

The Contribution of Smart Grid Integrated Battery Swapping Stations to the Electric Vehicle Ecosystem: A Review

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Abstract—The rapid growth of electric vehicles (EVs) and the uncoordinated charging of their batteries have created a need for refuelling infrastructure that is convenient for users and manageable for the power grid. Battery swapping stations (BSSs) replace a depleted battery with a charged one in a few minutes, while the batteries held in the station form a controllable load and storage resource. However, a BSS needs a large battery inventory, high capital investment and standardized packs, and its grid benefits depend on how it is planned and operated. This paper reviews Scopus-indexed journal articles published from 2022 to 2026 on the integration of BSSs with the smart grid. It explains the architecture and operating modes of a grid-integrated BSS and describes its grid services, namely load shifting, demand response, battery-to-grid (B2G) supply, frequency regulation, renewable energy integration, and support for network planning and resilience. Planning and scheduling models are compared, and the contribution of BSSs to users, fleets, grid operators and the battery life cycle is assessed along with standardization and safety issues. Overall, the review supports grid-integrated BSSs as part of the EV ecosystem, while noting that most reported benefits come from simulations.

Index Terms—Battery swapping station, battery-to-grid, electric vehicle ecosystem, frequency regulation, renewable energy integration, smart grid.

I. INTRODUCTION

The electrification of road transport is one of the main routes for reducing transport emissions, and the number of electric vehicles (EVs) connected to distribution networks is rising steadily. The time, location and power of plug-in charging depend on the travel behaviour and decisions of individual users [1]. When many vehicles charge without coordination, the charging load can coincide with the evening peak and overload local transformers and feeders. For this reason, the integration of EVs into active distribution grids through suitable power architectures, grid connection standards and vehicle-to-grid (V2G) control has received growing attention [2].

Plug-in charging also takes much longer than refuelling a conventional vehicle, which adds to the anxiety of users about driving range. Battery swapping offers an alternative in which the depleted battery is removed at a battery swapping station (BSS) and replaced with a charged one within a few minutes

[3]. Because the battery can be owned by the station operator and leased to the user, swapping also separates the battery cost from the vehicle price. In India, for instance, swapping has been shown to improve the total cost of ownership of electric two-wheelers enough to make them economical for private as well as commercial users [4].

The contribution of a BSS is, however, not limited to the vehicle user. The batteries in a station are charged under the control of one operator, which turns the station into a large and flexible load that can be scheduled according to electricity prices, renewable generation and grid constraints [5], [6]. With bidirectional converters, the station can also return energy to the grid, so that its battery inventory may act as distributed storage. Thus, the BSS sits at the meeting point of the transport and power systems, and its value depends largely on how it is integrated with the smart grid.

Earlier reviews have covered the operation modes of BSSs [3], the siting, sizing and scheduling of stations [6], and the optimization methods used for their operation [5], with the main focus on models and algorithms. The present review examines what grid-integrated BSSs contribute to the different participants of the EV ecosystem, using Scopus-indexed journal articles from the last five years. Section II describes the review method, Sections III and IV cover the station architecture and its grid services, Sections V and VI deal with planning models and the ecosystem contribution, and Sections VII–IX discuss challenges, future research and conclusions.

II. REVIEW METHOD

The literature was identified in the Scopus database by searching titles, abstracts and keywords with the string (“battery swapping” OR “battery swap”) AND (“grid” OR “smart grid” OR “distribution network” OR “renewable” OR “frequency regulation” OR “demand response”). The results were limited to journal articles and reviews in English published from 2022 to 2026, and conference papers, book chapters and reports were excluded.

Records were kept if they dealt with the interaction of BSSs with the power grid, with BSS planning or operation under grid or price signals, or with the economic, policy and standardization conditions under which BSSs serve the EV

ecosystem. Studies on plug-in charging alone were removed, and after full-text reading 36 articles were selected. Their distribution by year and theme is shown in Fig. 1. Most were published in 2023–2025, and the largest group deals with grid services and renewable integration, which reflects the growing interest in the station as a grid resource as well as a refuelling point.

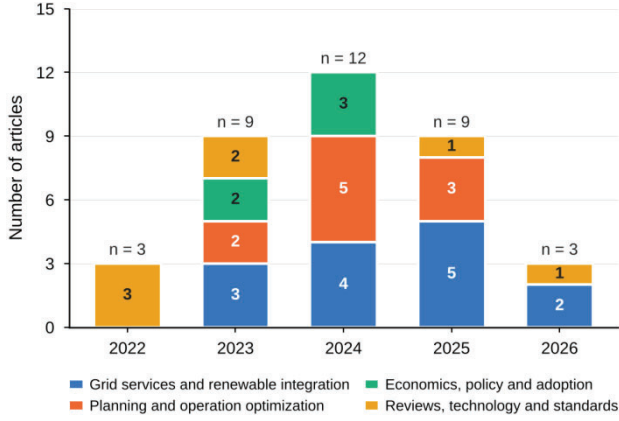


Fig. 1. Distribution of the 36 reviewed articles by publication year and research theme (2026 covers January–October).

III. ARCHITECTURE AND OPERATING MODES OF A GRID-INTEGRATED BSS

A. Station Components

A grid-integrated BSS consists of a swapping platform, a battery storage and charging area, a battery management system (BMS), a station energy management system (EMS) and a power electronic interface with the grid, as shown in Fig. 2. Swapping devices can be grouped into lifting, suspension, mobile vehicle, mobile robot and portable tool types, of which mobile robots are the most adaptable [7]. Such robots use vision and multi-sensor fusion to locate the pack, and a robot developed for light commercial trucks completed a swap in 4–6 min, compared with 5–8 min for existing systems [7].

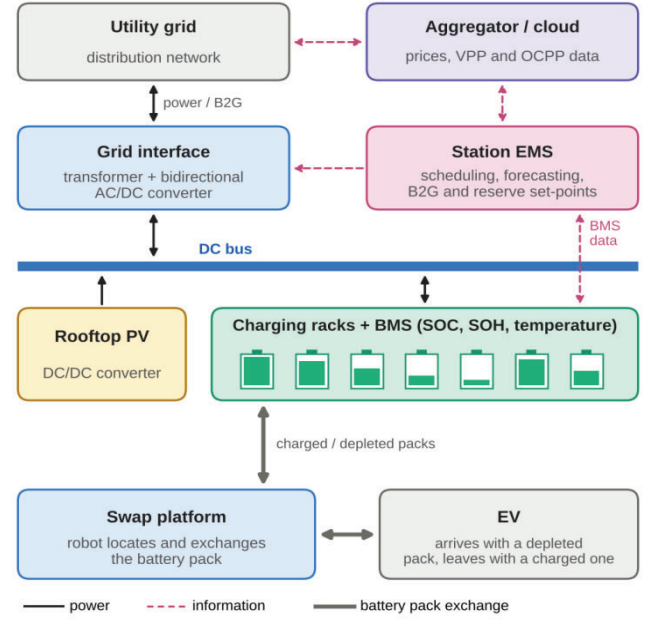


Fig. 2. Architecture of a smart grid integrated battery swapping station, showing power flows (solid) and information flows (dashed).

The removed batteries are placed in charging racks, where the BMS records their state of charge (SOC), state of health (SOH) and temperature. The EMS combines this information with electricity prices, expected swapping demand and network conditions to decide when and at what power each battery is charged or discharged. When the AC/DC and DC/DC converters of the grid interface are bidirectional, the station can supply power back to the grid in battery-to-grid (B2G) mode, and stations may also include rooftop photovoltaic (PV) panels [8], [9]. A generic form of the battery and station models used in the reviewed studies [5], [10] is

$$\text{SOC}_i(t+1) = \text{SOC}_i(t) + \frac{\Delta t}{E_i} [\eta_c P_{c,i}(t) - P_{d,i}(t)/\eta_d] \quad (1)$$

$$P_{\text{BSS}}(t) = \sum_{i=1}^N [P_{c,i}(t) - P_{d,i}(t)] + P_{\text{aux}}(t) - P_{\text{PV}}(t) \quad (2)$$

where $P_{c,i}(t)$ and $P_{d,i}(t)$ are the charging and discharging powers of battery i in time slot t , η_c and η_d are the efficiencies, and E_i is the battery capacity. In addition, Δt is the slot length, N is the number of batteries, $P_{\text{aux}}(t)$ is the auxiliary load and $P_{\text{PV}}(t)$ is the on-site PV output. The net power $P_{\text{BSS}}(t)$ seen by the grid is bounded by the rating of the connection point, and the scheduling problem minimizes the energy and degradation costs while keeping enough charged batteries for the swaps expected in each slot.

B. Operating Modes

Wu [3] classified BSS operation into four modes, namely a single BSS, several BSSs, a BSS integrated with a battery charging station (BCS), and several BSSs served by several BCSs. In the last two modes the batteries are charged at a central site and carried to the swapping stations. Qi et al. [11] showed that the benefit of this “swap-locally, charge-centrally” design comes mainly from faster central charging, which reduces the systemwide battery inventory, and not from

demand pooling alone. Because the central site concentrates the grid load at one point, Shaker et al. [12] planned BSSs together with the reinforcement of the distribution grid. In a mobile BSS, batteries are carried by vans to where they are needed, including loads cut off by an outage [13].

IV. SMART GRID SERVICES OF BSSs

The services that a grid-integrated BSS can provide are summarized in Fig. 3. They comprise load shifting and demand response, B2G supply and ancillary services, renewable energy integration and market participation, and support for network planning and resilience, all of which depend on an information and communication layer.

A. Load Shifting and Demand Response

The most direct grid contribution of a BSS is the shifting of battery charging to off-peak hours, since the station can choose when a returned battery is recharged, provided that the stock of charged batteries does not run out. Alberizzi et al. [8] simulated a full year of operation of a PV-integrated BSS in northern Italy, and the optimized schedule reduced power costs by up to 69% while raising PV self-consumption and lowering the peak grid demand. At the regional level, Yang et al. [14] proposed a demand response framework covering central charging stations, bus and taxi swap stations and mobile swap vehicles, in which coordinated charging reduced the peak–valley difference of the grid.

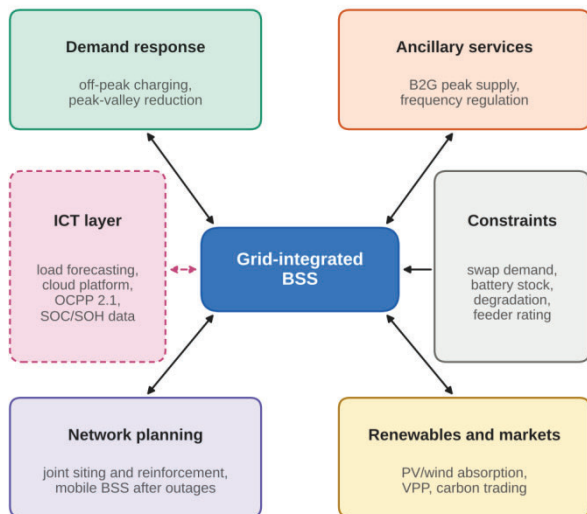


Fig. 3. Smart grid services that a battery swapping station can provide.

However, the grid impact of swapping is not automatically positive. Zhao et al. [15] modelled the load of battery-swapping heavy-duty trucks and found that the regional peak rose by 4.01% when trucks and stations did not share information. When a cloud platform exchanged travel, price and grid data, the rise was only 2.06% and the peak load was 4.08 MW lower. Thus, the load-shifting benefit of a BSS depends on coordination between vehicles, stations and the grid, and a station that recharges batteries as soon as they arrive may add to the peak.

B. Battery-to-Grid Supply and Ancillary Services

A BSS with bidirectional converters can discharge the batteries in its stock to the grid during peak hours. Yang et al. [16] grouped station batteries into three libraries according to their SOH and allocated them either to EV users or to B2G service, which raised profit compared with random allocation. Gull et al. [9] optimized a BSS supplied by the grid, PV and biogas, and operation in B2G mode increased profit by a further 8%. The inventory can also be offered as reserve for frequency regulation. Wang and Hou [17] set this reserve day-ahead with information-gap decision theory (IGDT) and adjusted the real-time response ratio, and tests with Pennsylvania–New Jersey–Maryland (PJM) regulation signals gave higher profits while the regulation performance was maintained.

However, grid services compete with the swapping service for the same batteries. In the BatRes model of Bin Arif and Deb [18], swapping produced about four times the revenue of grid arbitrage, and heavily loaded stations faced net costs because they had to charge batteries during peak hours. Hence, B2G and ancillary services are best treated as secondary revenue offered when swapping demand leaves spare batteries, with the degradation caused by extra cycling included in the decision.

C. Renewable Energy Integration and Market Participation

Battery swapping stations can absorb variable renewable generation, because their charging is flexible. Marchesano et al. [19] simulated a smart microgrid containing a BSS, a 500 kW wind turbine, a PV array of about 500 kW and storage made of second-life EV batteries, with renewable energy dispatched first, then storage, and finally grid purchases. Bian et al. [20] scheduled an integrated energy system with a BSS under source, load and N-1 contingency uncertainty, using SOC intervals with separate priorities for charging and discharging, and obtained a less conservative schedule that remained economic and stable.

Hu et al. [21] placed a BSS in a virtual power plant (VPP) and in carbon trading, with carbon credits based on the difference between local and grid carbon intensity. The coordinated schedule lowered emissions while keeping the economic return of the station. It could therefore be surmised that a BSS can act as an aggregated flexibility resource, although its participation in such markets depends on rules that allow small distributed resources to bid.

D. Distribution Network Planning and Resilience

A BSS also affects the planning of the distribution network to which it is connected. Shaker et al. [12] sited swapping stations with binary integer linear programming and selected the network branches to be reinforced with a genetic algorithm on the IEEE 69-bus system, including B2G revenue in the total cost. Hemmati [22] moved a BSS between two connection points every six months in a multi-stage expansion plan with rooftop PV, and the station discharged to the grid during the peak hours of 12–15 h and 18–21 h. This seasonal relocation gave about a 5% improvement over a fixed location.

Battery swapping can also support the grid after extreme events. Hemmati et al. [13] combined microgrid formation with mobile battery-swapping vans on the IEEE 33-bus network and restored 76% of the load within 24 h, which was 5.8% more than without swapping and 2.3% more than with stationary swapping stations. However, such results come from standard test feeders, and grid power constraints strongly influence the charging strategy of a station [23], so site-specific network data are needed before these benefits can be expected in practice.

E. Information and Communication Layer

These services need the exchange of data between batteries, vehicles, stations and the grid. Liu et al. [24] proposed a vehicle-to-cloud architecture in which electric trucks received the price and queue information of swapping stations and adjusted their speed, reducing swapping cost by 8.81–9.01% and driving energy by 10.48–15.56%. Zhu et al. [25] improved the station load forecasts needed for scheduling and market bidding with a hybrid deep learning model. On the standards side, the IEC 63584-210 specification of the Open Charge Point Protocol (OCPP) 2.1 includes battery swapping scenarios, but a common SOC/SOH data model for removable batteries is still missing [26].

V. PLANNING AND OPERATION OPTIMIZATION

A. Siting, Sizing and Battery Inventory

The location of a BSS, its number of chargers and its battery stock are linked decisions, because a small stock requires faster charging and therefore a larger grid connection [6], [11]. Guo et al. [27] located stations for commercial EV fleets with a mixed-integer model of construction, operating and detour costs under a budgeted uncertainty set. Their Benders decomposition solved the model more than 40% faster than a commercial solver on Shanghai data. Xie et al. [28] used taxi GPS records from Chengdu to size the battery stock of a station with a genetic algorithm. Lu et al. [29] minimized the life-cycle cost of the inventory, noting that an unsuitable inventory may severely reduce profitability. Representative planning and operation studies are compared in Table I.

TABLE I
 REPRESENTATIVE STUDIES ON THE PLANNING AND OPERATION OF GRID-
 INTEGRATED BSSs

Ref.	Focus and method	Grid-related result
[8]	PV-integrated BSS; MILP, full-year hourly prices	Power cost cut by up to 69%; lower peak demand
[9]	Grid, PV and biogas supply; MIP and dynamic programming	B2G mode added 8% to profit
[17]	Frequency regulation bidding; two-stage IGDT	Higher profit with regulation performance kept (PJM data)
[18]	Swapping plus grid services; LP (BatRes)	Swap revenue about four times arbitrage revenue
[12]	Joint BSS and grid planning; BILP and GA	Siting with grid reinforcement and B2G revenue (IEEE 69-bus)
[22]	Seasonal BSS relocation; stochastic planning	About 5% better than fixed-location BSS
[13]	Mobile BSS for resilience; MILP	76% of load restored within 24 h
[15]	Truck BSS load; Monte Carlo simulation	Peak rise of 2.06% (open) vs 4.01% (closed)
[27]	Fleet BSS location; budgeted uncertainty, Benders	Over 40% faster than commercial solver
[10]	Station scheduling; two-stage stochastic program	Extra inventory to avoid unmet demand
[32]	Large-station EMS; DRL with optimization	At least 33 times faster; 3,200 bays
[31]	Heavy-truck BSS; multi-stage PSO	About 10.8% better economic performance

MILP: mixed-integer linear programming; MIP: mixed-integer programming; BILP: binary integer linear programming; GA: genetic algorithm; LP: linear programming; PSO: particle swarm optimization.

B. Scheduling Under Uncertainty

Operational scheduling decides which batteries are charged, at what rate and when, under uncertain arrivals and prices. Nayak and Misra [10] used a two-stage stochastic program with several charging modes, time-of-use prices and the effect of fast charging on battery life to find the extra inventory needed to avoid unmet demand. Ali et al. [30] applied an adaptive grey wolf optimizer to a solar-powered central BSS in Patna, India, which gave the highest average profit among the tested algorithms. For heavy-duty trucks, Wang et al. [31] used SOC-dependent charging and raised the economic performance by about 10.8% compared with typical designs.

Learning-based methods address the size and uncertainty of real stations. Su et al. [32] combined deep reinforcement learning (DRL), which sets the total charging power in each time slot, with mathematical optimization, which allocates this power to individual charging bays. The cascade was at least 33 times faster than existing methods and scaled to stations with 3,200 bays.

C. Observations on the Models

The comparison in Table I should be read with some care. Most studies rely on test feeders or single-city data, with different objectives and cost assumptions, so the reported percentages are not directly comparable. Battery degradation is often represented by a simple cost per cycle, although the charging rate also affects battery life [10]. Furthermore, few studies treat the swapping service, grid services and network constraints in one model, even though these objectives

compete for the same batteries. Thus, the models are useful for comparing design options, but their absolute results have to be confirmed with operating data from real stations.

VI. CONTRIBUTION TO THE EV ECOSYSTEM

A. Vehicle Users

The contribution of a grid-integrated BSS to each participant of the EV ecosystem is shown in Fig. 4. For users, the main gains are the short refuelling time and the lower price of a vehicle sold without its battery. Kumar and Singh [4] estimated that India may need 42–291 GWh of batteries for 17.4–54.4 million electric two-wheelers by 2030, and found that swapping improves the total cost of ownership while needing less land than charging stations. Hu et al. [33] showed that a subscription scheme favours the early development of the market, whereas a pay-per-swap scheme is preferred once the market has matured, depending on battery depreciation, reserve inventory and customer time sensitivity.

B. Fleets and Commercial Vehicles

Swapping is particularly attractive for commercial operators whose vehicles have high daily utilization [4], and station models have been developed for taxi [28], bus [14] and truck [31] fleets. Zhu et al. [34] compared swapping, fast charging and supercharging for electric heavy-duty trucks and found swapping the most economical at medium recharge distances, with an optimum of about 156 km. Swapping was also cheaper than diesel trucks when station utilization exceeded 43% and average speed exceeded 32 km/h. Thus, the economics of swapping for fleets depend strongly on utilization, which links fleet operation to the planning problems in Section V.

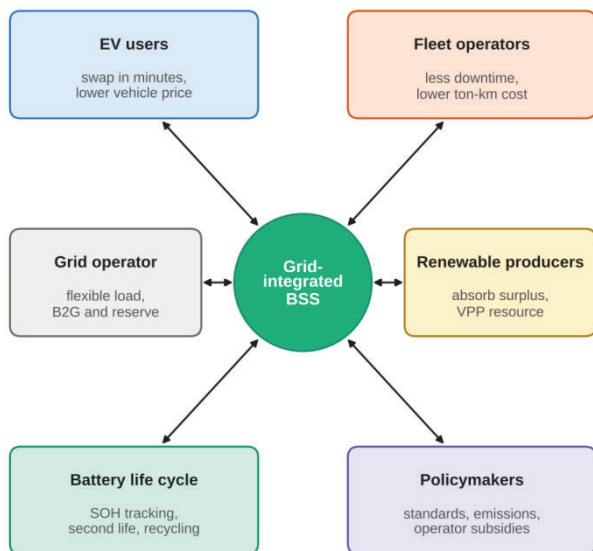


Fig. 4. Contribution of a grid-integrated BSS to the participants of the EV ecosystem.

C. Grid Operators, Emissions and Policy

At the system level, Patel et al. [35] used the Global Change Analysis Model (GCAM) for India and found that

swapping could reduce CO₂ emissions by 9% by 2070, with 6% higher EV adoption and 8% higher electricity demand. When swapping also received subsidies, EV penetration rose by 10% and emissions fell by 14% compared with point charging, although the authors concluded that swapping may not entirely replace point charging. Chu et al. [36] found with an evolutionary game that subsidies to station operators are more effective than subsidies to consumers. Hence, policy can speed the uptake of swapping, but the grid benefits described in Section IV appear only if stations are also rewarded for grid-friendly operation.

D. Battery Life Cycle

Since all batteries pass through the station, the operator can monitor their SOH and decide on reuse or recycling. Yang et al. [16] used the SOH of each battery to assign it to EV users or to the grid. Marchesano et al. [19] moved aged swapping batteries into the stationary storage of a microgrid, which extends their useful life before recycling. In this way, the BSS can link the transport use and the stationary use of the same battery, thereby supporting a circular economy for EV batteries. However, this environmental benefit still has to be shown by life cycle assessment that includes the extra batteries held in stock.

VII. CHALLENGES

The most serious barrier to the wider use of BSSs is the lack of standardized packs and interfaces. Van den Bossche et al. [26] reviewed the IEC 62840 family for battery swap systems, whose general and safety parts appeared in 2025, while the part on removable battery systems is still being developed. They identified gaps in mechanical interfaces, connectors, communication protocols and SOC/SOH data models, and also noted that Regulation (EU) No 168/2013 does not allow a light vehicle to be type-approved without a specific battery, which works against interchangeable packs. Without common packs, each manufacturer needs its own stations, which lowers utilization and raises cost.

The capital cost of a BSS is also high, since the operator has to buy more batteries than there are vehicles in service, and the size of this extra stock largely decides profitability [11], [29]. Fire safety is the main infrastructure concern, because many charged batteries are stored close together [26], while cloud-connected and multi-operator services need cybersecurity and data protection [24], [26]. Finally, profitability depends on high and steady utilization [34], and grid services can add only a modest share to the revenue of the swapping service [18].

VIII. FUTURE RESEARCH DIRECTIONS

Several research needs follow from this discussion. First, field data from operating stations are needed to validate the load profiles, degradation rates and grid benefits that are at present mostly simulated. Second, models should treat the swapping service, battery degradation, grid services and network constraints together, and learning-based methods such as that in [32] could make such models practical for large

stations. Third, standard packs, communication protocols and SOC/SOH data formats should be developed in step with grid codes, so that stations of different operators can be aggregated [26]. Finally, life cycle and techno-economic assessments should compare swapping with plug-in charging for the same transport service, including the extra batteries in stock and their second-life use [19], [35].

IX. CONCLUSION

Smart grid integrated battery swapping stations combine fast energy replenishment, centralized and controllable battery charging, and the use of the battery inventory as distributed storage into a single approach to EV refuelling. The reviewed studies show that such stations can shift charging to off-peak hours, provide demand response, frequency regulation and VPP services, absorb renewable generation and support distribution networks, while lowering the upfront cost for users and the downtime of fleets.

However, these benefits must be supported by data. Most of the reported gains come from simulations on test feeders or single-city data, grid services compete with the swapping service for the same batteries, and uncoordinated swapping loads can raise the network peak. Further improvements are needed in pack standardization, in joint models of service, degradation and grid constraints, in safety and cybersecurity, and in life cycle assessment. Progress on these points will decide whether grid-integrated battery swapping can move from pilot stations to a commercially viable part of the EV ecosystem.

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