Literature Review — EV Charging Optimization

# 1) How the literature frames the EV‑charging problem

Across our papers, EV charging is framed as (a) where to place and size chargers, (b) how to operate stations day‑to‑day, (c) how drivers and fleets actually behave, and (d) how pricing and markets should work.

* Planning & siting/sizing. Multi‑criteria approaches decide where and how much to build, balancing accessibility, grid stability, and cost (MCDM/AHP variants; voltage‑stability‑aware siting with stochastic power flow) [16], [17]. UK‑focused “infrastructure gap” analyses show how required charger counts swing with adoption scenarios—so siting choices matter as much as totals [21].
* Building‑integrated & routing realities. Building‑integrated charging adds practical constraints (local load, wiring, demand profiles) that affect feasibility [5]. EV‑routing syntheses (EVRP) remind us that real operations face time windows, service time, and battery limits that algorithms must obey [11].
* Demand characterization. Data‑driven UK studies (clustering/mining) extract when and how much we charge from real sessions, providing better inputs than stylized arrival assumptions [3].

What this tells us. Modern work blends grid security (voltage) and access equity with siting and operations—so when we evaluate algorithms, we should track not only cost and peak reduction but also service quality and fairness.

# 2) Deep reinforcement learning (DRL) for charging and hubs

Several papers apply DRL at household, station, hub, and fleet scales:

* Household / station controllers. DRL treats charging as sequential decision‑making under prices/tariffs and typically delivers meaningful bill savings and peak shaving versus heuristics or deterministic baselines [10], [20]. One hub‑level study reports large reductions in peak impact (up to ~80%) when coordinating charger output via DRL [20].
* Grid‑aware DRL. Two‑layer scheduling explicitly maintains distribution‑network voltage stability while optimizing charging under uncertainty [8].
* Hybrid / comparative DRL. A hybrid framework compares DDQN, DDPG, and SAC for charge/discharge; SAC achieves the lowest battery‑degradation cost in that setup—underscoring how algorithm choice shifts wear‑and‑tear outcomes [19].
* Fleets. A holistic RL environment for commercial EV fleets focuses on avoiding local overload while improving schedule quality versus static baselines [22].
* Surveys. Reviews catalog DRL’s strengths and gaps for power/energy, including deployment risks, resilience, and security [9], and end‑to‑end perspectives on smart electromobility infrastructure [2].

Design notes for our study. Most applied papers use enhanced value‑based methods (DQN family) or actor–critic (DDPG/SAC). For our efficiency comparison (DQN vs PPO), evidence supports (i) strengthening a DQN baseline with Double/Dueling/Replay, and (ii) considering actor–critic or PPO when we want continuous kW set‑points or multi‑term rewards (cost + voltage + queues) [8], [19], [20], [22].

# 3) Non‑RL optimization and multi‑criteria design

Deterministic and meta‑heuristic methods remain strong, transparent baselines:

* Multi‑criteria siting/design (AHP/MCDM) integrates location benefits, cost, and grid impacts [16].
* Voltage‑stability‑aware siting (with stochastic power flow) shows how grid security can pull optimal sites away from demand hot‑spots [17].
* EV routing syntheses document the operational constraints our schedulers must honor [11].
* Building‑integrated work surfaces practical deployment frictions (capacity, wiring, load management) that shape what’s feasible on the ground [5].

What this tells us. Keeping at least one deterministic baseline (e.g., MILP/MCDM for siting, or a constraint‑explicit scheduler) helps us isolate what RL actually buys us—in solution quality and in compute time.

# 4) Behavior, equity, and demand modeling

Behavioral realism isn’t optional:

* Data‑driven behavior (UK). Empirical UK charging data (clustering and pattern mining) yields realistic plug‑in times and energy needs for planning and operations [3].
* Household patterns. Residential behavior analyses show how time‑of‑use and daily routines shape charging windows; predictive models inform demand management [13].
* Full data‑chain approaches. Combining transport, mobility, and grid data helps reconstruct behavior more faithfully than single‑source models [14].
* Equity and access. Policy‑oriented synthesis raises “who benefits?” questions around placement and affordability, and maps gaps we should measure against [6].

What this tells us. When we evaluate controllers, we should use behavior‑aware rewards (e.g., wait/inconvenience penalties) and test scenarios that reflect home‑ vs public‑charging dependence, so we don’t optimize to unrealistic flexibility.

# 5) UK infrastructure and costs

Two strands anchor the UK lens:

* Infrastructure gap. UK‑specific quantification of the home/workplace/fast mix needed for 2030 targets shows capacity and where it sits both matter [21].
* Charging demand (UK case). Empirical UK behavior informs siting and day‑to‑day scheduling assumptions [3].
* Cost decomposition (US study, methodologically useful). Home charging often dominates total system costs at metro scale, reminding us that public‑only strategies may underperform at city‑system level [12].

# 6) Game theory, market design, and pricing

Several works model strategic behavior:

* Station competition (T‑ITS). A comprehensive equilibrium model links prices, queues, travel costs, and welfare under station competition [1].
* Mean‑field pricing/control. A mean‑field framework co‑optimizes station pricing and user flow under grid constraints for large populations [7].
* Dynamic pricing in multi‑agent ecosystems. Simulations suggest dynamic pricing can reduce congestion and balance loads under realistic interactions [15].
* Time resolution & temperature. A methods paper shows time‑step choice (and temperature) changes optimal decisions and costs—important for comparing price‑responsive algorithms fairly [18].
* Cost accounting. City‑scale studies break down how costs spread across home, workplace, and public infrastructure [12].

What this tells us. It’s worth stress‑testing our RL policies against strategic pricing (e.g., leader–follower/mean‑field settings) to check robustness beyond a single tariff.

# 7) Technical limitations: battery health, safety, compute

Key caveats recur in several papers:

* Battery aging. Degradation outcomes can be algorithm‑dependent—one hybrid RL paper finds SAC minimizes degradation cost in its scenario [19]; an IEEE Access review lists lithium‑ion issues and recommendations we should price into our reward models (depth‑of‑discharge, temperature) [23].
* Safety and resilience with DRL. Reviews flag constraint satisfaction, cybersecurity, and recovery as deployment risks we should handle with penalties, constraints, or safe‑RL techniques [9].
* Compute and stability. Value‑based methods usually need Double/Dueling/Replay for stability; actor–critic approaches trade some sample efficiency for smoother optimization and continuous control [9], [19], [20].

# 8) Synthesis: what this set implies for our DQN↔PPO efficiency study

Implications we will carry into our experiments:

* Baselines we keep. One deterministic (e.g., MCDM/MILP‑style for siting or a constraint‑explicit scheduler) and one modern value‑based controller (DQN + Double/Dueling/Replay), then compare with PPO/SAC for continuous power set‑points and richer reward terms [16], [17], [10], [19], [20].
* Behavior‑aware rewards. Ground inconvenience/wait and flexibility in observed UK patterns and equity considerations; vary the mix of home/public dependence in scenarios [3], [6], [13], [14], [21].
* Grid and market realism. Include voltage‑stability constraints and strategic pricing scenarios (Stackelberg/mean‑field/dynamic pricing) so policies don’t overfit a single tariff or time step [1], [7], [8], [15], [18].
* Battery health. Track degradation‑linked metrics (DoD, temperature) alongside cost and peaks—results can change with the algorithm we choose [19], [23].

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