

Electric Vehicle Battery Swapping Stations: A Focused Review of Siting, Sizing, and Operation

Shiyun Tong*

School of Transportation and Logistics, Southwest Jiaotong University, Chengdu, China

**Corresponding author: 735088757@qq.com*

Abstract: Battery swapping separates a vehicle's stop from battery charging, creating flexibility but coupling station location and capacity to battery inventory, queues, and local grid limits. This focused review examines 31 road-vehicle battery swapping station studies and one broader infrastructure review published through 25 August 2026. Twenty-seven primary studies were coded by decision layer, data basis, uncertainty, battery condition, service representation, and network detail. Thirteen explicitly model stochastic or robust uncertainty, nine use operational or case data, five include degradation or state of health, and seven represent network-level constraints; only four couple an infrastructure decision with operational or grid control. The literature has progressed from deterministic siting models to trajectory-based planning, stochastic inventory control, degradation-aware scheduling, reinforcement learning, and robust renewable integration. Yet no reviewed study closes the loop among user arrivals, queueing, heterogeneous battery health, and distribution-network feasibility. We therefore frame design as an iterative exchange among mobility, station, battery, and grid models, clarifying what is integrated and what remains an external assumption.

Keywords: Battery Swapping Station, Electric Vehicle, Infrastructure Planning, Battery Inventory, Charging Scheduling, Grid Integration

1. Introduction

For electric vehicles (EVs), battery swapping changes where and when energy replenishment occurs. A driver receives a service-ready pack, while the returned battery joins a centrally managed charging inventory. The arrangement can reduce vehicle dwell time and gives the operator some freedom to shift charging across the day. That flexibility comes with requirements that plug-in charging does not share to the same extent, including spare batteries, pack compatibility, queue management, and concentrated feeder demand. Recent reviews therefore describe the battery swapping station (BSS) as both a transport facility and an energy asset [1-4].

These transport, inventory, and power functions are coupled across space and time. Location affects access distance and the arrival process; bays, chargers, and battery stocks set service capacity and electrical demand. Charging decisions then alter energy cost, battery wear, renewable-energy use, and near-term pack availability. Charging-infrastructure research already recognizes the link between transport and distribution-network planning [5]. Swapping adds a detachable inventory whose condition evolves even when no vehicle is present. A BSS is therefore poorly represented as either a conventional fuel station or a plug-in charging site.

Earlier BSS reviews catalogued operating modes, planning formulations, and scheduling decisions [1-4]. Subsequent work has narrowed these broad categories into more specific decision problems. Trajectory data inform siting, vehicle classes are modeled separately, degradation enters inventory control, and grid interaction is treated under stochastic or robust uncertainty. The pieces have advanced, but they are usually evaluated one layer at a time. A result obtained for location, station operation, or grid services may therefore depend on untested assumptions elsewhere in the system.

This focused review examines how these decision layers fit together in practice. It asks how swap demand becomes a location and capacity decision, how a battery stock is converted into reliable service, and when grid support remains compatible with mobility demand. We organize the evidence as a multi-timescale chain from siting and sizing to inventory control and grid-responsive operation. This view distinguishes genuine integration from coordination that exists only through fixed inputs. The scope is limited to road-vehicle station design; mechanical swap equipment, battery chemistry, and stand-alone

policy or business analysis are outside it.

2. Review Scope and Analytical Framework

CrossRef and OpenAlex metadata were searched through 25 August 2026 using the concept string ("battery swapping station" OR "battery swap station") with the modifiers review, location, capacity, sizing, inventory, scheduling, queueing, demand response, microgrid, renewable energy, and grid integration. English-language journal articles and reviews were retained when a road-vehicle BSS was itself a design object and at least one infrastructure or operating decision was specified. Mechanical equipment, battery materials, authentication protocols, and studies that used swapping only as a routing constraint were excluded. The final corpus comprised 31 BSS records and one broader review of integrated charging-infrastructure planning [5]. Because no independent duplicate screening or formal study-quality score was applied, the corpus is presented as a focused evidence map rather than a systematic review.

The 27 primary studies [6-32] were coded from titles, abstracts, accessible publisher metadata, and article previews where available. Six non-exclusive indicators were recorded: use of operational or case data, uncertainty treatment, service representation, battery degradation or heterogeneity, network-level constraints, and cross-layer co-design. Absence from the coding means that an attribute was not explicit in the material examined; it does not prove absence from an unavailable full text. Table 1 reports the resulting evidence profile. Figure 1 then organizes the studies by decision time scale and makes the feedback path explicit: observed service, cost, grid, and battery outcomes update uncertainty descriptions and trigger a defined revision of sites, bays, chargers, or battery stocks.

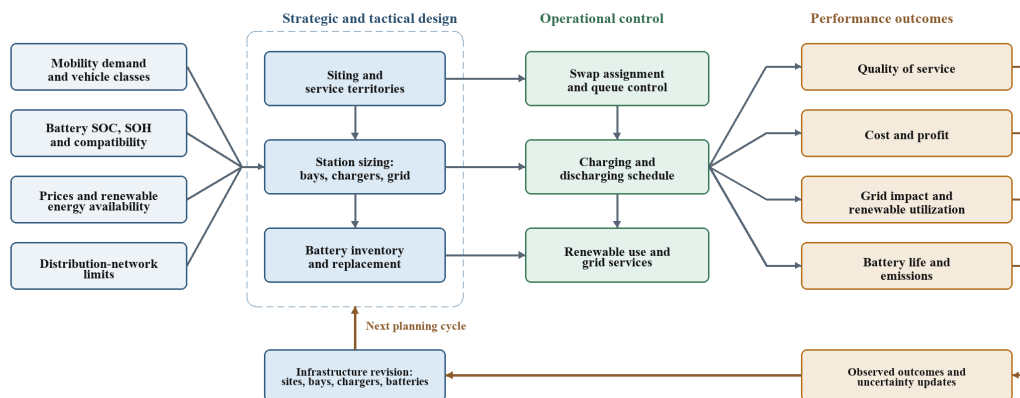


Figure 1: Multi-timescale design loop linking planning, operational control, performance evaluation, and evidence-based infrastructure revision.

Table 1: Descriptive coding of the 27 primary BSS studies [6-32]. Categories overlap; counts reflect explicit reporting in titles, abstracts, and accessible metadata.

Explicit indicator	n / 27	Studies	Interpretation
Operational, geospatial, or case data	9	[7,9,10,13,17,24,25,29,31]	Empirical inputs are present, but most evaluations remain case-specific.
Stochastic, robust, or explicit uncertainty model	13	[12,15-18,22,24-27,30-32]	Uncertainty is common in scheduling, but less consistently linked to siting.
Degradation, SOH, or heterogeneous battery state	5	[16,17,19,22,24]	Battery ageing is still rarely a structural planning variable.
Network-level power-system constraints	7	[6,13,14,23,24,28,30]	Grid detail is usually separated from mobility choice and queueing.
Infrastructure plus operational or grid co-design	4	[6,13,31,32]	Only a small subset spans more than one design time scale.

3. Siting and Capacity Planning

Planning models converge on one point: location is inseparable from the demand assigned to a site. In early bi-level work, demand-side management influenced both location and capacity [6]. Later data-driven and multi-objective formulations used operating records, user satisfaction, and cost to rank urban charging and swapping sites [7,8]. Across these approaches, spatial coverage is only the first step. The arrival profile generated by site choice sets the subsequent requirements for bays, chargers, batteries, and grid connection.

Demand representation becomes strongly vehicle-specific once real travel patterns are considered. Bus routes and timetables support route-based siting with relatively predictable visits [9]. Freight stations must align with trajectories, duty cycles, and payload-related energy use [10], whereas delivery micromobility produces dense short-haul chains that favor simulation-based multi-objective planning [11]. Commercial-fleet models now also represent demand through robust uncertainty sets [12]. These differences make a generic demand surface difficult to transfer among buses, trucks, taxis, delivery fleets, and private cars.

Capacity models usually choose swapping bays, chargers, reserve batteries, and a grid-connection limit. Treating these distinct assets as a single capacity measure is misleading. Bays relieve service congestion only when a charged pack is available; chargers restore inventory only within tariff and feeder limits. Batteries buffer arrivals but add capital cost and degradation exposure. Revenue-oriented station and microgrid planning makes these interactions explicit [13], while grid-aware formulations add network reconfiguration and technical power-system constraints [14].

Uncertainty is now entering capacity decisions rather than being left for operational sensitivity tests. Recent formulations co-constrain quality of service (QoS) and grid-shifting capability [31], or use two-stage robust optimization for photovoltaic, storage, charging, and swapping assets [32]. Validation across the linked decision layers remains the weakest part of this literature. Sites are often selected from representative demand and then tested against only a few operating scenarios. A credible planning workflow should return queueing, charging, and feeder violations to the sizing model, especially when travel and power-system peaks coincide.

4. Inventory, Charging, and Operational Scheduling

In practice, a BSS manages two interdependent inventories on different clocks. The visible inventory is the distribution of packs by state of charge (SOC), particularly the number ready for an immediate swap. The slower inventory is battery capability, captured through state of health (SOH) and replacement needs. Charging and service can be co-optimized within one operating model [15]. Stochastic scheduling extends this view to charging, discharging, allocation, and replenishment, with Markov decision processes used to manage dimensionality [16]. The distinction matters because aggressive cycling may preserve today's service level while increasing tomorrow's replacement cost.

Fixed daily schedules become fragile when arrivals and prices depart from forecasts. Priority-rule-enhanced deep reinforcement learning (DRL) has been applied to charging control [17], while stochastic scheduling models represent uncertain swap demand directly [18]. Other formulations track how battery functionality becomes heterogeneous with age [19]. For heavy-duty trucks, SOC-dependent control links large pack energy, service timing, and station configuration [20]. Together, these studies relax the full-or-empty, identical-pack assumption, although battery temperature and electrochemical detail are still represented sparingly.

Learning-based control is attractive because the state space grows with every battery, charger, SOC level, and uncertainty state. Hybrid approaches combine DRL with mathematical optimization to improve scalability [21], and renewable-powered scheduling has also been treated with reinforcement learning [22]. The benefit is adaptation across large state spaces, but feasibility becomes difficult to verify independently. Performance depends on the training distribution, reward design, and simulator. Hard limits on inventory, charging power, and grid exchange should therefore be enforced outside the learned policy or through a safety layer that can be audited.

The most reusable result across this literature is a design principle rather than a particular algorithm: flexibility must remain subordinate to service. A station can shift charging toward low-price or renewable-rich periods only after reserving enough usable energy and healthy packs for expected swaps. Control can then allocate the remaining inventory among economical charging, degradation management,

and grid services. Re-estimation as arrivals, prices, renewable output, and battery measurements change links real-time operation back to the capacity chosen at the planning stage.

5. Transportation-Station-Grid Coordination

To a power system, a BSS appears as a concentrated but partly controllable load backed by stationary battery inventory. Bi-level scheduling has coordinated an isolated microgrid and a station under real-time prices and multiple stakeholder objectives [23]. Related microgrid models treat the station and the microgrid as separate decision makers and include degradation cost [24]. This institutional separation matters because the mobility operator, station owner, and grid operator have different obligations and may not value the same flexibility.

Station-held batteries can provide services beyond vehicle replenishment, but the available reserve must be measured conservatively. Deep-Q-network scheduling has been used to estimate frequency-regulation capacity under uncertain signals and arrivals [25]. Other studies have examined three related tasks across different network settings. They size photovoltaic generation and storage for off-grid battery supply [26], schedule photovoltaic-based stations against joint uncertainty [27], and quantify distribution-system effects [28]. These studies support the energy-hub interpretation of a BSS, but only within limits set by swap reserves, interconnection capacity, market access, and degradation compensation.

Renewable coordination is becoming more closely tied to swapping demand. A Beijing case study assessed the interaction between variable renewable generation and station operation [29]. Later work introduced distributionally robust energy management for photovoltaic-enabled charging-swapping stations in active distribution systems [30]. Capacity models now combine QoS with grid shifting [31] and configure photovoltaic, storage, charging, and swapping assets under joint uncertainty [32]. The grid is thus moving from an external tariff in the model to an active network with constraints and uncertain conditions.

Full coupling is nevertheless difficult and may not always be desirable. Travel demand is spatial and behavior-dependent, power-flow feasibility is nonlinear and site-specific, and battery inventory changes much faster than infrastructure. A monolithic model may hide assumptions while becoming difficult to solve or audit. Iterative decomposition offers a more transparent alternative: a mobility model generates arrival distributions, a station model tests service and battery feasibility, and a network model checks power-flow and flexibility limits. Violations and marginal values can then revise the siting and sizing decisions.

6. Research Gaps and Outlook

Comparative progress remains limited by incompatible data sources and reporting practices. Demand often comes from a proprietary fleet, a synthetic curve, or one city. Studies should therefore document anonymized arrival distributions, vehicle classes, battery specifications, tariffs, renewable profiles, feeder parameters, and scenario construction. A common minimum set of service measures, including waiting time, unmet demand, ready-battery probability, and charger utilization, would allow planning and control methods to be compared on the same basis.

Planning and control decisions also require evaluation within the same scenarios. Site and capacity choices should face queueing, charging, battery-health, and power-flow simulations over ordinary days and rare correlated peaks. Controllers, in turn, should be tested across alternative station sizes and network layouts rather than against one fixed design. Decomposition, surrogate models, and rolling optimization are useful only when approximation error and convergence behavior are reported.

Battery heterogeneity remains underrepresented in both strategic planning and operational control. Packs differ in age, usable energy, power capability, temperature, and vehicle compatibility. Replacing that distribution with an average battery can overstate service reliability and grid-service capacity. Future models should link SOH estimation to duty-cycle assignment, maintenance, replacement, and second-life decisions, while making warranty and data-access assumptions explicit.

Learning-based controllers introduce a separate practical problem of deployment assurance. DRL policies should be compared with strong stochastic or model-predictive baselines and tested on seasons, demand shocks, and price patterns that were absent from training. Mean cost is not enough when a rare event leaves no charged pack available or violates a feeder limit. Risk-sensitive and distributionally

robust formulations can provide a bridge between adaptive control and verifiable service reliability.

Technical feasibility does not by itself create an operating agreement. Grid services depend on metering, market qualification, settlement, battery ownership, and compensation for wear. Network reinforcement belongs to the distribution operator, while station choice depends on the information and prices seen by drivers or fleet managers. Design studies need not become policy analyses, but they should state who controls each decision, who pays each cost, and what information is available when the decision is made.

7. Conclusions

Research on battery swapping stations now offers well-developed methods for location, capacity, inventory control, charging, and grid coordination. The remaining problem is their separation: assumptions that simplify one layer often determine whether another layer can deliver service or flexibility. Reading the evidence as one design chain suggests a practical architecture in which mobility, station, battery, and network models exchange constraints rather than collapse into a single opaque formulation. Within the road-vehicle scope reviewed here, this iterative coordination is a more credible basis for reproducible station design than isolated improvements evaluated in one scenario.

Data Availability

No new empirical dataset was generated for this focused review. The bibliographic records supporting the synthesis are identified by DOI in the reference list.

References

- [1] Ahmad, F., Saad Alam, M., Saad Alsaidan, I. and Shariff, S.M. (2020) *Battery swapping station for electric vehicles: opportunities and challenges*. *IET Smart Grid*, 3(3), 280-286. <https://doi.org/10.1049/iet-stg.2019.0059>
- [2] Wu, H. (2022) *A Survey of Battery Swapping Stations for Electric Vehicles: Operation Modes and Decision Scenarios*. *IEEE Transactions on Intelligent Transportation Systems*, 23(8), 10163-10185. <https://doi.org/10.1109/tits.2021.3125861>
- [3] Feng, Y. and Lu, X. (2021) *Construction Planning and Operation of Battery Swapping Stations for Electric Vehicles: A Literature Review*. *Energies*, 14(24), 8202. <https://doi.org/10.3390/en14248202>
- [4] Alhazmi, Y.A. (2026) *Electric vehicle battery swap stations: an overview and critical review*. *Journal of Umm Al-Qura University for Engineering and Architecture*, 17(1), 218-231. <https://doi.org/10.1007/s43995-025-00215-z>
- [5] Unterluggauer, T., Rich, J., Andersen, P.B. and Hashemi, S. (2022) *Electric vehicle charging infrastructure planning for integrated transportation and power distribution networks: A review*. *eTransportation*, 12, 100163. <https://doi.org/10.1016/j.etrans.2022.100163>
- [6] Liu, W., Niu, S., Xu, H. and Li, X. (2016) *A New Method to Plan the Capacity and Location of Battery Swapping Station for Electric Vehicle Considering Demand Side Management*. *Sustainability*, 8(6), 557. <https://doi.org/10.3390/su8060557>
- [7] Zeng, M., Pan, Y., Zhang, D., et al. (2019) *Data-Driven Location Selection for Battery Swapping Stations*. *IEEE Access*, 7, 133760-133771. <https://doi.org/10.1109/access.2019.2941901>
- [8] Zu, S. and Sun, L. (2022) *Research on location planning of urban charging stations and battery-swapping stations for electric vehicles*. *Energy Reports*, 8, 508-522. <https://doi.org/10.1016/j.egyr.2022.01.206>
- [9] Moon, J., Kim, Y.J., Cheong, T. and Song, S.H. (2020) *Locating Battery Swapping Stations for a Smart e-Bus System*. *Sustainability*, 12(3), 1142. <https://doi.org/10.3390/su12031142>
- [10] Wang, S., Shao, C., Zhuge, C., et al. (2022) *Deploying Battery Swap Stations for Electric Freight Vehicles Based on Trajectory Data Analysis*. *IEEE Transactions on Transportation Electrification*, 8(3), 3782-3800. <https://doi.org/10.1109/tte.2022.3160445>
- [11] Zhang, F., Lv, H., Xing, Q. and Ji, Y. (2024) *Deployment of battery-swapping stations: Integrating travel chain simulation and multi-objective optimization for delivery electric micromobility vehicles*. *Energy*, 290, 130252. <https://doi.org/10.1016/j.energy.2024.130252>
- [12] Guo, Y., Yan, K., Qian, X., et al. (2025) *A robust optimal battery swapping station location model for commercial electric vehicles under demand uncertainty*. *Energy*, 333, 137466. <https://doi.org/10.1016/j.energy.2025.137466>

- [13] Kocer, M.C., Onen, A., Jung, J., et al. (2023) *Optimal Location and Sizing of Electric Bus Battery Swapping Station in Microgrid Systems by Considering Revenue Maximization*. *IEEE Access*, 11, 41084-41095. <https://doi.org/10.1109/access.2023.3267801>
- [14] Al-Zaidi, W.K.M. and Inan, A. (2024) *Optimal Planning of Battery Swapping Stations Incorporating Dynamic Network Reconfiguration Considering Technical Aspects of the Power Grid*. *Applied Sciences*, 14(9), 3795. <https://doi.org/10.3390/app14093795>
- [15] Sarker, M.R., Pandzic, H. and Ortega-Vazquez, M.A. (2015) *Optimal Operation and Services Scheduling for an Electric Vehicle Battery Swapping Station*. *IEEE Transactions on Power Systems*, 30(2), 901-910. <https://doi.org/10.1109/tpwrs.2014.2331560>
- [16] Asadi, A. and Nurre Pinkley, S. (2021) *A stochastic scheduling, allocation, and inventory replenishment problem for battery swap stations*. *Transportation Research Part E: Logistics and Transportation Review*, 146, 102212. <https://doi.org/10.1016/j.tre.2020.102212>
- [17] Jin, J., Mao, S. and Xu, Y. (2023) *Optimal Priority Rule-Enhanced Deep Reinforcement Learning for Charging Scheduling in an Electric Vehicle Battery Swapping Station*. *IEEE Transactions on Smart Grid*, 14(6), 4581-4593. <https://doi.org/10.1109/tsg.2023.3250505>
- [18] Nayak, D.S. and Misra, S. (2024) *An operational scheduling framework for Electric Vehicle Battery Swapping Station under demand uncertainty*. *Energy*, 290, 130219. <https://doi.org/10.1016/j.energy.2023.130219>
- [19] Chen, X., Yang, Y., Wang, Z., et al. (2025) *Battery Swapping Station Management With Heterogeneous Battery Functionality Degradation*. *IEEE Transactions on Smart Grid*, 16(1), 478-490. <https://doi.org/10.1109/tsg.2024.3392259>
- [20] Wang, F.Y., Chen, Z. and Hu, Z. (2024) *Comprehensive optimization of electrical heavy-duty truck battery swap stations with a SOC-dependent charge scheduling method*. *Energy*, 308, 132773. <https://doi.org/10.1016/j.energy.2024.132773>
- [21] Su, Y., Yue, S., Qiu, L., et al. (2024) *Energy management for scalable battery swapping stations: A deep reinforcement learning and mathematical optimization cascade approach*. *Applied Energy*, 365, 123212. <https://doi.org/10.1016/j.apenergy.2024.123212>
- [22] Renga, D., Spoturno, F. and Meo, M. (2024) *Reinforcement Learning for Charging Scheduling in a Renewable Powered Battery Swapping Station*. *IEEE Transactions on Vehicular Technology*, 73(10), 14382-14398. <https://doi.org/10.1109/tvt.2024.3404108>
- [23] Li, Y., Yang, Z., Li, G., et al. (2018) *Optimal scheduling of isolated microgrid with an electric vehicle battery swapping station in multi-stakeholder scenarios: A bi-level programming approach via real-time pricing*. *Applied Energy*, 232, 54-68. <https://doi.org/10.1016/j.apenergy.2018.09.211>
- [24] Esmaeili, S., Anvari-Moghaddam, A. and Jadid, S. (2019) *Optimal Operation Scheduling of a Microgrid Incorporating Battery Swapping Stations*. *IEEE Transactions on Power Systems*, 34(6), 5063-5072. <https://doi.org/10.1109/tpwrs.2019.2923027>
- [25] Wang, X., Wang, J. and Liu, J. (2021) *Vehicle to Grid Frequency Regulation Capacity Optimal Scheduling for Battery Swapping Station Using Deep Q-Network*. *IEEE Transactions on Industrial Informatics*, 17(2), 1342-1351. <https://doi.org/10.1109/tii.2020.2993858>
- [26] Ban, M., Yu, J., Shahidepour, M. and Guo, D. (2019) *Optimal sizing of PV and battery-based energy storage in an off-grid nanogrid supplying batteries to a battery swapping station*. *Journal of Modern Power Systems and Clean Energy*, 7(2), 309-320. <https://doi.org/10.1007/s40565-018-0428-y>
- [27] Liu, H., Zhang, Y., Ge, S., et al. (2019) *Day-Ahead Scheduling for an Electric Vehicle PV-Based Battery Swapping Station Considering the Dual Uncertainties*. *IEEE Access*, 7, 115625-115636. <https://doi.org/10.1109/access.2019.2935774>
- [28] Zeng, B., Luo, Y. and Liu, Y. (2022) *Quantifying the contribution of EV battery swapping stations to the economic and reliability performance of future distribution system*. *International Journal of Electrical Power & Energy Systems*, 136, 107675. <https://doi.org/10.1016/j.ijepes.2021.107675>
- [29] Zhang, C., Lu, X., Chen, S., et al. (2024) *Synergies of variable renewable energy and electric vehicle battery swapping stations: Case study for Beijing*. *eTransportation*, 22, 100363. <https://doi.org/10.1016/j.etrans.2024.100363>
- [30] Kim, H., Lee, S. and Choi, D.H. (2026) *Energy Management of PV-Enabled Battery Charging Swapping Stations for Electric Vehicles in Active Distribution Systems Under Uncertainty*. *Energies*, 19(5), 1223. <https://doi.org/10.3390/en19051223>
- [31] Hu, J., Chen, J., Chen, X., et al. (2026) *QoS and Grid-Shifting Ability Guaranteed Optimal Capacity Sizing Method of Battery Swapping Station Considering Seasonal Characteristics*. *Electronics*, 15(3), 600. <https://doi.org/10.3390/electronics15030600>
- [32] Wang, Y., Fan, Y., Lu, G., et al. (2026) *A two-stage robust-optimization framework for capacity configuration of PV-storage charge-and-swap stations under generation-load uncertainties*. *Journal of Energy Storage*, 152, 120628. <https://doi.org/10.1016/j.est.2026.120628>