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AI-Based EV Charging Station Load Balancing: A Comprehensive Review of Data Sensing, Machine Learning Methods, and IoT Integration

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Abstract. The rapid growth of electric vehicles (EVs) concentrates charging demand in time and space, which can overload individual charging stations and local grid assets while neighbouring stations remain underused. Fixed-rule or first-come-first-served control cannot adapt well to uncertain arrivals, prices and grid limits. Artificial intelligence (AI), combined with IoT metering and communication, is increasingly proposed for forecasting charging demand and for balancing load across charging stations. This paper presents a focused narrative review of studies that use machine learning (ML), deep learning (DL) and reinforcement learning (RL) for EV charging load forecasting, scheduling and load balancing. It examines three connected themes: data sensing, learning methods, and IoT architectures. The reviewed literature reports LSTM-based short-term load forecasting on Adaptive Charging Network data with a mean absolute error of 4 kW, a graph-based RL approach that balances load across a station network through dynamic pricing in simulation, batch RL that coordinates several stations using real-world charging data, and surveys that classify RL methods into centralized and decentralized categories. However, most studies are simulation-based, single-dataset or single-campus, and few report field validation, communication failure handling, or closed-loop operation on physical chargers. The paper contributes a comparative table of representative studies, a conceptual data-to-decision architecture (not experimentally validated), and a prioritised list of research gaps.

Keywords: EV Charging, Load Balancing, Demand Forecasting, Reinforcement Learning, Internet of Things, Edge Computing

I. Introduction

EV charging load varies strongly in time and is uneven across sites: arrivals are uncertain, sessions differ in energy and duration, and a few popular stations can reach capacity while nearby stations stay underused [5]. Unplanned charging is a major concern for the power system, and accurate load forecasting followed by efficient charge scheduling could, to a large extent, reduce its impact [6]. Charging scheduling is difficult for conventional methods because the decision environment is complex [4]. In this paper, load balancing means distributing charging demand and power across chargers and stations so that no unit is overloaded and capacity is used evenly, through power allocation, scheduling, pricing or user guidance [5], [9].

Three developments converge: metering and communication hardware that records charging sessions continuously, ML and DL models that forecast demand from this history [6]–[8], and RL agents that learn control policies without an explicit model of the environment [1], [9]. IoT connectivity moves data from chargers to dashboards and decision systems. This review examines these strands together, asks how mature the evidence is for field deployment, and proposes a conceptual architecture that addresses the weaknesses identified.

II. Review Methodology

A focused web and publisher-platform search (MDPI, IEEE Access, Elsevier-hosted journals, university repositories and arXiv) was carried out using combinations of the terms EV charging, load balancing, reinforcement learning, demand forecasting, charging scheduling and smart grid. Studies were included when they reported EV charging forecasting, scheduling or load balancing with a stated method. Direct logged querying of Scopus and Web of Science was not performed, so the review is narrative rather than systematic and study counts are not reported. Some sources (preprints and journal records) were available only as abstracts or repository pages and are marked as such in Table I.

III. Sensing And Data Sources

1. Session and Station Data

Charging stations generate a stream of time-series records capturing the start and end of charging sessions, which can be processed to count demand, i.e. the number of charging requests [8]. Real-time Adaptive Charging Network (ACN) data were used for short-term load forecasting [6], and charging data from several parking garages on a dense urban campus were used for LSTM forecasting [7].

2. Network State for Balancing

In the graph-based balancing study, each charging station is a node and edges denote adjacency between stations; the RL agent uses station occupancy, maximum station capacity and demand forecasts to adjust prices and direct users to underutilised stations [5].

3. Grid and Market Signals

Grid constraints, renewable integration, user variability and dynamic pricing add to the complexity of charging station operation, which is why RL has been proposed as an adaptive, scalable control approach [3].

IV. Machine Learning and Reinforcement Learning Methods

1. Demand Forecasting

Short-term EV load forecasting with auto-regressive (AR) models, support vector regression (SVR) and LSTM on real-time ACN data found LSTM best, with a mean absolute error (MAE) of 4 kW and a root-mean-squared error (RMSE) of 5.9 kW [6]. An LSTM framework with normalisation and feature extraction predicted charging demand across daily, weekly and monthly scales for a campus [7]. A multivariate LSTM enhanced with an attention mechanism was applied to charging stations at California State University, motivated by dynamic pricing that balances demand more efficiently [8].

2. Reinforcement Learning for Coordination

RL does not need an explicit model of the environment and learns by maximising cumulative reward, which suits charging management under uncertainty [1]. Batch RL (fitted Q-iteration) with function approximation was used to coordinate a set of charging stations, with load flattening and load balancing as goals and real-world charging data in the evaluation [9]. A graph-based approach using double Q-learning adjusts station prices from occupancy, capacity and demand forecasts to avoid overload, and reported improved balance in simulation [5]. Surveys classify RL charging methods into centralized and decentralized categories [2], review frameworks, objectives and architectures for charging coordination [1], and examine agent structures, training schemes, coordination mechanisms, reward formulation and evaluation protocols for charging station operation [3]. A systematic review formulates charging scheduling problems as Markov decision processes and discusses open challenges [4].

3. Validation Practice

Charging demand is autocorrelated in time, so random train-test splits of neighbouring samples can leak information and inflate accuracy; splitting by time block or by site is preferable. The forecasting studies reviewed here rely on data from one network

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or campus [6], [7], and the RL balancing results come from simulation [5], [9]. A review of RL for charging management therefore assesses baselines, metrics and validation settings and links algorithmic development to real deployment needs [3]. Reported errors should be read cautiously.

V. IoT Integration and Edge Deployment

A typical IoT design joins charger controllers and energy meters, a communication network and a cloud back end with a dashboard for forecasts and control. Centralized RL needs data from many stations at one coordinator, whereas decentralized methods spread decisions among agents [2]; in practice this corresponds to cloud-side versus edge-side decision making. Edge inference lowers latency and dependence on site connectivity, whereas cloud processing simplifies model updates and cross-site analytics. Network-wide balancing as in [5] additionally needs live occupancy data and a channel to inform drivers. Among the sources examined here, evidence comes from historical datasets or simulation [5]–[9]; none of the abstracts reviewed reports long-term operation on a physical charger network with communication outages, meter errors or hardware safety limits.

VI. Comparative Analysis

Table I summarises representative studies. Reported values are not directly comparable because targets, datasets and validation differ.

Table 1: Comparison of Representative Studies

Author, year	Objective	Sensing / method	Major reported findings	Limitations
Abdullah et al., 2021 [1]	Review RL for EV charging management	RL; comparative analysis	Frameworks, objectives, architectures for coordination	Review; no field data
Shokati et al., 2024 [2]	Survey RL charging optimisation	RL + DL; centralized vs decentralized	Classifies methods; future directions	Preprint survey
Michailidis et al., 2025 [3]	Review RL for charging station management	Agent, reward, evaluation design	Scalability, uncertainty, interpretability, adaptability	Review (record only)
Scheduling review [4]	Charging scheduling with RL	MDP formulation	Challenges and open issues	Abstract only
Aghdam et al., 2025 [5]	Load balancing and pricing	Graph, double Q-learning	Reduced overload in simulation	Simulation; preprint
Vishnu et al., 2023 [6]	Short-term EV load forecast	AR, SVR, LSTM on ACN data	LSTM best: MAE 4 kW, RMSE 5.9 kW	Forecast only; one network
Ressler et al., 2025 [7]	Campus demand forecast	LSTM; garage data	Daily, weekly, monthly forecasts	Single campus; preprint
Forecasting study, 2025 [8]	Demand forecast for pricing	Multivariate LSTM + attention	Supports dynamic-pricing balance	Preprint; abstract level
Batch RL study [9]	Coordinate stations	Fitted Q-iteration	Load flattening/balancing with real data	Simulation-based; preprint

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VII. Proposed Conceptual Architecture

Fig. 1 presents a conceptual architecture derived from the reviewed systems; it is not experimentally validated. Meters and session logs capture power, energy, occupancy and price signals (layer 2) because forecasting and balancing both depend on them [5], [8]. An embedded unit timestamps and filters the signals (layer 3), and edge models perform demand forecasting, an RL allocation policy and anomaly detection with a confidence score (layer 4) [6], [9]. Results travel over a communication link to a cloud database and dashboard (layer 5). Decision support (layer 6) recommends or sets power set-points, prices or user routing, with a local fallback that works offline and a hard safety limit set by the hardware and the grid. Periodic comparison with metered reference data (layer 7) verifies predictions, and models are retrained only after independent re-testing.

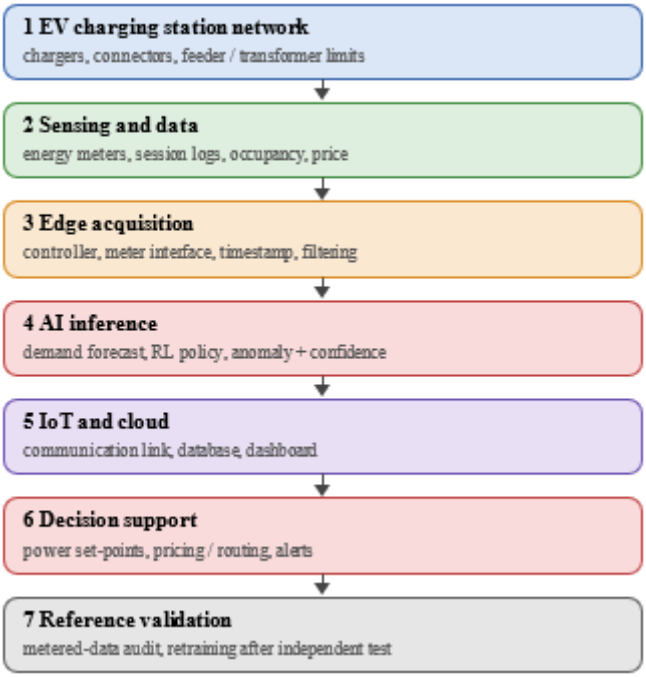


Fig. 1. Proposed conceptual architecture for AI and IoT-based EV charging station load balancing (conceptual, not experimentally validated)

Research Gaps and Future Directions

Gaps supported by the reviewed evidence. (i) Forecasting datasets come from one network or campus [6], [7]. (ii) Few field trials: balancing results are mainly from simulation [5], [9]. (iii) Limited evidence on communication latency, failure handling and cost of real-time control at charging sites. (iv) Weak validation reporting, with random splits risking leakage. (v) Limited interpretability and uncertainty reporting [3]. (vi) Scalability and adaptability of learned policies to new sites remain open issues [3].

Directions requiring investigation. Multi-site, multi-season datasets with metered reference labels; pilots on physical chargers with safety-constrained control; hybrid forecasting-plus-RL pipelines; calibrated confidence and out-of-distribution detection at the edge; grouped, site-wise and time-blocked validation; fair, user-centric pricing and routing [5]; charging and discharging coordination with the grid [1], [2]; and secure, open data sharing.

VIII. Conclusion

AI and IoT have moved EV charging management from fixed rules toward data-driven forecasting and adaptive load balancing: LSTM models forecast station demand with errors of a few kilowatts [6], and RL approaches balance load across station networks in simulation [5], [9]. The evidence, however, is dominated by simulation and single-dataset studies with limited independent validation. Reliable deployment will require larger and more diverse datasets, field pilots on real chargers, rigorous validation, safety-constained control and continuous reference-based model maintenance, as reflected in the proposed conceptual architecture.

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