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Second-Life Battery Supported PV–EV Charging for Workplaces: Optimal Sizing and Feasibility Assessment

Elif HACI[1], **Musa TERKEŞ**[1] **and Alpaslan DEMİRCİ**[1]

[1]*Department of Electrical Engineering, Faculty of Electrical and Electronics, Yıldız Technical University, İstanbul, Türkiye*

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Abstract

This paper presents an area-constrained multi-objective sizing and feasibility framework for photovoltaic (PV)-supported workplace electric vehicle charging stations (EVCSs) integrated with second-life battery energy storage systems (SLB-ESSs). The study addresses a key methodological issue in workplace PV–EV charging applications: excessive overlap between PV generation and daytime charging demand can make a PV-only baseline appear highly self-consuming, thereby masking the marginal value of storage. To obtain a more meaningful storage assessment, PV capacity is selected as a feasible high-penetration design constrained by rooftop/parking-area availability, inverter/connection limits, and PV–load temporal overlap. Under this common PV basis, SLB capacity, inverter capacity, and EVSE count are optimized using NSGA-III by minimizing net present cost and operational CO_2 emissions while maximizing self-sufficiency. The framework is evaluated for a Turkish workplace case using hourly PV simulation, stochastic EV charging demand, heterogeneous SLB state-of-health modeling, and life-cycle economic analysis. The selected PV design reaches 227.27 kWp and, in the PV-only case, yields 64.97% SCR with 119.07 MWh/yr exported energy. With SLB integration, SCR increases to 77.23%, SSR reaches 87.94%, and operational emissions decrease from 36.75 to 17.62 tCO_2/yr. Economically, the optimized PV+SLB+EVSE system reduces net present cost from 14.43 to 9.39 million TL relative to the PV-only configuration while maintaining full EV demand satisfaction. The findings indicate that second-life storage is most valuable in workplace charging sites where high PV penetration creates surplus energy that would otherwise be exported at limited economic value.

1. Introduction

1.1. Motivation

The increasing penetration of electric vehicles (EVs) changes workplace electricity demand from a mostly building-driven profile into a combined building–mobility load. Workplace charging is particularly important because vehicles often remain parked during daytime hours, when rooftop and parking-lot photovoltaic (PV) production is also available. This natural coincidence makes PV-supported electric vehicle charging stations (EVCSs) attractive; however, it also creates a methodological challenge for storage evaluation. If the PV capacity is too low, almost all PV generation may be consumed immediately by the workplace and EV load. In that case, a PV-only system can show an excessively high self-consumption ratio (SCR), and the added value of a battery energy storage system becomes difficult to observe.
Second-life batteries (SLBs), obtained from retired EV battery packs, offer a promising route to reduce the cost of stationary storage while supporting circular economy objectives. Nevertheless, SLB deployment cannot be evaluated only through unit cost. SLB packs are

Email addresses and ORCID numbers: elif.haci@std.yildiz.edu.tr (E. Hacı), musa.terkes@yildiz.edu.tr, 0000-0002-4411-411X (M. Terkeş), ademirci@yildiz.edu.tr, 0000-0002-1038-7224 (A. Demirci)
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heterogeneous in state-of-health (SoH), usable capacity, internal resistance, and remaining useful life (RuL). Therefore, sizing decisions must jointly consider PV surplus availability, storage capacity, grid import/export, life-cycle cost, operational emissions, and battery health.

1.2. Research Gap

The literature on PV–battery sizing for commercial buildings and EV charging has made important progress using deterministic energy balance models, linear programming, dynamic programming, and evolutionary multi-objective optimization [1–7]. However, three gaps remain critical for workplace PV–SLB–EVSE systems. First, many studies optimize PV and storage simultaneously without clearly separating the contribution of PV generation from the marginal contribution of storage. This is problematic in workplace charging, where PV–load overlap may be high. Second, second-life batteries are often represented as homogeneous energy reservoirs, although real retired modules exhibit heterogeneous SoH and degradation behavior [8–10]. Third, the storage effect is frequently reported through aggregate system performance only, without explicitly quantifying how SLB integration changes grid import, PV export, SCR, SSR, emissions, and life-cycle cost under a common PV basis.
This paper addresses these gaps by adopting an area-constrained PV penetration basis and then optimizing the SLB-ESS and balance-of-system components under the same PV production potential. The resulting scenario structure enables a cleaner interpretation: S0 represents grid-only charging, S1 isolates the effect of PV, and S2 quantifies the marginal technical, environmental, and economic value of SLB under the same PV capacity.

1.3. Contributions

The main contributions of this paper are as follows:

- An area-constrained PV penetration approach that accounts for workplace rooftop/parking-area feasibility, inverter/connection limits, and PV–load temporal overlap before storage sizing.
- A two-stage sizing formulation in which the PV capacity is first fixed as a feasible high-penetration design, and then SLB capacity, inverter capacity, and EVSE count are optimized using NSGA-III.
- A heterogeneous SLB representation in which module-level SoH affects usable capacity and remaining useful life, avoiding the oversimplification of treating SLB as a fully homogeneous storage block.
- A scenario-based feasibility comparison distinguishing the PV contribution (S0–S1) from the marginal SLB contribution (S1–S2) in terms of grid import, PV export, SCR, SSR, operational emissions, and life-cycle cost.
- Quantitative evidence from a Turkish workplace case study showing that SLB integration improves SCR, SSR, grid import, PV export, operational emissions, and life-cycle cost under high PV penetration.

2. System Model and Scenario Structure

2.1. System Architecture

The investigated system consists of four components: a PV generation unit, an SLB-ESS, an EVSE cluster, and a single grid connection point. The case study represents a workplace environment in İstanbul, Türkiye, where the daytime EV charging profile partially overlaps with solar production. The EVSE infrastructure is modeled as AC charging points serving workplace EV demand, while the PV and SLB units are coordinated through a rule-based energy management logic. The study focuses on optimal sizing and feasibility rather than on developing a new real-time controller.

2.2. PV Generation Model

PV output is calculated at hourly resolution using module-rated peak power and irradiance/temperature corrections following common PV simulation practice [13]. The plane-of-array irradiance is expressed as:

$$G_{\mathrm{POA}}(t) = G_b(t)R_b + G_d(t)\frac{1+\cos\beta}{2} + \rho G_h(t)\frac{1-\cos\beta}{2}, \tag{1}$$

where G_b, G_d, and G_h denote beam, diffuse, and global horizontal irradiance, respectively; R_b is the tilt factor; β is the panel tilt angle; and ρ is ground albedo. The AC PV output is limited by inverter capacity:

$$P_{\mathrm{PV}}(t) = \min\left(P_{\mathrm{DC}}(t)\eta_{\mathrm{sys}}\eta_{\mathrm{inv}}, P_{\mathrm{inv,max}}\right). \tag{2}$$

The final area-constrained PV design uses 417 panels of 545 Wp each, corresponding to 227.27 kWp.

2.3. Second-Life Battery Model

The SLB-ESS is represented through module-level SoH heterogeneity. For module m, usable energy and internal resistance are defined as:

$$E_m = \mathrm{SoH}_m E_{\mathrm{nom},m}, \tag{3}$$

$$R_{\mathrm{int},m} = R_0 + k_R(1-\mathrm{SoH}_m). \tag{4}$$

The pack-level nominal capacity is determined by the number of SLB packs, while the available capacity depends on the SoH distribution. Battery state-of-charge (SoC) evolves as:

$$\mathrm{SoC}(t+1) = \mathrm{SoC}(t) + \begin{cases} \dfrac{P_{\mathrm{bat}}(t)\eta_{\mathrm{ch}}\Delta t}{E_{\mathrm{pack}}}, & P_{\mathrm{bat}}(t) > 0, \\ \dfrac{P_{\mathrm{bat}}(t)\Delta t}{E_{\mathrm{pack}}\eta_{\mathrm{dis}}}, & P_{\mathrm{bat}}(t) < 0. \end{cases} \tag{5}$$

The operational range is constrained by $\mathrm{SoC}_{\min} \le \mathrm{SoC}(t) \le \mathrm{SoC}_{\max}$ and by the maximum C-rate. RuL is estimated from calendar and cycle aging components:

$$t_{\mathrm{RuL}} = \frac{\mathrm{SoH}_0 - \mathrm{SoH}_{\mathrm{EoL}}}{\Delta\mathrm{SoH}_{\mathrm{cyc}} + \Delta\mathrm{SoH}_{\mathrm{cal}}}. \tag{6}$$

This formulation allows the economic feasibility of SLB use to be evaluated together with battery health and replacement risk.

2.4. EV Charging Demand and Energy Balance

EV charging demand is generated from stochastic workplace charging behavior, including arrival time, connection duration, and initial SoC, consistent with uncertainty-aware EV charging demand models [11, 12]. The resulting hourly demand profile is combined with the workplace base load. The instantaneous energy balance is:

$$P_{\mathrm{PV}}(t) + P_{\mathrm{bat,dis}}(t) + P_{\mathrm{grid,imp}}(t) = P_{\mathrm{load}}(t) + P_{\mathrm{EV}}(t) + P_{\mathrm{bat,ch}}(t) + P_{\mathrm{grid,exp}}(t). \tag{7}$$

Self-sufficiency ratio (SSR) and SCR are computed as:

$$\mathrm{SSR} = 1 - \frac{E_{\mathrm{imp}}}{E_{\mathrm{load}}}, \tag{8}$$

$$\mathrm{SCR} = 1 - \frac{E_{\mathrm{exp}}}{E_{\mathrm{PV}}}. \tag{9}$$

Operational CO_2 emissions are calculated from grid import only:

$$CO_{2,\mathrm{op}} = E_{\mathrm{imp}}\, CEF_{\mathrm{TR}}, \tag{10}$$

where $CEF_{\mathrm{TR}} = 0.495$ kgCO_2/kWh. PV export credits are not subtracted from the main emission metric in order to avoid ambiguous negative-emission interpretations under high PV penetration.

2.5. Scenarios

Three scenarios are evaluated:

- **S0 – Grid+EVSE:** reference system without PV or storage.
- **S1 – PV+EVSE:** area-constrained PV-only system without storage.
- **S2 – PV+SLB+EVSE:** proposed optimized SLB-integrated system.

This compact scenario structure is intentionally selected for the conference paper. It focuses on the direct incremental effect of second-life storage by comparing S1 and S2 under the same PV capacity, rather than introducing an additional battery-technology comparison.

3. Optimization Methodology

3.1. Area-Constrained PV Penetration Selection

If the PV-only system consumes almost all PV generation instantaneously, the technical value of storage is masked. Therefore, before optimizing the battery, feasible PV capacities are scanned within the workplace area and connection constraints. The design point is chosen to represent a high but realistic PV penetration level where PV-only operation creates meaningful surplus:

$$N_{\mathrm{PV}}^{*} = \arg \min_{N_{\mathrm{PV}} \in \Omega_{\mathrm{PV}}} \left| SCR_{\mathrm{S1}}(N_{\mathrm{PV}}) - SCR_{\mathrm{ref}} \right|, \tag{11}$$

where $SCR_{\mathrm{ref}} \approx 0.65$ is used only as an analytical reference to avoid full PV–load coincidence, not as a hard-coded result. The selected PV size is $N_{\mathrm{PV}}^{*} = 417$ panels (227.27 kWp), which produces an S1 SCR of 64.97% and PV export of 119.07 MWh/yr.

3.2. SLB, Inverter, and EVSE Sizing

After fixing the PV capacity, the optimized decision vector is:

$$\mathbf{x} = \left[N_{\mathrm{pack}}, N_{\mathrm{inv}}, N_{\mathrm{EVSE}} \right]^{T}. \tag{12}$$

The objectives are:

$$\min f_1(\mathbf{x}) = NPC(\mathbf{x}), \tag{13}$$

$$\min f_2(\mathbf{x}) = E_{\mathrm{imp}}(\mathbf{x}) CEF_{\mathrm{TR}}, \tag{14}$$

$$\min f_3(\mathbf{x}) = -SSR(\mathbf{x}). \tag{15}$$

Net present cost (NPC) combines capital expenditure, operation and maintenance, grid electricity cost, SLB investment, possible replacement, export revenue, and salvage value within a discounted life-cycle model. The main constraints are SoC limits, battery power limits, inverter capacity, full EV demand satisfaction, and a minimum remaining useful life requirement.
NSGA-III is used to obtain Pareto-optimal solutions [6, 14, 15]. The algorithm employs a population size of 80, 60 generations, simulated binary crossover, polynomial mutation, and reference-direction based selection. All candidate solutions are evaluated with an 8760-hour annual simulation.

4. Results and Discussion

4.1. PV Penetration and Optimal System Size

Table 1 summarizes the PV penetration selection step. The S1 PV-only system does not consume all PV generation; instead, 119.07 MWh/yr is exported, indicating that storage has a meaningful surplus to shift into later demand periods.

Table 1: Area-constrained PV penetration selection for the PV-only baseline

Metric	Value	Interpretation
Selected PV panels	417	Feasible area/connection-based design
Installed PV capacity	227.27 kWp	545 Wp per panel
S1 SCR	64.97%	PV-only self-consumption behavior
S1 PV export	119.07 MWh/yr	Surplus available for storage

The optimized S2 design consists of 227.27 kWp PV, 1360 kWh nominal SLB, 200 kW inverter capacity, and 9 EVSE ports. This configuration is interpreted as the balanced design under the fixed area-constrained PV basis.

4.2. Economic Performance

Table 2 reports sizing and economic indicators for the three main scenarios. S0 has the highest NPC because all energy is imported from the grid over the project life. Adding PV sharply decreases NPC in S1. Adding SLB in S2 further decreases NPC despite the additional battery investment, because PV surplus is shifted from low-value export to higher-value local consumption. In this table, NPV is reported as the reference-relative net present benefit with respect to the grid-only S0 case.

Table 2: Scenario-level sizing and economic performance focused on the SLB effect

Scenario	PV (kWp)	SLB (kWh)	Inv. (kW)	EVSE (port)	NPC (M TL)	NPV (M TL)	IRR (%)	PBP (yr)
S0 – Grid+EVSE	0.00	0	0	10	114.64	0.00	–	–
S1 – PV+EVSE	227.27	0	200	9	14.43	100.20	61.85	4
S2 – PV+SLB+EVSE	227.27	1360	200	9	9.39	105.25	49.54	6

The key comparison is therefore S1–S2. Under the same 227.27 kWp PV basis, adding SLB reduces NPC from 14.43 to 9.39 M TL, corresponding to a 5.04 M TL life-cycle cost improvement relative to the PV-only configuration. The PBP increases from 4 to 6 years because the SLB adds upfront capital cost; however, the lower NPC indicates that the stored PV surplus reduces long-term grid electricity expenses sufficiently to offset this additional investment.

4.3. Technical and Environmental Performance

Table 3 summarizes the technical and environmental performance of the three physical operating scenarios.

Table 3: Technical and environmental performance of physical operating scenarios

Scenario	Grid import (MWh/yr)	Grid export (MWh/yr)	SSR (%)	SCR (%)	EV sat. (%)	CO_2 (t/yr)	Battery throughput (MWh/yr)	RuL (yr)
S0 – Grid+EVSE	295.06	0.00	0.00	0.00	100	146.05	0.00	–
S1 – PV+EVSE	74.24	119.07	74.84	64.97	100	36.75	0.00	–
S2 – PV+SLB+EVSE	35.59	77.38	87.94	77.23	100	17.62	80.34	8.65

The transition from S0 to S1 demonstrates the primary role of PV: grid import decreases by 220.82 MWh/yr and operational emissions decrease by 109.30 tCO_2/yr. The transition from S1 to S2 isolates the marginal effect of storage under the same PV capacity: grid import decreases by 38.65 MWh/yr, PV export decreases by 41.69 MWh/yr, SCR increases by 12.26 percentage points, and SSR increases by 13.10 percentage points. These results confirm that the SLB-ESS functions as a temporal flexibility asset that redirects otherwise exported PV energy toward later local demand.

The S2 battery throughput is 80.34 MWh/yr, corresponding to moderate cycling relative to the nominal capacity. The estimated 8.65-year remaining useful life is therefore interpreted as a combined effect of both cycle and calendar aging. This is important because SLB feasibility is not determined only by annual energy throughput; even lightly cycled second-life batteries may be constrained by calendar degradation and initial SoH.

4.4. Sensitivity and Battery Health Implications

Sensitivity results indicate that economic feasibility is strongly affected by electricity price escalation. Under low electricity price growth, investment attractiveness is limited; under medium-to-high price growth, avoided grid costs dominate and NPV increases substantially.

The electricity price escalation analysis shows NPV increasing from 0.95 M TL at 10% escalation to 105.25 M TL at 40%, while payback decreases from 16 to 6 years.
Battery health also has a direct effect on the feasibility of the SLB-integrated design. SoH analysis shows that increasing SLB SoH from 70% to 90% increases usable capacity from 952 to 1224 kWh and RuL from 4.71 to 12.88 years. Therefore, SLB procurement should not be based only on low purchase price. SoH validation, battery passport information, module-level screening, and a minimum remaining-life requirement are essential for avoiding an apparently low-cost but short-lived storage design.

5. Conclusions

This study developed an area-constrained multi-objective sizing and feasibility framework for PV-supported workplace EV charging stations with second-life battery storage. The central methodological point is that storage value must be evaluated under a PV baseline that produces meaningful surplus. If PV–load overlap is too high, PV-only SCR becomes excessively high and the marginal value of storage is hidden.
For the investigated Turkish workplace case, the selected area-constrained PV system reached 227.27 kWp. In the PV-only scenario, SCR was 64.97% and PV export was 119.07 MWh/yr. Under the same PV capacity, the optimized SLB-integrated design used 1360 kWh nominal SLB, 200 kW inverter capacity, and 9 EVSE ports. Compared with PV-only operation, the SLB reduced grid import by 38.65 MWh/yr, reduced PV export by 41.69 MWh/yr, increased SCR to 77.23%, increased SSR to 87.94%, and reduced operational emissions from 36.75 to 17.62 tCO_2/yr. Economically, the SLB system reduced NPC from 14.43 to 9.39 M TL relative to the PV-only case, showing that second-life storage can improve both energy performance and life-cycle economics when sufficient PV surplus exists.
The findings suggest that second-life battery systems are most valuable in workplace EV charging sites where high PV penetration produces surplus energy but grid export has limited economic value. Future work should extend the framework to multi-site industrial zones, stochastic re-optimization under tariff and demand uncertainty, real SLB passport data, thermal aging models, and advanced EMS strategies such as MPC or reinforcement learning with battery degradation treated as an active constraint.

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