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Intelligent charging and battery management for electric bicycles: a review of smart charging, state estimation, and battery protection

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ABSTRACT

The growing adoption of electric bicycles has increased the need for reliable battery charging and management systems that ensure safety, durability, and efficient energy utilization. Conventional charging arrangements often provide limited battery-state information and basic protection, making them less effective in responding to changing operating conditions and battery degradation. This review examines intelligent charging and battery management technologies for electric bicycles, focusing on battery management systems (BMSs), state-of-charge (SoC) estimation, state-of-health (SoH) assessment, and battery protection. Research published up to 2024 is evaluated, combining electric-bicycle and micromobility studies with broader lithium-ion battery research where direct application-specific evidence remains limited. The review compares coulomb counting, model-based estimation, Kalman filtering, and data-driven approaches, while discussing adaptive charging, cell balancing, thermal monitoring, and fault protection. Particular attention is given to the practical constraints of electric bicycles, including compact battery packs, limited cooling capacity, affordability, and embedded computing resources. The analysis identifies opportunities for integrated, low-cost, and health-aware BMS architectures. These developments can improve battery reliability, charging decisions, and user safety while supporting the long-term sustainability of electric bicycle transportation.

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1. INTRODUCTION

Electric bicycles have become an increasingly attractive transportation option because they combine human-powered mobility with electrical assistance. Their operational reliability depends strongly on battery performance, charging convenience, and the ability to protect battery cells under different environmental and usage conditions. Lithium-ion batteries are widely adopted because of their favorable energy density, weight, and cycle-life characteristics, but their performance deteriorates through repeated charging, discharging, and exposure to unsuitable temperatures [1], [2]. These characteristics create a need for intelligent battery management that goes beyond simple voltage monitoring and basic charging termination.

A conventional electric bicycle charging system generally consists of an external charger, a rechargeable battery pack, and a protection circuit or BMS. Basic protection circuits commonly address

overvoltage, undervoltage, overcurrent, and short-circuit conditions, but they may provide limited information about remaining capacity and long-term battery condition. Without reliable state estimation, users can receive inaccurate range information, while charging decisions may fail to account for battery aging or temperature-related constraints. Consequently, intelligent charging and battery management have become important research directions for improving the safety, usability, and lifetime of electric bicycle batteries [3], [4].

Research on battery management has produced several approaches to state estimation, adaptive charging, cell balancing, and fault diagnosis [5]–[10]. However, much of the available literature addresses electric vehicles and stationary battery systems rather than low-voltage electric bicycle packs. These technologies cannot always be transferred directly because electric bicycles have different cost constraints, pack configurations, cooling capabilities, and embedded processing resources. This review therefore evaluates the relevance of established lithium-ion battery management techniques to electric bicycles, identifies their advantages and limitations, and discusses practical directions for intelligent battery protection.

2. INTELLIGENT BATTERY MANAGEMENT SYSTEM ARCHITECTURE

A battery management system monitors battery operating conditions and coordinates charging and discharging within specified safety limits. Its basic functions include measuring cell voltage, pack current, and temperature, estimating battery states, balancing cells, and activating protective actions when abnormal conditions occur [3], [11]. Depending on the system architecture, the BMS may also communicate with the charger, motor controller, display, or external monitoring platform. For electric bicycles, the design must balance measurement accuracy and protection capability against limited space, cost, and power consumption.

BMS architectures are commonly classified as centralized, modular, distributed, or decentralized configurations. A centralized BMS can be appropriate for relatively small battery packs because it reduces hardware complexity and simplifies implementation. Modular or distributed architectures provide greater flexibility when the number of monitored cells increases, although their additional communication and electronic components can increase cost [11], [12]. The most appropriate architecture for an electric bicycle depends on the pack voltage, number of series-connected cells, monitoring requirements, and the manufacturer's maintenance strategy.

Table 1 presents the principal BMS functions and their importance in electric bicycle applications. It shows that battery monitoring, state estimation, cell balancing, and protective control are interdependent rather than isolated functions. A reliable BMS must use measured information to support both immediate safety decisions and longer-term battery management. This integrated approach is particularly important when battery packs are exposed to variable loads, outdoor temperatures, and frequent charging cycles.

Table 1. Main BMS functions and their relevance to electric bicycles

BMS function	Main purpose	Electric bicycle relevance
Voltage monitoring	Detect cell overvoltage and undervoltage	Prevents unsafe cell operation
Current monitoring	Measure charging and discharge current	Protects against excessive current
Temperature monitoring	Identify overheating or unsuitable charging temperatures	Reduces thermal risk
SoC estimation	Estimate remaining usable charge	Supports range indication and charging decisions
SoH estimation	Assess battery aging and degradation	Supports maintenance and replacement
Cell balancing	Reduce differences between series-connected cells	Improves usable pack capacity
Fault diagnosis	Identify abnormal electrical or thermal behavior	Enables early intervention
Communication	Exchange information with charger and user interface	Supports intelligent charging and monitoring

3. STATE-OF-CHARGE ESTIMATION

State of charge represents the estimated remaining charge relative to the battery's available capacity. It is a critical parameter because charging termination, discharge limitation, range estimation, and battery protection depend on its accuracy [5], [6]. However, SoC cannot generally be measured directly using a single sensor, so the BMS must estimate it from electrical measurements and a suitable battery model. Estimation errors can accumulate over time and become more significant when the battery ages or operates under changing temperatures.

Coulomb counting is one of the most widely used approaches because it estimates SoC by integrating the current entering or leaving the battery. Its implementation is relatively simple and computationally efficient, making it attractive for low-cost electric bicycle BMS hardware [6], [13]. However, current-sensor errors, inaccurate initial SoC values, and uncertainty in actual battery capacity can produce cumulative estimation errors. Periodic correction using voltage-based information or other estimation methods is therefore important for maintaining acceptable accuracy.

Model-based methods estimate SoC using battery electrical characteristics, commonly represented by equivalent circuit models. Kalman filtering approaches, including the extended Kalman filter and unscented Kalman filter, combine model predictions with measured voltage and current to correct estimation errors [7], [8], [14]. These methods can provide improved performance under dynamic operating conditions, although their accuracy depends on model quality, parameter identification, sensor reliability, and computational implementation. For electric bicycles, a simplified equivalent circuit combined with adaptive filtering may offer a practical compromise between estimation accuracy and processing requirements.

Data-driven methods use measured battery data to establish relationships between operating conditions and estimated SoC. Artificial neural networks, support vector machines, and deep-learning models have been investigated because they can capture nonlinear battery behavior that is difficult to represent using simple models [9], [10], [15]. Their main challenges include the need for representative training data, computational resources, and validation across different battery chemistries and operating temperatures. Hybrid approaches that combine physical battery models with machine-learning correction may be more suitable for practical BMS implementation than relying entirely on complex data-driven models.

4. STATE-OF-HEALTH ESTIMATION AND BATTERY AGING

State of health describes the condition of a battery relative to its original or reference condition. It is commonly evaluated using indicators such as remaining capacity, internal resistance, impedance, and energy capability [16], [17]. Battery aging results from interacting electrochemical and environmental processes, including loss of cyclable lithium, degradation of active materials, and changes in internal resistance [18]. These processes can reduce driving range, increase heat generation, and limit the battery's ability to deliver power safely.

Capacity-based SoH estimation compares the battery's available capacity with its reference capacity, while resistance-based methods examine changes in internal electrical characteristics. Direct capacity measurement can be informative but generally requires controlled charging and discharging procedures that may not be practical during normal electric bicycle operation. Model-based and data-driven methods offer opportunities for online estimation using operating history, voltage response, current profiles, and temperature information [16], [17], [19]. A practical electric bicycle BMS should therefore estimate SoH progressively rather than depending exclusively on occasional full-capacity tests.

Recent research has examined SoH estimation from individual cells to complete battery packs, emphasizing the effects of cell variation and operating conditions [17], [19], [20]. Pack-level estimation is particularly important because a battery pack may contain cells with different degradation rates even when they were initially manufactured to similar specifications. If the weakest cell reaches its voltage limit before the others, the usable capacity of the complete pack can be reduced. Future electric bicycle BMS designs should therefore consider both pack-level SoH and the identification of individual cells that contribute disproportionately to battery degradation.

5. SMART CHARGING AND BATTERY PROTECTION

Smart charging adapts charging behavior to battery condition rather than applying a fixed charging profile under all circumstances. For lithium-ion batteries, constant-current–constant-voltage charging is widely used because it provides controlled current during the initial stage and limits voltage during the final stage [21]. An intelligent charger can extend this approach by considering estimated SoC, SoH, battery temperature, charging history, and cell voltage differences. Such coordination can reduce unnecessary charging stress and improve the consistency of charging decisions.

Charging optimization must consider the relationship between charging speed, temperature, and battery degradation. High charging currents can increase internal heat generation and may accelerate degradation under unsuitable operating conditions [18], [22]. Temperature-aware charging can reduce current when the battery operates outside its preferred temperature range and prevent charging when critical limits are reached. Research on battery temperature estimation has demonstrated the importance of thermal information for health-conscious charging and advanced BMS development [23]. For electric bicycles, these strategies should be implemented with relatively simple sensors and control algorithms to maintain affordability.

Battery protection requires coordinated electrical, thermal, and operational safeguards. Electrical protection includes overvoltage, undervoltage, overcurrent, and short-circuit detection, while thermal protection monitors excessive temperature and abnormal temperature changes [11], [24]. Cell balancing also plays an important role because differences in cell voltage and capacity can cause premature charging termination or uneven degradation. Passive balancing is relatively simple and inexpensive, whereas active balancing transfers energy between cells but generally requires more complex circuitry [25], [26].

Thermal runaway is a particularly serious safety concern because an internal cell failure can trigger rapid heat generation and potentially propagate to neighboring cells. Research involving micromobility battery packs has demonstrated that a single-cell thermal runaway event can create substantial fire hazards in e-bikes and e-scooters [27]. Prevention therefore requires suitable cell selection, mechanical protection, reliable electrical connections, temperature monitoring, and effective fault isolation. The BMS should be treated as one layer of protection within a broader battery safety design, rather than as a complete substitute for appropriate pack construction and safe charging practices [24], [27], [28].

6. RESEARCH GAPS AND FUTURE DIRECTIONS

Despite considerable progress in lithium-ion battery management, several challenges remain for electric bicycle applications. First, many state-estimation methods have been evaluated using automotive battery datasets, which may not accurately represent the smaller pack capacities, different current profiles, and environmental exposure of electric bicycles. Second, advanced machine-learning approaches may require more memory and processing capability than low-cost embedded BMS hardware can provide. Third, practical SoH estimation remains challenging because accurate capacity and resistance measurements are difficult to obtain during ordinary bicycle use [9], [16], [20]. Future research should prioritize low-cost hybrid estimation methods that combine coulomb counting, equivalent circuit models, adaptive filtering, and selected machine-learning techniques. Smart charging should also incorporate battery temperature, cell imbalance, SoH, and user charging patterns to determine safe and appropriate charging limits. Further experimental work is needed to evaluate the effectiveness of these approaches using real electric bicycle battery packs under different temperatures, riding profiles, and aging conditions. Finally, standardized datasets and comparative evaluation procedures would help researchers assess estimation accuracy, protection response, computational requirements, and practical implementation cost [29]-[32].

7. CONCLUSION

Intelligent charging and battery management are essential for improving the safety, reliability, and service life of electric bicycle batteries. A well-designed BMS should integrate voltage, current, and temperature monitoring with SoC estimation, SoH assessment, cell balancing, and fault protection. Coulomb counting remains attractive for its simplicity, while model-based and data-driven approaches provide opportunities to improve estimation under changing operating conditions. Smart charging can further improve battery management by adapting charging current and voltage to battery state and temperature. The review highlights that advanced BMS technologies developed for electric vehicles provide a useful foundation, but their implementation in electric bicycles requires careful adaptation. Compact hardware, limited cooling, affordability, and embedded computing constraints must be considered alongside estimation accuracy and safety performance. Particular attention should be given to thermal monitoring, cell imbalance, and early fault detection because these functions contribute directly to battery protection. Overall, integrated and application-specific BMS development offers a promising route toward safer, more durable, and more intelligent electric bicycle battery systems.

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