Battery Health Monitoring and Smart Charging Slot Management in Electric Vehicles: A Review

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ABSTRACT

The adoption of electric vehicles (EVs) has accelerated rapidly, driven by the need for sustainable mobility and advancements in battery technologies. However, the large-scale deployment of EVs faces two key challenges: efficient monitoring of battery health and effective management of charging infrastructure. Batteries degrade over time, making it crucial to monitor state of charge (SOC) and state of health (SOH) to ensure safety, reliability, and extended lifespan. At the same time, congestion at charging stations and lack of coordinated slot allocation create bottlenecks that limit user convenience and grid stability. Recent developments in Internet of Things (IoT) platforms, smart communication protocols, and predictive analytics provide opportunities to integrate real-time battery health monitoring with intelligent charging slot reservation. This review paper examines the current state of research in battery monitoring systems, SOC/SOH estimation techniques, slot reservation algorithms, and communication technologies for EV applications. It also highlights prototype implementations, identifies gaps in existing approaches, and outlines future directions including AI-driven queue optimization, V2G integration, and scalable IoT architectures.

Keywords: Battery, IoT, SOC and SOH, LoRa, Slot Booking

INTRODUCTION

Electric vehicles (EVs) have become central to sustainable mobility due to their potential to reduce greenhouse gas emissions and dependence on fossil fuels [1]. Governments and industries are promoting EV adoption through incentives and the expansion of charging networks. However, this rapid growth has created new challenges, particularly in charging infrastructure. Unlike traditional refueling, EV charging requires longer durations and is constrained by the number of available stations. High adoption rates can cause overcrowding, queuing delays, and user dissatisfaction. In urban areas, uncoordinated charging during peak hours can strain the power grid, while uncertainty about station availability contributes to range anxiety. Addressing these issues requires not only increasing the number of charging points but also developing intelligent slot reservation and scheduling mechanisms [2]. Without such solutions, the rapid expansion of EVs may be hindered by inefficiencies in the charging ecosystem.

The battery remains the most crucial component of an EV, directly impacting its performance, safety, and cost. Monitoring parameters such as the State of Charge (SOC) and State of Health (SOH) ensures operational efficiency while minimizing risks like overheating or deep discharge [3]. Nevertheless, charging infrastructure availability equally affects user experience. Even if an EV can accurately assess its battery health, the lack of accessible charging slots reduces its utility. Integrating battery monitoring with intelligent slot below a threshold,

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reducing waiting times and preventing service interruptions. In fleet applications, predictive battery monitoring coupled with coordinated charging scheduling enhances operational efficiency and grid stability [4].

The Internet of Things (IoT) and communication technologies play a vital role in enabling such smart EV ecosystems. IoT platforms allow EVs to function as connected devices, transmitting SOC and SOH data to cloud systems for analytics and decision-making [5]. Communication technologies such as Wi-Fi, Zigbee, LoRa WAN, and 5G enable these interactions, each offering unique advantages. LoRa supports long-range, low-power communication suitable for fleet monitoring, while 5G delivers high-speed, low-latency data exchange ideal for real-time charging slot allocation. Cloud platforms and dashboards built on these networks provide visibility into vehicle health and infrastructure usage. Reliable communication thus bridges battery monitoring and charging slot management, ensuring seamless integration [6]. This review examines advancements in battery management, SOC/SOH estimation, IoT-enabled monitoring, and charging station scheduling. It identifies current challenges, including cost, scalability, and lack of integration, while outlining future opportunities such as AI-based optimization, V2G integration, and scalable IoT architectures for smart cities.

Battery Health Monitoring in Electric Vehicles

Battery Management Systems (BMS): Functions and Architecture

A Battery Management System (BMS) is the core unit responsible for monitoring and controlling the performance of EV batteries. Its primary functions include measuring voltage, current, temperature, and SOC of each cell, ensuring balanced charging and discharging, and providing safety mechanisms against overcharging, deep discharge, and thermal runaway [7]. Architecturally, BMS consists of sensors, data acquisition modules, microcontrollers, and communication interfaces that transmit battery parameters to external systems or cloud platforms. In modern EVs, BMS not only protects the battery but also optimizes energy usage and contributes to accurate range estimation. With the rise of connected mobility, BMS are increasingly being designed with IoT integration, enabling real-time data sharing with external dashboards and predictive analytics tools [8]. Despite these advancements, challenges remain, including cost, computational complexity, and scalability for large battery packs. Research is now focusing on making BMS more intelligent, adaptive, and compatible with smart charging networks.

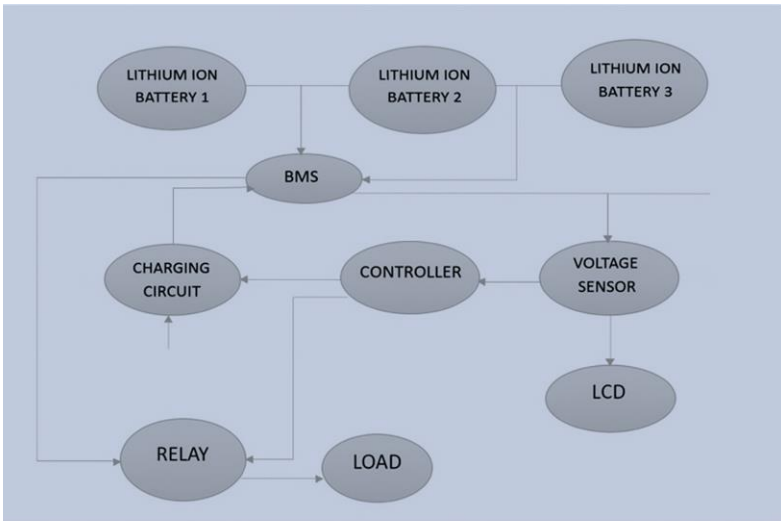

Fig 2.1 Block diagram of BMS [13]

SOC & SOH Estimation Techniques

The State of Charge (SOC) and State of Health (SOH) are vital for efficient EV battery management. SOC indicates the available capacity relative to the total and is crucial for range prediction, energy control, and charging decisions [9]. Estimation methods include Coulomb counting, which is simple but prone to cumulative errors, and model-based techniques like Kalman filters and Thevenin equivalent circuit models that offer better

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accuracy but require complex computation. Recently, machine learning and hybrid model–AI methods have improved adaptability to nonlinear behaviors [10]. SOH reflects the battery's condition compared to its initial capacity, helping predict its remaining useful life (RUL). Estimation techniques include direct measurement, model-based, and data-driven methods. Hybrid approaches combining physics-based and AI models enhance accuracy and interpretability, though challenges remain under diverse chemistries and conditions, demanding robust, adaptive monitoring solutions.

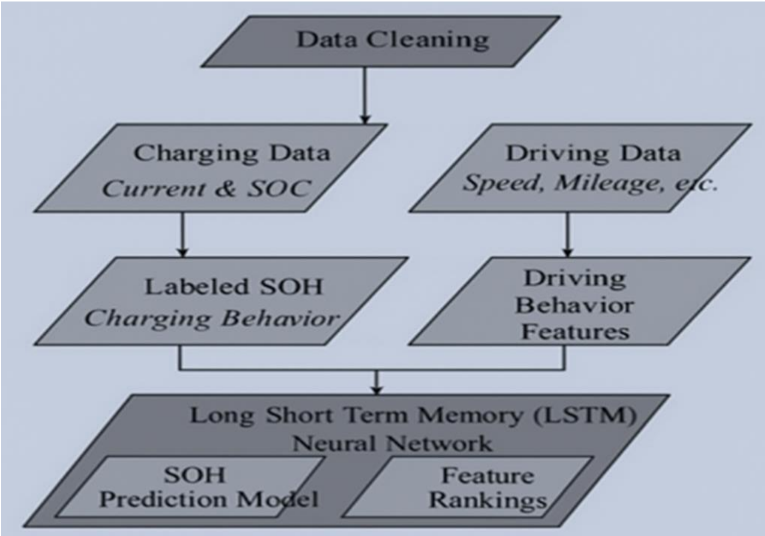

Fig 2.2 Battery SOH prediction framework [8]

IoT-Enabled Battery Monitoring Systems

The integration of IoT into EV battery monitoring systems has transformed the way SOC and SOH data are collected, analyzed, and utilized. IoT-enabled BMS can transmit battery health data to cloud platforms, enabling real-time visualization, predictive maintenance, and remote diagnostics [11]. With the use of wireless communication protocols such as LoRa, NB-IoT, and 5G, monitoring systems can cover large fleets of EVs while minimizing energy consumption. Cloud-based dashboards provide both users and operators with actionable insights, such as early warnings of battery degradation or automated scheduling of charging slots when the SOC falls below a threshold [12]. The use of edge computing further enhances these systems by allowing real-time decision-making closer to the vehicle, reducing latency. IoT-enabled monitoring not only improves safety and reliability but also enables integration with broader smart city infrastructures. However, challenges such as data security, interoperability, and scalability remain significant barriers to widespread deployment .

Limitations in Existing Battery Monitoring Approaches

Despite notable advancements, current battery monitoring approaches face several limitations. First, many SOC and SOH estimation methods lack robustness under highly dynamic driving and charging conditions, reducing their accuracy in real-world applications [13]. Second, model-based methods often require detailed battery parameters and calibration, making them impractical for large-scale deployment. Third, data-driven approaches rely on large datasets, which are not always available or standardized across different battery chemistries and manufacturer. Additionally, IoT-enabled systems, while powerful, face issues such as cybersecurity risks, high infrastructure costs, and limited scalability [14]. Another limitation is the lack of integration between battery monitoring and charging management; most systems operate in isolation, preventing optimal coordination. Finally, battery monitoring solutions must also consider computational efficiency, as EVs have constraints on onboard processing power. Addressing these limitations requires interdisciplinary research that combines electrochemistry, data science, IoT, and communication technologies to design adaptive, scalable, and secure monitoring frameworks.

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Smart Charging Slot Reservation and Queue Management

Traditional EV Charging Models

Traditional EV charging models are based on a first-come, first-served (FCFS) approach, where vehicles arrive at charging stations and wait for availability [15]. While simple to implement, this method often leads to inefficiencies such as long queues, unpredictable waiting times, and user dissatisfaction, especially during peak demand [15]. FCFS models also fail to account for the urgency of charging needs, as a vehicle with critically low SOC may wait behind one that still has sufficient range. Additionally, traditional models place unnecessary strain on the grid, as simultaneous charging surges are not optimized. Without predictive scheduling or reservation systems, station utilization remains suboptimal, with underuse during off-peak times and overloading at peak hours [16]. These drawbacks highlight the need for smarter, data-driven solutions that can dynamically allocate slots, prioritize vehicles based on SOC, and balance loads across multiple charging points. The shift away from traditional models is critical for scaling EV infrastructure in smart cities.

Reservation-Based Charging Systems

Reservation-based charging systems aim to eliminate the uncertainty of traditional models by allowing users or vehicles to book slots in advance . These systems leverage IoT platforms and communication protocols to enable real-time coordination between EVs and charging stations. When the SOC of a vehicle drops below a certain threshold, the system can automatically reserve a slot at the nearest available station, minimizing queuing time [17]. Reservation frameworks also allow operators to optimize grid loads by scheduling charging during off-peak periods. In practice, reservation systems have been implemented using mobile applications or vehicle-to-infrastructure communication, giving drivers confidence that a charging point will be available upon arrival [17]. However, challenges remain in ensuring fairness, preventing misuse of reservations, and handling no-shows. Despite these limitations, reservation-based systems represent a significant step forward in user convenience and charging efficiency, forming a foundation for more advanced, predictive slot allocation mechanisms.

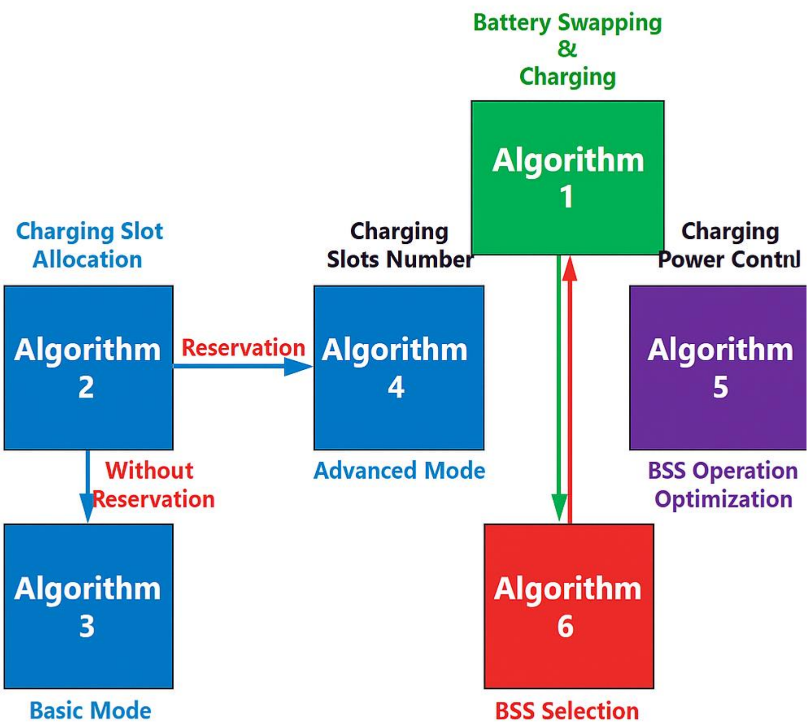

Fig 3.2 Computation logic of battery swapping service management [6]

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Queue Management and Scheduling Algorithms

Queue management is central to ensuring fair and efficient use of charging stations. Algorithms designed for scheduling consider multiple parameters, such as SOC, arrival time, energy demand, and charging station availability [18].

Simple approaches include FCFS with priority queuing for low-SOC vehicles, while advanced methods employ optimization models, linear programming, or reinforcement learning [18].

Some algorithms also integrate dynamic pricing to encourage off-peak charging, thereby reducing congestion.

For fleet operators, scheduling algorithms can coordinate multiple EVs to avoid simultaneous charging, optimizing fleet performance and minimizing downtime. Real-time scheduling supported by IoT systems enables dynamic adjustments when demand fluctuates.

Despite progress, practical deployment faces challenges such as scalability, user compliance, and balancing fairness with efficiency. Research continues to focus on adaptive scheduling frameworks that can respond to diverse conditions while ensuring grid stability and user satisfaction.

Gaps in Current Charging Slot Management Solutions

Despite advancements, current charging slot management solutions face limitations. Many reservation-based systems do not account for real-time traffic conditions or dynamic SOC levels, leading to mismatches between reservations and actual arrivals [19].

Queue management algorithms often prioritize efficiency but neglect fairness or user-specific constraints. Predictive models, while effective, rely heavily on accurate and large datasets, which may not always be available in developing regions.

Moreover, interoperability across different charging networks remains limited, preventing seamless slot booking for users traveling across regions. Cybersecurity and data privacy concerns also hinder widespread adoption, as personal and vehicle data must be securely managed [20].

Another gap is the lack of integration between battery health monitoring and charging management, with most systems operating independently. Bridging these gaps will require cross-disciplinary research in IoT, AI, and communication protocols to develop more adaptive, secure, and user-centric solutions.

Communication Technologies for EY Monitoring and Charging

Wi-Fi, Zigbee, and Cellular-Based Solutions

Short- and medium-range communication protocols such as Wi-Fi, Zigbee, and cellular networks form the foundation of IoT connectivity in EV applications. Wi-Fi offers high data rates and is well-suited for localized monitoring in charging stations, but it consumes significant power and has limited range [21].

Zigbee, on the other hand, provides low-power, short-range communication that is cost-effective but less reliable for large-scale EV deployment. Cellular networks, including 4G LTE, provide broader coverage and higher reliability, making them suitable for applications that require real-time connectivity between vehicles and cloud platforms.

However, cellular communication incurs recurring costs and may not be energy-efficient for continuous monitoring [22]. These technologies are widely deployed in current IoT-enabled EV prototypes but are often complemented by long-range solutions like LoRa or 5G in large-scale applications. Each has trade-offs, making hybrid communication strategies increasingly common in EV ecosystems.

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5G and Edge-Enabled Charging Infrastructure

Fig 14.3 LoRa communication protocol [9]

The emergence of 5G networks has opened new opportunities for EV infrastructure by offering ultra-low latency, high bandwidth, and massive device connectivity [23]. In smart charging stations, 5G enables real-time communication between EVs, grid operators, and cloud platforms, ensuring efficient slot booking and load balancing. When combined with edge computing, 5G allows data processing closer to the source, reducing reliance on centralized servers and improving response times. For example, SOC and SOH data can be processed at the edge to trigger immediate slot reservations or safety alerts [24]. This distributed approach enhances scalability, enabling thousands of EVs to connect simultaneously without bottlenecks. 5G also supports integration with other smart city systems, such as traffic management and renewable energy coordination. While deployment costs are high, 5G and edge-enabled solutions represent the future of EV communication, offering unparalleled reliability and efficiency in managing large fleets and urban charging networks.

LoRa and LoRa WAN for Low-Power Wide-Area Communication

LoRa and its networking layer, LoRa WAN, have emerged as popular solutions for long range, low-power communication in IoT applications, including EV monitoring [25]. Unlike WIFI or cellular networks, LoRa enables communication over several kilometers with minimal energy consumption, making it ideal for battery-operated devices and wide-area EV fleets. In the context of EVs, LoRa can transmit SOC and SOH data to cloud platforms or charging stations without requiring continuous cellular connectivity. LoRa WAN further enables secure, bidirectional communication, allowing vehicles not only to send battery data but also to receive updates such as slot reservation confirmations.

The cost-effectiveness and scalability of LoRa-based systems make them attractive for developing regions and rural areas where cellular coverage may be limited [26]. However, LoRa is constrained by low data rates and limited bandwidth, restricting its use for high-volume data applications. Thus, LoRa is often integrated with other protocols in hybrid communication frameworks.

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Comparative Analysis of Communication Protocols for EV Applications

Each communication protocol offers distinct advantages and limitations in EV applications. Wi-Fi and Zigbee are effective for localized communication within charging stations but are limited in range and scalability [27]. Cellular networks provide wide coverage and reliable connectivity but come with higher operational costs and power consumption. 5G, while still being rolled out globally, offers the best combination of speed, latency, and device density, making it suitable for urban EV ecosystems [27]. LoRa and LoRa WAN, though limited in bandwidth, excel in long-range, low-power communication and are particularly useful for fleet monitoring or rural deployments. A comparative analysis suggests that no single protocol can address all EV communication needs. Instead, hybrid architectures that combine protocols based on application requirements are most effective. For example, LoRa can be used for wide-area fleet monitoring, while 5G ensures real-time slot booking in urban centers. Such multi-protocol strategies represent the future of scalable EV communication.

Integration of Battery Monitoring with Smart Charging Systems

Existing Approaches for Integrated Solutions

Integrated solutions that combine battery monitoring with charging slot management are still in their early stages but show significant promise. Some pilot projects connect the BMS with cloud-based charging management platforms, allowing real-time SOC data to trigger automatic reservations. For example, if the SOC falls below a predefined threshold, the system communicates with nearby charging stations and books a slot, reducing user intervention [28]. Fleet operators have also experimented with integrated dashboards that combine health diagnostics with charging logistics. However, most of these implementations are localized prototypes rather than large-scale deployments. Interoperability remains a challenge, as different EV manufacturers use proprietary BMS designs that are not always compatible with external slot booking systems [29]. While the technical feasibility has been demonstrated, scaling these solutions requires standardization, robust communication frameworks, and integration with broader smart grid systems [29]. These approaches lay the groundwork for fully automated EV energy management in the future.

Role of Cloud Platforms and IoT Dashboards

Cloud platforms and IoT dashboards play a crucial role in bridging battery health monitoring with charging slot reservation. By aggregating real-time SOC and SOH data from vehicles, cloud systems can analyze fleet-wide battery performance and predict upcoming charging demand [30]. IoT dashboards present this information visually, enabling users to monitor their vehicle health while receiving notifications about slot reservations. In advanced systems, these dashboards also allow operators to dynamically schedule charging, allocate slots based on priority, and coordinate with energy providers. Cloud platforms provide the scalability needed to manage thousands of vehicles simultaneously, while edge computing ensures low latency responses for time-sensitive operations [31]. Security and data privacy remain key concerns, as sensitive battery and location data are continuously transmitted. Nonetheless, cloud-integrated dashboards represent a practical and user-friendly interface for real-world deployment, enabling seamless coordination between EV monitoring and charging infrastructure [31].

Challenges in Synchronizing Battery Health and Charging Slot Booking

Synchronizing battery monitoring with slot booking introduces several challenges. First, real time accuracy of SOC and SOH data is crucial, as errors can lead to incorrect reservations, wasted slots, or stranded vehicles. Second, communication latency and reliability issues can disrupt the booking process, particularly in rural or congested networks [32]. Third, interoperability between different EV models, charging station providers, and communication protocols is limited, making standardization critical. Another challenge lies in balancing fairness: if multiple EVs trigger booking simultaneously, priority must be assigned without bias [32]. Cybersecurity risks also arise, as malicious attacks could manipulate reservations or disrupt charging operation. Additionally, dynamic grid conditions must be factored into booking decisions, ensuring that power demand aligns with availability [33]. Addressing these challenges requires cross-disciplinary approaches that integrate

AI for prediction, blockchain for secure transactions, and IoT protocols for seamless communication across diverse platforms.

Research Gaps and Opportunities

Current research has yet to fully realize integrated EV ecosystems that combine battery health monitoring with charging slot management. Existing systems are often fragmented, focusing on either SOC/SOH estimation or charging optimization in isolation. There is a significant opportunity to develop unified frameworks that merge these domains into a holistic solution. Another gap lies in predictive integration: few studies explore how forecasting battery degradation trends can inform long-term charging strategies [34]. Scalability is also an open issue, as most prototypes address individual vehicles or small fleets rather than city-wide systems. Opportunities exist in leveraging AI for predictive analytics, blockchain for secure reservations, and digital twins for simulating battery–charging interactions [34]. Furthermore, integration with renewable energy and vehicle-to-grid (V2G) frameworks could transform EVs into active participants in energy ecosystems. Bridging these research gaps would enable the development of adaptive, resilient, and sustainable EV infrastructures.

Case Studies and Prototype Implementations

IoT-Based Battery Monitoring Prototypes

IoT-based prototypes for battery monitoring have demonstrated the feasibility of real-time data collection and visualization in EV systems. Many academic and industry projects use low-cost microcontrollers, such as Arduino or Raspberry Pi, connected with sensors to measure SOC, SOH, voltage, and temperature [35]. These systems typically transmit data via WIFI, Zigbee, or LoRa to cloud platforms for visualization. Dashboards built using platforms like Node-RED or Blynk allow users to monitor battery health remotely, receiving alerts when SOC drops below thresholds [35]. Some prototypes integrate predictive algorithms, providing early warnings for potential failures. While these systems are often developed at laboratory or small-scale levels, they validate the concept of IoT-enabled monitoring. Their low cost and modularity make them suitable for rapid prototyping and student projects. However, scalability, robustness, and cybersecurity remain significant barriers to real-world deployment, leaving room for more advanced and standardized solutions.

Slot Booking Demonstrations for Charging Stations

Several prototypes have been developed to demonstrate charging slot booking systems using IoT and mobile applications. These systems typically allow users to view real-time availability of charging stations and reserve slots in advance [36]. Some incorporate automatic booking triggered by SOC thresholds, ensuring proactive management. For instance, academic demonstrations have used MQTT protocols to facilitate communication between EVs and charging stations, with cloud dashboards visualizing reservations [36]. Advanced prototypes also integrate payment gateways, allowing users to book and pay simultaneously. While effective in reducing waiting times and improving user experience, these systems often face challenges such as handling cancellations, rescheduling, and no-shows [37]. Despite these issues, slot booking demonstrations highlight the potential of digital platforms to streamline EV charging operations, paving the way for large-scale adoption.

LoRa-Based Energy Monitoring Applications

LoRa-based systems are particularly well-suited for energy monitoring applications due to their long-range and low-power characteristics [38]. Several prototypes use LoRa to transmit battery health data from EVs or AGVs (Automated Guided Vehicles) to a central monitoring station. For example, SOC and SOH data can be transmitted across kilometers without requiring cellular infrastructure, making LoRa ideal for rural or wide-area deployments [38]. LoRa WAN enhances this by enabling bidirectional communication, allowing vehicles to not only send data but also receive slot booking confirmations. Academic projects have shown that LoRa can effectively support low-data-rate applications such as SOC monitoring and slot reservation, with minimal power overhead [39]. However, LoRa is limited in handling large datasets or real-time high-speed communication, restricting its use in data-intensive scenarios [39]. Nonetheless, LoRa remains a promising candidate for scalable, low-cost EV monitoring systems, particularly when integrated with cloud platforms.

AGV-Based Demonstrations as EV Prototypes

Automated Guided Vehicles (AGVs) are frequently used as scaled-down prototypes to simulate EV operations in research settings. By equipping AGVs with rechargeable batteries,

IoT-enabled monitoring, and slot booking systems, researchers can replicate the behavior of EV fleets in controlled environments. These prototypes allow testing of SOC/SOH monitoring algorithms, communication protocols, and slot reservation mechanisms at lower cost and complexity compared to full-scale EV [40]. For instance, an AGV can automatically book a charging slot when its battery drops below 50%, demonstrating the feasibility of autonomous scheduling [40]. Such demonstrations provide valuable insights into system integration, highlighting challenges such as latency, reliability, and algorithm performance. Although AGVs cannot replicate the full complexity of EV batteries, they serve as effective testbeds for validating concepts

DISCUSSION AND COMPARATIVE ANALYSIS

Comparison of Existing Battery Monitoring Methods

Battery monitoring methods vary in complexity, accuracy, and practicality. Model-based approaches, such as Kalman filters and equivalent circuit models, provide accurate SOC estimation but require detailed parameters and computational resources [41]. Data-driven methods, particularly those using machine learning, offer adaptability to diverse conditions but depend heavily on large, high-quality datasets [41]. Direct measurement methods, while simple, are impractical for continuous monitoring in EVs. IoT-enabled systems extend these approaches by adding connectivity and visualization capabilities but introduce concerns regarding security and scalability [42]. A comparative analysis suggests that hybrid approaches, combining physics-based and AI-based methods, offer the most balanced performance. Nonetheless, no single method addresses all scenarios, highlighting the importance of adaptable, multi-layered solutions tailored to specific EV applications.

Comparison of Charging Slot Allocation Techniques

Charging slot allocation techniques differ in their efficiency and fairness. FCFS methods are easy to implement but often lead to inefficiencies and user dissatisfaction [43]. Reservation-based systems reduce waiting times but face challenges in handling no-shows and cancellations [43]. Queue management algorithms, including priority scheduling, improve fairness by prioritizing low-SOC vehicles but may still lead to congestion under high demand. Predictive coordination represents the most advanced approach, using AI to forecast demand and optimize resource allocation [44]. However, predictive models are limited by data availability and computational overhead. A comparative analysis suggests that combining reservation systems with predictive analytics offers the best balance of efficiency and user satisfaction, though scalability remains a challenge for large deployments.

Analysis of Communication Technologies

Communication technologies form the backbone of integrated EV systems, each with tradeoffs. Wi-Fi and Zigbee are suitable for localized, low-cost applications but lack scalability [45]. Cellular networks provide reliable, wide-area connectivity but incur higher costs and energy consumption. 5G, though still emerging, offers unparalleled performance for real-time, largescale EV management but requires significant infrastructure investment [45].

LoRa and LoRa WAN excel in long-range, low-power applications, making them ideal for fleet monitoring and rural deployments [46]. A comparative analysis indicates that hybrid communication frameworks, combining short- and long-range protocols, are best suited for EV ecosystems. The choice of protocol depends on factors such as deployment scale, latency requirements, and data volume, with no single technology sufficient for all use cases.

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Key Insights from Literature

The literature review highlights several key insights. First, while battery monitoring and charging slot management have been extensively studied individually [47], integration between the two remains limited. Second, IoT and communication technologies provide a strong foundation for integration but face challenges of standardization, scalability, and cybersecurity. Third, predictive models and AI-driven approaches are emerging as powerful tools for both SOC/SOH estimation and charging coordination [48], though their deployment is still limited to prototypes. Fourth, hybrid strategies whether in monitoring methods, slot allocation, or communication protocol consistently outperform single approaches. Finally, the use of AGV-based prototypes and LoRa-based systems demonstrates the feasibility of low-cost, scalable solutions, though real-world validation at scale remains lacking [49].

Future Directions

Predictive Analytics for Proactive Charging

Future EV ecosystems will increasingly rely on predictive analytics to anticipate charging demand and battery degradation. By leveraging big data and machine learning, systems can forecast SOC decline and reserve slots in advance, ensuring seamless operation [50]. Predictive analytics can also inform grid operators of upcoming demand, enabling better load balancing and integration with renewable energy.

AI-Driven Queue Optimization

Artificial intelligence has the potential to revolutionize queue management by dynamically adjusting slot allocation based on real-time conditions [51]. Reinforcement learning and neural networks can learn optimal strategies for prioritizing vehicles, minimizing waiting times, and ensuring fairness [52].

V2G (Vehicle-to-Grid) and Renewable Energy Integration

Integrating V2G capabilities allows EVs to act as distributed energy storage units, supporting grid stability. Coupled with renewable energy, this transforms EVs into active participants in sustainable energy ecosystems [53].

Multi-AGV/EV Fleet Management

Large-scale fleet management will benefit from coordinated monitoring and charging strategies. Predictive scheduling and integrated dashboards can optimize operations for logistics companies, public transport, and shared mobility services [54].

Scalable IoT Architectures for Smart Cities

The future of EV integration lies in scalable IoT architectures that connect vehicles, charging stations, and smart city infrastructures [55]. Standardized communication protocols, blockchain security, and edge computing will form the backbone of these systems [56].

CONCLUSION

This review highlights the critical importance of integrating battery health monitoring with smart charging slot management in EVs. While battery monitoring methods and slot reservation techniques have advanced significantly, most research remains isolated. IoT and communication technologies, especially LoRa, 5G, and cloud platforms, provide the necessary infrastructure to bridge these domains. Case studies and prototypes, including AGV-based demonstrations, validate the feasibility of integration but highlight challenges in scalability, interoperability, and cybersecurity. Future opportunities lie in predictive analytics, AI-driven optimization, V2G integration, and scalable IoT systems tailored for smart cities. By addressing existing gaps and leveraging emerging technologies, the EV ecosystem can achieve greater reliability, efficiency, and

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sustainability. Moreover, integrating renewable energy sources with charging infrastructure can further enhance system efficiency and environmental benefits. Standardization of data exchange protocols and stronger cybersecurity frameworks will also play a vital role in ensuring seamless operation and user trust across the EV network.

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