Battery-Degradation-Aware V2G Scheduling Using an Optimization-Compatible BLAST-Lite Model

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***Abstract*—Despite the potential benefits of vehicle-to-grid (V2G) operation, concerns about accelerated battery degradation remain a major barrier to widespread participation. This paper develops a degradation-aware V2G scheduling framework based on the Battery Lifetime Analysis and Simulation Tool Lite (BLAST-Lite), a widely recognized battery lifetime model. Direct integration of BLAST-Lite into mathematical optimization is challenging because its native implementation evaluates degradation *only after* a battery operating profile has been prescribed and expresses the underlying degradation relationships through computational procedures rather than explicit optimization equations. To address these challenges, we derive an optimization-compatible mathematical representation of BLAST-Lite cycling degradation and integrate it with the battery operational constraints and V2G energy-arbitrage objective. The resulting optimization framework jointly determines the charge-discharge schedule and its associated degradation cost. Case studies demonstrate that the proposed mathematical formulation accurately reproduces the native BLAST-Lite model. They further show that directly incorporating battery degradation changes the optimal V2G operating schedule, nearly triples the average net economic value across a diverse population of real-world plug-in sessions, and eliminates economically unfavorable dispatch decisions.**

***Keywords*: Vehicle-to-grid (V2G), battery degradation, BLAST-Lite, optimization, distributed energy resources.**

I. Introduction

The rapid growth of transportation electrification is turning electric vehicles (EVs) into one of the largest distributed energy resources (DERs). Through vehicle-to-grid (V2G) operation, parked EVs can deliver power to the electric grid and provide a wide range of valuable grid services, including demand response, peak shaving, and ancillary services [1].

Despite these benefits, *battery degradation* remains a major barrier to large-scale participation in V2G programs. Repeated battery cycling accelerates battery aging and increases replacement costs. As a result, many EV owners remain reluctant to participate in V2G services [2]. Therefore, battery degradation must be explicitly considered in V2G scheduling in order to balance its economic benefits against the cost of battery aging.

Among the various battery degradation models available in the literature, the Battery Lifetime Analysis and Simulation Tool Lite (BLAST-Lite), developed by the National Renewable Energy Laboratory (NREL), is particularly attractive because it combines several desirable characteristics [3]. Specifically, BLAST-Lite provides a high-fidelity representation of lithium-ion battery degradation, explicitly relates battery aging to physically meaningful stress factors, such as state of charge, depth of discharge, battery temperature, and charge/discharge rate, and relies only on operating quantities that are readily available from battery telemetry. Consequently, BLAST-Lite has become a widely recognized tool for battery lifetime prediction and degradation analysis.

However, BLAST-Lite was developed to estimate battery degradation for *prescribed* operating profiles rather than to optimize them. Thus, it *cannot* be directly incorporated into V2G scheduling optimization. Addressing this limitation requires transforming the underlying BLAST-Lite degradation model into an optimization-compatible mathematical formulation.

Several prior studies have optimized V2G operation without explicitly modeling battery degradation within the scheduling objective. For example, in [4], a priority-based V2G scheduling strategy was developed to minimize grid load variance by coordinating valley filling, peak shaving, and priority charging based on EV state of charge. Similarly, [5] formulated an energy scheduling problem for an integrated energy system with V2G participation and wind-power uncertainty, focusing on renewable-energy utilization. These studies demonstrate the value of V2G scheduling, but battery degradation is not explicitly incorporated into the optimization process.

Some recent studies have incorporated battery degradation into V2G scheduling. For example, [6] included an EV battery degradation cost in a model predictive control framework for an EV charging station with V2G capability. In [7], an MILP-based V2G scheduling model was developed that includes calendar and cycle aging. While these studies demonstrate the importance of accounting for battery aging in V2G scheduling, they use degradation models *other than* BLAST-Lite.

Finally, the BLAST-Lite model has also been used in *other application contexts*, including the multi-service optimization of second-life battery systems in various grid applications [8] and battery modeling for data-center simulations [9].

To the best of our knowledge, no previous work has incorporated the BLAST-Lite degradation model directly into V2G scheduling optimization. We address this gap by formulating BLAST-Lite's underlying relationships as *explicit analytical equations* that fit into mathematical optimization while preserving the original model's degradation behavior. This representation is integrated with V2G operational constraints to formulate a unified framework that jointly optimizes the operating schedule and its associated battery degradation cost.

II. Methodology

A. High-Level Problem Statement

Consider the day-ahead scheduling problem for the charge and discharge operation of a battery electric vehicle participating in V2G services. The scheduling horizon consists of

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one day divided into $N = 96$ consecutive time intervals of duration $\Delta\tau = 15$ minutes. This setup is consistent with the typical smart meter load reporting intervals; e.g., see [10].

Let P_n denote the power exchange of the vehicle and the grid during time interval n. The optimization process determines the battery charging and discharging power profile $\{P_n\}_{n=1}^{96}$ over the scheduling horizon, where $P_n > 0$ denotes power exported from the vehicle to the grid (i.e., V2G operation), and $P_n < 0$ denotes battery charging from the grid.

Unlike conventional V2G scheduling methods, which optimize only the V2G revenue, the proposed framework considers *both* the economic benefit of energy transactions and the cost associated with the corresponding battery degradation. This leads to the following high-level optimization problem:

$$\begin{aligned} \underset{\{P_n\}}{\text{Maximize}} \quad & \text{V2G Revenue} - \text{Battery Degradation Cost} \\ \text{Subject to} \quad & \text{V2G Operation Model}, \\ & \text{Battery Degradation Model}. \end{aligned} \tag{1}$$

The first objective term in (1) represents the revenue generated by V2G operation, while the second term captures the cost associated with battery lifetime degradation. The first group of constraints establishes the V2G operation model that governs the power exchange, battery operation, and system operating limits, while the second group represents the battery degradation model that quantifies battery aging in the objective function along with its underlying degradation dynamics.

B. Challenges in Adopting the BLAST-Lite Model

In principle, the battery degradation components in the optimization problem in (1) can be modeled using various empirical or physical methods. In this paper, we adopt the BLAST Lite [3], which is an attractive choice; because it **(i)** explicitly relates battery degradation to major stress factors, including state of charge, depth of discharge, and charge/discharge current rate, **(ii)** relies only on operating quantities that are readily available from battery telemetry, and **(iii)** provides a high-fidelity representation of lithium-ion battery degradation.

However, incorporating BLAST-Lite into the mathematical optimization framework in (1) presents two major challenges:

- In its native workflow, BLAST-Lite accepts a *prescribed* battery operating profile as a *known* input and estimates the battery degradation as the output. However, in the optimization problem in (1), the operating profile is *unknown* and itself is the optimization variable *to be determined*. Hence, the required input to the native BLAST-Lite model is unavailable during the optimization process.
- BLAST-Lite is a computational battery lifetime simulator rather than a mathematical model: it evaluates degradation through computational procedures instead of explicit analytical equations. In contrast, mathematical optimization requires objective functions and constraints to be expressed explicitly in terms of the optimization variables. The underlying degradation relationships must therefore first be reformulated as explicit analytical equations that preserve the degradation behavior of the original model.

Next, we address the above challenges through a series of developments in the following subsections.

C. Mathematical Representation of BLAST-Lite Model

The BLAST-Lite framework captures battery degradation through two pathways: calendar-induced and cycling-induced degradation. Because the day-ahead V2G scheduling problem in (1) optimizes the battery charge-discharge profile over a single day, we focus only on cycling degradation, which is directly affected by the selected operating profile. Calendar degradation is primarily governed by elapsed time and storage conditions and is thus not included in the optimization model.

Let ΔSOH_n denote the incremental battery degradation during scheduling interval n. In this subsection, we express ΔSOH_n in a form that can be used directly inside the optimization problem. Based on the underlying cycling degradation relationships in BLAST-Lite [3], the following expression is obtained for the incremental degradation during interval n:

$$\Delta SOH_n = k_{\mathrm{cyc},n}\, p_{\mathrm{cyc}} \left(\frac{q_{n-1}}{k_{\mathrm{cyc},n}} \right)^{1-\frac{1}{p_{\mathrm{cyc}}}} \Delta EFC_n, \tag{2}$$

where q_{n-1} is the cumulative cycling-induced degradation at the beginning of interval n, p_{cyc} is the BLAST-Lite cycling degradation exponent, $k_{\mathrm{cyc},n}$ is the stress-dependent cycling degradation factor, and ΔEFC_n is the equivalent full cycles accumulated during interval n. The term ΔEFC_n quantifies the cycling throughput during interval n in units of equivalent full cycles. Since one full cycle corresponds to a complete discharge and charge of the battery, the equivalent full-cycle increment is calculated from the absolute battery current as

$$\Delta EFC_n = \frac{|I_n|\Delta\tau}{2Q_{\mathrm{nom}}}, \tag{3}$$

where I_n is the battery current during interval n, $\Delta\tau$ is the interval duration, and Q_{nom} is the nominal Coulombic battery capacity, measured in Ampere-hours (Ah).

The coefficient $k_{\mathrm{cyc},n}$ plays a central role in (2) because it captures how operating stress factors affect cycling degradation. In BLAST-Lite, it is represented as

$$k_{\mathrm{cyc}} = (p_4 + p_5 DOD + p_6 C_{\mathrm{rate}}) \left(e^{p_7/T} + e^{-p_8/T} \right), \tag{4}$$

where DOD is the depth of discharge, often calculated daily, C_{rate} is the battery charge/discharge C-rate, T is the battery cell temperature in Kelvin, and p_4, p_5, p_6, p_7, and p_8 are chemistry-specific BLAST-Lite parameters. The first factor captures the dependence of cycling degradation on depth of discharge and current rate, while the second factor captures the temperature dependence. Since thermal dynamics are outside the scope of this work, the battery temperature is assumed to remain constant over the day-ahead scheduling horizon. Therefore, the temperature-dependent factor in (4) is treated as a known constant during the optimization.

The C-rate in interval n is calculated as:

$$C_{\mathrm{rate},n} = \frac{|I_n|}{Q_{\mathrm{nom}}}. \tag{5}$$

The cumulative degradation state is updated as follows:

$$q_n = q_{n-1} + \Delta SOH_n. \tag{6}$$

Accordingly, the updated cumulative state q_n becomes the input for the subsequent interval. The optimization is initialized

using the known value q_0, i.e., the cumulative cycling-induced degradation at the beginning of the scheduling horizon.

D. Integrated Degradation-Aware V2G Optimization

Next, we integrate the degradation model developed in Section II.C with the V2G operational model to formulate the complete degradation-aware V2G scheduling problem. The resulting optimization simultaneously determines the charge-discharge schedule and the associated battery degradation cost.

Recall that the high-level optimization problem in (1) was introduced in terms of the battery power schedule $\{P_n\}_{n=1}^{96}$ because V2G operation is naturally defined based on the power exchanged between the vehicle and the grid. In contrast, the BLAST-Lite degradation model represents battery degradation as a function of battery current and charge throughput, where the latter is itself determined by the battery current.

Therefore, the proposed degradation-aware V2G optimization is formulated using the battery current $\{I_n\}_{n=1}^{96}$ as the *primary* decision variable, while the battery power schedule $\{P_n\}_{n=1}^{96}$ is treated as an *auxiliary* variable. The two types of variables are related to each other by

$$P_n = (V_{OC} - R_{DC} I_n)\, I_n, \tag{7}$$

where V_{OC} denotes the battery's open-circuit voltage and R_{DC} is the battery's equivalent internal DC resistance.

Next, we model how the battery state of charge evolves according to the Coulomb-counting relationship:

$$SOC_n = SOC_{n-1} - \frac{I_n \Delta\tau}{Q_{\mathrm{nom}}}. \tag{8}$$

To eliminate any artificial energy gain or loss over the optimization horizon, the battery is required to return to its initial state of charge at the end of the scheduling horizon, i.e.,

$$SOC_N = SOC_0. \tag{9}$$

The battery current and state of charge are limited by

$$-I_{\max} \le I_n \le I_{\max}, \tag{10}$$

$$SOC_{\min} \le SOC_n \le SOC_{\max}, \tag{11}$$

where $I_{\max}$ denotes the maximum allowable battery current, while $SOC_{\min}$ and $SOC_{\max}$ denote the minimum and maximum allowable battery state-of-charge limits.

The optimization problem is initialized using

$$SOC_0 = SOC_{\mathrm{init}}, \qquad q_0 = q_{\mathrm{init}}, \tag{12}$$

where SOC_{init} and q_{init} denote the state of charge and cumulative degradation at the start of the scheduling horizon.

The daily depth of discharge is obtained as

$$DOD = \frac{\max_m SOC_m - \min_m SOC_m}{SOC_{\max}}, \tag{13}$$

i.e., the swing of the daily state-of-charge trajectory normalized by the maximum state of charge, which lies within $[0, 1]$, consistent with the BLAST-Lite stress-factor convention.

Next, we formulate the objective function of the proposed optimization problem to maximize the net economic value of V2G operation. Let p_n denote the electricity price during scheduling interval n, expressed in \$/kWh. The resulting V2G revenue over the scheduling horizon is formulated as:

$$\sum_{n=1}^{N} p_n P_n \Delta\tau, \tag{14}$$

where $P_n \Delta\tau$ represents the energy exchanged with the grid during interval n, measured in kWh. The formulation in (14) represents V2G energy-arbitrage revenue, where the vehicle charges during low-price periods and discharges during high-price periods while returning to its initial state of charge according to (9). Other revenue models, such as peak shaving or ancillary services, can also be similarly accommodated.

Next, let C_{replace} denote the battery replacement cost and SOH_{EOL} denote the battery end-of-life threshold. We define the degradation cost coefficient by *prorating* the battery replacement cost over the battery capacity loss until end of life:

$$C_{\mathrm{deg}} = \frac{C_{\mathrm{replace}}}{1 - SOH_{\mathrm{EOL}}}. \tag{15}$$

Without loss of generality, we assume that $SOH_{\mathrm{EOL}} = 0.8$, corresponding to the widely adopted criterion that a battery reaches end of life after losing 20% of its original capacity. The resulting daily battery degradation cost is obtained as

$$\sum_{n=1}^{N} C_{\mathrm{deg}} \Delta SOH_n. \tag{16}$$

In summary, the complete integrated degradation-aware V2G scheduling optimization problem is formulated as

$$\begin{aligned} \underset{\{I_n\},\{P_n\}}{\text{Maximize}} \quad & \sum_{n=1}^{N} \left(p_n P_n \Delta\tau - C_{\mathrm{deg}} \Delta SOH_n\right) \\ \text{Subject to} \quad & \text{Eqs. (2)-(13).} \end{aligned} \tag{17}$$

E. Solution Method

The optimization problem in (17) is a smooth nonlinear program. It is solved using `GlobalSearch` in MATLAB, which repeatedly invokes the `fmincon` optimization solver from multiple starting points and returns the best locally optimal solution identified. Across repeated optimization runs and all case studies in this paper, the solver consistently converged to the *same* solution, indicating that the optimization results are *robust* with respect to the solver initialization.

III. Case Studies

The proposed framework is evaluated to assess: (i) the accuracy of the proposed optimization formulation relative to the native BLAST-Lite implementation, (ii) the impact of explicitly incorporating battery degradation into V2G scheduling, and (iii) the performance of the proposed framework across a population of real-world vehicle plug-in sessions.

The case studies consider a battery electric vehicle equipped with a 106 kWh lithium-ion battery pack whose electrical and degradation parameters are adopted based on the Lithium Iron Phosphate (LFP) batteries [3]. The battery replacement cost is $C_{\mathrm{replace}} = \$17{,}000$, which together with $SOH_{\mathrm{EOL}} = 0.8$ yields $C_{\mathrm{deg}} = \$85{,}000$ per unit of fractional capacity loss.

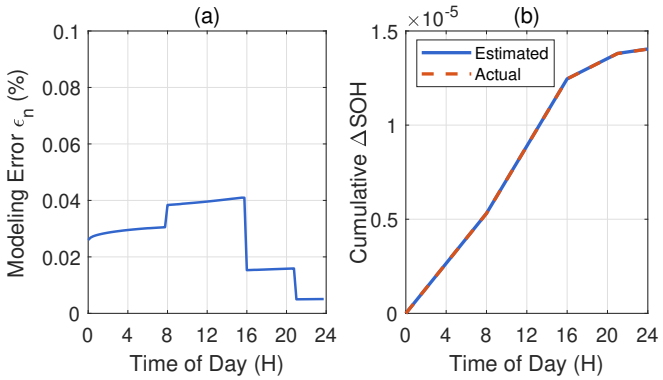


Fig. 1. Validation of the proposed mathematical formulation against the native BLAST-Lite implementation. (a) Percentage error ϵ_n between the incremental degradation values ΔSOH_n calculated using the proposed formulation and the native BLAST-Lite model. (b) Cumulative cycling degradation predicted by the two models over the 24-hour scheduling horizon.

Electricity prices follow the seasonal Southern California Edison tariffs [10]. Unless stated otherwise, all optimization parameters remain unchanged throughout the case studies.

A. Validation Against Native BLAST-Lite Tool

We first validate the mathematical formulation developed in Section II-C against the native BLAST-Lite implementation. For this purpose, the same battery operating profile is evaluated using both the proposed analytical formulation and the native BLAST-Lite model over the 96 scheduling intervals.

To quantify the agreement between the two models, we define the percentage error at each scheduling interval n as

$$\epsilon_n = 100 \frac{|\Delta SOH_n^{\mathrm{Opt}} - \Delta SOH_n^{\mathrm{BLAST}}|}{\Delta SOH_n^{\mathrm{BLAST}}}, \qquad (18)$$

where $\Delta SOH_n^{\mathrm{Opt}}$ denotes the incremental degradation calculated using the proposed mathematical formulation in (2), and $\Delta SOH_n^{\mathrm{BLAST}}$ denotes the corresponding incremental degradation obtained from the native BLAST-Lite implementation in [3] for the exact same battery operating profile.

Fig. 1 confirms that the proposed mathematical formulation accurately reproduces the native BLAST-Lite model. The interval-level error remains below 0.041% across all 96 scheduling intervals, while the cumulative degradation trajectories are nearly indistinguishable and converge to approximately 1.4×10^{-5} at the end of the scheduling horizon. These results validate the optimization-compatible representation of BLAST-Lite and justify its direct incorporation into the V2G scheduling optimization developed in Section II.

B. Impact of Degradation-Aware V2G Scheduling

Next, we compare the proposed degradation-*aware* method with a degradation-*unaware* benchmark obtained by solving the optimization problem in (17) with the degradation-cost term *removed* from the objective function. However, since the degradation-*unaware* method considers only revenue, its solution is non-unique whenever schedules are revenue-equivalent; hence, a throughput penalty is included in the objective function to prevent gratuitous cycling. All other constraints and model parameters are identical in the two cases.

Fig. 2(a)–(c) shows the corresponding scheduling results. Although both methods respond to the same electricity price signal, the degradation-unaware method repeatedly operates at the battery power limits to maximize V2G revenue. In contrast, the proposed method moderates both charging and discharging power, producing a shallower daily cycling profile and reducing the daily depth of discharge from 0.847 to 0.638. This behavior emerges naturally because the BLAST-Lite degradation model is embedded directly within the optimization objective, allowing the scheduler to balance immediate arbitrage revenue against the long-term cost of battery degradation.

Fig. 2(d) summarizes the resulting economic tradeoff. Although the degradation-*unaware* method earns a higher gross arbitrage revenue ($3.49 versus $2.58), the additional revenue is outweighed by the increase in battery degradation cost ($4.91 versus $1.79). In fact, the degradation-*unaware* schedule produces *a net loss* of $1.42, whereas the proposed degradation-*aware* schedule achieves a *net gain* of $0.79. Therefore, maximizing arbitrage revenue alone does not necessarily maximize the overall economic value of V2G operation.

C. Performance Across Multiple Plug-In Sessions

The previous results illustrate the proposed framework for a representative 24-hour operating scenario. We next investigate whether the observed benefits persist across a diverse population of real-world vehicle plug-in sessions.

The plug-in sessions are obtained from the residential EV charging dataset collected by SINTEF in Norway [11]. Three vehicles are selected, and for each vehicle the first 25 winter sessions and the first 25 summer sessions are considered, resulting in a total of 150 optimization instances. Each session defines one scheduling horizon, whose duration equals the recorded plug-in window. The recorded arrival state of charge is used as the initial condition, while the terminal constraint in (9) requires the vehicle to depart at the same state of charge.

Among the 150 sessions, 61 have a *constant* electricity price throughout the *entire* plug-in period. Because no arbitrage opportunity exists in these sessions, both methods correctly remain idle and produce zero net value. These sessions are retained in the analysis, and all statistics reported below are computed over the complete population of 150 sessions.

Fig. 3(a) summarizes the resulting net value obtained for each session. The proposed degradation-aware method consistently shifts the distribution toward higher economic value, increasing the average net value from $0.11 to $0.26 per session while reducing the percentage of sessions with negative net value from 9.3% to zero. Furthermore, the proposed method never produces a lower net value than the degradation-unaware method in any of the 150 sessions, confirming that accounting for battery degradation either improves or preserves the economic outcome for *every* operating scenario considered.

The cumulative impact of these improvements is shown in Fig. 3(b). Because the proposed formulation is never outperformed on any individual session, its cumulative net value remains above that of the degradation-unaware benchmark throughout the evaluation period, ultimately reaching $39.22 compared with $16.30. Notably, the degradation-unaware strategy incurs cumulative losses during the early winter sessions

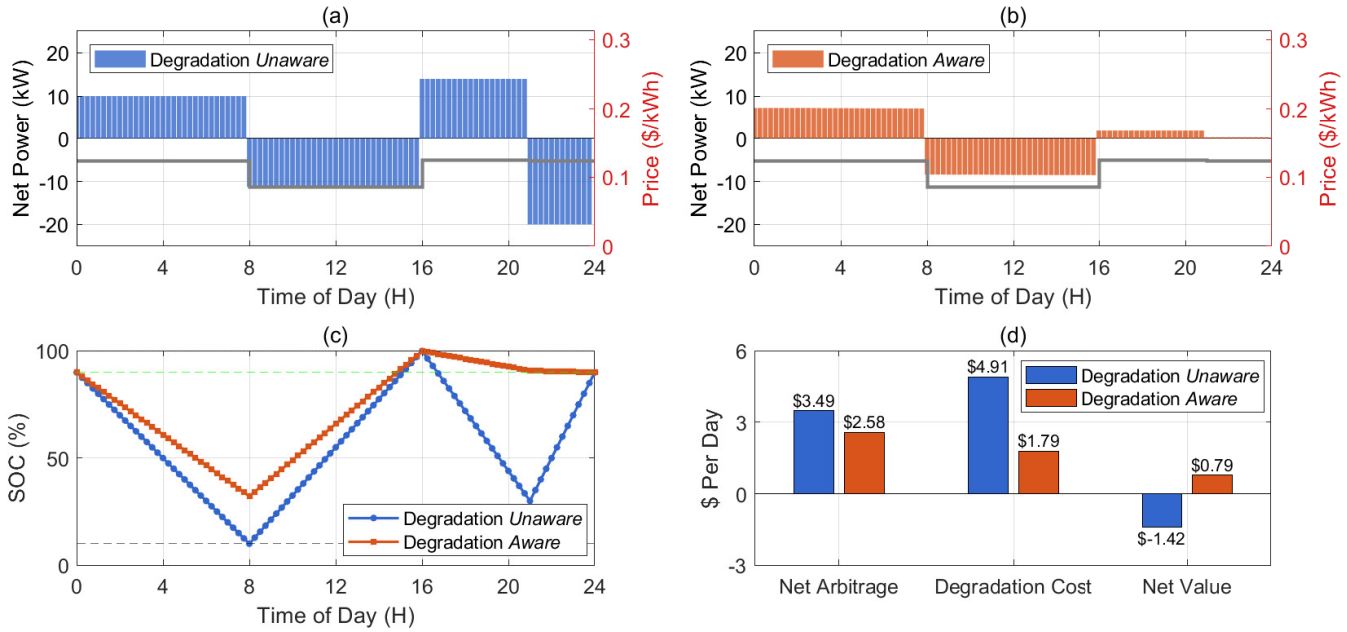


Fig. 2. Comparison of degradation-*unaware* and degradation-*aware* V2G scheduling under the Southern California Edison winter tariff. (a)–(b) Net battery power over the 24-hour scheduling horizon (discharge positive, charge negative) together with the electricity price, for the degradation-*unaware* and -*aware* methods, respectively. (c) Battery state-of-charge trajectories. (d) Breakdown of the gross arbitrage revenue, battery degradation cost, and resulting net value.

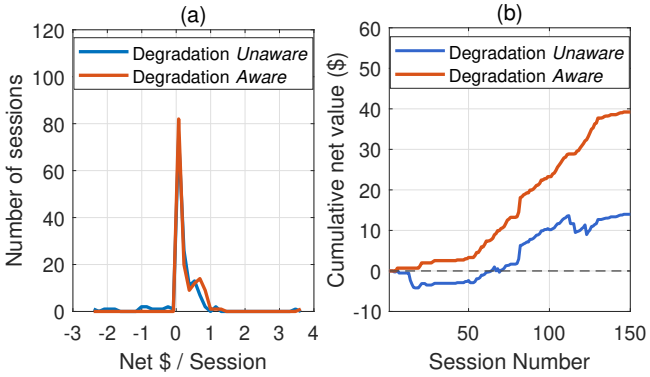


Fig. 3. Comparison of degradation-*unaware* and degradation-*aware* V2G scheduling across 150 real-world vehicle plug-in sessions under the Southern California Edison seasonal (mix of winter and summer) tariffs (a) Distribution of the *per-session* net value (gross arbitrage revenue minus battery degradation cost). (b) Cumulative net value as the sessions are evaluated sequentially.

before recovering under more favorable summer price spreads, whereas the proposed formulation maintains a nonnegative cumulative net value throughout the entire evaluation period. These results demonstrate that explicitly incorporating battery degradation into the optimization not only increases long-term economic value but also provides more consistent financial performance across diverse real-world charging behaviors.

IV. Conclusions

This paper developed an optimization-compatible mathematical representation of the BLAST-Lite battery degradation model and integrated it into a degradation-aware V2G scheduling framework. The proposed formulation enables BLAST-Lite degradation to be evaluated directly within the optimization process while preserving the degradation behavior of its native implementation. Case studies demonstrated the accuracy of the proposed mathematical formulation and showed that accounting for battery degradation changes the optimal V2G operating schedule and improves its overall economic value.

Future work will extend the proposed framework to incorporate battery thermal dynamics, V2G applications beyond energy arbitrage, and real-world field implementation.

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