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Review

Intelligent Monitoring Systems for Electric Vehicle Charging

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Featured Application: This paper reviews EV charging challenges and existing monitoring methods to pinpoint key gaps. From our review, we propose a practical monitoring framework that leverages IoT sensors, edge computing, and cloud services for real-time oversight, predictive maintenance, and responsive analysis of user behavior.

Abstract: The growing adoption of electric vehicles (EVs) presents new challenges for managing parking infrastructure, particularly concerning charging station utilization and user behavior patterns. This review examines the current state-of-the-art in intelligent monitoring systems for EV charging stations in parking facilities. We specifically focus on two key inefficiencies: vehicles occupying charging spots beyond the optimal fast-charging range (80% state-of-charge) and remaining connected even after reaching full capacity (100%). We analyze the theoretical and practical foundations of these systems, summarizing existing research on intelligent monitoring architectures and commercial implementations. Building on this analysis, we also propose a novel monitoring framework that integrates Internet of things (IoT) sensors, edge computing, and cloud services to enable real-time monitoring, predictive maintenance, and adaptive control. This framework addresses both the technical aspects of monitoring systems and the behavioral factors influencing charging station management. Based on a comparative analysis and simulation studies, we propose performance benchmarks and outline critical research directions requiring further experimental validation. The proposed architecture aims to offer a scalable, adaptable, and secure solution for optimizing EV charging infrastructure utilization while addressing key research gaps in the field.

Keywords: electric vehicle charging; infrastructure monitoring; smart parking systems; edge computing; Internet of things; predictive analytics; user behavior analysis; energy management systems

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Academic Editor: Pedro Couto

Received: 29 January 2025
Revised: 19 February 2025
Accepted: 24 February 2025
Published: 4 March 2025

Citation: Martins, J.A.; Rodrigues, J.M.F. Intelligent Monitoring Systems for Electric Vehicle Charging. *Appl. Sci.* **2025**, *15*, 2741. https://doi.org/10.3390/app15052741

1. Introduction

The accelerating transition to electric vehicles (EVs) is reshaping urban transportation infrastructure. As global public charging installations increased by over 40% in 2023 [1], cities now face unprecedented challenges in managing this rapid expansion. A particularly critical issue emerges in urban areas, i.e., where 55% of the global population resides [2], as EVs routinely occupy charging spots well beyond optimal charging periods, especially during the 80–100% "slow charging phase", which can extend occupation times three-fold. This inefficient utilization creates substantial opportunity costs and reduces charging point availability during peak hours, significantly impacting both commercial viability and user experience [3].

While next-generation parking technologies have achieved notable successes, e.g., reducing search times by 43% and parking-related congestion by 30% through automated systems and smart controls [4], the unique challenges of EV charging infrastructure demand more advanced solutions. Current implementations using Internet of things (IoT) sensors and artificial intelligence (AI) demonstrate promising approaches for optimizing both parking efficiency and charging infrastructure utilization [5]. However, these systems often operate in isolation, lacking the integrated approach necessary for addressing the inherent complexity of EV charging management.

A fundamental challenge lies in the stochastic nature of user behavior and charging patterns [6]. Critical variables, including arrival times, battery requirements, and charging durations, exhibit significant uncertainty [7]. This variability undermines traditional optimization approaches that assume deterministic behavior, highlighting the need for more adaptive models capable of responding to the probabilistic nature of user interactions. Current systems lack the monitoring and control mechanisms needed to effectively manage these uncertainties while maintaining optimal infrastructure utilization.

This paper addresses these challenges through two primary contributions:

1. A review of current EV charging monitoring technologies, evaluating their effectiveness and limitations. The review analyzes key performance indicators, including anomaly response times, detection accuracy, and station resource utilization, to identify potential best practices and areas for improvement.
2. An architectural framework that builds on established technologies while introducing approaches to system integration and behavioral analysis. This framework combines distributed processing for fault detection and improved security [8], real-time data management for high-availability systems [9], and IoT-based monitoring for anomaly detection in car parks [10] with the goal of achieving improvements in system performance and reliability.

This framework reviews existing methodologies and proposes performance benchmarks to inform future implementations, focusing on system-level architectural patterns and integration strategies for EV charging monitoring systems. This strategy aims to support operational capabilities and provide a scalable platform for incorporating emerging technologies. We explore distributed monitoring architectures using edge computing, IoT sensors, and cloud services, which may contribute to low response times [11], enhanced detection accuracy [12], improved resource utilization [3], and increased system reliability [9]. The analysis emphasizes broader architectural implications, without focusing on lower-level implementation details, hardware specifications, installation practices, maintenance procedures, or specifics of charging algorithms and communication protocols.

To address the identified challenges, this paper offers three primary contributions: (1) a conceptual monitoring architecture that systematically combines edge computing, IoT sensors, and cloud services, aiming for improved latency, enhanced anomaly detection accuracy, and high system availability; (2) a behavioral analysis framework integrating real-time monitoring, anomaly detection, and user behavior models to improve operational efficiency and predictive modeling; (3) an advanced fault detection system integrating thermal analysis, electrical monitoring, and usage pattern analysis to enhance safety and reliability.

The remainder of this paper is structured as follows: Section 2 examines current implementations of smart parking systems and EV charging management, analyzing their capabilities and limitations. Section 3 combines these findings to identify technological gaps and system requirements. Section 4 presents the proposed monitoring framework, detailing its layered architecture and core functionalities. The concluding section evaluates implementation considerations and outlines directions for future research.

2. Related Work

This section reviews three interconnected aspects of EV charging infrastructure: smart parking systems, EV-specific parking and monitoring solutions, and integration challenges. The analysis progresses from fundamental parking technologies to specialized EV monitoring systems, synthesizing current limitations and opportunities. We begin with a brief overview of our review methodology.

2.1. Review Methodology and Selection Criteria

This review focused on peer-reviewed journal articles and conference proceedings published between 2018 and 2024. We searched major academic databases (IEEE Xplore, ACM Digital Library, and Science Direct) using keywords related to "EV charging monitoring", "smart charging infrastructure", "charging station management", "IoT", "edge computing", and "user behavior analysis". We prioritized publications focusing on system architecture, integration strategies, and implementation challenges with quantifiable performance metrics. Studies focused solely on charging algorithms or hardware specifications without system-level considerations were excluded. Quality assessment considered methodological rigor, clarity of architectural description, validation of proposed solutions, and relevance to the current technological landscape. Data extraction documented key aspects of each publication, enabling comparative analysis and identification of common themes and research gaps.

2.2. Smart Parking

Recent advances in smart parking technologies have focused on improving space management by using sensor networks and real-time monitoring systems. These innovations address critical urban challenges: reducing search times, minimizing traffic congestion, and optimizing space utilization. The evolution of these systems reveals a progression from simple occupancy detection to complex, AI-driven management solutions.

Early implementations, such as Saraiva and Rodrigues' computer vision system [13], demonstrated the feasibility of low-cost solutions by combining Raspberry Pi hardware with custom image processing algorithms. While effective for basic occupancy detection, this approach faced challenges with varying lighting conditions and occlusion—issues that informed later design improvements. Luque-Vega et al. [14] addressed these limitations in SPIN-V through a multi-sensor approach, integrating distance sensors with visual data to enhance detection reliability.

Another advancement came from Perković et al. [15], who addressed the critical challenge of power-efficient communication in distributed sensor networks. Their implementation of LoRa technology achieved reliable data transmission while reducing power consumption significantly when compared to traditional wireless protocols.

Recent work by Elfaki et al. [5] represents the current state of the art, combining IoT infrastructure with machine learning for dynamic space allocation. Their system's key innovations include real-time demand-based allocation of parking slots, pre-booking capabilities, and automated occupancy detection. Raj and Shetty's analysis [16] of smart parking developments highlights how these technologies are becoming integral to smart city initiatives, with particular emphasis on their role in reducing urban congestion and emissions through efficient space utilization.

2.3. EVs Smart Parking

While traditional smart parking systems provide a foundation for EV infrastructure management, the unique requirements of electric vehicles demand specialized monitoring and control capabilities. Key challenges include optimizing charging schedules, managing peak loads, and integrating with smart grid systems. Recent advances in battery management systems, charging protocols, and IoT integration have enabled newer approaches to these challenges [3,17].

IoT and Real-time Monitoring. The integration of IoT technologies has enabled real-time monitoring of critical parameters across charging networks. Modern IoT-enabled charging stations can track not just basic metrics—like occupancy and power consumption—but also detailed charging profiles, thermal characteristics, and grid conditions. This granular data collection, combined with edge computing capabilities, allows operators to implement predictive maintenance strategies that have been shown to reduce downtime in real-world deployments [18]. Ding et al. [3] implemented an IoT-based system that predicts the initial state of charge for vehicles entering parking facilities while tracking vehicle locations and connection durations within the charging infrastructure. Santhoshkumar et al. [19] developed a PIC microcontroller-based monitoring system for EV charging stations that enables real-time tracking of voltage, current, and temperature parameters. The system implements configurable current limits and automated safety protocols that trigger protective relays when measurements exceed defined thresholds. Integration of GSM communication enables immediate status notifications via SMS when anomalous conditions are detected, facilitating rapid response to potential safety concerns.

System Architecture and Security. The evolution of EV charging infrastructure has seen significant architectural innovation. Ashwin Vishnu and Sivraj [20] developed an approach that tightly integrates vehicle-side systems (like ECU-based battery management) with infrastructure components through V2I communication. This bidirectional information flow enables features like dynamic space allocation and predictive charging management. Jahangir et al. [21] analyze charge manipulation attacks (CMAs) against EV charging infrastructure, where malicious actors modify data exchanges during smart charging processes to manipulate aggregated EV demand patterns. Their analysis demonstrates how CMAs can bypass existing security protocols in EV communication standards. Through modeling of market participation in day-ahead and real-time energy trading, they quantify the economic impact of CMAs on EV aggregator profitability. To address these vulnerabilities, they propose an unsupervised deep learning framework that monitors charging parameters to detect attack signatures.

Charging Optimization. Zhang and Cai [22] addressed the challenge of optimizing charging schedules in workplace settings. Their dynamic charge scheduling scheme (DCSS) demonstrated how intelligent load management could reduce peak demand while maintaining charging effectiveness through careful coordination of grid and solar power sources. The integration of energy storage systems (ESS) represents another important advancement in smart charging infrastructure. Mohammadi and Rashidzadeh [23] highlighted how ESS can serve as a buffer between charging demand and grid capacity, enabling more efficient power management and grid stabilization. Their implementation of IoT-enabled battery management systems improved the overall charging efficiency while reducing strain on the local power infrastructure.

Morais [7] developed an energy management framework for EV parking facilities that optimizes charging allocation based on fairness indices, installed capacity constraints, and minimal EV-to-infrastructure communication requirements. Their mixed-integer linear programming approach incorporates multiple contract types (standard, premium, and extended duration) to enhance billing equity. The system's performance was evaluated against first-come-first-served baseline scheduling through comparative fairness metrics across charging configurations. Wang and Wu [24] proposed a semi-decentralized real-time charging scheduling framework that optimizes coordination between individual charging stations and a central operator. Their methodology employs a chance-constrained model at the central operator level to estimate aggregate charging demand through rolling optimization at coarse temporal resolution. The framework incorporates a Gaussian mixture model to characterize uncertainty in arrival and departure demand patterns. Individual charging stations determine power allocation based on station-specific urgency metrics and discharge availability, utilizing the centrally computed energy references. The fine-grained scheduling at each station considers charging dynamics and departure uncertainty scenarios through a detailed temporal resolution. Empirical validation demonstrates that the system achieves efficient minute-scale charging optimization for large EV fleets while maintaining near-optimal revenue performance when key parameters, including urgency factors, temporal granularity, and discount rates, are properly calibrated.

User Behavior Analysis. Alinejad et al. [6] evaluated profit maximization strategies for parking lot operators while minimizing costs for EV owners. Their analysis demonstrates that intelligent parking lot (IPL) design must account for real-world constraints and the stochastic nature of user behavior. The proposed solutions include implementing incentive mechanisms for partial charging scenarios, which enable increased charging throughput while reducing peak-hour grid demand by load shifting to off-peak periods. Anwar et al. [25] conducted a review of managed EV charging implementations in the United States, analyzing deployment costs and reported cost–benefit metrics. Their assessment identified key technical and operational gaps in EV-grid integration, highlighting the value of controlled charging strategies.

Phipps et al. [26] developed an uncertainty quantification framework for personalized EV charging predictions using probabilistic modeling. Their analysis, which was conducted on both real-world EV journey data and a semi-synthetic mobility dataset, demonstrated effective error control even under high-variance conditions typical of real charging scenarios. The framework's ability to provide individualized uncertainty bounds can be important for user-centric smart charging applications. Zhou et al. [27] conducted an empirical analysis of EV charging patterns in Changshu City, China, developing an integrated database to examine charging behavior. Their study analyzed charging initiation timing, state-of-charge transitions, and session durations across charging platforms. Through cluster analysis, they identified distinct behavioral patterns between plug-in hybrid and battery-electric vehicle users, with battery-electric vehicles exhibiting five clusters and plug-in hybrids showing four primary patterns. The analysis revealed varying manifestations of range anxiety across both user groups, including pre-trip complete charging, destination charging, and partial charging strategies. Notable differences emerged in high-range anxiety scenarios, with plug-in hybrid users favoring complete charging while battery electric vehicle users demonstrated route-specific complete charging behavior. The study also identified a significant preference for overnight complete charging among battery-electric vehicle users.

Grid Integration. Tan et al. [28] proposed a multi-agent simulation architecture for commercial parking facilities that captures individual EV behavior through autonomous agents. Their framework implements two primary agent types: a power distribution center agent that coordinates solar, storage, and grid resources and a scheduling agent that optimizes charging patterns considering stochastic departure times. The system employs a two-stage optimization approach, first implementing priority-based scheduling to ensure equitable charging access, followed by genetic algorithm optimization to determine optimal charging/discharging windows that maximize user benefits. Gharibi et al. [29] developed a deep neural network framework for 24 h ahead market price prediction, validated using the German energy market and Caltech charging session data. Their results demonstrate significant cost reductions through intelligent price-aware scheduling of parking lot charging operations.

Martin et al. [30] developed a feeder-level EV detection system utilizing sliding-window feature extraction and machine learning classification. Their non-intrusive load monitoring technique enables EV charging detection through analysis of load measurement data, providing an efficient solution suitable for both offline and online deployment. Adhikary et al. [31] implemented bidirectional communication between EVs and charging infrastructure through a converter-based system supporting vehicle-to-grid (V2G) and grid-to-vehicle (G2V) operations. Their implementation incorporates time-based energy tariffs for G2V charging costs while implementing variable pricing for V2G operations. The system ensures synchronized voltage levels between the vehicle and the grid during bidirectional power transfer, enabling reliable grid support capabilities when required.

Harighi et al. [32] developed an aggregated model to quantify the flexibility potential of multi-station EV parking facilities. Their framework employs stochastic optimization to predict maximum flexibility margins, enabling EV aggregators to provide intraday grid services through controlled power absorption variations. The model facilitates distribution system operators' requests for charging modifications while maintaining service quality. Validation tests across parking configurations with varying station counts demonstrated the model's effectiveness in handling stochastic arrival and departure patterns, with results indicating reliable flexibility prediction capabilities.

3. Analysis of Current State and Implications

Analysis of current research reveals several fundamental aspects of EV charging infrastructure: communication protocols, energy management, and user interfaces. Recent developments demonstrate progress in charging station placement optimization, distributed energy control systems, and urban EV integration frameworks. While cloud-based management solutions show quantifiable gains in operational efficiency and charging optimization, critical aspects like cybersecurity and privacy in networked charging stations remain only partially addressed [3]. The integration of these systems with future transportation infrastructure presents additional technical challenges [33].

The literature includes extensive reviews of EV infrastructure, addressing fundamental technologies and implementation challenges [34], optimization of vehicle routing [35], strategic infrastructure deployment [36], power consumption forecasting [37], intelligent parking systems [38,39], charging mechanisms [40,41], and microgrid management approaches [42]. Recent developments continue to advance these capabilities [43–45].

We identify five key requirements for effective EV charging infrastructure management based on the reviewed literature: (i) charging optimization: monitoring systems must ensure optimal power delivery by implementing condition-based maintenance and adaptive charging protocols that account for battery characteristics (i.e., real-time battery characteristic monitoring) and grid conditions [22,46]; (ii) system reliability: redundant architectures and predictive maintenance algorithms (e.g., fault prediction) are essential to minimize downtime, enabled by distributed sensor networks and real-time analytics [18]; (iii) thermal monitoring: continuous temperature monitoring of connectors, power electronics, and cooling systems is required to prevent component degradation and ensure safety, with thermal anomalies preceding most major failures [19]; (iv) user interaction optimization: integration between charging status monitoring and behavioral analysis enables accurate prediction of charging duration and station availability (i.e., predictive scheduling), increasing user satisfaction [6]; (v) grid integration: real-time communication between charging infrastructure and grid operators (V2G-enabled systems) is necessary to implement load management and prevent network overload, improving power quality metrics [47]. These requirements emerge from both the technical limitations of current systems and the practical challenges observed in operational charging networks.

This analysis indicates that effective charging infrastructure management necessitates integrated monitoring systems capable of simultaneously addressing multiple technical domains. The following section presents a framework for intelligent EV charging monitoring that implements these requirements through a layered architectural approach.

4. Intelligent EV Charging Monitoring System

This section introduces a conceptual architecture for an intelligent EV charging monitoring system designed to address the infrastructure challenges identified in Section 3. This framework integrates three core technologies: IoT sensor networks for distributed data collection [5,48], edge computing for localized analytics [3,49], and cloud-based platforms for system-wide management [6,50]. Figure 1 illustrates the proposed architecture, and subsequent sections provide further detail. The architecture is designed to enable multi-domain monitoring, incorporating three conceptual modules: real-time charging diagnostics, infrastructure utilization modeling, and behavioral pattern analysis [27,51].

The conceptual design includes four functional planes: (i) adaptive parking management, potentially achievable through probabilistic space allocation [14,15]; (ii) energy optimization, potentially using theoretical machine learning models [28,46]; (iii) privacy-preserving interface prototypes [52,53]; (iv) integrated security frameworks. Drawing from recent studies [3,7,24], the proposal aims to address key requirements for next-generation systems, including low monitoring latency (aiming for sub-second), hybrid edge-cloud processing, multi-agent behavior modeling, adaptive control structures, and cryptographic protection. The architectural design is further supported by simulation-based performance projections and theoretical validation, as discussed in the following sections.

4.1. System Architecture Overview

The proposed monitoring system uses a layered architecture with three tiers: physical sensors, edge computing, and cloud services (Figure 1). Each layer has a specific role, but data flows continuously between them. Physical components collect data, edge computing performs local analysis, and cloud services manage the overall system. This design allows for both distributed control and centralized management, using standard protocols. Fault-tolerant channels handle inter-layer communication, and security measures (encryption, authentication, and access control) are implemented at each level.

4.1.1. Physical Layer

The physical layer is the hardware foundation of the system, integrating sensors and components to collect data from the charging environment. This layer includes interconnected monitoring subsystems that operate simultaneously for complete data collection, balancing reliability, accuracy, and cost [10].

Smart Charging Stations serve as the primary interface between vehicles and the monitoring system [46,54]. Each station should incorporate high-precision power monitoring sensors designed to reliably measure EV voltage and current as required by relevant standards (e.g., Level 3 EV chargers) [17]. Sensors should offer sufficient measurement accuracy and consistent sampling capabilities to support the system's monitoring objectives [19]. While a measurement accuracy of at least ±0.5% and a consistent sampling rate of at least one sample per second is desirable, lower-cost sensors with slightly reduced accuracy (e.g., ±1%) can be considered for cost optimization [19]. The selected charging station models need to prioritize reliability, adherence to relevant charging standards (e.g., IEC61851 [55], ISO15118 [56], and

IEC62196 [57]), and ease of maintenance. Each of these should feature built-in power quality analysis and support bidirectional power flow measurement for energy storage systems (ESS) and vehicle-to-grid (V2G) applications [31], with integrated temperature compensation ensuring measurement stability across varying environmental conditions. Modular construction allows for future upgrades (e.g., integration with additional components like solar panels) and maintenance without requiring extensive system downtime [40].

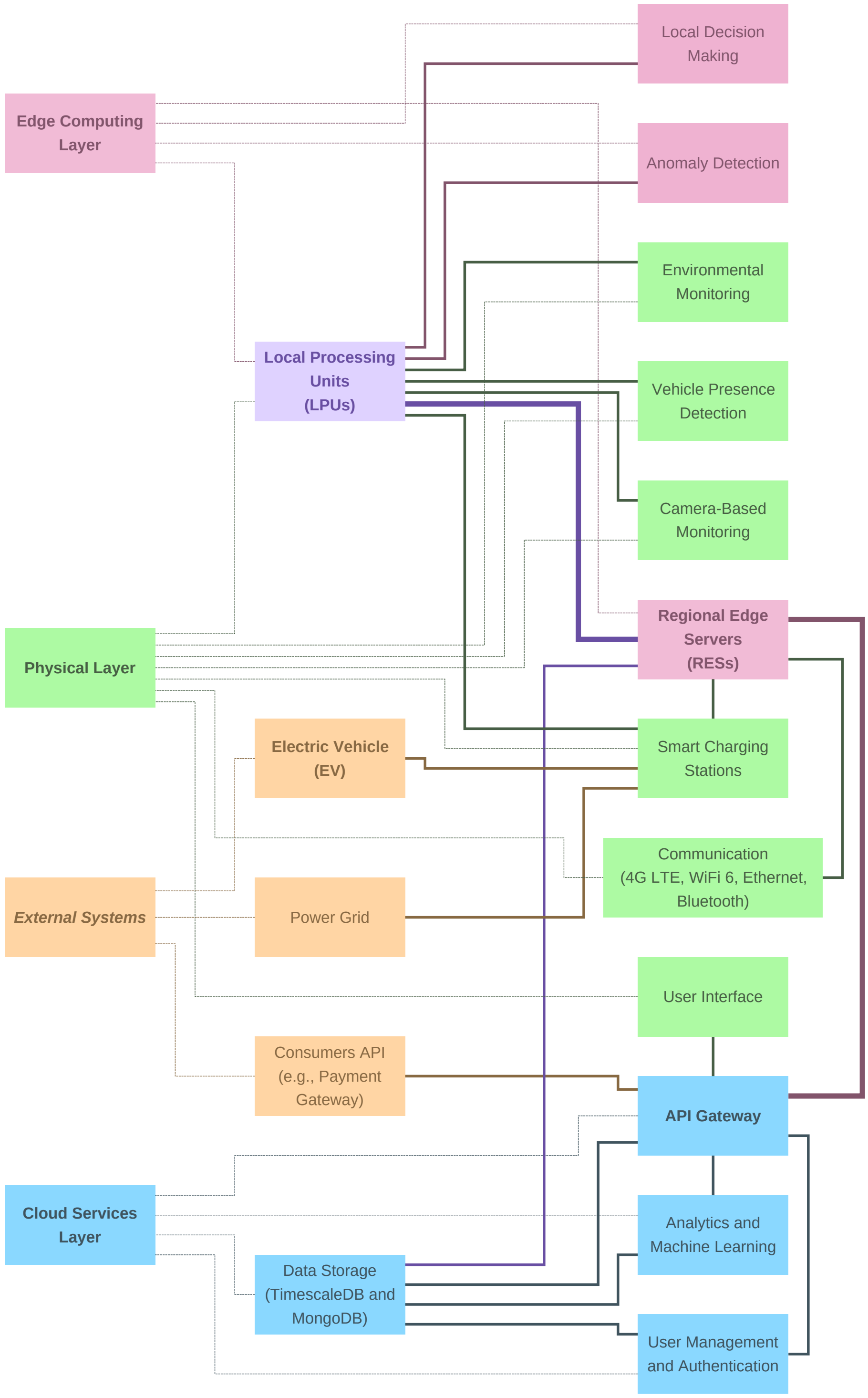

Figure 1. System architecture overview of the intelligent EV charging monitoring system. Colors differentiate layers and their components. Solid lines indicate data flow, while dotted lines represent component relationships.

For *vehicle presence detection*, a dual-technology approach combining magnetic field [58,59] and ultrasonic sensors [15,60] is recommended for enhanced reliability. Magnetic sensors should reliably detect metallic objects within a practical range and with a prompt response, while ultrasonic sensors should provide accurate positioning with frequent updates [5,14]. This combination, suitable to be enhanced by cross-validation logic, could help ensure reliable detection and minimize false positives while incorporating anti-tampering mechanisms. The choice of specific sensor technologies should take into account cost, power consumption, ease of installation, and environmental resilience [51].

The *communication capabilities* would best be implemented through a multi-protocol architecture centered on 4G LTE technology with future 5G integration (particularly 5G NR Sub-6 GHz and mmWave bands) as it becomes cost-effective [61,62]. The system will need to support standard 4G LTE bands, with built-in redundancy and automatic fallback to 3G in areas with limited 4G coverage [63]. Additional communication options could include WiFi 6 compatibility with dual-band support and MIMO capability, secured through WPA3 protocols [53]. A gigabit Ethernet backbone can also provide reliable connectivity for fixed installations, while Bluetooth 5.0–5.4 facilitates local diagnostics and maintenance operations [48].

For *local processing*, we recommend cost-effective, industrial-grade computing units (e.g., based on ARM Cortex-A architecture with appropriate memory and storage) [64]. These units can run real-time operating systems and incorporate hardware-based encryption for security [52]. System reliability is further ensured through watchdog timer implementations and uninterruptible power supply backup systems, providing sufficient runtime under full load [65]. The processing capacity should be enough to handle data from multiple sensors and charging stations, with scalability achieved through a distributed processing architecture at the edge computing layer, allowing for load balancing and fault tolerance [49]. Local processing units perform data aggregation, preprocessing, and preliminary analysis, executing edge AI algorithms and predictive maintenance routines [3]. The architecture should implement standardized interfaces (Modbus, CAN, and MQTT) to facilitate integration with existing charging infrastructure [66].

Environmental monitoring is accomplished through a sensor array designed to track essential parameters such as temperature, humidity, and, optionally, air quality (e.g., particulate matter, volatile organic compounds, and CO2) [19,67]. Environmental sensors are housed in protective enclosures (e.g., IP66-rated) with appropriate shielding [65]. The system is designed for easy installation, maintenance, and expansion, supporting remote calibration and automatic error reporting [11,18].

An optional *Vision Monitoring System* can enhance security and provide supplementary visual analytics. This system should integrate high-resolution IP cameras with wide dynamic range capabilities, supporting low-light operation and infrared illumination for continuous monitoring [14]. Computer vision algorithms can enable advanced functionalities, including flame detection [12], automated license plate recognition, vehicle classification, and occupancy verification [13]. Edge-based privacy-preserving processing minimizes bandwidth requirements while maintaining data protection. The system interfaces with local processing units for real-time video analysis and event detection, supporting both local and cloud storage architectures [5]. This vision system remains an optional component, deployed based on specific site requirements and compliance with local regulatory frameworks [51].

Environmental protection measures ensure reliable operation in outdoor installations through a comprehensive, standards-compliant design [40]. We propose a robust design that includes a wide operating temperature range, ingress protection against dust and water, and impact resistance. Material protection is achieved through UV-stabilized enclosures, corrosion-resistant components, and specialized coatings for harsh environments [65]. Thermal and humidity management systems can be optionally included to maintain optimal internal conditions [18,31]. Environmental qualification is verified through testing [41].

System integration employs a modular architecture with standardized interfaces that enable component interoperability and simplified maintenance [63,65]. Key design elements include hot-swappable modules, rapid servicing capabilities, and diagnostics [11]. The diagnostic framework should implement automated error logging, self-test routines, and remote monitoring functionality [21]. Component specifications should define expected operational lifespans and maintenance intervals [18], while the integration strategy must prioritize system availability and cost-effectiveness [41]. Local diagnostic ports and remote monitoring capabilities can also enable predictive maintenance [19].

The *user interface design* should prioritize intuitive operation [3]. This includes incorporating high-brightness, high-contrast touchscreens for optimal outdoor visibility [54]. The interface should clearly display charging status information, offer user authentication options [53], and facilitate payment processing [66]. To enhance usability for all users, including those with disabilities, accessibility features such as voice guidance and tactile feedback should be implemented [51]. The interface should support multiple languages and be customizable to individual user preferences [68]. Design should emphasize easy navigation, quick access to essential functions, clear visual indicators, and informative error messages [63]. Remote access and control capabilities, secured with robust authentication mechanisms, are also necessary to protect user data and privacy [21]. Regular user feedback and usability testing are essential to identify areas for improvement and optimize the user experience [6].

The physical layer components are designed to work in concert, providing a monitoring solution that ensures reliable operation, user-friendly interfaces, and seamless integration with existing charging infrastructure. The system architecture is designed to be scalable, flexible, and secure, enabling efficient monitoring and control of EV charging infrastructure in diverse environments.

4.1.2. Edge Computing Layer

The edge computing layer performs distributed processing and real-time analytics at charging sites, reducing cloud bandwidth and latency [49,64]. This layer uses a hierarchical architecture with multiple processing tiers, each specialized for specific tasks and data management [3,46]. This design prioritizes rapid local decisions through real-time analytics, anomaly detection, and adaptive data handling while maintaining security and interoperability [52]. These capabilities are essential for autonomous operation and reliability.

Local processing units (LPUs) form the base of the hierarchy, integrated within each charging station for real-time analytics of raw sensor data streams [19,46]. These units utilize parallel processing hardware, such as multi-core ARM processors, to concurrently monitor multiple charging parameters [64,65]. Specifically, current draw, voltage levels, and power factor are measured with a high resolution (e.g., 100 ms) using sliding window analysis, which facilitates the rapid detection of charging state transitions and potential anomalies [3,11]. Adaptive thresholding mechanisms should be implemented to ensure accuracy across diverse EV models and varying environmental conditions by dynamically adjusting based on learned patterns and real-time context [18].

Another critical function of the edge layer is *anomaly detection*, which is designed to enhance the safety and efficiency of the charging process [3,21]. To identify and classify deviations from expected charging patterns, a multi-stage filtering approach should be implemented [69]. This approach can include an initial stage relying on statistical methods such as Kalman filtering and exponential smoothing, with parameters dynamically adjusted based on historical data and operational context to identify potential anomalies [3]. Subsequently, lightweight neural networks optimized for edge deployment with a small memory footprint (e.g., under 100 MB) may be used to classify these deviations [46]. These neural networks should be designed to achieve high detection accuracy for known anomaly types [43]. The neural network models can be trained using a dataset of charging session data, incorporating both supervised and unsupervised learning techniques and continuous online learning to adapt to evolving anomaly patterns [50]. A secure model update system, allowing for incremental over-the-air updates, could also ensure optimal performance while minimizing disruption to charging operations [18], and backwards compatibility can be maintained by allowing local processing units (LPUs) to temporarily operate multiple model versions.

Efficient *data management* at the edge layer requires adaptive sampling based on charging session phases [3,49]. During critical transitions like charge initiation and termination, the sampling frequency increases to capture detailed behavior patterns, whereas routine charging phases can employ reduced rates to conserve resources [19]. To optimize data handling efficiency, the system could use compression algorithms with dynamic ratios, which are adjusted according to network conditions and storage availability [63].

For autonomous operation and rapid response, LPUs implement *Local Decision-Making* through a hybrid system combining rule-based expert systems with fuzzy logic controllers [70,71]. The expert system encodes industry standards and regulatory requirements into deterministic rules—for example, automatically terminating charging if battery temperature exceeds safety thresholds [17]. Fuzzy logic controllers manage scenarios with inherent uncertainty, such as optimizing charging rates under variable grid conditions [24]. Membership functions for fuzzy variables derive from empirical data and domain expertise [7]. This architecture enables intelligent local decisions with low response latencies for critical events while identifying optimization opportunities, such as load balancing across charging stations [28,32].

Regional edge servers (RESs) form an intermediate hierarchical layer, implementing distributed data processing and storage for charging station clusters [49,64]. These servers utilize a distributed database architecture optimized for time-series data [9], designed to handle high write throughput and maintain low query latencies. The storage infrastructure employs multi-tiered data management: hot data in DRAM, warm data in solid-state storage, and automated migration of cold data to long-term storage [50,66]. This approach optimizes performance-cost efficiency across the data lifecycle. RESs can execute advanced analytics, including predictive maintenance algorithms, load forecasting models, and real-time anomaly detection [29], with very low processing latencies for critical events. The analytics framework leverages distributed computing to optimize charging infrastructure through continuous monitoring and adaptive control [18,46]. RESs establish secure communication with LPUs, cloud services, and peer RESs through encryption and authentication mechanisms that ensure data integrity and confidentiality across the edge computing infrastructure [52,53].

Network management in the edge layer employs software-defined networking (SDN) principles to optimize data flow between LPUs and RESs [49,72]. An SDN controller can dynamically adjust routing paths based on real-time latency measurements and bandwidth utilization metrics, implementing quality-of-service guarantees for critical data streams through traffic classification and prioritization [61,62]. For *security and privacy*, the edge layer should implement a detailed protection framework. LPUs can integrate hardware security modules for cryptographic operations and secure key storage; deep packet inspection engines can help detect and mitigate network-based threats in real-time [21,52]. The architecture implements a security framework based on zero-trust principles, requiring mutual authentication and authorization between all system components [73]. Cryptographic processing overhead is kept minimal to maintain overall system responsiveness [53], with end-to-end encryption managed through dedicated hardware security modules to ensure data transmission security [74,75]. System integrity relies on secure boot verification and code-signing mechanisms that prevent unauthorized firmware modifications [65]. This access control system combines role-based permissions with granular authorization policies enforced at edge nodes [52]. Privacy preservation incorporates differential privacy techniques and data anonymization methods, which maintain analytical utility while protecting sensitive information [53]. The security framework further includes automated vulnerability scanning, penetration testing, and secure over-the-air update mechanisms to ensure continuous system protection and regulatory compliance [21].

The edge layer implements *fault tolerance* and horizontal *scalability* through an architecture of redundant processing capabilities and automated failover mechanisms [49,63]. Both LPUs and RES maintain hot standby capabilities, potentially enabling seamless transition during hardware failures or excessive load conditions [65]. System resilience is achieved through a distributed consensus protocol (e.g., Raft or Paxos) that maintains state consistency across redundant nodes [76], with design failsafes to ensure prompt failover and minimal delays during state synchronization.

Interoperability and standards compliance. The edge layer is expected to implement full support for multiple industry-standard protocols and interfaces to ensure seamless integration between diverse EV charging infrastructure and vehicles [17,40]. The system could support multiple communication protocols, including OCPP (open charge point protocol), Modbus, MQTT, and OPC UA, along with vehicle interfaces, such as ISO 15118 [61,63]. LPUs could communicate with other edge nodes and cloud services using standardized RESTful APIs (Representational State Transfer Application Programming Interfaces), enabling robust data exchange and synchronization across distributed components [66]. The architecture is designed to be vendor-agnostic and standards-compliant, adhering to relevant industry specifications for data formats, communication protocols, and security requirements [41]. This commitment to standards and interoperability would promote broader adoption while enabling easy integration of new components and services as the system evolves [48]. LPUs should be modular and extensible by design, supporting a wide range of charging station models and sensor types through open standards and protocols [31,68].

4.1.3. Cloud Services Layer

The cloud services layer is proposed to implement the system's centralized intelligence through a scalable, multi-tenant architecture designed to process aggregated data from distributed edge computing nodes [50,77]. Containerized microservices deployed across geographically distributed data centers would ensure high availability while maintaining regional data compliance [73]. The cloud infrastructure would also require advanced storage and processing capabilities to effectively manage diverse data streams and support complex analytics workloads [66].

For the centralized *Data Storage Infrastructure*, we propose implementing a hybrid database architecture that integrates relational and non-relational systems optimized for high-throughput time-series data management [9]. The architecture could center on a distributed TimescaleDB cluster as the primary time-series store, leveraging its query optimization capabilities and native temporal data handling [76]. This configuration would enable efficient querying of historical charging patterns while maintaining sub-second query performance across multi-year datasets at a petabyte scale [78]. The selection of TimescaleDB is justified by its proven performance with continuous sensor data streams and SQL compliance, facilitating integration with enterprise analytics and reporting frameworks [63]. The system should aim to achieve consistent low query latencies while supporting subsecond-level temporal resolution, which is essential for the detailed analysis of charging patterns and infrastructure utilization [79].

For *security operations*, the system should ideally implement a defense-in-depth strategy adhering to NIST 800-53 standards [52,53]. Data encryption could require AES-256 with FIPS 140-2 validated modules, employing automated 30-day key rotation through hardware security modules (HSM) [74]. Network protection would ideally need real-time deep packet inspection capable of 100 Gbps+ throughput analysis [72], complemented by adaptive rate limiting and traffic filtering for mitigating distributed denial-of-service (DDoS) attacks [21]. This multi-layered security framework would aim to ensure data confidentiality, integrity, and availability while maintaining system performance under adverse conditions [73].

For *advanced analytics* capabilities, we propose implementing a distributed processing framework based on Apache Spark [77], enabling parallel processing of large datasets through its mature ecosystem [9]. While Spark provides proven performance for batch and stream processing, the architecture would maintain flexibility to incorporate alternative frameworks like Apache Flink as requirements evolve [78]. The analytics pipeline would aim to process charging session data with sub-500 ms latency, utilizing machine learning models trained on historical patterns [3]. Deep neural networks, particularly temporal convolutional networks (TCNs) [79] and long short-term memory (LSTM) architectures [80], could analyze temporal sequences to predict 24-h demand forecasts [29]. This hybrid approach would combine the ability of TCNs to capture hierarchical patterns with LSTM's capacity to model long-term dependencies, enhancing accuracy for both short and long-term predictions [46].

For *data analytics pipelines*, stream processing frameworks should be implemented to enable real-time analysis of charging patterns. Apache Kafka [9] streams could potentially process telemetry data with throughput exceeding 100,000 messages per second per processing node [63]. Machine learning models could be deployed using KubeFlow [78], enabling automated retraining as new data becomes available [50]. This architecture could implement both batch and online learning approaches: daily batch training for stable pattern detection and continuous online updates for rapid adaptation to emerging trends [29,46].

For *operational intelligence*, it is advisable to maintain proper monitoring and logging systems. Distributed tracing, potentially utilizing OpenTelemetry [76], could provide end-to-end visibility of request flows across microservices [78]. The monitoring systems could collect hundreds of distinct metrics per charging station, enabling detailed performance analysis and predictive maintenance scheduling [18]. Based on these metrics, ML models should be developed to analyze operational data and potential system degradation [11], aiming for proactive maintenance with high accuracy in failure prediction up to at least 72 h in advance [19].

The cloud services layer should facilitate seamless cross-platform data exchange through standardized interfaces, including JSON-LD for semantic interoperability and Protocol Buffers for efficient binary serialization [63,65]. The API management platform would ideally provide monitoring capabilities, including distributed tracing with OpenTelemetry [76], real-time metrics aggregation [9], and predictive scaling based on traffic patterns [78]. Future extensibility could be ensured through modular design supporting gRPC integration and GraphQL federation across distributed services [48,66].

4.2. Core Monitoring Functions

The system is proposed to implement a set of core monitoring functions, enabling real-time tracking, analysis, and optimization of the charging infrastructure [3,65]. These functions are designed to address key challenges associated with EV parking and charging, including charging status monitoring and user behavior analysis [18,19].

The *charging status monitoring* system could implement a multi-resolution temporal architecture that enables both instantaneous state assessment and longitudinal trend analysis across charging sessions [3,11]. Its core monitoring infrastructure would likely employ a distributed sensor network to sample key electrical parameters such as current, voltage, power factor, and energy transfer [17]. System-wide measurement synchronization could be ensured using precise timing protocols [19]. Current monitoring may employ hall-effect sensors with high measurement accuracy, with options available to balance cost and precision [17,31]. Digital signal processing algorithms could enhance reliability through real-time filtering and adaptive compensation techniques, effectively compensating for temperature-induced drift and environmental noise [11].

Adaptive sampling and data management strategies should utilize adaptive sampling techniques to optimize computational resources [46,49]. For example, a variable timestep algorithm could increase sampling frequency during periods of rapid power fluctuation, such as transitions between charging phases, while reducing sampling rates during steady-state charging [32]. To track energy usage, accumulated energy transfer calculations should integrate these instantaneous power measurements [31], while the system performs uncertainty quantification using propagation of errors analysis [26]. Maintaining separate accumulator registers for bidirectional energy flow ensures precise tracking of vehicle-to-grid energy transfer where supported [30,31].

The *charging time estimation* system is expected to implement a hybrid prediction model combining physical battery modeling with machine learning techniques [24,46]. The physical model can incorporate temperature-dependent charging characteristics and account for battery chemistry-specific parameters, including internal resistance and capacity [17,41]. The ML component should adapt to individual battery ageing patterns and environmental conditions [29,46]. This hybrid approach is designed to provide estimates for remaining charging time, aiming for reasonable accuracy, informed by the performance of similar systems in the literature [7]. Model refinement occurs continuously, with retraining performed at least weekly using real-time charging data to adapt to evolving battery characteristics [50]. For battery state of charge determination, the system should employ multiple estimation techniques based on available data sources [11]. For vehicles supporting direct SOC reporting through standard protocols (e.g., ISO 15118 or manufacturer-specific APIs), the system should maintain bidirectional communication with frequent updates [31]. In scenarios where direct SOC reporting is unavailable, coulomb counting could be employed, with drift compensation techniques to maintain accuracy [17]. This approach could be supplemented by voltage-based SOC estimation during key charging phases [40]. The multi-modal estimation approach aims for reasonable SOC accuracy, based on the capabilities of similar systems in the literature [11,46].

Charging phase detection can rely on a state machine implementation, augmented by fuzzy logic controllers to manage transitions between charging phases [70,71]. The system architecture should recognize distinct charging phases, including initial constant current charging (0–80% SOC), the transition to the constant voltage or slow charging phase (80–100% SOC), and the completed charging state [7,17]. Detection mechanisms should analyze multiple parameters—such as current reduction patterns, voltage stability metrics, and thermal characteristics—to ensure accurate phase identification [19,31]. The transition to the slow charging phase can be detected through analysis of current tapering patterns and voltage stability [11]. Similarly, the completed charging state should be confirmed through multiple mechanisms, including sustained current reduction below a predefined threshold (typically 1/20 of the maximum charging current) and, where available, direct charging completion signals from the vehicle [3,17]. The monitoring system should maintain a state history with temporal resolution adapted to the specific charging phase [24,32].

During rapid charging phases, state information could be recorded at short intervals, while slower charging phases may use adaptive recording intervals tailored to the operational context [3,46]. This state history should encompass charging curve characteristics, environmental parameters, and power quality metrics, enabling detailed post-session analysis and long-term charging pattern evaluation [29,50]. As a paramount consideration, all monitoring functions should incorporate fault tolerance [18]. Redundant measurement paths and real-time consistency checking could mitigate the impact of sensor failures or communication issues [11,65]. When detected, measurement anomalies should trigger automated cross-validation routines that identify the source of the error, allowing the system to maintain monitoring continuity, albeit in a potentially degraded operation mode [19,21]. The system architecture targets high monitoring availability through hierarchical failover mechanisms and self-healing capabilities [49]. While this multifaceted approach ensures robust monitoring, careful consideration of the associated data processing and storage demands remains essential [9,76]. The distributed processing architecture, outlined in Section 4.1.2, should handle these demands efficiently [49,64]. However, future investigation into data compression techniques and tiered storage solutions will be crucial for long-term scalability [63,78].

User Behaviour Analysis

Our literature review (Section 3) suggests that existing systems often lack detailed behavioral analytics, with most implementing basic usage tracking [3,24] but few using advanced behavioral modeling [24,29]. The proposed framework addresses this limitation by using a multi-modal approach combining real-time monitoring with predictive analytics to characterize and predict EV charging patterns through spatiotemporal analysis. Our approach goes beyond traditional temporal analysis [27,81], by incorporating spatial correlations and contextual factors crucial for accurate behavior prediction. Specifically, we combine real-time monitoring data with historical usage patterns to develop predictive models of charging station utilization. Empirical studies [27,81,82] demonstrate that charging behavior exhibits distinct temporal patterns that significantly influence infrastructure optimization. By conducting analysis at both individual and aggregate levels, we may enable greater infrastructure management efficiency [6,7,25], through behavioral data integration [24,28].

Statistical analysis may employ Cox proportional hazards models [83] to quantify factors affecting post-charging occupancy duration [26]. These models have robust handling of time-to-event data and capacity to integrate both static and dynamic covariates [83]. Feature extraction could utilize an adaptive sliding window, with dimensions dynamically optimized based on observed charging patterns [3,30]. This approach would enable the capture of both short-term post-charging dynamics and extended occupancy trends. The window dimension adaptation algorithm could respond to temporal variations in occupancy patterns [26]. The feature set should encompass multiple temporal dimensions: historical session durations, inter-session intervals, and spatiotemporal occupancy patterns across both target and adjacent charging stations. This represents a feature engineering approach capable of capturing both individual usage patterns and local infrastructure dynamics [24,27]. The model would incorporate contextual variables, including temporal cycles (daily and weekly) and event-based factors that demonstrate significant influence on parking behavior. System performance targets would likely aim for high accuracy in overstay prediction shortly after charging completion [29]. This accuracy threshold would balance the operational requirement for prompt intervention with practical considerations for user response time.

Temporal pattern identification could employ advanced unsupervised learning methodologies [3,29]. The core algorithm may implement a modified time-series clustering approach utilizing Dynamic Time Warping (DTW) distance metrics [24,84]. DTW is considered due to its capacity to handle variable-length sequences and inherent robustness to temporal distortions characteristic of real-world charging data [27]. The algorithm could incorporate a novel warping penalty mechanism [26], potentially preventing spurious pattern matches while maintaining sensitivity to genuine behavioral similarities. Pattern classification is expected to employ Ward's method for hierarchical clustering [28]. This hierarchical approach could reveal both dominant usage patterns and significant deviations from typical behavior. While alternative clustering methods are possible, hierarchical clustering has shown promising capability in identifying nested behavioral patterns and multi-scale temporal structures [7]. The clustering implementation would aim for a silhouette coefficient [85] threshold of 0.8, ensuring robust cluster separation and internal cohesion. This metric represents an established quality benchmark in unsupervised pattern analysis, particularly for behavioral data. We propose to integrate STL (Seasonal and Trend decomposition using Loess) decomposition for multi-scale temporal analysis, enabling the identification of daily, weekly, and monthly usage cycles [32].

The notification response analysis module could implement high-precision real-time monitoring of user-system interactions, extending established IoT monitoring architectures [18,63]. The module would be designed to capture response latencies with millisecond resolution, implementing categorical classification by notification characteristics (e.g., completion alerts and overstay warnings) and criticality levels [3,19]. Response pattern modeling may employ advanced survival analysis techniques, enabling probabilistic prediction of response intervals through the integration of historical behavioral data and contextual parameters [26,83]. Module predictions will probably rely on gradient-boosted decision trees (GBDT), considered for their demonstrated efficacy in charging infrastructure applications [24,29]. The GBDT architecture could provide optimal handling of feature interactions, robust performance with non-linear relationships, and effective management of outlier effects. System performance targets may include high accuracy in response prediction within an appropriate time window after notifications [6,28]. This predictive capability could enable the implementation of adaptive engagement strategies, including progressive notification protocols and dynamic incentive adjustments [7].

The predictive modeling framework proposes to implement an ensemble architecture integrating multiple analytical methodologies [29,50]. This hybrid system could combine supervised and unsupervised learning paradigms with the goal of maximizing analytical capabilities [3,46]. The analytical pipeline architecture would emphasize modularity and adaptability, incorporating three primary components: temporal pattern analysis, behavioral clustering, and anomaly detection. This structure reflects recent advances in charging behavior analysis [24,26], aiming for robust pattern identification across multiple temporal scales while maintaining system adaptability to emerging behavioral trends. The model is expected to implement online learning capabilities, continuously updating model parameters as new behavioural data becomes available, thus adapting to evolving user behaviours and improving long-term accuracy.

Predictive accuracy could be improved by integrating multi-dimensional contextual data, including environmental conditions, event schedules, and grid utilization patterns [29,50]. We propose an advanced feature fusion architecture using attention mechanisms for optimal data source integration, a technique showing superior performance in recent EV charging analyses [3,24]. This architecture could enable adaptive weighting of information streams based on their predictive significance for specific behavioral patterns [26,28].

The system architecture could also incorporate a scalability framework to accommodate expanding user bases and charging infrastructure. The distributed architecture, described in Section 4.1, could allow for efficient horizontal scaling through optimized workload distribution. Privacy preservation can be achieved through edge-layer data anonymization protocols, ensuring secure handling of personally identifiable information before cloud transmission. This multi-tiered approach is intended to balance computational efficiency with robust privacy protection, enabling system growth while maintaining operational security.

4.3. Optimization Framework

We propose a formal optimization framework to address the complex trade-offs in EV charging infrastructure management, through constrained multi-objective optimization. The mathematical formulation balances four critical operational dimensions: power distribution efficiency, economic viability, user satisfaction, and grid stability, employing adaptive weight allocation to dynamically prioritize competing objectives.

4.3.1. Problem Formulation

The core multi-objective optimization problem for N charging stations over T time intervals is formulated as follows:

$$\min_{\mathbf{P}} \sum_{k=1}^{4} w_k \hat{f}_k(\mathbf{P}) \quad \text{subject to} \quad (6)\text{–}(10), \tag{1}$$

where $\mathbf{P} \in \mathbb{R}_+^{N\times T}$ is the power allocation matrix, $w_k \in [0,1]$ are normalized weights ($\sum w_k = 1$), and $\hat{f}_k = (f_k - f_k^{min})/(f_k^{max} - f_k^{min})$ are normalized objectives. The original objectives are as follows:

Objective 1 (Peak Shaving):

$$f_1 = \max_{t\in T} \sum_{i=1}^{N} P_{i,t} + \lambda \sum_{t=1}^{T-1} \left| \sum_{i=1}^{N} (P_{i,t+1} - P_{i,t}) \right|, \tag{2}$$

where $\lambda > 0$ (kW^{-1}) penalizes power gradient norms.

Objective 2 (Economic Efficiency):

$$f_2 = \sum_{t=1}^{T} \sum_{i=1}^{N} \left[c_t P_{i,t} + \alpha (P_{i,t} - P_i^{\text{target}})^2 + \beta \max(0, P_{i,t} - P_i^{\text{rated}}) \right], \tag{3}$$

with c_t (\$/kWh) as the time-varying electricity price, P_i^{target} (kW) as station-specific power targets, and P_i^{rated} (kW) as the maximum rated power.

Objective 3 (User Satisfaction):

$$f_3 = -\sum_{i=1}^{N} \sum_{j\in\mathcal{J}_i} \left[\beta_1 \frac{P_{i,t}}{P_j^{\text{req}}} + \beta_2 \eta_{i,t} + \beta_3 \exp\left(-\frac{|P_{i,t} - P_j^{\text{pref}}|}{P_j^{\text{tol}}} \right) \right], \tag{4}$$

where $\mathcal{J}_i$ denotes users at station i, P_j^{req} (kW) is the required charging power, P_j^{pref} (kW) is the preferred power level, and P_j^{tol} (kW) is the tolerance threshold.

Objective 4 (Grid Stability):

$$f_4 = \sum_{t=1}^{T} \left[\gamma_1 (\Delta f_t)^2 + \gamma_2 (\Delta V_t)^2 + \gamma_3 \sum_{i=1}^{N} |Q_{i,t}| + \gamma_4 \mathrm{THD}_t^2 \right], \quad (5)$$

where $\Delta f_t = f_t - f_0$ (Hz) and $\Delta V_t = V_t - V_0$ (V) are frequency/voltage deviations from nominal values, $Q_{i,t}$ (kVAR) is the reactive power, and THD_t (%) is the total harmonic distortion.

4.3.2. System Constraints

The optimization is bound by the following:

$$P_{\min} \leq P_{i,t} \leq P_{\max} \quad \forall i \in \mathcal{N}, t \in T, \quad (6)$$

$$T_{i,t} \leq T_{\max} \quad \forall i \in \mathcal{N}, t \in T, \quad (7)$$

$$\sum_{i=1}^{N} P_{i,t} \leq P_{\mathrm{grid,max}} \quad \forall t \in T, \quad (8)$$

$$|f_t - f_{\mathrm{nominal}}| \leq \Delta f_{\max} \quad \forall t \in T, \quad (9)$$

$$\mathrm{THD}_t \leq \mathrm{THD}_{\max} \quad \forall t \in T. \quad (10)$$

4.3.3. Hierarchical Solution Strategy

The three-layer optimization architecture ensures scalability and real-time responsiveness through time-scale separation:

- *Local layer:* Station-level optimization $\min_{P_i} \sum w_k f_k^i(P_i)$ with equipment constraints, operating at fast timescales (seconds to minutes).
- *Regional layer:* Cluster coordination via $P_i^{k+1} = P_i^k + \eta \sum_{j \in \mathcal{N}_i} (P_j^k - P_i^k)$ for load balancing, acting at intermediate timescales (minutes to hours).
- *Global layer:* Weight adaptation $\mathbf{w}^{k+1} = \mathbf{w}^k - \alpha \nabla L(\mathbf{w}^k)$ using gradient-based meta-optimization, operating at slower timescales (hours to days).

This hierarchical decomposition guarantees convergence through Lyapunov stability analysis while maintaining operational constraints across all system layers. The separation of timescales reduces communication overhead and ensures robustness to network delays and intermittent connectivity between charging stations. For effective implementation, key parameters require careful calibration: the coordination step size $\eta \in (0,1)$ should be selected based on network topology, with smaller values for densely connected clusters to prevent oscillation; the meta-learning rate α should follow an adaptive schedule, starting with $\alpha \approx 10^{-2}$ and gradually decreasing to 10^{-4} to ensure convergence to stable weight configurations.

The system incorporates adaptive mechanisms to handle dynamic operating conditions. During periods of high network volatility or rapid changes in EV arrival/departure patterns, the algorithm automatically increases regional layer update frequency while temporarily freezing global weight updates until system metrics stabilize. Conversely, during periods of predictable demand, the system can reduce computational load by extending the interval between regional coordination steps. This adaptability ensures robust performance across varying operational scenarios while preserving computation resources.

5. Discussion

The rapid shift towards electric vehicles (EVs) as a mainstream mode of transportation necessitates a corresponding evolution in the management of parking infrastructures [34,36]. This paper has explored current monitoring strategies for EV charging stations within parking facilities, highlighting persistent gaps in charging station utilization and user behavior [26]. Two specific behaviors demand particular attention: (i) the tendency of users to exceed the optimal 80% fast-charging threshold, occupying stations during a prolonged trickle-charging phase [17], and (ii) the continued occupation of charging spots even after vehicles reach 100% capacity [6,27]. These issues stem from a complex interplay of individual user needs, limited technological integration, and inadequate infrastructure management [24]. Addressing these challenges is crucial, as they directly impact the availability of charging resources and contribute to increased anxiety among EV drivers [7,25].

Current architectural approaches exhibit three critical limitations: fragmented data integration between parking and charging systems, over-reliance on deterministic control strategies, and inadequate temporal resolution for behavior pattern analysis [19,40]. While modern charging stations implement basic electrical parameter monitoring [17], few systems effectively correlate this data with contextual factors like temporal patterns, environmental conditions, and user preferences [29,82]. This disconnect persists despite demonstrated correlations between charging behavior and external variables such as weather patterns, electricity pricing fluctuations, and local event schedules [25,27].

Our proposed framework addresses these limitations through tripartite integration of IoT sensing, edge computing, and cloud-based analytics. The physical layer's multi-modal sensor network captures high-resolution temporal data streams while maintaining compatibility with legacy infrastructure [48,65]. Edge computing nodes implement localized machine learning models that adapt to regional usage patterns through continuous online learning [46,49]. This distributed intelligence enables real-time response to critical events like thermal anomalies or grid instability while preserving bandwidth through adaptive data compression [18,64]. Cloud services provide system-wide optimization through federated learning architectures that harmonize local models without compromising data privacy [50,53].

The architecture's dual emphasis on charging state monitoring and behavioral analytics enables novel optimization strategies. By correlating real-time electrical signatures with historical usage patterns, the system can predict individual charging trajectories with sufficient accuracy to implement proactive load balancing [7,28]. This capability proves particularly valuable for managing high-density urban deployments where charging demand exhibits strong spatiotemporal correlations with commercial activities and commuting patterns [26,36].

Several emerging research directions promise to enhance monitoring system effectiveness. Explainable AI techniques like SHAP/LIME values and counterfactual explanations could bridge the gap between deep learning performance and operational transparency [29,50]. For instance, local interpretability methods may reveal how specific battery parameters or user demographics influence charging duration predictions, enabling targeted infrastructure adjustments. Causal inference methodologies could disentangle the complex web of factors influencing charging behavior, distinguishing true causal relationships from spurious correlations [24,81]. Structural equation modeling applied to large-scale usage datasets could even quantify how policy interventions affect long-term behavioral changes versus temporary adaptations.

The integration of physics-informed neural networks with reinforcement learning architectures presents a particular promise for charging optimization [32,46]. By embedding battery degradation models and power grid constraints directly into reward functions, such systems could balance immediate charging demands with long-term infrastructure preservation. Hybrid digital twin architectures, combining real-time sensor data with electrochemical battery models, could enable personalized charging protocols that optimize both user convenience and battery health [31,41].

Privacy-preserving computation techniques will prove essential for maintaining user trust while leveraging sensitive behavioral data. Homomorphic encryption implementations could enable secure analysis of charging patterns across jurisdictions with varying data protection regulations [73,74]. Federated learning architectures could facilitate collaborative model training between competing charging networks without direct data sharing [3,50]. These approaches must be complemented by rigorous security frameworks capable of detecting novel attack vectors in increasingly connected infrastructure [21,52].

Emerging technologies like quantum machine learning and neuromorphic computing could address current limitations in processing latency and energy efficiency [29,64]. Quantum annealing implementations could potentially solve complex scheduling optimization problems intractable for classical computers, particularly in large-scale deployments with thousands of interdependent charging points [50]. Neuromorphic edge processors could enable real-time anomaly detection through spiking neural networks that mimic biological processing efficiency [49,79].

The impending proliferation of autonomous electric vehicles introduces additional complexity to charging infrastructure management. Self-driving fleets will likely exhibit fundamentally different charging patterns compared to human-operated vehicles, prioritizing system-level efficiency over individual convenience [6,28]. Developing hybrid simulation frameworks that combine discrete-event modeling with multi-agent reinforcement learning would help anticipate these behavioral shifts [7,24]. Such systems must account for vehicle-to-grid integration scenarios where autonomous fleets actively participate in grid stabilization through bidirectional charging strategies [31,32].

Ultimately, the evolution of EV charging infrastructure demands interdisciplinary approaches combining technical innovation with socio-economic insights. Behavioral economic models could inform incentive structures that promote efficient charging practices without compromising user autonomy [27,82]. Cultural psychology perspectives may explain regional variations in charging behavior, guiding the development of locally adaptive management systems [25,26]. By synthesizing these diverse strands of research, next-generation monitoring systems can transcend their current role as passive infrastructure components to become active enablers of sustainable mobility ecosystems.

6. Concluding Remarks

This study presents a detailed review of EV charging challenges and proposes an architectural framework for intelligent EV charging monitoring systems, addressing critical infrastructure management challenges. Our analysis highlights persistent operational inefficiencies stemming from prolonged station occupancy during slow charging (80–100% SOC) and post-charging overstays [6,27]. These behaviors, influenced by range anxiety and incentive structures [25,82], limit charging availability while existing solutions often lack adaptive optimization [3,19,24,26].

The proposed architecture integrates the following: (1) edge computing for localized decision-making [49,64], (2) IoT sensor networks for high-resolution spatiotemporal monitoring [10,48], and (3) cloud-based analytics for system-wide optimization [50,66]. This security-conscious framework [21,52] uses distributed machine learning at edge nodes and federated learning in the cloud [24,29], enabling real-time responsiveness and scalability [9,63]. The system goes beyond conventional parameter tracking by integrating behavioral analytics, correlating electrical signatures [19] with contextual factors, including temporal patterns, environmental conditions, and user preferences.

Three critical research trajectories emerge: First, developing explainable AI with local interpretability [29,50] to clarify relationships between battery parameters and charging behaviors [6,27]. Second, implementing causal inference to disentangle mechanisms governing charging patterns [24,26]. Third, integrating physics-informed neural networks with reinforcement learning [7,32] to optimize charging, balancing immediate demands with long-term infrastructure preservation. Complementary extensions could address privacy-preserving computation [53,73], battery degradation models [17,31], and quantum machine learning.

System validation requires empirical evaluation in high-density urban environments with complex spatiotemporal dynamics [7,27]. Key metrics include sensor network robustness [19,65], adaptive control performance in grid stabilization [28,29], and protocol efficacy across heterogeneous ecosystems [17,36,40,42]. While performance projections are currently based on analytical models, this framework provides a structured approach for addressing infrastructure–behavior–energy interdependencies in evolving EV landscapes.

As transportation electrification accelerates, next-generation architectures must accommodate autonomous fleet charging and implement advanced privacy-preserving computation. By integrating technical innovation, socio-economic insights, and rigorous validation, monitoring systems will become active enablers of sustainable mobility.

Author Contributions: Conceptualization, J.A.M. and J.M.F.R.; Methodology, J.A.M. and J.M.F.R.; Investigation, J.A.M.; Writing—original draft preparation, J.A.M. and J.M.F.R.; Writing—review and editing, J.A.M. and J.M.F.R.; Visualization, J.A.M. and J.M.F.R.; Project administration, J.M.F.R.; Funding acquisition, J.M.F.R. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by national funds (FCT/MEC, Fundação para a Ciência e a Tecnologia/Ministério da Educação e Ciência) through projects UIDB/00631/2020 CEOT Base, UIDP/00631/2020 CEOT Programático, and UID/04516/NOVA Laboratory for Computer Science and Informatics (NOVA LINCS). This study also received funding from Diâmetro Numérico Unipessoal, Lda. (Faro, Portugal). The funder was not involved in the study design, collection, analysis, interpretation of data, the writing of this article or the decision to submit it for publication.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. International Energy Agency. Global EV Outlook 2024. 2024. Available online: https://www.iea.org/reports/global-ev-outlook-2024 (accessed on 28 August 2024).
2. United Nations, Department of Economic and Social Affairs, Population Division. World Urbanization Prospects 2018. 2018. Available online: https://population.un.org/wup/ (accessed on 20 January 2025).
3. Ding, X.; Gan, Q.; Shaker, M.P. Optimal management of parking lots as a big data for electric vehicles using internet of things and Long–Short term Memory. *Energy* **2023**, *268*, 126613. [CrossRef]
4. Revolutionising Parking Experiences: The Latest Smart Solutions for Seamless and Efficient Parking. Available online: https://www.intertraffic.com/news/latest-smart-solutions-seamless-efficient-parking (accessed on 28 August 2024).
5. Elfaki, A.O.; Messoudi, W.; Bushnag, A.; Abuzneid, S.; Alhmiedat, T. A Smart Real-Time Parking Control and Monitoring System. *Sensors* **2023**, *23*, 9741. [CrossRef] [PubMed]
6. Alinejad, M.; Rezaei, O.; Kazemi, A.; Bagheri, S. An Optimal Management for Charging and Discharging of Electric Vehicles in an Intelligent Parking Lot Considering Vehicle Owner's Random Behaviors. *J. Energy Storage* **2021**, *35*, 102245. [CrossRef]
7. Morais, H. New approach for electric vehicles charging management in parking lots considering fairness rules. *Electr. Power Syst. Res.* **2023**, *217*, 109107. [CrossRef]
8. Torabi, H.; Mirtaheri, S.L.; Greco, S. Practical autoencoder based anomaly detection by using vector reconstruction error. *Cybersecurity* **2023**, *6*, 1. [CrossRef]
9. Raptis, T.P.; Cicconetti, C.; Falelakis, M.; Kalogiannis, G.; Kanellos, T.; Lobo, T.P. Engineering Resource-Efficient Data Management for Smart Cities with Apache Kafka. *Future Internet* **2023**, *15*, 43. [CrossRef]
10. Sultanabanu, K.; Liyakat, S.; Kutubuddin, K. IoT in Electrical Vehicle: A Study. *J. Control Instrum. Eng.* **2023**, *9*, 15–21.
11. Zhang, Y.; Li, T.; Yan, X.; Wang, L.; Zhang, J.; Diao, X.; Li, B. Electric vehicle charging fault monitoring and warning method based on battery model. *World Electr. Veh. J.* **2021**, *12*, 14. [CrossRef]
12. Gao, D.; Zhang, S.; Ju, Y.; Yang, Q. A real-time fire and flame detection method for electric vehicle charging station based on machine vision. *J. Real-Time Image Process.* **2023**, *20*, 38. [CrossRef]

13. Saraiva, D.; Rodrigues, J.M.F. Low cost vision-guided parking system. In Proceedings of the 21st Portuguese Conference on Pattern Recognition, Faro, Portugal, 30 October 2015; pp. 32–33.
14. Luque-Vega, L.F.; Michel-Torres, D.A.; Lopez-Neri, E.; Carlos-Mancilla, M.A.; González-Jiménez, L.E. IoT Smart Parking System Based on the Visual-Aided Smart Vehicle Presence Sensor: SPIN-V. *Sensors* **2020**, *20*, 1476. [CrossRef]
15. Perković, T.; Šolić, P.; Zargariasl, H.; Čoko, D.; Rodrigues, J.J. Smart Parking Sensors: State of the Art and Performance Evaluation. *J. Clean. Prod.* **2020**, *262*, 121181. [CrossRef]
16. Raj, A.; Shetty, S.D. Smart parking systems technologies, tools, and challenges for implementing in a smart city environment: A survey based on IoT & ML perspective. *Int. J. Mach. Learn. Cybern.* **2024**, *15*, 2673–2694. [CrossRef]
17. Thangavel, S.; Mohanraj, D.; Girijaprasanna, T.; Raju, S.; Dhanamjayulu, C.; Muyeen, S.M. A Comprehensive Review on Electric Vehicle: Battery Management System, Charging Station, Traction Motors. *IEEE Access* **2023**, *11*, 20994–21019. [CrossRef]
18. Harizaj, M.; Bisha, I.; Basholli, F. IoT integration of electric vehicle charging infrastructure. *Adv. Eng. Days* **2023**, *6*, 152–155.
19. Santhoshkumar, R.; Jabez, I.; Kannan, S.B.; Kumar, K. Intelligent Monitoring and Learning System for Electric Vehicle Charging Stations. In Proceedings of the 4th International Conference on Artificial Intelligence and Smart Energy, Coimbatore, India, 22–23 March 2024; Manoharan, S., Tugui, A., Baig, Z., Eds.; Springer: Cham, Switzerland, 2024; pp. 198–207. [CrossRef]
20. Ashwin Vishnu, P.K.S.; Sivraj, P. Smart Parking and Charging Management of Electric Vehicles in Public Parking Space. In Proceedings of the Second International Conference on Intelligent Computing and Control Systems (ICICCS), Madurai, India, 14–15 June 2018; pp. 1401–1406. [CrossRef]
21. Jahangir, H.; Lakshminarayana, S.; Poor, H.V. Charge Manipulation Attacks Against Smart Electric Vehicle Charging Stations and Deep Learning-Based Detection Mechanisms. *IEEE Trans. Smart Grid* **2024**, *15*, 5182–5194. [CrossRef]
22. Zhang, Y.; Cai, L. Dynamic Charging Scheduling for EV Parking Lots With Photovoltaic Power System. *IEEE Access* **2018**, *6*, 56995–57005. [CrossRef]
23. Mohammadi, F.; Rashidzadeh, R. An Overview of IoT-Enabled Monitoring and Control Systems for Electric Vehicles. *IEEE Instrum. Meas. Mag.* **2021**, *24*, 91–97. [CrossRef]
24. Wang, W.; Wu, L. A Semi-Decentralized Real-Time Charging Scheduling Scheme for Large EV Parking Lots Considering Uncertain EV Arrival and Departure. *IEEE Trans. Smart Grid* **2024**, *15*, 5871–5884. [CrossRef]
25. Anwar, M.B.; Muratori, M.; Jadun, P.; Hale, E.; Bush, B.; Denholm, P.; Ma, O.; Podkaminer, K. Assessing the value of electric vehicle managed charging: A review of methodologies and results. *Energy Environ. Sci.* **2022**, *15*, 466–498. [CrossRef]
26. Phipps, K.; Schwenk, K.; Briegel, B.; Mikut, R.; Hagenmeyer, V. Customized Uncertainty Quantification of Parking Duration Predictions for EV Smart Charging. *IEEE Internet Things J.* **2023**, *10*, 20649–20661. [CrossRef]
27. Zhou, X.; Ji, Y.; Chen, C.; Liu, X. Exploring correlated parking–charging behaviours in electric vehicles: A data-driven study. *Proc. Inst. Civ. Eng. Transp.* **2024**, 1–12. [CrossRef]
28. Tan, M.; Zhang, Z.; Ren, Y.; Richard, I.; Zhang, Y. Multi-Agent System for Electric Vehicle Charging Scheduling in Parking Lots. *Complex Syst. Model. Simul.* **2023**, *3*, 129–142. [CrossRef]
29. Gharibi, M.A.; Nafisi, H.; Askarian-abyaneh, H.; Hajizadeh, A. Deep learning framework for day-ahead optimal charging scheduling of electric vehicles in parking lot. *Appl. Energy* **2023**, *349*, 121614. [CrossRef]
30. Martin, C.; Ke, F.; Wang, H. Non-Intrusive Load Monitoring for Feeder-Level EV Charging Detection: Sliding Window-Based Approaches to Offline and Online Detection. In Proceedings of the 2023 IEEE 7th Conference on Energy Internet and Energy System Integration (EI2), Hangzhou, China, 15–18 December 2023; pp. 4958–4963.
31. Adhikary, S.; Biswas, P.K.; Sain, C.; Thanikanti, S.B.; Nwulu, N.I. Bidirectional converter based on G2V and V2G operation with time of usage-based tariff analysis and monitoring of charging parameters using IoT. *Energy Rep.* **2023**, *9*, 5404–5419. [CrossRef]
32. Harighi, T.; Borghetti, A.; Napolitano, F.; Tossani, F. Flexibility modeling for parking lots with multiple EV charging stations. *Electr. Power Syst. Res.* **2024**, *234*, 110732. [CrossRef]
33. Imbayah, I.; Eseid, O.A.; Akter, K.; Alsharif, A.; Ahmed, A.A. Recent Developments in EV Charging Infrastructure: Opportunities and IoE Framework Challenges. *Int. J. Electr. Eng. Sustain.* **2023**, *1*, 47–63.
34. Sanguesa, J.A.; Torres-Sanz, V.; Garrido, P.; Martinez, F.J.; Marquez-Barja, J.M. A Review on Electric Vehicles: Technologies and Challenges. *Smart Cities* **2021**, *4*, 372–404. [CrossRef]
35. Kucukoglu, I.; Dewil, R.; Cattrysse, D. The electric vehicle routing problem and its variations: A literature review. *Comput. Ind. Eng.* **2021**, *161*, 107650. [CrossRef]
36. Unterluggauer, T.; Rich, J.; Andersen, P.B.; Hashemi, S. Electric vehicle charging infrastructure planning for integrated transportation and power distribution networks: A review. *eTransportation* **2022**, *12*, 100163. [CrossRef]
37. Adedeji, B.P. Electric vehicles survey and a multifunctional artificial neural network for predicting energy consumption in all-electric vehicles. *Results Eng.* **2023**, *19*, 101283. [CrossRef]
38. Channamallu, S.S.; Kermanshachi, S.; Rosenberger, J.M.; Pamidimukkala, A. A review of smart parking systems. *Transp. Res. Procedia* **2023**, *73*, 289–296. [CrossRef]

39. Zulfiqar, H.; Ul Haque, H.M.; Tariq, F.; Khan, R.M. A survey on smart parking systems in urban cities. *Concurr. Comput. Pract. Exp.* **2023**, *35*, e6511. [CrossRef]
40. Ravindran, M.A.; Nallathambi, K.; Vishnuram, P.; Rathore, R.S.; Bajaj, M.; Rida, I.; Alkhayyat, A. A Novel Technological Review on Fast Charging Infrastructure for Electrical Vehicles: Challenges, Solutions, and Future Research Directions. *Alex. Eng. J.* **2023**, *82*, 260–290. [CrossRef]
41. Savari, G.F.; Sathik, M.J.; Raman, L.A.; El-Shahat, A.; Hasanien, H.M.; Almakhles, D.; Abdel Aleem, S.H.; Omar, A.I. Assessment of charging technologies, infrastructure and charging station recommendation schemes of electric vehicles: A review. *Ain Shams Eng. J.* **2023**, *14*, 101938. [CrossRef]
42. Tkac, M.; Kajanova, M.; Bracinik, P. A Review of Advanced Control Strategies of Microgrids with Charging Stations. *Energies* **2023**, *16*, 6692. [CrossRef]
43. Khaleghian, S.; Tran, T.; Cho, J.; Harris, A.; Sartipi, M. Electric Vehicle Identification in Low-Sampling Non-Intrusive Load Monitoring Systems Using Machine Learning. In Proceedings of the IEEE International Smart Cities Conference (ISC2), Manchester, UK, 7–10 September 2021; pp. 1–7. [CrossRef]
44. European Automobile Manufacturers' Association. Charging Ahead: Accelerating the Roll-Out of EU Electric Vehicle Charging Infrastructure. 2024. Available online: https://www.acea.auto/publication/automotive-insights-charging-ahead-accelerating-the-rollout-of-eu-electric-vehicle-charging-infrastructure/ (accessed on 28 August 2024).
45. Zero Emission Vehicles. Electric Vehicle Chargepoint and Infrastructure Grant Guidance for Installers. 2024. Available online: https://www.gov.uk/guidance/electric-vehicle-chargepoint-and-infrastucture-grant-guidance-for-installers (accessed on 28 August 2024).
46. Shi, T.; Zhao, F.; Zhou, H.; Qi, C. Research on intelligent energy management method of multifunctional fusion electric vehicle charging station based on machine learning. *Electr. Power Syst. Res.* **2024**, *229*, 110037. [CrossRef]
47. Haji-Aghajani, E.; Hasanzadeh, S.; Heydarian-Forushani, E. A novel framework for planning of EV parking lots in distribution networks with high PV penetration. *Electr. Power Syst. Res.* **2023**, *217*, 109156. [CrossRef]
48. Dasi, S.; Kuchibhatla, S.M.; Ravindra, M.; Kumar, K.S.; Chekuri, S.S.; Kavuru, A.K. IoT-Based Smart Energy Management System to Meet the Requirements of EV Charging Stations. *J. Theor. Appl. Inf. Technol.* **2024**, *102*, 2116–2127.
49. Deng, Q.; Zeng, F. Vehicular Edge-Computing Framework for Making Use of Parking and Charging Electric Vehicles. *Appl. Sci.* **2023**, *13*, 4065. [CrossRef]
50. Aldossary, M.; Alharbi, H.A.; Ayub, N. Optimizing Electric Vehicle (EV) Charging with Integrated Renewable Energy Sources: A Cloud-Based Forecasting Approach for Eco-Sustainability. *Math* **2024**, *12*, 2627. [CrossRef]
51. Biyik, C.; Allam, Z.; Pieri, G.; Moroni, D.; O'Fraifer, M.; O'Connell, E.; Olariu, S.; Khalid, M. Smart parking systems: Reviewing the literature, architecture and ways forward. *Smart Cities* **2021**, *4*, 623–642. [CrossRef]
52. Basnet, M.; Ali, M.H.; Basnet, M.; Ali, M.H. Exploring Cybersecurity Issues in 5G Enabled Electric Vehicle Charging Station with Deep Learning. *arXiv* **2021**, arXiv:2104.08553. [CrossRef]
53. Sarieddine, K.; Sayed, M.A.; Torabi, S.; Atallah, R.; Assi, C. Investigating the Security of EV Charging Mobile Applications as an Attack Surface. *ACM Trans. Cyber-Phys. Syst.* **2023**, *7*. 1–28. [CrossRef]
54. Shern, S.J.; Sarker, M.T.; Ramasamy, G.; Thiagarajah, S.P.; Farid, F.A.; Suganthi, S.T. Artificial Intelligence-Based Electric Vehicle Smart Charging System in Malaysia. *World Electr. Veh. J.* **2024**, *15*, 440. [CrossRef]
55. *IEC 61851-1:2017*; Electric Vehicle Conductive Charging System—Part 1: General Requirements. IEC: Geneva, Switzerland, 2017.
56. *ISO 15118-1:2019*; Road Vehicles—Vehicle to Grid Communication Interface—Part 1: General Information and Use-Case Definition. ISO: Geneva, Switzerland, 2019.
57. *IEC 62196-1:2022*; Plugs, Socket-Outlets, Vehicle Connectors and Vehicle Inlets—Conductive Charging of Electric Vehicles—Part 1: General Requirements. IEC: Geneva, Switzerland, 2022.
58. Ren, C.; Lee, S.; Jeong, D.; Chen, H.; Xiao, Y. Parking Guidance System Based on Geomagnetic Sensors and Recurrent Neural Networks. *J. Sens.* **2022**, *2022*, 7481064. [CrossRef]
59. Zhang, Z.S.; Yuan, H.Q.; Chen, L. A parking vehicle detection algorithm using magnetic sensor. *Appl. Mech. Mater.* **2013**, *409–410*, 1353–1356. [CrossRef]
60. Rego, R.C.; Semente, R.S. Presence Sensors: A Comparison Between the Ultrasonic and the Infrared in the Detection of People and Vehicles. *Smart Innov. Syst. Technol.* **2021**, *201*, 563–571. [CrossRef]
61. Răboacă, M.S.; Bizon, N.; Thounthong, P. Intelligent charging station in 5G environments: Challenges and perspectives. *Int. J. Energy Res.* **2021**, *45*, 16418–16435. [CrossRef]
62. Elghanam, E.; Hassan, M.; Osman, A.; Ahmed, I. Review of Communication Technologies for Electric Vehicle Charging Management and Coordination. *World Electr. Veh. J.* **2021**, *12*, 92. [CrossRef]
63. Lobato, E.; Prazeres, L.; Medeiros, I.; Araújo, F.; Rosário, D.; Cerqueira, E.; Tostes, M.; Bezerra, U.; Fonseca, W.; Antloga, A. A Monitoring System for Electric Vehicle Charging Stations: A Prototype in the Amazon. *Energies* **2023**, *16*, 152. [CrossRef]

64. Liang, S.; Jin, S.; Chen, Y. A Review of Edge Computing Technology and Its Applications in Power Systems. *Energies* **2024**, *17*, 3230. [CrossRef]
65. Khan, W.Z.; Rehman, M.H.; Zangoti, H.M.; Afzal, M.K.; Armi, N.; Salah, K. Industrial internet of things: Recent advances, enabling technologies and open challenges. *Comput. Electr. Eng.* **2020**, *81*, 6522. [CrossRef]
66. Chimakurthi, V.N.S.S. An Optimal Cloud Based Electric Vehicle Charging System. *Asia Pac. J. Energy Environ.* **2021**, *8*, 39–48. [CrossRef]
67. Giechaskiel, B.; Maricq, M.; Ntziachristos, L.; Dardiotis, C.; Wang, X.; Axmann, H.; Bergmann, A.; Schindler, W. Review of motor vehicle particulate emissions sampling and measurement: From smoke and filter mass to particle number. *J. Aerosol Sci.* **2014**, *67*, 48–86. [CrossRef]
68. Qahtan, M.H.; Mohammed, E.A.; Ali, A.J. Charging Station of Electric Vehicle Based on IoT: A Review. *Open Access Libr. J.* **2022**, *9*, 1–22. [CrossRef]
69. Wyk, F.V.; Wang, Y.; Khojandi, A.; Masoud, N. Real-time sensor anomaly detection and identification in automated vehicles. *IEEE Trans. Intell. Transp. Syst.* **2020**, *21*, 1264–1276. [CrossRef]
70. Viegas, M.A.A.; da Costa, C.T. Fuzzy Logic Controllers for Charging/Discharging Management of Battery Electric Vehicles in a Smart Grid. *J. Control. Autom. Electr. Syst.* **2021**, *32*, 1214–1227. [CrossRef]
71. Madhuri, G.; Madhuri, K.V.; Navya, M.; Reddy, G.P. Fast Charging Electric Vehicle using Fuzzy Logic Controller. *Int. J. Eng. Res. Technol.* **2020**, *9*, 499–502.
72. Chica, J.C.C.; Imbachi, J.C.; Vega, J.F.B. Security in SDN: A comprehensive survey. *J. Netw. Comput. Appl.* **2020**, *159*, 102595. [CrossRef]
73. Dixit, R.; Ravindranath, K. Identity and Access Control Techniques for Enhanced Data Communication in Cloud. *Contemp. Math.* **2024**, *5*, 1–16. [CrossRef]
74. Wilson, Y.; Hingnikar, A. OpenID Connect. In *Solving Identity Management in Modern Applications*; Apress: Berkeley, CA, USA, 2023. [CrossRef]
75. Hardt, D. *The OAuth 2.0 Authorization Framework [RFC 6749]*; IETF: Fremont, CA, USA, 2012.
76. Casse, C.; Berthou, P.; Owezarski, P.; Josset, S. A Tracing Based Model to Identify Bottlenecks in Physically Distributed Applications. In Proceedings of the International Conference on Information Networking, Barcelona, Spain, 7–10 January 2020. [CrossRef]
77. Salloum, S.; Dautov, R.; Chen, X.; Peng, P.X.; Huang, J.Z. Big data analytics on Apache Spark. *Int. J. Data Sci. Anal.* **2016**, *1*, 145–164. [CrossRef]
78. Kuzmich, M.; Gordiyenko, T. Application of Kubeflow as a Universal Approach for the Development and Implementation of Artificial Intelligence Systems. *ARPN J. Eng. Appl. Sci.* **2023**, *18*, 2311–2320. [CrossRef]
79. Lara-Benítez, P.; Carranza-García, M.; Luna-Romera, J.M.; Riquelme, J.C. Temporal convolutional networks applied to energy-related time series forecasting. *Appl. Sci.* **2020**, *10*, 2322. [CrossRef]
80. Xia, K.; Huang, J.; Wang, H. LSTM-CNN Architecture for Human Activity Recognition. *IEEE Access* **2020**, *8*, 56855–56866. [CrossRef]
81. Yeo, S.; Lee, D.J. Selecting the Optimal Charging Strategy of Electric Vehicles Using Simulation Based on Users' Behavior Pattern Data. *IEEE Access* **2021**, *9*, 89823–89833. [CrossRef]
82. Weldon, P.; Morrissey, P.; Brady, J.; O'Mahony, M. An investigation into usage patterns of electric vehicles in Ireland. *Transp. Res. Part D Transp. Environ.* **2016**, *43*, 207–225. [CrossRef]
83. Kumar, D.; Klefsjö, B. Proportional hazards model: A review. *Reliab. Eng. Syst. Saf.* **1994**, *44*, 177–188. [CrossRef]
84. Cai, B.; Huang, G.; Samadiani, N.; Li, G.; Chi, C.H. Efficient Time Series Clustering by Minimizing Dynamic Time Warping Utilization. *IEEE Access* **2021**, *9*, 46589–46599. [CrossRef]
85. Bagirov, A.M.; Aliguliyev, R.M.; Sultanova, N. Finding compact and well-separated clusters: Clustering using silhouette coefficients. *Pattern Recognit.* **2023**, *135*, 109144. [CrossRef]