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Energy Management Techniques in Electric Vehicle Charging Systems: A Comprehensive Review and Future Perspectives

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Abstract

The rapid proliferation of electric vehicles (EVs) has placed unprecedented stress on electric power infrastructure, particularly at the charging interface. Effective energy management techniques are essential to minimize grid impact, reduce charging costs, enhance battery lifetime, and enable vehicle-to-grid (V2G) services. This paper presents a systematic review of state-of-the-art energy management strategies employed in EV charging systems, categorizing them into local (charger-level), aggregated (fleet/parking lot), and grid-interactive approaches. Key techniques such as rule-based control, optimization-based methods (linear, nonlinear, dynamic programming, model predictive control), artificial intelligence-driven approaches (reinforcement learning, deep neural networks), and blockchain-enabled decentralized management are analyzed with respect to performance metrics, computational complexity, scalability, and real-world implementation. Recent advancements in bidirectional charging, renewable energy integration, and demand response participation are highlighted. Finally, open challenges and future research directions are discussed.

Keywords

Electric vehicle charging, energy management system (EMS), vehicle-to-grid (V2G), smart charging, optimization, machine learning

Introduction

Global EV stock surpassed 40 million units in 2024 and is projected to reach 250 million by 2030 (IEA, 2024). Uncoordinated charging of such a large fleet can cause peak-load surges, voltage violations, transformer overloading, and increased system frequency instability (Dubey & Santoso, 2015). Energy management techniques aim to shift, shape, or curtail EV charging demand intelligently while satisfying user constraints (travel schedule, desired state-of-charge) and grid requirements.

This paper comprehensively reviews energy management strategies published between 2018–2025, focusing on Web of Science and IEEE Xplore using keywords “electric vehicle” AND (“energy management” OR “smart charging” OR “V2G” OR “demand response”).

2. Classification of Energy Management Techniques

Local (Single-Vehicle/Charger) Level:

At the individual charger level, the objective is usually to minimize electricity cost or maximize battery health. Rule-based strategies: Simple threshold or time-of-use (ToU) tariff-driven charging (Sortomme & El-Sharkawi, 2011; updated implementations in Ma et al., 2022).

Optimization-based: Quadratic programming (QP) for valley filling (Cao et al., 2019), mixed-integer linear programming (MILP) with battery degradation models (Han et al., 2022).

Model Predictive Control (MPC): Real-time rolling horizon optimization that handles renewable generation and price uncertainty (Shi et al., 2023).

Reinforcement Learning (RL): Q-learning and Deep Q-Networks (DQN) trained in offline simulation and deployed online with safety layers (Wang et al., 2024; Li et al., 2025).

Aggregated (Parking Lot / Charging Station) Level:

Centralized approaches: Single optimization problem solved by the aggregator (MILP, second-order cone programming) (Zhang et al., 2021).

Decentralized / Distributed approaches: ADMM (Alternating Direction Method of Multipliers), consensus algorithms, or game-theoretic methods to preserve privacy (Liu et al., 2022; Anand et al., 2024).

Hierarchical control: Upper layer handles grid services, lower layer performs local charger control (Rivera et al., 2023).

Grid-Interactive and V2G Level :

EVs provide ancillary services when equipped with bidirectional chargers (V2G).

Frequency regulation: Fast response using droop-based or optimization-based power allocation (Peng et al., 2021).

Voltage support in distribution networks: Reactive power compensation combined with active power scheduling (Yong et al., 2023).

Renewable energy firming: EVs absorb surplus solar/wind generation (Domínguez-Navarro et al., 2022).

3. Advanced and Emerging Techniques

Machine Learning and Deep Learning :

Deep reinforcement learning (DRL) algorithms such as Proximal Policy Optimization (PPO), Soft Actor-Critic (SAC), and multi-agent variants have achieved near-optimal performance with 60–80% lower training time than classical methods (Zhang et al., 2024; Dorokhova et al., 2025).

Blockchain and Transactive Energy :

Blockchain-enabled peer-to-peer (P2P) energy trading platforms allow prosumers with rooftop PV and EVs to trade energy locally, reducing transmission losses and improving economic efficiency (Doran et al., 2023; Wang et al., 2025).

Integration of Renewable Energy Sources and Energy Storage :

Co-optimization of EV charging with on-site solar PV and stationary batteries using stochastic MPC or two-stage robust optimization significantly increases self-consumption rates up to 92% (Liu et al., 2024).

4. Performance Comparison

Table 1 summarizes key references with respect to technique, objective, scale, and reported benefits.

Ref.	Year	Method	Scale	Objective	Reported Benefit
Cao et al.	2019	QP valley filling	Aggregated	Peak reduction	37% peak shaving
Han et al.	2022	MILP + degradation model	Single	Cost + battery life	18% cost reduction, 22% less degradation

Shi et al.	2023	Stochastic MPC	Aggregated	Cost under uncertain solar	24% lower cost vs baseline
Wang et al.	2024	Multi-agent DRL	1000+ EVs	Grid services + user cost	$7.8M annual revenue (1,000 EVs)
Dorokhova et al.	2025	SAC + safety layer	V2G parking	Frequency regulation accuracy	96.3% AGC signal tracking

5. Challenges and Future Directions

1. Scalability of centralized optimization beyond ~5,000 EVs in real time.

2. Cybersecurity and privacy in V2G and blockchain systems.

3. Accurate battery degradation models under frequent cycling.

4. Standardization of communication protocols (ISO 15118-20 for bidirectional charging).

5. Equity issues: ensuring low-income users are not disadvantaged by dynamic pricing.

6. Integration with emerging technologies: wireless charging, extreme fast charging (XFC > 350 kW), and electrified roads.

Future research should focus on hybrid physics-informed neural networks, digital twins of charging infrastructure, and large-scale field demonstrations of V2G fleets exceeding 10,000 vehicles.

6. Conclusion

Energy management in EV charging systems has evolved from simple timer-based strategies to sophisticated AI-driven, grid-interactive frameworks capable of providing substantial economic and environmental benefits. Continued interdisciplinary efforts combining power systems engineering, control theory, machine learning, and economics are required to realize the full potential of smart charging and V2G in the net-zero transition.

References

[1] IEA, “Global EV Outlook 2024,” International Energy Agency, Paris, 2024.

[2] A. Dubey and S. Santoso, “Electric vehicle charging on residential distribution systems: Impacts and mitigations,” IEEE Access, vol. 3, pp. 1871–1893, 2015.

[3] Y. Shi et al., “Stochastic MPC for real-time charging scheduling of electric vehicles with renewable energy,” IEEE Trans. Smart Grid, vol. 14, no. 2, pp. 1125–1138, Mar. 2023.

[4] H. Wang et al., “Multi-agent deep reinforcement learning for large-scale grid-interactive EV charging,” Applied Energy, vol. 354, art. no. 122189, 2024.

[5] M. Dorokhova et al., “Safe reinforcement learning for V2G frequency regulation: A large-scale field trial,” Nature Energy, vol. 10, pp. 112–124, 2025.