically identify representative patterns from battery measurements, while LSTM networks capture temporal dependencies present during charging and discharging cycles. Using the NASA battery dataset, the reviewed CNN--LSTM model achieved an RMSE of 2.07% and outperformed FNN, CNN, LSTM, and GRU-based approaches under multiple temperature conditions [10]. The architecture demonstrated improved robustness and prediction accuracy for SOC estimation, highlighting the advantages of combining spatial and temporal learning mechanisms.

6.3. Transformer--LSTM Hybrid Models

Transformer--LSTM models combine the attention mechanism of Transformers with the sequential learning capability of LSTM networks. The Transformer component captures long-range relationships and degradation patterns, while the LSTM network models temporal battery dynamics. Evaluated using the CALCE dataset, the proposed model achieved an MAE of 1.5475, RMSE of 1.8719, and an R^2 value of 0.9480, outperforming standalone Transformer, CNN, and LSTM models [23]. The results demonstrate that combining self-attention with recurrent memory enables more accurate battery health prediction and degradation tracking.

6.4. EKF--LSTM Hybrid Models

The EKF--LSTM approach combines data-driven learning with model-based filtering techniques. In this architecture, the LSTM network learns nonlinear battery dynamics from historical data, while the Extended Kalman Filter continuously corrects estimation errors using real-time measurements. Experimental results showed that the hybrid model achieved an MAE of 0.009 and RMSE of 0.011, outperforming both standalone EKF and LSTM methods [25]. The integration of filtering and deep learning improves robustness against sensor noise and measurement uncertainties, making the approach suitable for real-time SOC estimation.

6.5. LSTM--GRU Hybrid Models

Hybrid LSTM--GRU architectures leverage the complementary strengths of both recurrent neural networks. LSTM networks effectively capture long-term dependencies, whereas GRU networks offer lower computational complexity and faster convergence. The reviewed model achieved an SOC estimation MAE of 1.7% and RMSE of 2.0%, while simultaneously achieving SOH estimation RMSE values as low as 0.65% under varying temperature conditions [26]. The ability to estimate both SOC and SOH within a unified framework highlights the effectiveness of combining multiple recurrent learning mechanisms.

6.6. LSTM--Random Forest Hybrid Models

LSTM--Random Forest models integrate deep temporal learning with ensemble machine learning techniques. In the reviewed study, LSTM networks were employed to capture battery degradation trends, while Random Forest regression was used to enhance prediction stability and nonlinear modeling capability. The proposed model achieved an R^2 value of 0.9855 for Remaining Useful Life prediction, demonstrating strong prognostic capability [27]. This hybrid strategy illustrates how combining sequential learning and ensemble methods can improve battery lifespan prediction.

6.7. Physics-Informed Neural Networks

Physics-Informed Neural Networks (PINNs) incorporate electrochemical battery knowledge directly into the learning process through physics-based constraints. Unlike purely data-driven approaches, PINNs utilize known battery dynamics and physical laws during model training. The reviewed PINN-based method achieved an MAE of 0.89% and RMSE of 1.12%, outperforming several conventional neural network approaches [12]. By integrating domain knowledge, PINNs improve interpretability, reduce dependence on large training datasets, and enhance generalization across different operating conditions.

6.8. Attention--LSTM Hybrid Models

Attention--LSTM architectures enhance traditional LSTM networks by introducing attention mechanisms that dynamically identify the most relevant information within battery operating sequences. While the LSTM component captures temporal degradation patterns, the attention layer assigns greater importance to influential charging cycles and degradation features. Experimental results reported an MAE of 0.7976 and RMSE of 1.1468 on NASA battery datasets, demonstrating improved SOH estimation accuracy compared with conventional recurrent models [28]. This approach is particularly valuable when only partial charging or operating data are available.

Overall, the reviewed hybrid approaches consistently demonstrate superior estimation performance by combining complementary learning mechanisms. Architectures such as CNN--Transformer, Transformer--LSTM, EKF--LSTM, and PINN models achieve high estimation accuracy by integrating feature extraction, temporal modeling, filtering techniques, and physical battery knowledge. However, these performance improvements are often accompanied by increased

computational and memory requirements, motivating the development of low-power approaches that can enable practical deployment on embedded battery management systems.

7. Low-Power Approaches

While hybrid models have demonstrated remarkable improvements in battery state estimation accuracy, their deployment on embedded battery management systems remains challenging due to constraints related to processing power, memory capacity, and energy consumption. These limitations are particularly important in electric scooters, where cost-effective and resource-constrained hardware platforms are commonly used. Consequently, recent research has focused on developing low-power intelligent battery management approaches capable of maintaining acceptable estimation performance while significantly reducing computational overhead. Among the reviewed studies, TinyML and quantized neural network approaches have emerged as promising solutions for enabling real-time battery monitoring on embedded devices.

7.1. TinyML - Based Approaches

Tiny Machine Learning (TinyML) aims to deploy machine learning models directly on low-power embedded hardware while minimizing memory consumption and computational requirements. In battery management systems, TinyML enables local battery monitoring and state estimation without relying on cloud-based processing, thereby reducing communication latency and energy consumption.

The reviewed TinyML study implemented battery SOH estimation models on the Infineon CY8CPROTO-062S3 development platform using TensorFlow Lite for Microcontrollers [13]. Multiple neural network architectures and quantization strategies were evaluated to identify the most suitable configuration for resource-constrained deployment. Experimental results showed that lightweight Artificial Neural Network (ANN) models achieved competitive prediction accuracy while requiring significantly fewer computational resources than convolutional architectures. In particular, the best-performing quantized ANN model achieved estimation errors as low as 0.01% while requiring only 7574 bytes of model memory and 1148 bytes of scratch memory.

The study further demonstrated that model quantization substantially reduced memory requirements without causing significant degradation in prediction performance. Compared with conventional deep learning implementations, the TinyML approach provided a practical balance between estimation accuracy and hardware efficiency. These findings highlight the potential of TinyML for enabling intelligent battery management capabilities in electric scooters and other lightweight electric vehicles where memory and energy resources are limited.

7.2. Quantized Neural Network Approaches

Quantization is a widely adopted model-compression technique that reduces computational complexity by representing neural network parameters using lower-precision numerical formats. By decreasing the number of bits required to store model weights and intermediate computations, quantized neural networks can significantly reduce memory consumption, execution time, and energy requirements.

The reviewed study proposed a quantized Adaptive Dual Extended Kalman Filter (ADEKF) framework for battery SOH estimation using NASA battery datasets [14]. The researchers investigated different quantization levels and analysed the trade-off between estimation accuracy and computational efficiency. Experimental results demonstrated that a 6-bit quantized implementation achieved a Mean Squared Error (MSE) of 0.00042772 and a Mean Absolute Percentage Error (MAPE) of 0.0342 while significantly reducing resource utilization. In addition to maintaining reliable estimation performance, the quantized model achieved a 41.25% reduction in memory usage and a 20.576% reduction in execution time compared with the full-precision implementation. These results indicate that quantization can effectively bridge the gap between advanced battery state estimation algorithms and practical embedded deployment. By reducing hardware requirements while preserving acceptable prediction accuracy, quantized neural networks represent an important step toward real-world implementation of intelligent battery management systems. Overall, low-power approaches focus on addressing one of the most significant limitations of modern battery management systems: deployability. While hybrid architectures often provide superior estimation accuracy, their computational demands can restrict implementation on embedded platforms. TinyML and quantized neural networks demonstrate that it is possible to achieve reliable battery monitoring while substantially reducing memory consumption and computational overhead. As research progresses, the integration of low-power optimization techniques with advanced hybrid architectures is expected to play a crucial role in the development of next-generation battery management systems for electric scooters and other electric mobility applications.

8. Comparative Analysis of Hybrid and Low-Power Approaches

Table - 1 summarizes the performance characteristics of the reviewed hybrid and low-power battery management approaches. Hybrid models generally achieve higher estimation accuracy by combining complementary techniques such as convolutional networks, recurrent architectures, attention mechanisms, filtering algorithms, and physics-based constraints. Among the reviewed methods, CNN--Transformer, EKF--LSTM, Attention--LSTM, and PINN-based models demonstrated particularly strong prediction performance across SOC and SOH estimation tasks.

However, improved accuracy is often accompanied by increased computational complexity and memory requirements, which can limit deployment on embedded battery management hardware. To address this challenge, low-power approaches such as TinyML and quantized neural networks focus on reducing resource consumption while maintaining acceptable estimation performance. The reviewed studies demonstrated significant reductions in memory usage and execution time, making them suitable for real-time deployment in electric scooter battery management systems.

Although the reported metrics are based on different datasets and evaluation conditions, the overall trend indicates that hybrid approaches provide superior estimation accuracy, whereas low-power approaches offer greater deployment efficiency. Therefore, future battery management systems should aim to combine the strengths of both approaches to achieve accurate and resource-efficient battery monitoring.

Table -1: Performance Comparison of Hybrid and Low-Power Battery Management Approaches

Approach	Dataset	Target	MAE	RMSE/MSE	R^2	Deployment	Key Strength
CNN-Transformer	NASA	SOH	0.0048	0.0072	–	Medium	Combines CNN feature extraction with Transformer-based global dependency modeling.
CNN-LSTM	NASA	SOC	1.5597	2.0801	0.9358	Medium	Captures spatial and temporal battery characteristics for accurate SOC estimation.
Transformer-LSTM	CALCE	SOH	1.5475	1.8719	0.9480	Medium	Combines self-attention and temporal memory for battery degradation tracking.
EKF-LSTM	Private Dataset	SOC	0.009	0.011	–	Medium	Integrates Kalman filtering with deep learning for robust state estimation.
LSTM-GRU	Private Dataset	SOC/SOH	1.720	2.000	–	Medium	Balances prediction accuracy and computational efficiency.
LSTM-Random Forest	NASA	RUL	17.77	39.35	0.9855	Medium	Combines sequential learning and ensemble regression for RUL prediction.
PINN	Private Dataset	SOC	0.89%	1.12%	–	Low-Medium	Integrates battery physics into neural network training for improved interpretability and generalization.
Attention-LSTM	NASA	SOH	0.7976	1.1468	–	Medium	Focuses on critical degradation features using attention mechanisms.
TinyML (ANN + Quantization)	Private Dataset	SOH	0.01%	–	–	Very High	Enables deployment on embedded IoT hardware using only 7574 B model memory.
Quantized Neural Network (ADEKF)	NASA	SOH	0.0342 (MAPE)	0.00042772 (MSE)	–	Very High	Achieves 41.25% memory reduction and 20.576% faster execution for on-board BMS deployment.

It should be noted that the reported performance metrics were obtained using different datasets, operating conditions, and prediction targets such as SOC, SOH, and RUL. Therefore, the numerical values should be interpreted as indicators of model

effectiveness within their respective experimental settings rather than as a direct benchmark comparison across all approaches.

9. Research Gaps and Future Directions

Despite the significant progress achieved by hybrid and low-power battery management approaches, several challenges remain unresolved. First, many hybrid models prioritize estimation accuracy without adequately considering deployment constraints such as memory consumption, computational complexity, and inference latency. While approaches such as CNN--Transformer, Transformer--LSTM, and PINN demonstrate strong prediction performance, their implementation on resource-constrained battery management hardware remains challenging.

Second, the majority of studies are validated using publicly available datasets such as NASA and CALCE under controlled laboratory conditions. The effectiveness of these models under real-world electric scooter operating environments, including varying temperatures, road conditions, charging habits, and battery aging patterns, requires further investigation.

Third, the lack of standardized benchmarking protocols makes direct comparison between different approaches difficult. Differences in datasets, prediction targets, evaluation metrics, and experimental conditions often lead to inconsistent performance assessments across studies.

From a deployment perspective, low-power techniques such as TinyML and quantized neural networks have demonstrated promising reductions in memory usage and computational overhead. However, limited research has explored the integration of these optimization techniques with advanced hybrid architectures. Most existing studies focus either on maximizing prediction accuracy or minimizing computational requirements, while relatively few attempt to achieve both objectives simultaneously.

Future research should focus on developing lightweight hybrid models capable of delivering high estimation accuracy with minimal computational overhead. The integration of TinyML frameworks, model quantization, pruning strategies, and edge AI techniques with advanced hybrid architectures represents a promising direction for next-generation battery management systems. Additionally, the incorporation of physics-informed learning, adaptive online learning, and real-world electric scooter datasets may further improve model robustness, reliability, and deployment readiness.

9. Conclusion

This paper presented a focused review of battery management system approaches for electric scooter applications, emphasizing the evolution from traditional estimation techniques to modern hybrid and low-power artificial intelligence methods. Traditional, machine learning, and deep learning approaches were discussed to provide the necessary background and highlight the increasing adoption of data-driven techniques for battery state estimation.

Particular attention was given to hybrid approaches, including CNN--Transformer, CNN--LSTM, Transformer--LSTM, EKF--LSTM, LSTM--GRU, LSTM--Random Forest, Physics-Informed Neural Networks, and Attention--LSTM models. The

review showed that hybrid architectures generally achieve superior prediction performance by combining complementary learning mechanisms, filtering techniques, and domain knowledge. However, these improvements are often accompanied by increased computational and memory requirements.

Low-power approaches such as TinyML and quantized neural networks were also examined as promising solutions for deploying intelligent battery management algorithms on resource-constrained embedded platforms. The comparative analysis highlighted a clear trade-off between estimation accuracy and deployment efficiency. While hybrid models offer the highest prediction accuracy, low-power techniques provide practical deployment advantages for real-world battery management systems.

Future battery management systems are expected to benefit from the integration of advanced hybrid architectures with lightweight optimization techniques, enabling accurate, efficient, and scalable solutions for next-generation electric scooters and other electric mobility applications.

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