Leveraging on-Site EVs for Enhanced Stationary Battery Utilization and Reliability in Base Stations

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***Abstract*—High-reliability telecom base stations (BSs) are a key enabler of sustainable 6G networks, yet guaranteeing resilience to power grid outages often forces their stationary battery energy storage systems (BESSs) to operate conservatively, leading to underutilization during normal operation. This paper presents a novel framework that integrates electric vehicles (EVs) parked at BS sites as a dynamic energy reserve, improving BS resilience during power grid outages while simultaneously reducing operating costs under normal conditions. By leveraging EV availability, the stationary BESS can safely operate at deeper depths of discharge (DOD) without compromising backup reliability, enabling energy arbitrage when the grid is available. The proposed methodology incorporates detailed models of battery aging, stochastic power grid outages, probabilistic EV availability, and the associated EV reserve compensation costs. Comparative case studies show that EV involvement reduces unmet energy demand during outages by 74% and more than triples the served traffic, while lowering total operating costs by 6.7% during normal operation. These results demonstrate that EV-assisted BESS management effectively decouples resilience requirements from economic operations, thereby strengthening the robustness and cost efficiency of next-generation telecommunications infrastructure.**

***Index Terms*—6G infrastructure, BESS, Vehicle-to-grid, Energy management, Reliability, Battery aging.**

I. Introduction

Telecommunication BSs represent a major source of operational expenditure (OPEX) for mobile network operators, with energy costs accounting for an increasing share of total expenses. To ensure continuity of service during grid outages, BSs are equipped with stationary BESS, which are primarily dimensioned as backup but are also used during normal operation for energy arbitrage, to store energy purchased during low-energy-price hours, and to reduce OPEX [1].

In practice, this dual-use operation is strongly limited by conservative minimum State of Charge (SOC) constraints enforced to guarantee backup availability. These constraints prevent deep discharge, leaving a large fraction of the installed battery capacity unused during grid-connected operation and reducing arbitrage revenues. While deeper cycling would improve cost efficiency, it would also accelerate battery degradation and increase total cost of ownership (TCO) if backup reliability is compromised [2].

At the same time, the rapid diffusion of EVs introduces a large, distributed energy storage resource that remains idle for most of its lifetime [3]. This work leverages parked EVs co-located at BS sites as an auxiliary energy reserve, enabling a more aggressive and economically efficient operation of the stationary BESS. While practical deployment requires a financial incentive mechanism for EV owners and bidirectional charging infrastructure, these costs are explicitly modeled as an EV reserve payment and internalized within the optimization framework.

By integrating parked EVs into the operational loop, an additional energy reserve becomes available. This secondary reserve enables a fundamental shift in BESS operation: the stationary battery can be discharged below its conventional minimum SOC during high-energy-cost hours, increasing the economically usable capacity of existing storage assets, increasing arbitrage revenue and reducing grid dependence. Backup reliability is preserved because, in the event of a grid outage, energy can be supplied from the connected EV fleet to supplement or replace the stationary BESS. Thus, EVs act as an enabling layer that relaxes conservative SOC constraints without compromising resilience and can also provide emergency power during extended outages.

The key challenge is to coordinate these heterogeneous storage assets under uncertainty. The BS must satisfy stringent reliability requirements while maximizing economic benefits and limiting battery degradation. Existing strategies typically enforce conservative BESS operation, leading to substantial opportunity costs, or pursue aggressive cycling that risks degrading backup performance. As a result, current approaches fail to achieve an optimal trade-off between arbitrage revenue, battery aging, and BS service continuity during power grid outages.

Prior work has extensively studied BESS sizing and dispatch for grid services and backup applications, as well as EV participation in V2G services such as frequency regulation and peak shaving [4]. Battery aging models that distinguish between calendar and cycle degradation are well established [5], and outage modeling has been explored in power distribution systems [7]. However, existing frameworks do not address:

1) The use of on-site EVs as a stochastic secondary reliability layer for critical telecommunication infrastructure.
2) The relaxation of minimum SOC constraints for stationary BESS enabled by EV energy reserves.
3) The joint optimization of arbitrage revenue, BESS degradation, and outage resilience under this integrated architecture, including EV owner compensation costs.

This paper proposes an integrated operational framework that leverages parked EVs as a dynamic auxiliary energy reserve for

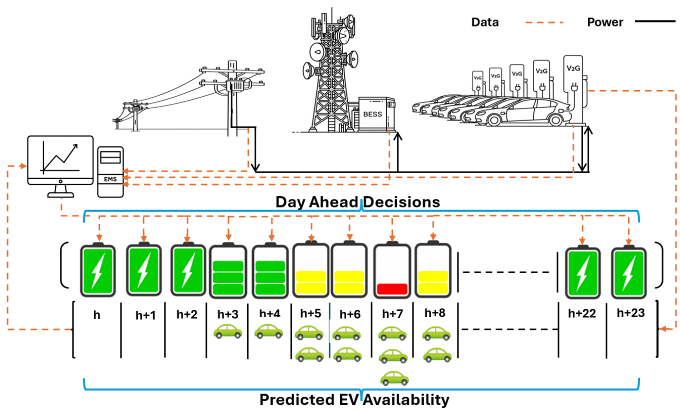

Fig. 1: Day-ahead reserve coordination

telecommunication BSs. Using bidirectional charging infrastructure, the framework enables deeper discharge of the stationary BESS during grid-connected operation while maintaining backup reliability during outages. EV owner participation is incentivized through a reserve payment explicitly accounted for in the total cost of ownership, without requiring additional CAPEX on the BS infrastructure.

The main contributions of this work are:

- **EV-enabled BESS operation:** A novel paradigm in which parked EVs act as an enabling reserve, allowing the stationary BESS to safely operate beyond conventional minimum SOC limits, increasing usable energy capacity and reducing OPEX.
- **Stochastic modeling framework:** Integrated models capturing BESS degradation, probabilistic EV availability, stochastic grid outages, and EV reserve compensation costs, enabling realistic evaluation of energy availability under both normal and emergency conditions.
- **Quantitative trade-off analysis:** Joint evaluation of energy arbitrage gains, battery aging, EV participation costs, and base station resilience, showing how EV-assisted operation improves outage survivability while maintaining cost efficiency.

II. System Model and Methodology

The proposed framework minimizes the BS's total operational cost while enforcing a strict energy-based outage reliability requirement. Specifically, during normal operation, the BS must maintain a minimum reserve of R^{req} energy, which is allocated exclusively to sustaining the load in the event of a power grid outage. This reserve requirement can be jointly fulfilled by the stationary BESS and the batteries of on-site parked EVs, forming a distributed backup pool available at all times.

To achieve this, the framework enables the stationary BESS to participate in energy arbitrage while leveraging on-site EVs as a dynamic secondary reserve that complements the stationary backup capacity. As illustrated in Fig. 1, the system architecture consists of two layers: the **Data Layer**, which enables bidirectional information exchange between the Energy Management System (EMS) and the Battery Management System (BMS) to monitor the BESS SOC and State of Health (SoH); and the **Power Layer**, which facilitates controlled power exchange among the power grid, the stationary BESS, the EV charging interfaces, and the BS load, according to EMS and BMS decisions. The methodology is structured into two sequential phases to decouple economic optimization from real-time resilience management.

Phase 1: Day-Ahead Economic Dispatch: This phase is executed prior to each 24-hour operating cycle, assuming normal grid availability. The EMS solves a stochastic mixed-integer linear program (S-MILP) using forecasts of electricity prices and EVs' energy availability, $\hat{A}_t$. The objective is to minimize expected energy procurement costs while ensuring that the total available backup energy remains above the required threshold R^{req} at all times.

During this phase, the stationary BESS may be charged or discharged for arbitrage purposes. However, the discharge depth is constrained by the aggregate reserve formed by the BESS and the forecast available EV energy. Available EVs are treated as a *virtual reserve*: their energy is not consumed during grid-connected operation, but it contributes to satisfying the backup requirement R^{req}. This allows the stationary BESS to operate at a higher effective DOD while preserving outage preparedness. The output of this phase is the optimal hourly schedule for buying grid energy and charging/discharging the stationary BESS.

Phase 2: Real-Time Resilience Response: This phase is activated only upon a power grid outage. Prior to its activation, the EMS operates according to the day-ahead schedule determined in *Phase 1*. When a grid outage starts, the EMS solves a resilience-oriented optimization problem to minimize Energy Not Served (ENS) by coordinating power delivery from the stationary BESS and available EV reserves, subject to their physical and operational constraints.

Rather than performing a secondary economic optimization, the EMS applies a prioritized depletion strategy. The stationary BESS initially supplies the load using the SOC determined in Phase 1. As the outage persists and the BESS approaches deeper discharge levels, where cycle aging costs become significant, the EMS progressively shifts load support to the available EV batteries $\hat{A}_t$. Since the total reserve available at outage onset satisfies R^{req}, this coordinated depletion strategy ensures service continuity for the required backup duration while limiting high-cost deep discharge of the stationary BESS.

The proposed framework is characterized by two distinct objectives, corresponding to the operational phases, which will be defined in Section III.

A. Phase 1 Mathematical Formulation

In phase 1, we formulate a day-ahead S-MILP to minimize the expected operational cost of the BS by balancing grid energy expenses, battery degradation, and reserve requirements across all realizations $s \in \mathcal{S}$ and time steps $t \in \mathcal{T}$:

$$\min \sum_{s\in\mathcal{S}} \frac{1}{S} \sum_{t\in\mathcal{T}} \left[E^t_{\text{grid},s} C^t_{\text{grid}} + C^t_{\text{deg},s} + C_{\text{res}} E^t_{\text{req},s}\right] \tag{1}$$

where $E^t_{\text{grid},s}$ is the energy drawn from the grid at price C^t_{grid}, and $C_{\text{res}} E^t_{\text{req},s}$ denotes the *conditional reserve payment*. Here, $E^t_{\text{req},s}$ is the capacity required from the EV fleet to cover the BS load when the BESS operates beyond its standard backup limits. This ensures that payments are only incurred for the specific reserve that enables deeper arbitrage. This optimization is subject to the system constraints, which will be defined in (4)–(18). The term $C^t_{\text{deg},s}$ represents the monetized BESS wear at each time step, defined as:

$$C^t_{\text{deg},s} = \alpha \left(\text{AG}^t_{\text{cal},s} + \text{AG}^t_{\text{cyc},s}\right) \quad \forall t, s \tag{2}$$

where $\text{AG}^t_{\text{cal},s}$ and $\text{AG}^t_{\text{cyc},s}$ are the physical capacity losses due to calendar and cycle aging, respectively. To align short-term savings with long-term asset preservation, we define the unit degradation cost as $\alpha = \kappa\alpha^\star$. Here, κ is a unitless sensitivity weight, and $\alpha^\star$ is the baseline monetary value of lost capacity derived from the battery's net present value:

$$\alpha^\star = \frac{C_{\text{rep}}(1 - r_{\text{sv}})}{(1 + i)^L} \tag{3}$$

where C_{rep} is the replacement cost, r_{sv} the salvage value, i the discount rate, and L the financial lifetime. Increasing κ raises the marginal cost of capacity loss internalized by the optimizer, which suppresses deep cycling and typically increases grid purchases.

1) Stationary BESS Modeling: The BESS is modeled by operational constraints and an aging-aware degradation formulation. It provides primary backup during outages and enables energy arbitrage, with degradation costs explicitly internalized in the objective function.

The battery dynamics and power limits are modeled as follows:

$$\text{SOC}^{t+1}_s = \text{SOC}^t_s + \frac{\eta_{\text{ch}} P^t_{\text{ch},s} \Delta t}{E_{\text{SB}}} - \frac{P^t_{\text{dis},s} \Delta t}{\eta_{\text{dis}} E_{\text{SB}}} \quad \forall t, s \tag{4}$$

$$\text{SOC}^t_{\text{min},s} \le \text{SOC}^t_s \le \text{SOC}_{\max} \quad \forall t, s \tag{5}$$

$$P^t_{\text{ch},s} \le u^t_{\text{ch},s} P^{\max}_{\text{ch}}, \quad P^t_{\text{dis},s} \le u^t_{\text{dis},s} P^{\max}_{\text{dis}} \quad \forall t, s \tag{6}$$

$$u^t_{\text{ch},s} + u^t_{\text{dis},s} \le 1, \quad u^t_{\text{ch},s}, u^t_{\text{dis},s} \in \{0, 1\} \quad \forall t, s \tag{7}$$

Eq. (4) describes the SOC evolution, where η_{ch} and η_{dis} are efficiencies and E_{SB} is the nominal capacity. Eq. (5) enforces SOC limits. Crucially, $\text{SOC}^t_{\text{min},s}$ is not a static hardware limit but a dynamic reliability threshold, computed at each time step as:

$$\text{SOC}^t_{\text{min},s} = \max\left(\text{SOC}_{\text{hw}}, \frac{R^{\text{req}} - \hat{A}_t}{E_{\text{SB}}}\right) \quad \forall t, s \tag{8}$$

where SOC_{hw} is the fixed hardware safety limit. When $\hat{A}_t$ is large, this threshold decreases, allowing the EMS to facilitate deeper arbitrage without violating the BS backup requirements.

Eqs. (6) and (7) utilize binary variables $u^t_{\text{ch},s}$ and $u^t_{\text{dis},s}$ to enforce mutual exclusivity between states and ensure that charging and discharging powers remain within the converter's maximum ratings, $P^{\max}_{\text{ch}}$ and $P^{\max}_{\text{dis}}$.

2) Battery Degradation Modeling: Battery degradation is a primary driver of the operational costs internalized in the objective function. To ensure technical accuracy, the degradation formulas and battery specifications used in this study are adopted from the semi-empirical models established in [8]. These models account for the two dominant aging mechanisms: calendar and cycle aging, which collectively determine the BESS lifespan and the economic viability of arbitrage.

a) Calendar Aging: Calendar degradation represents time-dependent capacity loss occurring regardless of battery usage. Following the specifications in [8], it is primarily influenced by the SOC and ambient temperature:

$$\text{AG}^t_{\text{cal},s} \;=\; f_{\text{cal}}\big(\text{SOC}^t_s,\, T,\, \Delta t\big) \quad \forall t, s \tag{9}$$

where T is the temperature and $f_{\text{cal}}(\cdot)$ is the Arrhenius-type relation that returns the capacity loss in Wh per time step.

b) Cycle Aging: Cycle degradation is induced by active charge/discharge cycles. We utilize the segment-based, Rainflow-free formulation from [8] to maintain MILP tractability while capturing non-linear wear:

$$\text{AG}^t_{\text{cyc},s} \;=\; f_{\text{cyc}}\big(\text{DoD}^t_s,\, \text{DoD}^{t-1}_s,\, u^t_{\text{dis},s},\, u^t_{\text{ch},s}\big) \quad \forall t, s \tag{10}$$

where f_{cyc} calculates capacity loss (Wh) based on the DOD transitions. In Phase 1, this model allows the optimizer to determine if the profit from energy arbitrage exceeds the combined cost of BESS aging and the EV reserve payment. In Phase 2, these aging costs act as the driving factor that dictates when the system should switch from BESS depletion to EV discharge to protect the stationary battery from high-cost deep-discharge zones.

3) EV Reserve Availability Model: Integrating EVs as a viable reserve resource requires a stochastic representation to account for the uncertainty in individual driving and charging behaviors. We propose a parametric model that rigorously captures the temporal behavior and SOC dynamics of the fleet, following the framework in [9]. The model characterizes the random arrival times, parking durations, and initial energy states of individual vehicles to quantify the total aggregated reserve available to the system.

a) Arrival and Temporal Dynamics: The temporal presence of each EV e in realization s is modeled using truncated probability distributions to reflect realistic usage patterns:

$$T^{\text{arr}}_{e,s} \sim \mathcal{TN}(\mu_{\text{arr}}, \sigma_{\text{arr}}), \quad D_{e,s} \sim \mathcal{TLN}(\mu_D, \sigma_D) \quad \forall e, s \tag{11}$$

$$T^{\text{dep}}_{e,s} = T^{\text{arr}}_{e,s} + D_{e,s} \quad \forall e, s \tag{12}$$

$$\delta^t_{s,e} = \mathbf{1}\{t \in [T^{\text{arr}}_{e,s}, T^{\text{dep}}_{e,s})\} \quad \forall e, t, s \tag{13}$$

where $T^{\text{arr}}_{e,s}$ is the arrival time, $D_{e,s}$ is the parking duration, and $T^{\text{dep}}_{e,s}$ is the departure time. The indicator variable $\delta^t_{s,e}$ equals 1 if vehicle e is connected at time t in scenario s, and 0 otherwise.

b) Energy State and Aggregate Reserve: The initial energy state upon arrival, $\mathrm{SOC}^{\mathrm{init}}_{e,s}$, follows a Beta distribution. While connected, the EV follows a charging trajectory to reach its target level $\mathrm{SOC}^{\mathrm{target}}_{e,s}$ (here for simplicity, 0.8) by its departure:

$$\mathrm{SOC}^{\mathrm{EV}}_{e,t,s} = \mathrm{SOC}^{\mathrm{init}}_{e,s} + \sum_{\tau=T^{\mathrm{arr}}_{e,s}}^{t} \eta_{e,\tau,s}\eta^{\mathrm{EV}}_{\mathrm{ch}} \frac{r^{\mathrm{EV}}_{e}\Delta t}{E^{\mathrm{nom}}_{e}} \quad \forall e,t,s \tag{14}$$

where r^{EV}_e is the charging rate and E^{nom}_e is the nominal battery capacity. The *usable reserve* $E^{\mathrm{usable}}_{e,t,s}$ is the energy stored above a driver-defined minimum threshold $\mathrm{SOC}^{\mathrm{min}}_e$ that ensures mobility requirements are met. Finally, the aggregate virtual reserve $\hat{A}_t$ is computed across the fleet $\mathcal{E}$ for each scenario s:

$$E^{\mathrm{usable}}_{e,t,s} = (\mathrm{SOC}^{\mathrm{EV}}_{e,t,s} - \mathrm{SOC}^{\mathrm{min}}_{e})^{+} E^{\mathrm{nom}}_{e} \delta^{t}_{s,e} \quad \forall e,t,s \tag{15}$$

$$\hat{A}_t = \sum_{e\in\mathcal{E}} E^{\mathrm{usable}}_{e,t,s}, \quad \forall t,s \tag{16}$$

This aggregated term $\hat{A}_t$ serves as the core input for the day-ahead S-MILP, providing the necessary buffer to safely expand the BESS depth of discharge.

4) Reserve Coordination and Reliability Evaluation: To ensure consistent energy units (Wh), the reserve target R^{req} is defined as the total energy required to support the site load D^t over a fixed autonomy window of $H = 8$ hours:

$$R^{\mathrm{req}} = \sum_{\tau=t}^{t+H} D^{\tau} \tag{17}$$

This requirement serves as the reliability benchmark for the Day-Ahead coordination. The total system reserve is met by the combined contributions of the stationary BESS and the aggregated EV fleet, governed by the following constraint:

$$E_{\mathrm{SB}}(\mathrm{SOC}^{t}_{s} - \mathrm{SOC}_{\mathrm{min}}) + \hat{A}_t \geq R^{\mathrm{req}} \quad \forall t \tag{18}$$

where the first term represents the usable energy stored in the BESS and $\hat{A}_t$ is the virtual reserve available from the EV fleet. To ensure the system satisfies the base station demand at every time step during the planning phase, the total energy influx from the grid and the BESS discharge must equal the sum of the base station load and the energy used for BESS charging:

$$(P^{t}_{\mathrm{grid},s}\Delta t) + (P^{t}_{\mathrm{dis},s}\Delta t) = D^{t} + (P^{t}_{\mathrm{ch},s}\Delta t) \quad \forall t,s \tag{19}$$

where D^t represents the forecasted energy demand of the base station.

B. Phase 2 Mathematical Formulation

Upon a grid outage, phase 2 begins. The system transitions from economic arbitrage to a resilience-driven operation. The objective shifts from cost minimization to the maximization of service continuity by minimizing the Energy Not Served (ENS) across the outage duration $\mathcal{T}_{\mathrm{out}}$:

$$\min \sum_{t\in\mathcal{T}_{\mathrm{out}}(s)} \mathrm{ENS}^{t}_{s} \tag{20}$$

TABLE I: Input Parameters Used in the MILP Formulation

Parameter	Value
Stationary BESS	
Capacity / Max power, E_{SB} / $P^{\max}_{\mathrm{ch,dis}}$	10 kWh / 2 kW
Efficiency, $\eta_{\mathrm{ch}} = \eta_{\mathrm{dis}}$	0.95
HW SOC floor / Max, $\mathrm{SOC}_{\mathrm{hw}}$ / $\mathrm{SOC}_{\max}$	0.2 / 1.0
Replacement / Salvage, C_{rep} / r_{sv}	150 €/kWh / 0.3
Discount rate / Lifetime, i / L	2% / 15 yr
Degradation weight, κ	1
EV Fleet	
Fleet size / Battery, $\lvert\mathcal{E}\rvert$ / E^{nom}_e	4 / 40 kWh
Charging power, $P^{\mathrm{EV}}_{\mathrm{ch}}$	3.7 kW
SOC limits / Target, $\mathrm{SOC}^{\min}_e$ / $\mathrm{SOC}_{\max}$ / $\mathrm{SOC}^{\mathrm{target}}_e$	0.4 / 0.9 / 0.8
Arrival, μ_{arr} / σ_{arr}	08:00 / 2 h
Parking duration, μ_D / σ_D	7 h / 2 h
Grid, Outage & Simulation	
Autonomy window, H / Time step, Δt	8 h / 1 h
Outage rate, Λ_m	15/yr
Outage duration (min / avg / max)	2 / 8 / 12 h
Scenarios, $\lvert\mathcal{S}\rvert$	100

This phase enforces the system power balance within the physical limits established in Section II.A. During an outage, the grid import is strictly governed by the grid status variable:

$$P^{t}_{\mathrm{grid},s} \leq (1 - O^{t}_{s}) P^{\max}_{\mathrm{grid}} \quad \forall s, t \in \mathcal{T}_{\mathrm{out}} \tag{21}$$

where $O^t_s \in \{0,1\}$ is a binary variable equal to 1 during a power outage and 0 otherwise. When $O^t_s = 1$, the grid contribution is eliminated, and the general power balance previously defined in (19) reduces to the resilience-focused balance:

$$P^{t}_{\mathrm{dis},s} + P^{t,\mathrm{EV}}_{\mathrm{dis},s} + \mathrm{ENS}^{t}_{s} = D^{t} \quad \forall s, t \in \mathcal{T}_{\mathrm{out}} \tag{22}$$

In this stage, the BESS state of charge optimized in Phase 1 serves as the initial condition. The EMS utilizes a prioritized depletion logic to bridge the outage: the stationary BESS satisfies the initial load, but as its DOD increases, the system dynamically shifts the load to the available aggregate EV fleet $\hat{A}_t$ (as computed in (16)). This approach ensures that ENS^t_s, which acts as the primary reliability metric, is minimized by linking the day-ahead economic planning to actual resilience outcomes.

C. Stochastic Power Outage Modeling

To evaluate BS resilience under realistic grid conditions, we model power interruptions using a Non-Homogeneous Poisson Process (NHPP) [7]. To maintain mathematical consistency, we define a joint scenario space $s \in \mathcal{S}$ where each realization represents a concurrent outcome of EV fleet behavior and grid status, assigned a binary mask O^t_s. The NHPP is calibrated using standard utility metrics: the monthly outage rate $\Lambda_{\mathrm{m}} \approx$ SAIFI/12 and the mean duration set to CAIDI (SAIDI/SAIFI).

III. Simulation and Case Study

To evaluate the effectiveness of our methodology, we consider a BS in Turin, Italy, with realistic traffic and power-demand profiles, as shown in Fig. 2. The proposed approach follows a strictly sequential process: Phase 1 solves the S-MILP to determine the optimal day-ahead BESS schedule, which the EMS uses for energy arbitrage. In the event of power grid outages, Phase 2 starts for maximizing BS resilience, evaluating system resilience exclusively during outage hours.

We quantify the performance of our methodology in terms of BS resilience using the following indicators:

1) Loss of Load Probability (LOLP): The probability of failing to meet the site load during power grid outages, averaged across all scenarios:

$$\mathrm{LOLP} = \frac{1}{|\mathcal{S}|} \sum_{s \in \mathcal{S}} \left(\frac{\sum_{t \in \mathcal{T}_{\text{out}}(s)} \mathbf{1}(\mathrm{ENS}_s^t > 0)}{|\mathcal{T}_{\text{out}}(s)|} \right) \tag{23}$$

2) Expected Energy Not Served (EENS): The average magnitude of unmet energy demand (Wh) during power grid outages, representing the severity of power shortfalls:

$$\mathrm{EENS} = \frac{1}{|\mathcal{S}|} \sum_{s \in \mathcal{S}} \sum_{t \in \mathcal{T}_{\text{out}}(s)} \mathrm{ENS}_s^t \tag{24}$$

3) Traffic Reliability Index (TRI): The fraction of total communication traffic successfully served during power grid outages:

$$\mathrm{TRI} = \frac{1}{|\mathcal{S}|} \sum_{s \in \mathcal{S}} \left(\frac{\sum_{t \in \mathcal{T}_{\text{out}}(s)} T_{t,s}^{\text{served}}}{\sum_{t \in \mathcal{T}_{\text{out}}(s)} T_{t,s}^{\text{total}}} \right) \tag{25}$$

By comparing these indicators, we assess how the inclusion of the EV virtual reserve internalizes the risk of grid failures into the day-ahead economic dispatch while preserving site resilience. The evaluation is conducted under (i) the **Baseline** scenario, used as a benchmark, where the BESS is the sole reliability resource, and (ii) the **Proposed Framework**, which integrates EVs as a virtual reserve (see section II).

IV. Results and Discussion

To evaluate the proposed EV-assisted framework, we compare its performance against a conventional baseline in which EVs are not included in the BS power supply system. We focus on normal operating conditions, i.e., in the absence of power grid blackouts. Fig. 2 reports the power purchased from the grid for the baseline (red) and the proposed framework (blue) on the left y-axis, together with the corresponding electricity price profile on the right y-axis, during the day. Fig. 3 shows the associated BESS SOC.

In the baseline scenario, a conservative safety policy enforces a minimum SOC of 80% (red curve in Fig. 3) to guarantee resilience against potential grid outages. As a result, the BESS is rarely used during normal operation, and BS demand is almost entirely met by grid-purchased power.

In contrast, when EVs are leveraged as a virtual reserve, the system can partially relax the BESS SOC constraint while still satisfying the required reserve margin. This additional flexibility allows the SOC to drop below 80% (blue curve in Fig. 3) and enables energy arbitrage. Specifically, the system draws energy from the BESS during high-priced periods (approximately 6:00

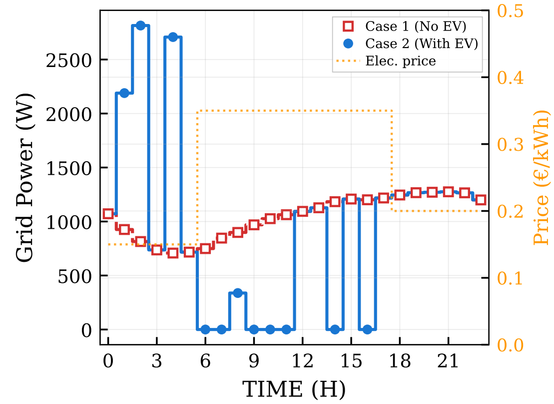

Fig. 2: Hourly power taken from the power grid and electricity price.

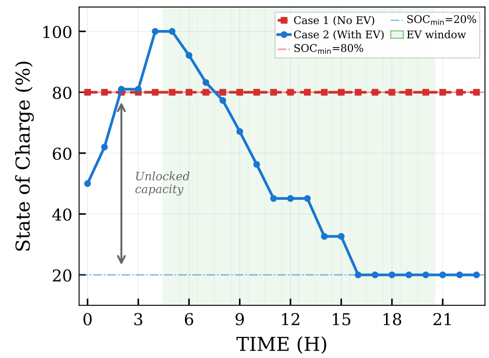

Fig. 3: Battery SOC profiles.

to 17:00) and recharges it during off-peak hours, reducing reliance on grid power during expensive periods.

A. Operating Cost Comparison

Fig. 4 compares the energy cost from the power grid, battery calendar aging cost, cycle aging cost, EV reserve cost, and total operating cost for the baseline case and the proposed framework. The baseline, shown in red, corresponds to conventional operation in which the BS is supplied exclusively by the power grid and its on-site BESS, while the proposed framework, shown in blue, incorporates on-site EVs as a virtual reserve. In the baseline case, the Grid Cost is the highest (213.69 €), since all operational demand is met by the grid while the BESS is maintained at a high state of charge to ensure outage preparedness. Consequently, Cycle Aging is negligible due to the absence of energy arbitrage, but the sustained high SOC results in a non-negligible Calendar Aging Cost of 9.47 €. Although no EV Reserve Cost is incurred, this operating strategy is economically inefficient, as the BESS remains largely unused while still degrading over time.

Under the proposed framework, the situation is different. The aggregated virtual energy storage from on-site EVs satisfies the reserve requirement R^{req} (see (18)), allowing the EMS to temporarily relax the BESS SOC constraint when EVs are connected. This flexibility enables controlled energy arbitrage, leading to a 16% reduction in Grid Cost to 179.93 €by shifting energy purchases to lower-price hours. At the same time, the

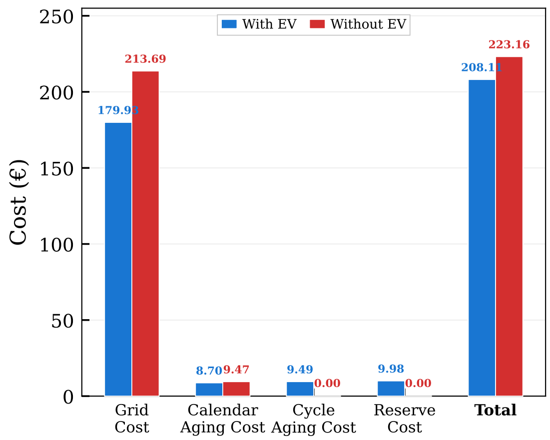

Fig. 4: Cost breakdown and total for EV-Enabled vs No-EV.

TABLE II: Resilience metrics.

Metric	Without EV	With EV	Change (%)
EENS [Wh]	30938.47	8037.10	−74.02
LOLP	0.96	0.83	−13.65
TRI [%]	24.17	77.70	221.43

Calendar Aging Cost decreases by 8.5% to 8.66 €, as the BESS no longer remains at a persistently high SOC . The increased utilization of both the BESS and the EV fleet introduces a Cycle Aging Cost of 9.74 €and an EV Reserve Cost of 9.98 €. Despite these additional costs, the total operating cost is reduced to 208.11 €, corresponding to a 6.7% reduction relative to the baseline. This highlights the effectiveness of the proposed framework in lowering operating expenses by partially replacing physical BESS reliability margins with a virtual reserve.

B. *Real-Time Reliability Evaluation*

This section focuses on the resilience of the BS during power grid outages when operating under the proposed framework. Table II reports EENS, the LOLP, and the TRI, discussed in section III, for both the proposed solution and the benchmark scenario.

As shown in Table II, the integration of EV-based reserves reduces the EENS by approximately 74% and the LOLP by 13.65%, while more than tripling the TRI. These results indicate that the proposed framework not only reduces operating costs, as discussed previously, but also significantly improves BS resilience during power grid outages.

This improvement stems from the complementary roles of the BESS and the EV fleet. While the standalone BESS is dimensioned to guarantee approximately 8 hours of BS autonomy, prolonged outages eventually lead to battery depletion and service interruption. By contrast, the inclusion of EV reserves extends the available energy capacity beyond the physical limits of the BESS, enabling the BS to sustain operation for longer outage durations.

V. Conclusion and Future Works

This work introduces a novel strategy in which on-site EVs act as an enabling energy reserve, enhancing BS resilience during power grid outages. By leveraging EV availability, the proposed framework provides two complementary benefits: (i) during normal operation, the BS BESS can safely operate at deeper DoD, enabling energy arbitrage without compromising backup reliability and lowering Opex; (ii) during power grid outages, the additional energy capacity from EVs extends BS autonomy beyond the physical limits of the standalone BESS, allowing sustained operation during prolonged outages. Instead of maintaining the BESS at a fixed high SOC , the framework dynamically adapts its operating range based on EV availability through a stochastic MILP that jointly optimizes operating costs, battery aging, and reliability constraints.

Numerical results show that this approach reduces power grid energy costs by 16%, total operating costs by 6.7%, and calendar aging by 8.5% during normal operation, while significantly strengthening outage resilience by reducing EENS and LOLP by 74% and 14%, respectively, and more than tripling the TRI. Overall, the proposed framework transforms the BESS from a passive backup component into a flexible and economically valuable asset enabled by EV-based virtual reserves.

Future work will investigate incentive-compatible EV participation mechanisms and the coordinated operation of multiple BS sites under network and mobility constraints.

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