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Aging Mitigation for Battery Energy Storage System in Electric Vehicles

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***Abstract*—Battery energy storage systems (BESS) have been extensively investigated to improve the efficiency, economy, and stability of modern power systems and electric vehicles (EVs). However, it is still challenging to widely deploy BESS in commercial and industrial applications due to the concerns of battery aging. This paper proposes an integrated battery life loss modeling and anti-aging energy management (IBLEM) method for improving the total economy of BESS in EVs. The quantification of BESS aging cost is realized by a multifactorial battery life loss quantification model established by capturing aging characteristics from cell acceleration aging tests. Meanwhile, a charging event analysis method is proposed to deploy the built life loss model in vehicle BESS management. Two BESS active anti-aging vehicle energy management models: vehicle to grid (V2G) scheduling and plug-in hybrid electric vehicle (PHEV) power distribution, are further designed, where the battery life loss quantification model is used to generate the aging cost feedback signals. The performance of the developed method is validated on a V2G peak-shaving simulation system and a hybrid electric vehicle. The work in this paper presents a practical solution to quantify and mitigate battery aging costs by optimizing energy management strategies and thus can further promote transportation electrification.**

***Index Terms*—Battery energy storage system, electric vehicle, battery aging assessment, battery aging mitigation, energy management, vehicle power distribution, vehicle to grid.**

ABBREVIATIONS

BESS	Battery energy storage system.
IBLEM	Integrated battery life loss modeling and anti-aging energy management.
Crate	Charging and discharging rate.
DOD	Depth of discharge.
SoC	State of charge.
V2G	Vehicle to grid.
PHEV	Plug-in hybrid electric vehicle.
GEVs	Grid-connected electric vehicles.
CLC	Cycle life correction.
CTUDC	Chinese typical urban drive cycles.
EMS	Energy management strategy.
MPC	Model predictive control.

NOMENCLATURE

SoC_0	Initial battery SoC value in operation cycles [%].
SoC_d	Final battery SoC value in an operation cycle [%].
I	Working current of the battery [A].
Q_{bat}	Rated capacity of the battery [Ah].
DoD	DoD of the battery [%].
$Crate$	Crate of the battery [C].
CTF	Battery cycle to failure value.
f_d	Function to quantify the influence of DOD.
CLC	Battery cycle life correction factor.
f_{clc}	Function to quantify the influence of Crate.
DOD_k	Depth of discharge of the battery at k [%].
$Crate_k$	Crate of the battery at k [C].
f_l	Function to quantify percentage battery life loss.
SoC_k	Battery SoC value at k [%].
Ad_k	Variable to judge extreme points in SoC profile.
$E_{bat,k}$	Accumulated battery output energy at k [kWh].
$P_{bat,k}$	Working power of the battery pack at k [kW].
Δt	Duration of an energy management interval [s].
$U_{bat,k}$	Terminal voltage of the battery at k [V].
BL_k	Quantified batter life loss at k [%].
f_{ibl}	Function to quantify battery life loss in EMS.
$\mathbf{V}^{ref}$, $\mathbf{B}^{ref}$	V2G and BESS working power in PHEV [kW].
PB	Grid power balance state [kW].
P_{ref}	Reference peak-shaving value [kW].
$P_{load,k}$	Grid demand at k [kW].
C_{bat}	Unit cost of battery pack [$].
$C_{aging,k}$	quantified battery aging cost at k [$].
J	Cost function of BESS management.
$SoC_{\min}$	Minimum limit of battery SoC value [%].

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$SoC_{\max}$ Maximum limit of battery SoC value [%].
$P_{i,dis}^{\max}$ Maximum V2G discharging power of EV_i [kW].
$P_{i,ch}^{\max}$ Maximum V2G charging power of EV_i [kW].
$\mathrm{SoC}_{i,k}$ Battery SoC state of EV_i at k [%].
$\mathrm{SoC}_{cu,k}$ Benchmark battery SoC value at k [%].
C_{fuel} , C_{elec} Fuel and electricity cost of PHEV [$].
SoC_k^{ref} PHEV battery SoC reference trajectory [%].
π_V , π_B Online BESS management strategy.
T_e , T_m Engine and electric motor torque [N·m].
n_e , n_m Engine and electric motor speed [RPM].
$P_{\mathrm{m,k}}$, $P_{\mathrm{e,k}}$ Motor and engine working power [kW].
P_d PHEV power requirement [kW].
$\mathbf{V}^{ol}$ Scheduled online V2G power [kW].
B^{ol} Scheduled online BESS working power [kW].
$P_{m\_\min}$, $P_{m\_\max}$ Minimum and maximum motor power [kW].
$P_{\mathrm{e}\_\min}$, $P_{\mathrm{e}\_\max}$ Minimum and maximum engine power [kW].

I. INTRODUCTION

BATTERY energy storage systems (BESS) have been recognized as one of the most effective ways to improve the efficiency and economy of power systems in the distribution network and electric transportation sector [1, 2]. According to the four Future Energy Scenarios carried out by National Grid ESO in the UK, around 50 GWh and 120 GWh energy storage capacity will be provided by establishing grid battery energy storage and deploying vehicle-to-grid (V2G) technologies in 2050 [3]. Meanwhile, the plug-in hybrid electric vehicle (PHEV), which uses the battery as an auxiliary power unit to reduce the fuel costs of internal combustion engines, has also been widely adopted in many countries [4]. BESS is characterized by high power density and energy conversion efficiency. The adoption of V2G and PHEV technologies with BESS brings a bright prospect to improve the efficiency, stability, and economy of the power grid and vehicular power systems. However, the expected lifetime of the battery is much shorter than most other energy storage devices [5]. The concerns with battery aging costs make it difficult to widely deploy BESS in commercial and industrial applications [6, 7]. Therefore, BESS should be effectively protected to enable the benefits of V2G and PHEV.

Understanding battery degradation mechanisms and establishing an accurate aging model is fundamental for quantifying battery life loss in daily operations [8, 9]. Meanwhile, properly designed energy management and protection algorithms are indispensable for prolonging battery life and reducing usage costs. Many studies have investigated vehicle battery aging mechanism, and the data-driven methods have been commonly used in predicting and quantifying battery capacity losses [10, 11]. In the data-driven method, aging datasets under the whole life cycle are used to extract and generate battery life loss trajectories. In [12], a data-driven battery cycle life prediction model is established based on a machine learning algorithm. A comprehensive dataset containing 124 sets of operation aging data of lithium iron phosphate batteries was obtained under rapid charging conditions. The aging model is established based on aging data under different working conditions, and the predicted battery life loss can be limited to 9.1%.

Data-driven methods can characterize the aging mechanism of battery cells during the whole life cycle. However, limited by the dataset integrity and model extrapolation, it can hardly be deployed in commercial BESS management issues. Unlike common mechanical and electrical devices, the battery pack is a complex electrochemistry system. Therefore, a large amount of data is required to accurately simulate its operational characteristics [13-15]. According to [16], a comprehensive database that reflects battery aging characteristics under the whole life cycle is indispensable for establishing a battery model with satisfactory performance. However, aging experiments are costly and time-consuming, and it is very challenging to obtain the experimental aging data during the whole battery life cycle [17]. Furthermore, data driven methods are usually carried out to model the aging phenomenon of a single cell, but battery packs in real-world energy storage devices usually consist of thousands of cells, each with different aging characteristics [18, 19]. Therefore, the established degradation quantification models are usually with limited extrapolation on the whole battery pack. Most existing papers focus on battery cell state of heath estimation, but to the best of the authors' knowledge, aging quantification models for BESS energy management have not been well investigated.

To reduce BESS usage costs, battery aging should also be actively mitigated in energy management algorithms [19, 20]. Some references have investigated off-line battery anti-aging BESS energy management approaches. In [21], the rain-flow cycle counting algorithm is used to analyze aging cycles in a grid-connected battery storage system. The proposed method enables distribution network operators to optimally schedule the day-ahead battery anti-aging bidding for energy storage systems in power markets. Reference [22] models the life loss of BESS as a function of the number of cycles and depth of discharge (DOD). The heuristic algorithm is used in [23] to optimize the operational schedule of energy storage systems in micro-grids for improving the power transmission efficiency and extending battery life expectancy. Limited by the analyticity of the battery aging quantification model, most existing methods can only schedule the operation of BESSs day ahead [24]. However, system dynamic performance is also emphasized in BESS management in engineering applications.

BESS operation can be dynamically scheduled based on the sampled power system and BESS state information, which indicates that energy storage capacity can be better utilized to respond to system transient power fluctuations. In aggregated V2G coordinator [25], the deployment of dynamic V2G management strategies further improves renewable energy sources utilization and power system economy by 12% and 3.3% in a microgrid with grid-connected electric vehicles (GEVs) penetration. In PHEV energy management deployed in vehicle control units, system dynamic performance is also of great significance to vehicle power system stability and economy [26, 27]. Nevertheless, reference [28] points out that battery aging is a cumulative process, and it is challenging to quantify and mitigate battery aging costs in dynamic energy management.

Based on the above discussion, this paper proposes an integrated battery life loss modeling and anti-aging energy management (IBLEM) method for mitigating the degradation cost of BESS in EVs. Battery anti-aging energy management is realized by a two-stage framework: i) the establishment of multifactorial battery aging quantification model, and ii) deployment of the battery aging model in dynamic BESS energy management. In the first stage, a multifactorial battery life loss quantification model is established by learning general degradation characteristics extracted from cell acceleration aging test datasets. In the second stage, the deployment of the established battery model is realized by a charging event and cycle analysis method. Further, battery active anti-aging energy management is modeled as a mathematical problem based on the established BESS life loss model. The two most common scenarios: V2G scheduling and PHEV energy management, are used as case studies to verify the developed methods.

The main contributions of this paper are:

1) It develops a novel multifactorial battery life loss modeling method to quantify the usage cost of BESS in EVs. Compared to existing literature, the proposed method can comprehensively reflect battery aging mechanisms under different working conditions (DoDs and Crates) by only utilizing cell aging test datasets provided by the manufacturer.
2) It for the first time proposes an analyzable BESS degradation cost quantification method, where battery aging cycle, DoD, and Crate information are dynamically extracted by analyzing the change of charging states in SoC profiles. The developed event-based method provides a single-step battery life loss feedback signal for facilitating anti-aging vehicle BESS energy management.
3) The established BESS aging quantification model is further deployed in V2G scheduling and PHEV power distribution scenarios to realize anti-aging vehicle battery energy management. Compared to existing vehicle energy management methods, the proposed method can efficiently schedule BESS operation while significantly mitigating battery aging.

Furthermore, the theoretical and practical significance of the developed method can be summarized as follows:

1) The developed battery aging modeling method provides an economic and efficient scheme for vehicle BESS life loss quantification in commercial applications. GEV battery aging modeling and anti-aging management can be realized by using the open-access cell experimental databases provided by the manufacturer.
2) The BESS life loss quantification model and anti-aging energy management method also improve the total economy of PHEV. With the developed method, the usage cost of vehicle owners can be significantly reduced.

The remainder of this paper is organized as follows. Section II presents the developed IBLEM framework. Section III proposes the cell experimental data-driven BESS life loss quantification model. Then, a event-based battery aging quantification model is established in Section IV. Section V demonstrates the implementation of the established battery aging model in V2G scheduling and PHEV energy management. Section VI validates the efficacy of the proposed method. The conclusions are drawn in Section VII.

II. INTEGRATED BATTERY LIFE LOSS QUANTIFICATION AND ANTI-AGING ENERGY MANAGEMENT FRAMEWORK

This section develops an integrated battery life loss modeling and anti-aging energy management framework to reduce the operation cost and improve the total economy of BESS. As shown in Fig. 1, the built IBLEM framework consists of 2 stages: the establishment of a multifactorial battery life loss quantification model, and the deployment of the battery aging model in BESS energy management.

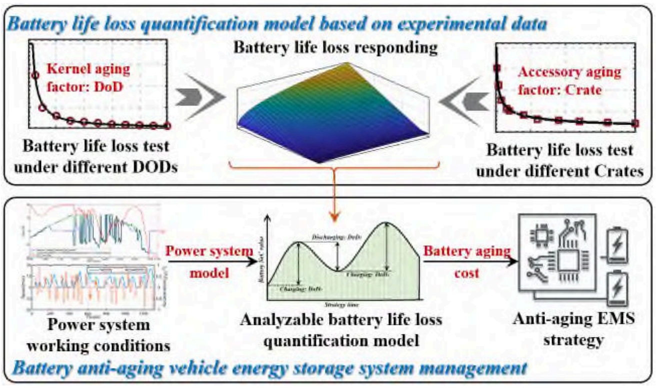

Fig. 1. Integrated battery life loss modeling and anti-aging energy management framework.

In the first stage, an experimental data-driven multifactorial battery aging model is established to quantify battery life loss under different working conditions. Compared to the battery pack, aging experiments are easily carried out under single cells. Therefore, this study uses the aging characteristics of a single battery cell to model and mitigate the aging phenomenon of the whole pack in energy management strategy. As shown in Fig. 1, in the developed IBLEM method, the kernel aging factor of the battery is modeled by cell aging tests under different DODs. Similarly, the accessory aging factor of the battery is derived by battery aging tests under different Crates. Battery DoD and Crate in the aging test are quantified by the following equations [29]:

$$DoD = (SoC_0 - SoC_d) \times 100\% \tag{1}$$

$$Crate = \frac{I}{Q_{bat}} \tag{2}$$

Where: SoC_0 and SoC_0 are the initial and final SoC value of the battery in the studied discharging cycle. I and Q_{bat} are the working current and rated capacity of the battery. The battery life loss responding profile, which models BESS aging characteristics under different working conditions, is constructed by integrating the influence of both kernel and accessory factors.

In the second stage, the established life loss responding profile is used to provide a single-step battery aging cost signal for BESS energy management. Firstly, based on the working condition and mathematical model of the power system, the output power profile of BESS system is calculated. Then, battery cycles and the corresponding Crate and DOD information are extracted by analyzing the charging events in output power profiles. BESS aging cost is quantified by the established battery life loss responding profile. With the battery aging cost feedback signal, energy management unit schedules the optimal anti-aging strategy to satisfy power system operation requirements while effectively protecting the battery pack.

III. Establishment of Multifactorial Battery Life Loss Quantification Model Based on Cell Experiment Data

This section establishes an experimental data-driven battery life loss quantification model. Firstly, the impacts of DOD and Crate on battery aging are quantified by cell acceleration aging test data. Then a life loss responding profile is constructed for evaluating battery aging costs under various working conditions.

Commercial EVs normally use standard cells to form battery packs, such as 18650 and 21700 cells provided by LG Chem, Samsung, Panasonic, and Sanyo. According to [30] and [31], battery packs consisting of cells produced by the same manufacturer have extremely similar aging characteristics. In [32], the large-scale battery energy storage system simulation is realized by only using the operation data collected from 9 cells. The characteristic similarity between the battery pack and cell is validated through both theoretically and experimentally analyses. The published open-access cell experimental databases also make it convenient to model battery aging through cell datasets in commercial applications [30, 33, 34]. Therefore, this study uses battery cell degradation data to characterize the aging characteristic of EV batteries for simplifying the life loss quantification process.

Battery undergoes cycles with various DoDs and Crates in engineering applications. However, it is challenging and costly to carry out the corresponding battery aging experiment under every different DoDs and Crates. It has been proved that curve fitting is effective in inferring the aging characteristics of BESS in energy bidding [35], renewable energy systems [36, 37], and electric vehicles [38] under different working conditions. In [9], BESS remaining capacity estimation is realized by fitting cycling test data. The established model is widely recognized by both academic and industry circles. Therefore, a piecewise function is used in this study to model battery cycle to failure characteristics under different DoD and Crate states. Battery life under different DoD states in the cell experiment [39] is shown in Fig. 2 (a). 11 independent battery aging experiment is conducted to characterize battery life under different DoD range from 5% to 100%. Based on the experimental data, the following function is established to represent battery life loss under different DoDs:

$$CTF = f_d(DOD) = \begin{cases} 40000 & DOD < 5\% \\ 946.1 \cdot DOD^{-1.079} & 5\% \le DOD \le 100\% \end{cases} \tag{3}$$

Where: CTF is battery cycle to failure value. f_d is the function to quantify battery life under different DoD states.

This paper defines a cycle life correction (CLC) factor to quantify the impact of discharging current on battery life. Battery CTF value under 1C current and 100% DOD scenario is selected as the benchmark. Battery life loss test data under different Crates and 100% DOD are used to describe the influence, and the failure cycles of the battery when its capacity declines by 20% are labeled as CTF_{Crate}. The impact of different Crates on battery life is quantified by calculating the ratio between battery CTF under different Crates and benchmark value:

$$CLC = \frac{CTF_{Crate}}{CTF \mid DOD = 100\%} \tag{4}$$

Based on (4), the correction factors in 11 experiments are calculated, and the corresponding discrete experimental data points are given in Fig. 2 (b). Meanwhile, based on the calculated discrete results, the following piecewise function is used to fit the relationship between CLC value and battery Crate:

$$CLC = f_{clc}(Crate) = \begin{cases} 4 & \text{Crate} < 0.2 \\ 1.041 \cdot Crate^{-0.445} & 0.2 \le Crate \le 10 \end{cases}$$
(5)

Where: CLC is calculate battery Crate correction factors. f_{clc} is the function to quantify the influence of Crate on battery life.

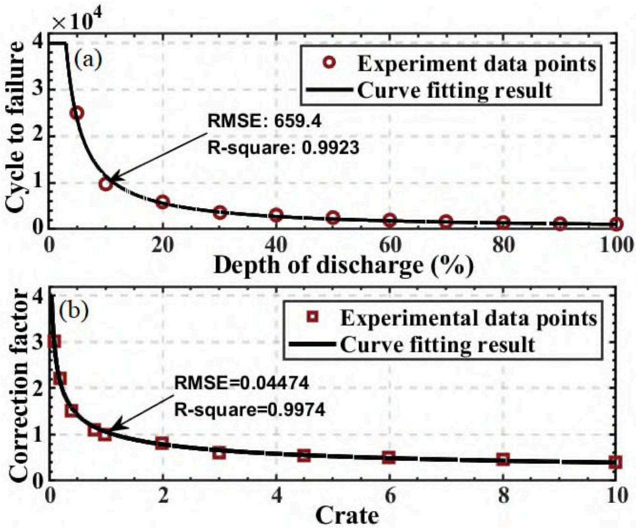

Fig. 2. Battery aging characteristic profile. (a) Battery cycle to failure value under different DODs; (b) correction factor value under different Crates.

In the established life loss quantification model, f_d quantifies battery life under different DoDs, f_{clc} reflects the impact of Crate. This study assumes that the Crate impacts battery life in the same way under different DODs to simplify the modeling process and reduce data requirements. Therefore, the product of f_d and f_{clc} is used to reflect maximum battery life under the current working state. The reciprocal of its value is used to describe battery percentage life loss under different DOD and Crate working states, which can be described by the following equation:

$$f_l(DOD, Crate) = \frac{1}{f_d(DOD) \cdot f_{clc}(Crate)} \times 100\% \tag{6}$$

Where: f_l is the function to quantify percentage battery life degradation degree.

IV. BATTERY AGING QUANTIFICATION BY ANALYZING CHARGING EVENTS

In vehicle energy storage system management, battery life loss should be dynamically calculated to derive optimal active anti-aging strategies. This section develops an analyzable deployment method for the establishment battery aging model based on charging event analysis.

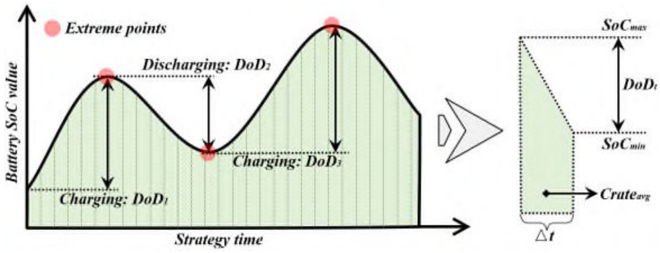

Fig. 3. Battery aging quantification model based on charging event analysis.

As shown in Fig. 3, in energy storage system management, the whole scheduling period can be divided into several dispatch time intervals. In each interval, the energy management controller schedules the charging and discharging power of the battery dynamically, and it is necessary to provide a battery life loss feedback signal to enable active anti-aging control. In this study, battery state of charge (SoC) values in energy management strategy are used as the observation variable to quantify the aging cost. Firstly, extreme points, where battery charging state changes, are labeled to divide the SoC profile into several independent discharging and charging events:

$$Ad_k = \begin{cases} 1 & (SoC_{k-1} - SoC_k)\cdot(SoC_k - SoC_{k-1}) > 0 \\ 0 & (SoC_{k-1} - SoC_k)\cdot(SoC_k - SoC_{k-1}) \le 0 \end{cases} \tag{7}$$

When extreme points appear, the value of Ad_k is labeled as 0, which indicates that a discharging or charging event is completed. Otherwise, the value of Ad_k will be labeled as 1 to indicate that battery is still in an incomplete charging or discharging half-cycle. Battery DoD is an accumulative process in a completed charging or discharging cycle. Therefore, the DoD is calculated under multi-intervals to quantify its impact on battery life loss in this study. Ad_k is used to decide whether the energy exchange in the previous interval will be accumulated. The accumulated energy output of the battery at k can be calculated by the following equation:

$$E_{bat,k} = Ad_k \cdot E_{bat,k-1} + P_{bat,k} \cdot \Delta t \tag{8}$$

Where: Δt is the duration of an energy management dispatch time interval; $P_{bat,k}$ is the working power of the battery pack at k. A complete cycle ends when the value of Ad_k is 0, and $E_{bat,k}$ is only decided by the battery discharging power in the current interval. Otherwise, $E_{bat,k-1}$ in previous intervals will be accumulated.

Based on the operation power and energy exchange, battery Crate and DOD at k can be calculated by the following equations:

$$\text{Crate}_k = \frac{P_{bat,k}}{U_{bat,k} \cdot Q_{bat}} \tag{9}$$

$$DoD_k = \frac{E_{bat,k}}{U_{bat,k} \cdot Q_{bat}} \tag{10}$$

Where: $U_{bat,k}$ and Q_{bat} are the terminal voltage and capacity of the battery. Battery life loss in current discharging and charging events can be represented as:

$$BL_k = f_l(DoD_k, \text{Crate}_k) \tag{11}$$

The instant battery life loss signal is calculated by constructing the following differential signal that compares the difference between BL_k and BL_{k-1}, which can be represented by the following function:

$$f_{ibl}(P_{bat,k}) = BL_k - Ad_k \cdot BL_{k-1} \tag{12}$$

The value of Ad_k is calculated based on (7), which judges the extreme points in the SoC profile. When a new cycle appears, its value will be set as 0, and battery life loss is fully influenced by battery charging and discharging behavior in the current interval. Otherwise, the value of Ad_k will be set to 1, and the battery life loss will be determined by the difference between BL_k and BL_{k-1} to avoid repetitive calculation.

V. BATTERY ANTI-AGING VEHICLE BESS ENERGY MANAGEMENT METHOD

Based on the established battery life loss quantification model, this section further proposes an anti-aging energy management method for vehicle BESS in V2G and PHEV power distribution scenarios.

A. *Battery anti-aging V2G behavior management*

V2G scheduling is a complex optimization problem that relates to the electricity market and trading. This study mainly focuses on the quantification and mitigation of BESS aging. Therefore, a most basic and simple V2G mode: aggregated GEVs oriented peak-shaving services, are studied.

In the developed anti-aging V2G behavior management model, the decision variable $\mathbf{V}^{ref}$ is designed as the charging and discharging power of GEVs, which can be represented as:

$$\mathbf{V}_i^{ref} = \begin{bmatrix} V_{i,k}^{ref} & V_{i,k+1}^{ref} & \cdots & V_{i,k+T}^{ref} \end{bmatrix} \tag{13}$$

$$\mathbf{V}^{ref} = \{\mathbf{V}_1^{ref}, \cdots, \mathbf{V}_n^{ref}\} \tag{14}$$

Where: $V_{i,k}^{ref}$ is vehicle V2G power of i^{th} GEVs at k; T is the length of the scheduling period; n is the number of GEVs.

Based on the presumed V2G power of GEVs, the grid power balance state is calculated by the following equation:

$$PB_k = \sum\nolimits_{i=1}^{n} V_{i,k}^{ref} + P_{load,k} - P_{ref} \tag{15}$$

Where: P_{load} represents grid demand state. P_{ref} is the peak-shaving reference value provided by the distribution network operator [40].

The established battery life loss model in Sections III and IV is used to quantify BESS aging cost in V2G services by analyzing the impact of Crate and DoD caused by charging and discharging power of GEVs:

$$C_{aging,k} = \sum_{i=1}^{n} C_{bat,i} \cdot Q_{bat,i} \cdot f_{ibl}(V_{i,k}^{ref}) \tag{16}$$

Where: C_{bat} is the unit cost of the vehicle battery system.

The optimization target is designed to reduce battery aging cost of all GEVs while providing peak-shaving services:

$$J_V = \sum_{k=1}^{k+T} \alpha_1 \cdot C_{aging,k} + \alpha_2 \cdot PB_k \tag{17}$$

Where: α_1 and α_2 are the weight factors between different optimization targets.

BESS management constraints in V2G are set to subject the battery discharging power (17) and SoC states (18) in the scheduling period. Furthermore, the battery SoC value at k should be higher than the benchmark value $\mathrm{SoC}_{cu,k}$ that reflects the charging urgency [41] of GEVs to satisfy the charging requirement, as described in (19). The detailed constraints are listed as follows:

$$-P_{i,\mathrm{dis}}^{\max} \le V_{i,k}^{ref} \le P_{i,\mathrm{ch}}^{\max} \tag{18}$$

$$\mathrm{SoC}_{\min} \le \mathrm{SoC}_{i,k}^{ref} \le \mathrm{SoC}_{\max} \tag{19}$$

$$\mathrm{SoC}_{i,k}^{ref} \ge \mathrm{SoC}_{cu,k} \tag{20}$$

Where: $P_{i,\mathrm{dis}}^{\max}$ and $P_{i,\mathrm{ch}}^{\max}$ are the maximum discharging and charging power of GEVs; $\mathrm{SoC}_{\min}$ and $\mathrm{SoC}_{\max}$ are the minimum and maximum battery SoC values. $\mathrm{SoC}_{i,k}^{ref}$ is battery SoC value at k, which is calculated based on V2G power of GEVs. The calculation of $\mathrm{SoC}_{i,k}^{ref}$ can be represented as:

$$\mathrm{SoC}_{i,k}^{ref} = \mathrm{SoC}_{i,k-1}^{ref} + \frac{V_{i,k}^{ref} \cdot \Delta t}{Q_{bat,i}} \tag{21}$$

The anti-aging V2G strategies are derived by minimizing (17) subject to constraints (18)-(20), which can be represented by the following optimization problem:

$$\begin{aligned} &\min_{\mathbf{V}^{ref}} J_V(\mathbf{V}^{ref}) \\ &\text{subject to } (18) \sim (20) \end{aligned} \tag{22}$$

B. Battery anti-aging PHEV energy management

In PHEV, BESS is used to work with the fuel engine for providing power ancillary services. In this study, the decision variable is designed as the output power of BESS to facilitate flexible vehicle power system operation scheduling, which can be represented as:

$$\mathbf{B}^{ref} = \begin{bmatrix} B_k^{ref} & B_{k+1}^{ref} & \cdots & B_{k+T}^{ref} \end{bmatrix} \tag{23}$$

Battery aging cost in PHEV energy management strategies is quantified based on the established BESS aging model in Sections III and IV by the following equation:

$$C_{aging,k} = C_{bat} \cdot Q_{bat} \cdot f_{ibl}(B_k^{ref}) \tag{24}$$

Vehicle fuel and electricity cost is calculated according to the engine and motor efficiency maps shown in Fig. 4 by the following equations:

$$C_{elec,k} = \rho_{elec} \cdot \eta_{bat} \cdot B_k^{ref} \cdot \eta_m(n_m, T_m) \tag{25}$$

$$C_{fuel,k} = \rho_{fuel} \cdot (P_d - \eta_{bat} \cdot \eta_m \cdot B_k^{ref}) \cdot b_e(n_e, T_e) \tag{26}$$

Where: ρ_{elec} and ρ_{fuel} are the unit cost of electricity and fuel. η_{bat} and P_d are BESS efficiency and vehicle power requirement. b_e and η_m are calculated according to the motor efficiency map (a) and engine fuel consumption map (b) based on engine speed n_e, engine torque T_e, motor speed n_m, and motor torque T_m. The detailed system efficiency and dynamic coupling relationship between n_m, T_m, n_e, T_e, and P_d of the studied PHEV can be found in [42].

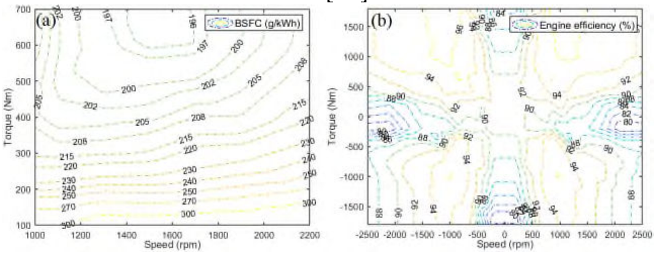

Fig. 4. The (a) fuel consumption map of the engine and (b) working efficiency map of the driving motor.

The optimization target is to reduce fuel cost, electricity cost, and battery aging cost while providing power ancillary services to PHEV. Accordingly, the following optimization objective function is formulated to derive the energies management strategies:

$$J_B = \sum_{k=1}^{k+T} (C_{fuel,k} + C_{elec,k} + C_{aging,k}) \tag{27}$$

Scheduling constraints are set to subject the output power of the electric motor (28) and internal combustion engine (29). Furthermore, the battery SoC state is constrained by (30). The detailed constraints adopted in the PHEV energy management are listed as follows:

$$P_{m\_\min} \le P_{\mathrm{m,k}}^{ref} \le P_{m\_\max} \tag{28}$$

$$P_{\mathrm{e}\_\min} \le P_{\mathrm{e,k}}^{ref} \le P_{\mathrm{e}\_\max} \tag{29}$$

$$\mathrm{SoC}_{\min} \le \mathrm{SoC}_k^{ref} \le \mathrm{SoC}_{\max} \tag{30}$$

Where: $P_{m\_\min}$, $P_{\mathrm{e}\_\min}$, $P_{m\_\max}$, and $P_{e\_\max}$ are minimum and maximum working power of motor and engine. $P_{\mathrm{m,k}}^{ref}$, $P_{\mathrm{e,k}}^{ref}$, and SoC_k^{ref} are the working power of engine, motor, and battery SoC at k, which are calculated based on BESS working power and PHEV power requirement:

$$P_{\mathrm{m,k}}^{ref} = \eta_{bat} \cdot B_k^{ref} \tag{31}$$

$$P_{\mathrm{e,k}}^{ref} = P_{d,k} - \eta_{bat} \cdot \eta_m \cdot B_k^{ref} \tag{32}$$

$$\mathrm{SoC}_k^{ref} = \mathrm{SoC}_{k-1}^{ref} - \frac{B_k^{ref} \cdot \Delta t}{Q_{bat}} \tag{33}$$

The optimal BESS operation strategies are derived by minimizing (27) subject to constraints (28)-(30), which can be represented by the following optimization problem:

$$\begin{aligned} &\min_{\mathbf{B}^{ref}} J_B(\mathbf{B}^{ref}) \\ &\text{subject to } (28) \sim (30) \end{aligned} \tag{34}$$

C. Strategy deployment and model solving

The deployment of the established online vehicle BESS operation scheduling model is realized in a two-stage optimization framework as shown in Fig. 5. In the first stage, anti-aging strategies are derived based on the established optimization model in (22) and (34). Both the defined V2G behavior management and PHEV power distribution models are nonlinear programming problems with multiple time periods due to the use of a nonlinear instant battery life loss quantification function. The Generic Dynamic Programming Matlab Function in [43], which is specially designed for solving nonlinear vehicle BESS operation optimization problems, is employed in this study to solve the established optimization model. It has great versatility and can solve the optimization problem with various cost functions (even the table look-up function is acceptable). For this reason, it has been commonly used in BESS energy management problems in electric vehicles [44, 45], grid energy storage systems [46, 47], and intelligent transportation systems [48]. Based on the optimization problem in (22) and (34), the optimal anti-aging V2G strategy $\mathbf{V}^{ref}$ and PHEV distribution strategy $\mathbf{B}^{ref}$ are solved by the dynamic programming algorithm.

Fig. 5. The solving of the established anti-aging vehicle BESS operation scheduling model.

In practical vehicle BESS management, vehicle charging demand and PHEV torque requirement may differ from those in ideal conditions due to the uncertain vehicle usage and operation states. Different from the management of conventional stationary energy storage systems, vehicle BESS should be online scheduled to respond to the unplanned vehicle charging and operation conditions [42, 49]. The anti-aging BESS management model can only provide day-ahead or hour-ahead strategies, which dramatically limits the flexibility of vehicle BESS operation. Therefore, to facilitate strategy deployment in practical vehicle energy management, this study further proposes an online deployment scheme for the derived anti-aging BESS energy management strategy. As shown in Fig. 5, in the second stage, vehicle BESS operation is online scheduled by following the anti-aging strategies $\mathbf{V}^{ref}$ and $\mathbf{B}^{ref}$. The anti-aging target is realized by following the optimal solution from the first stage. Dynamic vehicle charging requirements and PHEV power requirements are strictly satisfied by setting constraints on online BESS working power in the second stage.

In online V2G behavior management, the decision variable is designed as the practical charging and discharging power of GEVs. The actual V2G power of i^{th} GEV is labeled as V_i^{ol}, and the online V2G behavior coordination is modeled as a quadratic programming problem:

$$
\begin{aligned}
&\pi_V = \arg\min_{\mathbf{V}_k^{ol}} \sum\nolimits_{i=1}^{n} (V_{i,k}^{ol} - V_{i,k}^{ref})^2 \\
&s.t. \\
&-P_{i,\mathrm{dis}}^{\max} \le V_{i,k}^{ol} \le P_{i,\,\mathrm{ch}}^{\max} \\
&\mathrm{SoC}_{\min} \le \mathrm{SoC}_{i,k}^{ol} \le \mathrm{SoC}_{\max} \\
&\mathrm{SoC}_{i,k}^{ol} \ge \mathrm{SoC}_{cu,k}
\end{aligned}
\tag{35}
$$

Where: $\mathbf{V}_k^{ol}$ is the collection of $V_{i,k}^{ol}$, which represents the actual V2G power of all GEVs at k. $\mathrm{SoC}_{i,k}^{ol}$ is the actual battery SoC value, which is calculated based on $V_{i,k}^{ol}$ by Eq. (21). The online V2G strategy π_V is derived by solving the constrained optimization problem in (35).

In PHEV energy management, the decision variable is designed as the practical working power of BESS. The actual BESS working power at k is labeled as B_k^{ol}. Online PHEV power distribution is realized by following the anti-aging strategy B_k^{ref} in the scheduling period to provide dynamic auxiliary power for the vehicle driving system, which can be described as:

$$
\begin{aligned}
&\pi_B = \arg\min_{B_k^{ol}} (B_k^{ol} - B_k^{ref})^2 \\
&s.t. \\
&P_{m\_\min} \le P_{\mathrm{m,k}}^{ol} \le P_{m\_\max} \\
&P_{\mathrm{e}\_\min} \le P_{e,k}^{ol} \le P_{\mathrm{e}\_\max} \\
&\mathrm{SoC}_{\min} \le \mathrm{SoC}_k^{ol} \le \mathrm{SoC}_{\max}
\end{aligned}
\tag{36}
$$

Where: $P_{\mathrm{m,k}}^{ol}$, $P_{e,k}^{ol}$, and SoC_k^{ol} are the actual working power of motor, engine, and battery SoC state, which are calculated based on B_k^{ol} by Eq. (31)~(33). The online PHEV energy management strategy π_B is derived by solving the constrained optimization problem in (36).

Both the established strategy deployment model in V2G scheduling and vehicle power distribution are solved by a mixed-integer programming toolbox provided by Gurobi 9.1.0 optimizer [50].

VI. Case Study

This section verifies the effectiveness of the established multifactorial battery life loss quantification model and anti-aging energy management method. Two cases are employed to evaluate performance: V2G peak-shaving services in distribution networks and PHEV energy management. Battery active anti-aging vehicle charging management

GEVs are considered to provide peak-shaving services to a distribution network in this study for verifying the effectiveness of the established battery aging model in V2G scheduling. Grid demand data [51] comes from the Stentaway Primary substation near Plymouth, which is open-access provided by Western Power Distribution in the UK, is used in this study as a basic load profile. The period (16:00~08:00) that owns the most active grid energy consumption and GEVs charging requirement is studied, and the corresponding grid demand profiles within 30 working days are shown in Fig. 6. In this study, V2G scheduling for aggregators at the charging station and residential area, where GEVs can be regarded as fixed energy storage devices in a specific timeframe, is carried out to explore the potential benefit of the developed method. The national household travel survey data [52] is employed to characterize the trip behavior of GEVs, and the Monte Carlo simulation model is used to simulate GEVs' grid-connected timeframe. This paper mainly focuses on mitigating BESS aging in V2G services. Therefore, GEVs are assumed to be with firm connection timeframes in the simulation period and their uncertainty is not considered.

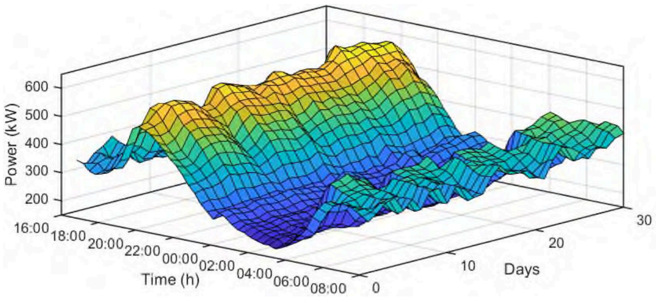

Fig. 6. The demand profile within 30 days of the studied distribution network.

In this study, charging behaviors of 30 GEVs each with a 60 kWh battery pack, are simulated to provide peak-shaving service, and the peak-shaving reference value is set as 400 kW. The peak-shaving and battery anti-aging performance of the developed method (Case 4) is quantitively compared with conventional online scheduling method (Case 2) and off-line rain-flow anti-aging (ORA) method [53] (Case 3) in Fig. 7. The V2G behavior of the whole GEV fleet within 30 working days is simulated. In terms of power balancing service, as shown in (a) and (b), all three methods can significantly stabilize the grid demand. Compared to baseload (Case 1), average grid load fluctuation and the peak-valley difference can be reduced by around 68.6% and 57.4% in the simulation period, which validates the effectiveness of V2G scheduling. It should be figured out that the set of battery aging mitigation targets shows a very limited impact on V2G power balancing performance. Battery utilization degree decreases 4.3% in the developed IBLEM method.

The battery anti-aging performance of different methods is compared in Fig. 7 (c) and (d). After the anti-aging optimization target is deployed, battery DoD and aging cycles can be significantly reduced by around 22.9% and 56.1% on average in ORA method and the developed IBLEM method. Compared to the ORA method, IBLEM method shows more outstanding performance (4.7% more) in mitigating battery DoD. The reason is that the developed life loss quantification model can better characterize the aging mechanism of the vehicle battery. However, due to lacking global optimization mechanism, the battery undergoes 17.2% more cycles in the IBLEM method compared to the ORA method. In quantitative analysis, more than 54.3% battery life loss can be avoided while providing the same peak-shaving service to the grid, which validates the effectiveness of the developed IBLEM method in GEVs charging management.

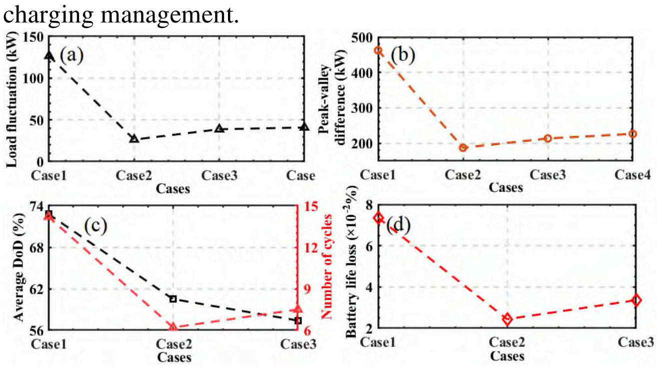

Fig. 7. Quantitative performance comparison of different methods on GEVs fleet. (a) load fluctuation mitigation; (b) peak-shaving difference; (c) battery cycles and DoD; (d) quantified battery life loss.

In engineering applications, the benefits of joining peak-shaving services and the cost of battery aging can be balanced by minimizing the total cost of V2G service, which can be calculated based on bi-directional peak-valley electricity price and battery unit cost. Various power systems and GEVs are with different electricity price states and battery unit costs. Therefore, the balance between the benefit of joining peak load shaving services and the cost of battery aging changes in different V2G scenarios. This study further verifies the anti-aging performance of the developed IBLEM-based V2G scheduling method under different peak-shaving intensities. Fig. 8 shows the vehicle battery life loss under different peak-shaving reference values. The lower the preset peak-shaving value, the more the V2G auxiliary power is required, and the more the battery life will be depleted. Vehicle battery life loss reduces with the improvement of peak-shaving reference value. When the peak-shaving reference value improves by 40%, battery life loss can be limited to 2.03×10-2%, which validates the battery anti-aging effectiveness of the developed IBLEM method. It should be figured out that battery life loss dramatically increases when the change of peak-shaving value reaches -30%. The reason is that the satisfying of peak-shaving requirements is emphasized in the developed scheduling algorithm. When GEVs' energy storage capacity is not enough to support V2G services, battery anti-aging targets will be neglected in the scheduling algorithm to some extent.

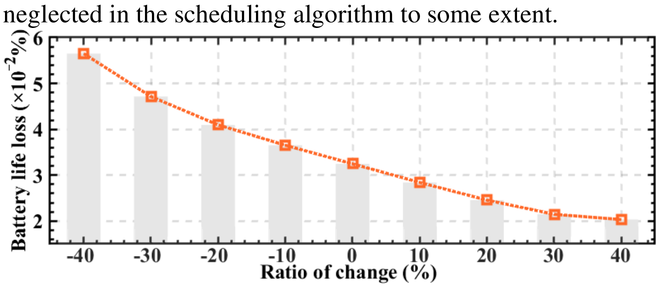

Fig. 8. Vehicle battery life loss under different grid peak-shaving reference values.

It should be noted the realization of bi-directional V2G services from residential EVs is still challenging because it highly depends on the electricity market, energy trading, and smart charging pile technologies. This study mainly focuses on quantification and mitigation of BESS aging, and V2G is simplified to a peak-shaving optimization problem. Future work can be conducted on deploying the battery life loss quantification model and aging mitigation methods in V2G with a realistic energy market and trading scenario.

A. Hybrid electric vehicle energy management

A plug-in hybrid electric bus [54] weights 18000 kg with a 147 kW fuel engine, a 65 kW ISG motor, a 168 kW main driving motor, and a 34.5 kWh battery pack is studied in this part to verify the performance of the developed battery anti-aging energy storage system management method. The Chinese Typical Urban Drive Cycles (CTUDC) is used in this study to simulate vehicle daily operation, the velocity and acceleration profiles are shown in Fig. 9 (a) and (b). Battery energy storage system is used to work with the fuel engine and ISG motor to improve the vehicle working efficiency. Based on the engine and ISG efficiency map and battery aging model, vehicle power requirement in driving cycles is distributed between fuel engine and battery pack by the developed time-windowed energy management method, the corresponding engine and battery output power profiles in 6 CTUDC cycles are shown in (c). Instead of fuel engine, battery is used as the main power source to power vehicle driving systems in most of the simulation period (more than 84%). With the anti-aging feedback signal and economic objectives, fuel engine only works under the following two scenarios: (1) when the peak power requirement appears during the vehicle acceleration, fuel engine works with BESS to reduce the Crate of the battery and prolong its life. (2) fuel engine works with ISG motor to charge energy back to the battery to sustain its SoC level and mitigate DoD of operation cycles. In the whole simulation period, fuel engine can work within a high-efficiency area for 86% more time, which highlights the effectiveness of the developed time-windowed optimal control method.

Battery SoC profiles in conventional energy management strategy (EMS) [55] and the developed active anti-aging method are further compared in Fig. 9 (d). In the conventional EMS method, the improvement of engine fuel economy is used as the single optimization objective; thus, the battery undergoes many cycles with high Crate to satisfy vehicle power requirements. Compared to the conventional method, battery anti-aging is also considered in the developed energy management method. Therefore, as shown in the detailed view, battery number of cycles and the corresponding Crates are significantly reduced after the multifactorial battery life loss model and the aging feedback signal is deployed. It should be figured out that the mitigating of battery aging cost is not realized by sacrificing vehicle fuel economy. As shown in (d), battery SoC profiles end at almost the same points after 6 CTUDC cycles, which indicates that the battery provides a similar energy output in both methods.

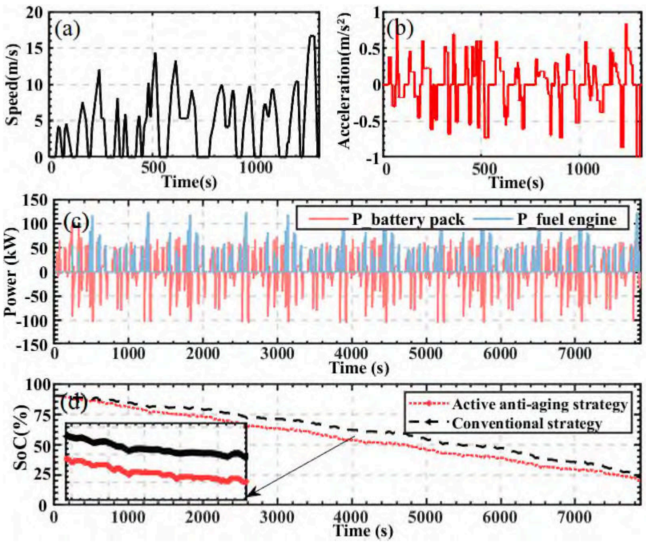

Fig. 9. PHEV power distribution results with the developed anti-aging method. (a) vehicle speed profile; (b) vehicle acceleration profile; (c) engine and battery power profile; (d) battery SoC profile.

The long-term operation cost of different PHEV energy management strategies is quantitatively compared in Table I to better illustrate the improvement. It is assumed that each PHEV needs to operate 12 CTUDC cycles per day and 300 days per year, and its set life is assumed to be 10 years. The unit price of the battery is set as 600\$/kWh, the price of diesel is set as 1.04\$/liter, and the electric price is assumed to be 0.18\$/kWh. In terms of fuel cost, the deployment of anti-aging algorithm is not able to reduce its value. On the contrary, the set of anti-aging target limit the use of battery in energy management algorithm, and thus the working period of the fuel engine is inevitably increased. The bucket model [56] limits the sum of battery discharging energy directly, and vehicle fuel cost is elevated by 26.1% compared to conventional EMS. The developed IBLEM method can better model the aging characteristics and improve the utilization degree of the battery. Both energy management strategies that consider degradation cost consume less electricity because of the set of battery anti-aging target, but the IBLEM method can provide 15.1% more electricity to improve vehicle fuel economy. As a result, EMS with the IBLEM method keeps a similar (4% higher only) fuel cost compared to conventional EMS. The use of the bucket model can directly limit the discharging energy of the battery in the energy management algorithm. Therefore, as shown in Table I, the battery degradation cost is reduced by 26.3% compared to conventional EMS. Compared to the bucket model, the developed IBLEM method can comprehensively evaluate battery life loss, and thus the degradation cost in energy management strategy is further reduced by 8.9% compared to the bucket model.

TABLE I. LONG-TERM OPERATION COST COMPARISON OF PHEV WITH DIFFERENT ENERGY MANAGEMENT STRATEGIES

Parameters	Conventional EMS	Anti-aging bucket model	Anti-aging MPC method	IBLEM method
Fuel cost (\$/year)	1865.3	2352.5	1896.4	1939.4
Electricity cost (\$/year)	1426.5	1074.2	1211.7	1288.7
Battery degradation cost (\$/year)	3874.6	2855.8	2946.3	2494.3
Total cost (\$/year)	7166.4	6282.5	6054.4	5722.4
Cost comparison (%)	100	87.7	84.5	79.8

In Table I, the developed IBLEM method is also compared with the model predictive control (MPC) method [57], the most commonly used PHEV energy management scheme in the existing literature. The IBLEM method greatly outperforms the MPC in terms of reducing battery degradation costs. The battery anti-aging target can hardly be realized by using the simple MPC method because of the limited observation window length. PHEV battery aging cost is reduced by 15.3% in the IBLEM method, which validates its battery aging mitigation performance. From the total operation cost perspective, the developed IBLEM method can further improve 20.2%, 7.9%, and 4.7% vehicle economy compared to conventional EMS, bucket model, and MPC method, which validates the effectiveness of the developed multifactorial battery life loss quantification model and anti-aging energy management method.

VII. CONCLUSION

An integrated battery life loss modeling and anti-aging energy management method is developed in this paper for mitigating the degradation cost of BESS. BESS aging cost is quantified by establishing a multifactorial degradation model based on cell acceleration aging test datasets. Meanwhile, the deployment of the aging model is realized by a charging event analysis method. The built battery life loss quantification model is deployed in V2G scheduling and PHEV power distribution to realize anti-aging energy management. Some key findings are given:

- The established multifactorial battery life loss model can accurately quantify BESS usage cost under different working conditions (DoDs and Crates). Battery aging costs in both V2G scheduling and PHEV energy management can be significantly reduced by using the generated life loss feedback signal.
- In V2G scheduling, the anti-aging method shows a significant advantage in mitigating battery number of cycles and DoDs while guaranteeing peak-shaving performance.
- In vehicle energy management, the developed IBLEM method yields less-conservative strategies, and thus the total economy of PHEV can be improved while mitigating battery aging.

The proposed IBLEM method presents a practical solution to quantify and mitigate battery aging by optimizing energy management strategies. It also brings a promising solution to improve the total economy of BESS in providing V2G services and PHEV usage, thus helping incentive the adoption of EVs in the future transport sector to reduce emissions.

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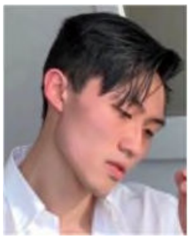

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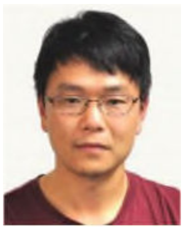

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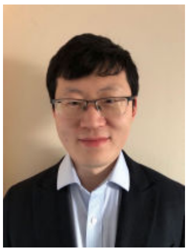

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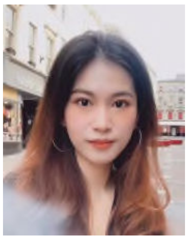

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Ageing mitigation for battery energy storage system in electric vehicles

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