Grid Interfaces to Electric Vehicle Chargers Using Statistically-Structured Power Conversion for Second-Use Batteries as Energy Buffering

Xiaofan Cui*, Student Member, IEEE, Alireza Ramyar†, Student Member, IEEE, Jason Siegel†, Member, IEEE, Peyman Mohtat†, Student Member, IEEE, Anna Stefanopoulou†, Fellow, IEEE, and Al-Thaddeus Avestruz§, Member, IEEE

Abstract—The rapid growth of electric vehicles (EVs) will include electric grid stress from EV chargers and produce a large number of diminished EV batteries. EV batteries are expected to retain about 80% of their original capacity at the end of vehicle life. Employing these in second-use battery energy storage systems (2-BESS) as energy buffers for EV chargers further reduces the environmental impact of battery manufacturing and recycling. One of the obstacles that limits performance and cost to 2-BESS is the heterogeneity of second-use batteries. In this paper, we show that a structure for power processing within a 2-BESS with hierarchical partial power processing can be optimally designed for stochastic variation in EV demand, dynamic grid constraints, and statistical variation in battery capacity. Statistically-structured hierarchical partial power processing shows better battery energy utilization, lower derating, and higher captured value in comparison to conventional partial power processing and full power processing for similar power conversion cost.

I. INTRODUCTION

As the number and power levels of electric vehicle chargers increase, electric grid stress will escalate [1]. Energy buffering, consisting of intermediate energy storage, smooths peak power stress on the grid while supplying EV charging demand [2]. Additionally, energy buffering reduces the capital expense of grid upgrades in commissioning EV chargers [3] [2] while reducing the cost from utility tariffs associated with peak demand requirements [4].

An EV charging plaza consists of one grid connection with several EV chargers that are connected to multiple second-life battery energy storage systems (2-BESS) through a dc microgrid [5] as illustrated in Fig. 1 [6]. The EV charging plaza employs three coordinated controllers. The Grid Interface Controller (GIC) communicates with the grid operator to determine the power that is available from the grid for the EV charging plaza; an AC-DC power converter is the power interface to the grid and determines the dc bus voltage of the microgrid. The Charging Management System (CMS) is the controller tasked with the decisions and control of the EV chargers. The BESS Management System (BeMS) is the controller for the battery energy storage systems on the microgrid. The CMS uses information from the GIC and BeMS for its policies and actions. For example, grid operators can impose demand response restrictions by communicating both pricing and hard power constraints in real time to the GIC, which allows the charging microgrid to respond [7], [8].

Second-use batteries represent an opportunity for a sustainable outlet for the influx of used batteries that will accompany the proliferation of electric vehicles [9]. The goal of this research is to enable second-use EV batteries as a cost-competitive solution for energy storage. There are several economic obstacles. These include the cost of power electronics, transportation, inventory, and the cost of testing [10]. Transportation costs can be reduced by locally supplying the production centers, inventory costs by just-in-time production, and testing costs by trading off uncertainty in the battery parameters in the design.

These cost reduction solutions require a power processing and storage architecture that can be optimized over statistical variation. We present a power conversion architecture together with a design framework that uses partial power processing to increase system efficiency, reduce converter ratings and hence capital cost, and lessen power processing and hence cost of thermal management.

This new hierarchical structure uses sparse power processing, where fewer numbers of power converters than batteries are used for the bulk power processing, together with built-in economies of scale by modularizing converters into a small number of discrete power ratings. The design framework uses stochastic models for EV charging, time-varying models for grid capability, and statistical models for battery supply heterogeneity. The design framework results in statistically-optimal energy storage systems towards minimizing the levelized cost of charging [11].

This design paradigm for second-use battery energy storage systems (2-BESS) aims to optimize: (i) production parameters like specific converter types (e.g. power ratings) so that they are optimal for the local battery supply statistics; and (ii) individual storage units as they are produced. For example, for a two-level power conversion hierarchy, the first level of power conversion is sparse and handles the average statistical mismatch among batteries, and between the batteries and the output trajectories. This first level topology is designed using multiple objectives and constraints, which renders as...
a mixed-integer optimization together with the embedded linear programming for energy flow optimization within this combined battery and power converter network. This step allows the optimal selection of power converter ratings for production ordering by the battery storage manufacturer. The second level of power conversion consists of a set of low power converters to handle the statistical variation among batteries (e.g. supply deviation), and between the batteries and the output trajectories. The overall power flow of the entire hierarchy is optimized based on the statistical deviations, from which the second-level converter ratings can be derived and similarly used by the manufacturer to order power converters.

During 2-BESS production, the set of available converters is pre-determined. During operation, the energy flow of the battery and power converter network within the energy storage system is optimized using linear programming at every time step while ensuring battery and power converter constraints related to power output and battery state of charge are satisfied.

In practice, an EV charging plaza with 350–450 V chargers will employ 50 V modules extracted from second-use EV battery packs in a series connection. In the following sections, these modules will be interchangeably referred to as batteries.

Among the seminal papers in partial power processing, [12] employ these methods to process only mismatch power to batteries including hierarchical active balancing architectures [13], interleaving the batteries together with the power electronics [14] and active balancing architecture using virtual bus [15].

II. SYSTEM MODELING

Several abstractions are needed to simplify the modeling of the interactions between the grid, EV charging, and second-use battery energy storage. These simplifications are manifested in the modeling of grid constraints, charging demand and operation, and battery energy storage system design and operation. These models allow us to compare different 2-BESS architectures by enabling us to untangle the effects on performance of multiple stochastic and statistical constraints.

The charging plaza consists of three coordinated controllers: (i) Grid Interface Controller (GIC); (ii) Charging Management System (CMS); and (iii) BESS Management System (BeMS). The GIC determines the ultimate power constraints for the dc microgrid. The grid operator communicates with the GIC to set the grid capability at the connection point, which is determined by physical and electrical constraints, and other loads. The CMS controls power partitioning among EV chargers, charger availability, and scheduling. The CMS can also control the variable pricing for EV charging, which is indirectly related to demand response pricing controls from the grid. The BeMS interfaces with individual 2-BESS units. The BeMS treats each 2-BESS as an energy storage monolith with a well-defined data and information interface; this interface exposes aggregate parameters and external states, such as external state of charge, as an abstraction. The BeMS controls power partitioning among the 2-BESS units, external depth of discharge, recharging, scheduling, and use leveling, among others. The GIC, CMS, and BeMS coordinate their optimization and control efforts for the best performance of the EV charging plaza.

A. Three-Actor Model Reduction

The control and optimization of EV charging microgrids with energy storage is complex and an active research topic [16], [17]. In this paper, we examine a simplified case with three actors for the charging plaza: (i) source of allocated grid power; (ii) singular EV charger; and (iii) singular 2-BESS.

The control and optimization of EV charging microgrids with energy storage is complex and an active research topic [16], [17]. In this paper, we examine a simplified case with three actors for the charging plaza: (i) source of allocated grid power; (ii) singular EV charger; and (iii) singular 2-BESS. We abstract the grid interface as a time-varying available grid power $P_{ag}(t)$, which represents the portion of the grid power that is allocated to the singular subset of one charger and one 2-BESS. We also apply a quasistatic approximation to some of the trajectories, meaning that the variable is constant over a particular charge cycle time interval $t_{ev}[n]$ shown in Fig. 3.

This model reduction allows us to perform comparisons of 2-BESS architectures with multiple deterministic time-varying and stochastic constraints over different parameter ensemble statistics. These stochastic constraints model the expected behavior of different aspects of the EV chargers, and implicitly the deviation from the expected behavior. The heterogeneity in the energy capacity of the battery supply is modeled statistically and parameterized by expected values and deviations from the expected values.

The available grid power to the 2-BESS and EV charger embeds the actions of the GIC and BeMS to the demand response controls from the grid. The available grid power is modeled as a constraint that is time-varying and deterministic.

The EV charging demand trajectory embeds the stochastic EV arrivals as an interarrival time that manifests as a standby...
time $T_d$ that has an exponential distribution. EV charging energy demand $E_{ev}[n]$ is quasistatic over the charging time interval $n$ and is represented by a Gaussian distribution, which is parameterized by an expected value and a standard deviation. The EV charger constraints are parameter specifications, inputs, outputs, and control policy:
(a) Parameter Specification: maximum charging power;
(b) Input: available grid power;
(c) Input: available 2-BESS power;
(d) Input: standby time;
(e) Output: EV charging energy demand, i.e. the energy required by the vehicle per EV charging.
(f) Control policy detailed below.

A statistical model for the second-use battery energy storage system is employed to represent the battery supply heterogeneity. We use a Gaussian probability distribution for the battery energy capacity, parameterized by an expected value and a standard deviation that represents the supply heterogeneity. The 2-BESS constraints are:
(a) Maximum 2-BESS output/discharge power is equal to the maximum charger power;
(b) Maximum 2-BESS output energy per EV charging cycle is determined by the energy capacity or a specified depth of discharge;
(c) Maximum recharge power is equal to the maximum grid power.

The 2-BESS output energy $E_{out}$ is the energy delivered by the 2-BESS during a particular time interval, e.g. charging cycle.

The aggregate power converter rating is $P = \sum p_i$ and the 2-BESS intrinsic energy capacity is $E^b = \sum E^b_i$. The energy-normalized aggregate power converter rating

$$R \triangleq \frac{P}{E^b} T,$$

where $T$ is the time required to deplete the 2-BESS intrinsic energy capacity $E^b$ of the battery at $P$.

### B. Simplified Control Policy for Three Actors

The control policy for the three actors is illustrated in Fig. 2.

The following properties are enforced:
- Both the 2-BESS and available grid power are used to charge an EV unless the 2-BESS energy is depleted.
- If the 2-BESS is depleted and then only the grid is used for EV charging at this curtailed charging level.
- The EV charger operates either at its maximum power or the curtailed charging power. Note that the curtailed charging power is the available grid power for the EV charging interval.
- The 2-BESS is recharged completely after every EV charging cycle.
- The 2-BESS recharge is the quasistatic available grid power for the EV charging interval.
- The available grid power is constant, i.e. quasistatic, during the entire EV charging cycle.
- The standby time between EV charging cycles is nonzero.

### III. Second-Use Battery Energy Storage Systems

A battery energy storage system is composed of batteries and power converters that are interconnected as a network with an input-output power port, as illustrated in Fig. 3. We compare our (i) LS-HiPPP architecture to two current state of the art approaches; (ii) Full Power Processing and (iii) Conventional Partial Power Processing (C-PPP), as illustrated in Fig. 5. The specific configuration for LS-HiPPP for our comparison is a series interconnection of batteries with bidirectional power converters shaping the energy flow as illustrated in Fig. 5(c). Output voltage regulation for LS-HiPPP is performed by a bidirectional power converter; in general, this power converter can output both negative and positive voltages to accommodate different required output voltages and battery voltage heterogeneity. It is worth noting that accommodating battery voltage heterogeneity is homologous to accommodating different output voltages.
A. 2-BESS Modeling

The following 2-BESS model makes the 2-BESS optimization tractable because linear programming can be used. This is important because repeated invocations of linear programming are needed for the 2-BESS mixed-integer optimization of interconnection, and for energy flow optimizations in the Monte Carlo evaluations of performance metrics over ensemble statistics. This reduced computational complexity allows us to compare different 2-BESS architectures with battery heterogeneity through optimal tradeoff curves.

There are several key approximations that enable the formulation of the energy flow optimization as a linear program:

- Zero power converter losses.
- Zero battery losses.
- Quasistatic available grid power \( P_{av}[n] \) for the \( n \)th charging cycle.
- Quasistatic EV charging energy demand.
- Singular depletion model for 2-BESS.
- Each battery voltage can be different, but time-invariant over discharge.

The optimality gap from power converter and battery losses is expected to be small. Partial power processing architectures that include LS-HiPPP and C-PPP are designed to process only the mismatch power. Typically less than 20% of the system output power is processed. Even if lower efficiency and therefore lower cost converters are used, the overall system losses can be small, as shown in Fig. 7. For example, if power converters with an efficiency of 85% are used in a system where only 15% of the power is processed, then the losses are only 2.25% of the system output power. Battery losses are expected to be even smaller than the converter losses [18].

The 2-BESS energy is considered depleted when a chosen number of battery modules reaches it depth of discharge limit. In a series configuration, when a battery is depleted, it is bypassed, causing the battery stack voltage to drop. This requires the bus voltage regulator to process more power to accommodate this voltage drop, hence causing the system efficiency to decrease and also requiring this power converter to have a higher rating. Second-use batteries have the longest lifetime when operated in the state of charge where the battery voltage is nearly constant [19]. To reduce complexity, we choose the threshold for depletion to be when one battery is depleted, i.e. singular depletion model for 2-BESS.

B. Battery Storage Network Design

Battery storage network design can be considered as a topology design problem on a directed graph \( G = (V, A) \). \( V \) is a node set whose elements are the battery modules. \( A \) is the set of ordered pairs of battery modules. The elements of \( A \) are edges of \( G \), which represents the electrical interconnection among battery modules.

The states of each battery module include energy capacity \( E_i^0 \) and voltage \( V_i^0 \). To show the statistical benefits of the proposed architecture, the \( E_i^0 \) are modeled as random variables. Their probabilistic distributions \( p(E_i^0) \) can be extracted from heterogeneous second-life battery supply statistics. We introduce multiple statistical indicators \( \varphi : \mathbb{X} \rightarrow \mathbb{R} \), where \( \mathbb{X} \) is the space of random variables, so that we can easily describe the behavior of battery modules and overall 2-BESS. The statistical indicators \( \varphi \) that we consider in this paper include the mean, standard deviation, and interdecile range (IDR) [20]. The energy processing design will be discussed in the following section.

C. Energy Processing Design

Energy processing design is a network topology design and flow calculation problem on a directed graph \( G^* = (V^*, A^*) \). \( G \) in Section II-B is a subgraph of \( G^* \) [21]. \( V^* \setminus V \) represents the node set whose elements are power converters, input ports, and output ports. \( A^* \setminus A \) is a set of ordered pairs between batteries and power converters, batteries and input/output ports, and power converters and input/output ports. \( A^* \) consists of edges of \( G^* \), which represent circuit interconnections. \( A^* \) also contains the weight of each edge, which represents the energy flow on the circuit interconnection. The power converter node is characterized by its power converter ratings \( p_i \) and voltage ratings \( v_i \). The nodes which represent the input/output ports contain multiple properties, e.g., power, energy, and voltage.

\( G^* \) is a temporal graph [21] in either continuous time, discrete time, or event-driven sampled space. The time-varying nodal state can cause time-varying weights in \( A^* \). For example, if the input and output node represent the available grid constraint and vehicle charging demand, respectively, the time-varying input/output can cause the energy flow on each converter and batteries to evolve with time. Electrical contactors and relays can enable the dynamic connectivity structure [21] on \( G^* \). \( A^* \) can be temporarily enlarged and shrunk. \( V^* \) can vary as batteries are placed in and out of service.

In this paper, the node set in the battery storage network \( V \), is randomly sampled from the heterogeneous second-life
battery supply statistics, which follow a Gaussian distribution. Therefore the statistical indicators \( \varphi \) include the mean and standard deviation. The edge set in battery storage network \( \mathcal{A} \) forms a series-string topology.

We focus on a new LS-HiPPP architecture for 2-BESS, whose node and edge sets \( \mathcal{V}^s \) and \( \mathcal{A}^s \) are shown in Fig. 5(c). The LS-HiPPP structure clearly exhibits a two-layer energy processing architecture. Layer 1 and 2 can be represented by graph \( \mathcal{G}_1 \) and \( \mathcal{G}_2 \) which are subgraphs of \( \mathcal{G}^s \). Layer 1 is considered sparse because the number of converter nodes in \( \mathcal{G}_1 \) (i.e. the order of \( \mathcal{G}_1 \)) is much smaller than the number of battery nodes in \( \mathcal{G} \) (i.e. the order of \( \mathcal{G} \)). Layer 2 is considered dense because the order of \( \mathcal{G}_2 \) is equal to the order of \( \mathcal{G} \) minus one. In Fig 5(c), Layer 2 is realized by placing a power converter between each battery and its adjacent battery in the string.

The energy design can be divided into two phases. In the first phase, given the battery supply statistics, we need to select the sets of power converters that will be used in the production of 2-BESS units. The second phase occurs when all power converters have been purchased.

**D. Power Conversion Design**

Power conversion design is a network topology design and flow optimization problem. The design variables in Layer 1 include power converter ratings, denoted by \( p^{(1)}_1, \ldots, p^{(1)}_M \) and the number of converters, denoted by \( M \). The design variables in Layer 1 also include the interconnections between batteries and power converters, i.e. set \( \mathcal{A}^s \setminus \mathcal{A} \). The design variables in Layer 2 include power converter ratings of converters, denoted by \( p^{(2)}_1, \ldots, p^{(2)}_{N-1} \). The number of power converters in Layer 2 is pre-selected to be one less than the number of batteries. The interconnections between batteries and power converters are predetermined as the adjacent module-to-module structure shown in Fig 5(c).

In the battery discharging scenario, each battery module is considered as the energy source with capacity \( E^b_j \). The load is modeled as the energy sink \( E_{out} \). The optimization objective is to maximize the energy utilization of the 2-BESS, defined as the ratio of energy delivered to the load \( E_{out} \) and the summation of the available energy sources

\[
U_E \triangleq \frac{E_{out}}{\sum E^b_j}.
\]  

The power ratings can be selected by averaging the energy over the discharging period. This required discharge time is determined by the EV charging application.

Our design utilizes two well-accepted techno-economic approximations: (i) The cost of a power converter is nearly proportional to its power rating. Smaller sum of power converter ratings results in a lower cost [18]; and (ii) Fewer types and larger numbers of power converters are favorable for economies of scale. The power ratings of Layer 2 converters are chosen to be identical; the Layer 1 converters are chosen to be identical, but in general different from Layer 2. The detailed design procedure in Layer 1 and 2 will be discussed in the next section.

**E. Power Processing Design Using Energy Flow Optimization**

1) Distribution Flattening: The Distribution Flattening method can map the battery statistical distribution to a string of batteries. Given an arbitrary distribution of battery characteristics, the method can generate a finite set of batteries that represent the expected performance. We would like to map this statistical distribution, which is a continuous function, to a finite expected set of batteries of size \( N \).

The expected set is an ordered set. The elements of this set are a particular representation of the expected values for \( N \) batteries drawn from the supply distribution. The set is constructed in the following manner:
1) Divide the distribution into $N$ intervals of equal probability: $[E_1, E_2], [E_2, E_3], \ldots, [E_N, E_{N+1}]$. $E_1$ and $E_{N+1}$ are the lower and upper bounds of battery energy. The $n$th interval satisfies

$$
\int_{E_n}^{E_{n+1}} p(E) \, dE = \frac{1}{N}.
$$

(3)

2) Assign each interval its expected value (1st moment),

$$
\bar{E}_n = \int_{E_n}^{E_{n+1}} p(E) E \, dE.
$$

(4)

3) The finite expected set $\mathcal{B}$ is constructed as $\mathcal{B} = \{B_1, B_2, \ldots, B_N\}$.

4) This set maps to a set of expected ratings $\{\bar{E}_1, \bar{E}_2, \ldots, \bar{E}_N\}$.

2) **Layer 1 Power Processing Design:** The power processing design of Layer 1 is a mixed-integer stochastic optimization problem because the battery storage network is stochastic and the design variable $\mathcal{A} \setminus \mathcal{A}$ is combinatorial. We convert the stochastic optimization problem to a deterministic optimization problem by the Distribution Flattening method. Given an arbitrary probabilistic distribution of the battery capacity $p(E^b)$ and number of batteries $N$, the Distribution Flattening method can generate the expected set $\mathcal{B} = \{B_1, B_2, \ldots, B_N\}$, the $N$-element set of batteries that represent the expected performance. In the series-string battery storage network discussed in this paper, $B_1 \ldots B_N$ are placed from lowest to highest expected energy $\bar{E}_1 \ldots \bar{E}_N$.

Given a small number of batteries and a sparse arrangement of power converters, we exhaustively search the set of feasible interconnection, under the constraint of converter voltage ratings. For every feasible interconnection, the optimal energy flow is found using linear programming

$$
\max_{e_1^{(1)} \cdots e_M^{(1)}} \sum_{1 \leq j \leq N} e_{j, \text{out}}^{(1)}
$$

subject to

$$
e_{j}^{(b)} \leq E_{j}^{b},
$$

(6)

$$
e_{j}^{(b)} = \sum_{i \in K_{j}^{(1)}} e_{i}^{(1)} + e_{j, \text{out}}^{(1)},
$$

(7)

$$
e_{j, \text{out}}^{(1)} = Q_{\text{string}} V_{j}^{b}, \quad j = 1, 2, \ldots, N,
$$

(8)

where $e_{j, \text{out}}^{(1)}$ is the energy delivered from the $j$th battery to the output, $e_{j}^{(b)}$ represents the output energy of the $j$th battery, $K_{j}^{(1)}$ is the index set of the Layer 1 converters whose inputs are connected to the $j$th battery.

The design space consists of the energy processed by $M$ Layer 1 converters, denoted by $e_1^{(1)} \cdots e_M^{(1)}$. The optimization objective is to maximize the total energy delivered to the output. Constraint (6) limits the available battery energy capacity. The constraint indicates that the entire 2-BESS is considered to be depleted if any battery module is depleted. Constraint (7) represents the energy conservation law for each battery. Constraint (8) indicates the direct energy transfer from the $j$th battery to the output linearly depends on battery voltage $V_{j}^{b}$ because the charge through the whole battery string is the same $Q_{\text{string}}$.

Finally, the maximum energy output $E_{\text{out}}^{(1)}$, the corresponding optimal circuit topology $K_{j}^{(1)}$, and optimal energy flow $e_1^{(1)} \cdots e_M^{(1)}$ are selected by maximizing battery energy utilizations among all feasible topologies.

The optimal set of processed power can be obtained by averaging the optimal processed energy by the required discharging period $T$ defined in $\mathbb{I}$

$$
p_{i}^{(1)} = \frac{e_{i}^{(1)} \cdot T}{T}, \quad i = 1, 2, \cdots, M.
$$

(9)

The Layer 1 converter rating is selected to be the maximum of the optimal set of the processed power.

3) **Layer 2 Power Processing Design:** Compared to the goal of maximizing expected performance in Layer 1, Layer 2 aims at processing the mismatch energy from the statistical deviation of the batteries from the expected set. Layer 2 power processing design is a stochastic optimization problem. Monte Carlo methods are exploited to optimize over statistical deviations.

The design of Layer 2 follows the design of Layer 1. The optimal interconnection, maximum energy processed, and power ratings of the Layer 1 converters are treated as the constraints in the design of Layer 2. The optimization goal is to determine the power rating $p_{\text{max}}^{(2)}$.

The optimization starts by setting the hierarchical parameter $\lambda_{\text{H}}$, defined as the ratio of the aggregate power rating between the two layers,

$$
\lambda_{\text{H}} = \frac{\sum_{i=1}^{N-1} p_{\text{max}}^{(2)}}{\sum_{i=1}^{M} p_{i}^{(1)}}, \quad (10)
$$

Smaller $\lambda_{\text{H}}$ indicates a stronger hierarchical power processing architecture. By setting $\lambda_{\text{H}} = 0$, LS-HiPPP is diminished to sparse partial power processing. By increasing $\lambda_{\text{H}}$, LS-HiPPP converges to C-PPP. As $\lambda_{\text{H}} \rightarrow \infty$, power processing is dominated by Layer 2, which is identically interconnected like C-PPP. Each $\lambda_{\text{H}}$ determines the power rating of the Layer 2 converters. The battery energy utilization can consequently be calculated by the following linear programming problem

$$
\max_{e_1^{(2)} \cdots e_{N-1}^{(2)}} \sum_{1 \leq j \leq N} e_{j, \text{out}}^{(2)}
$$

subject to

$$
e_{j}^{(b)} \leq (\bar{E}_{j}^{b} + \delta E_{j}^{b}),
$$

(12)

$$
e_{j}^{(b)} = \sum_{i \in K_{j}^{(1)}} e_{i}^{(1)} + \sum_{k \in K_{j}^{(2)}} e_{k}^{(2)} + e_{j, \text{out}}^{(2)},
$$

(13)

$$
e_{j, \text{out}}^{(2)} = Q_{\text{string}} V_{j}^{b}, \quad j = 1, 2, \ldots, N,
$$

(14)

$$
e_{k}^{(2)} \leq \frac{\lambda_{\text{H}} M e_{i}^{(1)}}{(N-1)}, \quad k = 1, 2, \ldots, N-1,
$$

(15)

$$
e_{i}^{(1)} \leq e_{i}^{(1)}, \quad i = 1, 2, \ldots, M,
$$

(16)

where $K_{j}^{(2)}$ is the index set of the Layer 2 converters whose inputs are connected to the $j$th battery.

The design space consists of the energy processed by $N-1$ Layer 2 converters, represented by $e_1^{(2)} \cdots e_{N-1}^{(2)}$. The optimization objective is to maximize the total energy
transferred to the output, given the ratings and interconnection of Layer 1 and Layer 2 converters. In Constraint (12), the extra $\delta E^j$ represents the energy deviation of the $j^{th}$ battery to the expected value $\bar{E}^j$. Constraint (13) represents the energy conservation for each battery. Constraint (14) expresses the direct power transfer from the $j^{th}$ battery to the output. Constraint (15) indicates the power ratings for all Layer 2 converters identically equal to $p^{(2)}_{\text{max}}$. Constraint (16) enforces that the Layer 1 converter ratings are kept fixed in the Layer 2 power processing design.

For each Monte Carlo sample from the battery supply distribution, an optimal battery energy utilization is obtained. The Monte Carlo method results in a distribution of optimal battery energy utilizations. The mean and standard deviation as well as other statistical indicators can be calculated from this distribution and designated to the secondary converter rating $p^{(2)}_{\text{max}}$.

By changing the hierarchical parameter $\lambda_H$, the tradeoff curve between the Layer 2 converter rating and battery energy utilization metric is obtained.

F. Deployment of 2-BESS Units

In production, all the power converters are procured in mass quantities, which are determined by the 2-BESS product demand. For each 2-BESS, the batteries are sorted from the lowest to highest in power capability and then connected in series. The power converters are connected according to section III-E.

The optimal power flows are recalculated using linear programming during operation given the actual battery energy capacities in the 2-BESS unit and the output load. As we show in Section IV, the design method for LS-HiPPP results in a better cost-performance tradeoff as it relates to battery energy utilization and normalized aggregate converter rating in comparison to competing approaches. 2-BESS with an LS-HiPPP architecture performs well with a sparse set of Layer 1 converters at moderate power ratings and a dense set of Layer 2 converters at lower power ratings.

G. Derating and Confidence of Performance Metrics

The confidence in the unit-to-unit performance of a 2-BESS can be inferred from statistical measures of dispersion. For example, a $3\sigma$ confidence in the 2-BESS energy capacity means that there is a 99.85% probability for a normal distribution that the deployed 2-BESS units will have at least this capacity.

A typical approach to achieving the required confidence in a level of performance is to derate the unit. For example, a 2-BESS unit of a particular technology rated with an expected energy capacity of 200 kWh might only be used in an application that requires a $3\sigma$ confidence at 150 kWh; this corresponds to a derating factor $D_f$ of 75%. Conversely, this means that for this 2-BESS technology, an application that requires 150 kWh of energy capacity requires purchasing a more expensive 200 kWh unit to achieve a $3\sigma$ confidence. It is worth noting that derating can be applied to impose a confidence level to any performance metric, not just energy capacity.

H. Captured Value of the 2-BESS

Both derating factor $D_f$ and energy utilization $U_E$ affect the value of the 2-BESS as a means of energy storage. The captured value can be defined as the product of the derating, energy utilization, and expected intrinsic energy capacity $\bar{E}_I$

$$C_v \triangleq D_f U_E \bar{E}_I,$$  \hspace{1cm} (17)

where

$$\bar{E}_I = \sum_{j=1}^{N} \bar{E}^j.$$  \hspace{1cm} (18)

IV. RESULTS

The tradeoffs for several performance metrics were evaluated using Monte Carlo methods to compare LS-HiPPP to current state-of-the-art approaches for power processing in 2-BESS. In this section, the following specifications are enforced:

- Maximum EV charging power is 150 kW, which is equivalent to a Level III charging rate.
- Expected 2-BESS power capability is 150 kW.
- Battery energy heterogeneity is a Gaussian distribution with a mean of 37.5 kWh and a standard deviation of 9.4 kWh, corresponding to a 25% heterogeneity.
- Nine battery modules are connected in series.
- Identical aggregate power converter ratings are used to compare LS-HiPPP to C-PPP and Full Power Processing.
- Three identical Layer 1 power converters are used for LS-HiPPP.
- Eight identical Layer 2 power converters are used for LS-HiPPP.
- Individual power converters within a C-PPP 2-BESS have identical power ratings.
- Individual power converters with a Full Power Processing 2-BESS have identical power ratings.
- Individual power converters are used for bus voltage regulation in LS-HiPPP, C-PPP, and Full Power Processing.
- The bus voltage regulator absorbs all the battery voltage heterogeneity.

For a fair comparison between LS-HiPPP and C-PPP, the following are enforced:

- Identical sampling of batteries and hence identical individual capabilities and capacities.
- Identical battery interconnection.
- Identical EV charging energy demand trajectory.
- Identical trajectory of available grid power.

A. Battery Energy Utilization

The battery energy utilization $U_E$ in (2) is a metric for the amount of battery energy internal to the 2-BESS that is available to the output port. As previously mentioned, the 2-BESS is considered depleted when any battery has reached its depth of discharge limit. Fig. 6 shows a comparison of the utilization for LS-HiPPP, C-PPP, and Full Power Processing for different aggregate converter ratings at 25% deviation in battery energy.
Lower aggregate power converter ratings mean lower cost. Fig. 6 shows that LS-HiPPP has significantly better \( U_E \) than both C-PPP and Full Power Processing at lower aggregate power converter ratings. At 20% aggregate power converter rating, LS-HiPPP has a battery utilization of 94% versus 78% for C-PPP; Full Power Processing is below the scale.

B. System Efficiency

The system efficiency in Fig. 7 is calculated by assuming all the power converters in the LS-HiPPP, C-PPP, and Full Power Processing designs have identically flat efficiencies. This approximation enables a comparison among the 2-BESS power processing approaches. The system efficiency can be calculated by

\[
\eta_s = 1 - (1 - \eta_c)R,
\]

where \( \eta_c \) is the efficiency of all power converter and \( R \) is the normalized aggregate converter rating. For partial power processing approaches, as power converter ratings are reduced, less power is processed, hence a higher system efficiency, albeit at lower battery utilization. Full power processing has a constant system efficiency because all the output power is necessarily processed.

C. Single-Day Time Series for Three Actor Plaza

A single-day time series illustrates the dynamic behavior of the EV charger, grid, and 2-BESS. A comparison between a 2-BESS with LS-HiPPP and a 2-BESS with C-PPP is shown in Fig. 8. Together, the available grid power (Grid Constraint), 2-BESS power output (2-BESS Power), 2-BESS remaining energy (2-BESS Energy), and EV charging power comprises the trajectory set for this exemplar single-day time series. The available grid power and EV charging power comprise the external trajectory set that determines the behavior of the 2-BESS, represented by the 2-BESS power and energy, which comprise the 2-BESS trajectory set.

For LS-HiPPP, Fig. 8a shows that nearly all the 2-BESS internal energy is utilized in comparison to C-PPP in Fig. 8b. C-PPP also results in a larger amount of curtailed charging from the smaller available 2-BESS energy output because of the worse battery energy utilization. Curtailed charging is indicated by the low power pedestals in the EV charging power trajectory. These pedestals correspond to using only the available grid power for EV charging. C-PPP has 200% more curtailed charging than LS-HiPPP.

This data suggests that 2-BESS can support fast charging. LS-HiPPP results in better performance with high utilization of the intrinsic battery energy and smaller curtailed charging pedestals.

D. Ensemble Performance Over Single-Day Trajectory

The statistical performance of LS-HiPPP and C-PPP over battery energy heterogeneity is evaluated over the same trajectory set in section IV-C. Monte Carlo simulations were performed with individual battery energy capacity as the
random variable. The output random variable is battery energy utilization as shown in Fig. 9. This output random variable is drawn from the statistics of the charging interval. For interval \( n \), the interval statistical distribution is \( Q_n \).

The grid-EV energy gap is the difference between the EV charging energy demand and the available grid energy. The available grid energy \( E_{ag}[n] \) is the quasistatic available grid power integrated over the germane charging time interval \( n \),

\[
E_{ag}[n] = P_{ag}[n] t_{ev}[n].
\]

It can be observed that at high energy gap, the mean battery energy utilization for LS-HiPPP is approximately 94.7% versus 80.8% for C-PPP. It is worth noting that at low energy gap, the 2-BESS output may be low, which makes both LS-HiPPP and C-PPP underutilized as illustrated at 2.2 h and 24.4 h.

E. Statistical Dispersion of Performance

The statistical measures of dispersion of a performance metric are an indicator of the unit-to-unit variability in the production of 2-BESS for a particular battery heterogeneity. Fig. 10a shows that the IDR of energy output of LS-HiPPP is significantly lower than that for C-PPP. Lower IDR at large grid-EV energy gap means higher consistency of performance when the 2-BESS is needed the most; from Fig. 10a at 10 h, the IDR for LS-HiPPP is 10.4% versus 32.7% for C-PPP.

A derating factor can be inferred from the worst-case 3σ spread in Fig. 10b. The derating factor for LS-HiPPP is significantly better at 84.3% than C-PPP at 63.1%. From the derating factor and battery energy utilization at the worst-case energy gap, the captured value for LS-HiPPP is 79.8% versus 51.0% for C-PPP.

F. Resilience to Usage Uncertainty

By examining the effect of the stochastic deviation in the normalized grid-EV energy gap on expected battery energy utilization in Fig. 11, we can compare the resilience of LS-HiPPP and C-PPP to uncertainties in usage. At large deviations, e.g. 0.5, the utilization for LS-HiPPP is at 80%, in comparison to that for C-PPP at 68%.

G. Curtailed Charging from Usage Uncertainty

When the stochastic deviation from expected usage is high, the 2-BESS is more likely to deplete in energy, resulting in curtailed EV charging. Fig. 12 shows that a 0.5 deviation in the normalized grid-EV energy gap, the mean curtailed charging time for individual EVs is 67% longer in C-PPP (25 minutes) than LS-HiPPP (15 minutes), which implies a degradation in quality of service to the EV charging customer. This suggests that LS-HiPPP is better at mitigating the energy gap to maintain quality of service.

V. CONCLUSION

We investigated the performance of second-use battery energy storage systems (2-BESS) as an energy buffer for
Future work includes extending the model to more complex stochastic interactions between the grid, multiple EV chargers, and multiple 2-BESS units.

**Fig. 11.** Comparison of the effect of stochastic deviation of grid-EV energy gap on battery energy utilization.

**Fig. 12.** Comparison of the mean curtailed charging time for each EV.

**REFERENCES**

[1] S. Deb, K. Tammi, K. Kalita, and P. Mahanta, “Impact of electric vehicle charging station load on distribution network,” *Energies*, vol. 11, no. 1, pp. 1–25, 2018.

[2] T. S. Bryden, G. Hilton, B. Dimitrov, C. Ponce De León, and A. Cruden, “Rating a Stationary Energy Storage System Within a Fast Electric Vehicle Charging Station Considering User Waiting Times,” *IEEE Trans. Transp. Electrific.*, vol. 5, no. 4, pp. 879–889, 2019.

[3] M. D’Arpino and M. Cancian, “Design of a grid-friendly DC fast charge station with second life batteries,” in *SAE Tech. Pap.*, vol. 2019-April, no. April. SAE International, apr 2019.

[4] L. Yang and H. Ribberink, “Investigation of the potential to improve DC fast charging station economics by integrating photovoltaic power generation and/or local battery energy storage system,” *Energy*, vol. 167, pp. 246–259, 2019.

[5] S. Leomori, G. Rizzoni, F. M. Frattale Mascioli, and A. Rizzi, “Intelligent energy flow management of a nanogrid fast charging station equipped with second life batteries,” *Int. J. Electr. Power Energy Syst.*, no. April, p. 106602, 2020.

[6] NKL, “Guidelines for the realisation of charging plazas,” The Netherlands Knowledge Platform for Public Charging Infrastructure (NKL), Tech. Rep., 2019.

[7] L. Yao, W. H. Lim, and T. S. Tsai, “A Real-Time Charging Scheme for Demand Response in Electric Vehicle Parking Station,” *IEEE Trans. Smart Grid*, vol. 8, no. 1, pp. 52–62, Jan 2017.

[8] Y. Xiong, B. Wang, C. C. Chu, and R. Gadh, “Vehicle grid integration for demand response with mixture user model and decentralized optimization,” *Appl. Energy*, vol. 231, pp. 481–493, Dec 2018.

[9] L. C. Casals, B. Amante García, and C. Canal, “Second life batteries lifespan: Rest of useful life and environmental analysis,” *J. Environ. Manage.*, vol. 232, no. November 2018, pp. 354–363, Feb 2019.

[10] J. Neubauer, K. Smith, E. Wood, and A. Pesaran, “Identifying and Overcoming Critical Barriers to Widespread Second Use of PEV Batteries,” *Natl. Renew. Energy Lab.*, no. February, pp. 23–62, 2015.

[11] B. Borlaug, S. Salisbury, M. Gerdes, and M. Muratori, “Levelized Cost of Charging Electric Vehicles in the United States,” *Joule*, vol. 4, no. 7, pp. 1470–1485, 2020.

[12] P. S. Shenoy, K. A. Kim, B. B. Johnson, and P. T. Krein, “Differential power processing for increased energy production and reliability of photovoltaic systems,” *IEEE Trans. Power Electron.*, vol. 28, no. 6, pp. 2968–2979, 2013.

[13] Z. Zhang, H. Gui, D. J. Gu, Y. Yang, and X. Ren, “A hierarchical active balancing architecture for lithium-ion batteries,” *IEEE Trans. Power Electron.*, vol. 32, no. 4, pp. 2757–2768, 2017.

[14] C. C. Hua and Y. H. Fang, “A charge equalizer with a combination of APWM and PFM control based on modified half-bridge converter,” *2015 18th Int. Conf. Electr. Mach. Syst. ICEMS 2015*, vol. 31, no. 4, pp. 2147–2150, 2016.
[15] M. Evzelman, M. M. Ur Rehman, K. Hathaway, R. Zane, D. Costinett, and D. Maksimovic, “Active Balancing System for Electric Vehicles With Incorporated Low-Voltage Bus,” IEEE Trans. Power Electron., vol. 31, no. 11, pp. 7887–7895, 2016.

[16] Q. Yang, S. Sun, S. Deng, Q. Zhao, and M. Zhou, “Optimal Sizing of PEV Fast Charging Stations with Markovian Demand Characterization,” IEEE Trans. Smart Grid, vol. 10, no. 4, pp. 4457–4466, 2019.

[17] M. Faisal, M. A. Hannan, P. J. Ker, A. Hussain, M. B. Mansor, and F. Blaabjerg, “Review of energy storage system technologies in microgrid applications: Issues and challenges,” IEEE Access, vol. 6, pp. 35143–35164, may 2018.

[18] K. Mongird, V. Fotedar, V. Viswanathan, V. Koritarov, P. Balducci, B. Hadjerioua, and J. Alam, “Energy storage technology and cost characterization report,” Pacific Northwest Natl. Lab., no. July, pp. 1–120, 2019.

[19] S. Saxena, C. Hendricks, and M. Pecht, “Cycle life testing and modeling of graphite/LiCoO2 cells under different state of charge ranges,” J. Power Sources, vol. 327, pp. 394–400, sep 2016.

[20] Michel Jambu, Exploratory and Multivariate Data Analysis. Elsevier, 1991.

[21] J. A. Bondy and U. S. R. Murty, Graph theory with applications. Macmillan London, 1976.