

Linearizing Battery Degradation for Health-aware Vehicle Energy Management

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Abstract—The utilization of battery energy storage systems (BESS) in vehicle-to-grid (V2G) and plug-in hybrid electric vehicles (PHEVs) benefits the realization of net-zero in the energy-transportation nexus. Since BESS represents a substantial part of vehicle total costs, the mitigation of battery degradation should be factored into energy management strategies. This paper proposes a two-stage BESS aging quantification and health-aware energy management method for reducing vehicle battery aging costs. In the first stage, a battery aging state calibration model is established by analyzing the impact of cycles with various Crates and depth of discharges based on a semi-empirical method. The model is further linearized by learning the mapping relationship between aging features and battery life loss with a linear-in-the-parameter supervised learning method. In the second stage, with the linear battery life loss quantification model, a neural hybrid optimization-based energy management method is developed for mitigating vehicle BESS aging. The battery aging cost function is formulated as a linear combination of system states, which simplifies model solving and reduces computation cost. The case studies in an aggregated EVs peak-shaving scenario and a PHEV with an engine-battery hybrid powertrain demonstrate the effectiveness of the developed method in reducing battery aging costs and improving vehicle total economy. This work provides a practical solution to hedge vehicle battery degradation costs and will further promote decarbonization in the energy-transportation nexus.

Index Terms—Electric vehicle, battery energy storage system, battery aging, model-data-driven method, energy management, vehicle to grid.

ABBREVIATIONS

BESS	Battery energy storage system.
V2G	Vehicle to grid.
PHEV	Plug-in hybrid electric vehicle.
EVs	Electric vehicles.
GEVs	Grid-connected electric vehicles.
ICE	Internal combustion engine.

Crate	Charging and discharging rate.
SoC	State of charge.
DoD	Depth of discharge.
RFCC	Rain-flow cycle counting.
ELM	Extreme learning machine.
ISG	Integrated starter generator.
CTUDC	Chinese typical urban drive cycles.

NOMENCLATURE

S_k	BESS working state vector at k .
SoC_k	BESS energy state at k .
P_k	BESS working power states at k .
RI	RFCC algorithm input matrix.
RO	Extracted battery aging feature matrix.
$f_{rainflow}$	RFCC function for extracting aging cycles.
C_i	Extracted battery aging features in i^{th} cycle.
DoD_i	Battery DoD in i^{th} cycle.
$Crate_i$	Battery Crate in i^{th} cycle.
Φ, Ψ	Function to quantify the influence of DoD and Crate on battery aging.
ζ_i	Battery cycle life loss contributed by i^{th} cycle.
L	Quantified battery life loss state.
f_{loss}	Battery life loss quantification function.
A_n^s, A_n^p	Battery SoC and output power time-series at n .
F^{ag}	Constructed aging feature matrix.
BS, BP	BESS SoC and output power states matrixes.
$D_{m,n}$	Battery life loss in the period of $n-m$.
H	ELM network weight matrix.
f_{linear}	Linear battery aging quantification function.
L	Quantified battery life loss by ELM model.
x_k, y_k	System state and output vector in EMS.
u_k, d_k	System input and the disturbance vector in EMS.
S_{EV_i}	SoC of BESS in GEV_i .
P_{EV_i}	Auxiliary V2G power provided by GEV_i .
S_{EV_i}	Battery SoC profile in energy management.

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$\mathbf{P}_{EV_i}$	Battery power profile in energy management.
$\hat{L}_{bat,i}$	Quantified BESS life loss of GEV_i .
$C_{bat,i}$	Unit cost of the battery pack in GEV_i .
$Q_{bat,i}$	Capacity of the vehicle battery pack in GEV_i .
J_{vag}	Battery aging cost function in V2G management.
f_{phev}	PHEV power system state transfer function.
C_{aging}	Function to calculate battery aging cost of PHEV.
C_{fuel}	Function to calculate fuel cost of PHEV.
C_{elec}	Function to calculate electricity cost of PHEV.
J_{eco}	Vehicle operation cost function in PHEV.

I. INTRODUCTION

IN recent years, the electrification of the automotive industry has been identified as a potential solution for mitigating energy and environmental issues. The adoption of electric vehicles (EVs), including battery and hybrid electric vehicles, makes it possible to reduce fossil fuel consumption and shift air pollution to energy generation sectors. For example, the concept of plug-in hybrid electric vehicles (PHEV), which uses electrical driving systems for improving internal combustion engine (ICE) efficiency and vehicle fuel economy, has been recognized by many countries as an effective way to realize carbon neutrality. Further, the extra energy storage capacity provided by EVs also brings a bright prospect to improve the efficiency, economy, and renewable energy penetration of the power grid. According to [1], by deploying vehicle-to-grid (V2G) technology, more than 95% of carbon dioxide emissions can be reduced in future electricity scenarios in the UK.

The electrification of the transportation system and the adoption of EVs has become an irreversible trend in all the attached sectors. However, to enable this benefit, the most costly and delicate equipment: the battery energy storage system (BESS), should be effectively protected. The bucket model is the most commonly used anti-aging model in the existing literature, where BESS protection is realized by directly limiting minimum battery energy throughput, maximum charging and discharging rate (Crate), and state of charge (SoC) level through online energy management algorithms [2, 3]. BESS aging is modeled as a function of energy throughput under different SoC states in [4]. The established model shows great effectiveness in prolonging the life of a battery and supercapacitor hybrid energy storage system. In [5] and [6], Crate is further considered to better characterize battery aging. The optimal BESS energy storage capacity dispatching is realized by a rule-based control model, where battery energy throughput and Crate are limited to prolong the system lifespan.

Limiting battery energy throughput and Crate is the most straightforward BESS aging mitigation method with better algorithm interpretability [7]. However, strict limitations negatively also impact energy storage capacity utilization in auxiliary services. According to [6], in a PHEV with ICE and battery hybrid energy storage system, vehicle fuel economy decreases by around 7.5% after battery aging mitigation constraints are deployed. The limitation of battery Crate inevitably burdens the ICE system workload. Further, the

battery pack is an electrochemical system with complex degradation mechanisms, and its aging can hardly be described by energy throughput and Crate directly. Literature [8] and [9] point out that the hidden aging features, which represent in an accumulative way with BESS operation, also greatly impact battery lifespan. The battery number of cycles and the corresponding depth of discharge (DoD) are the most significant hidden aging features that impact BESS aging. A multi-factor battery cycle life prediction method is proposed in [10] to quantify BESS life loss. Results on a smartphone and a household BESS validate the necessity of identifying accumulative aging parameters in battery life prediction.

The rain-flow cycle counting (RFCC) algorithm, which has been widely used in analyzing the accumulative aging phenomenon of metallic material [11], mechanical systems [12], and power electronic devices [13], also shows great effectiveness in extracting battery aging cycles and quantifying battery degradation [14, 15]. In the existing literature, RFCC-based battery aging quantification models are mainly used for offline BESS operation scheduling and energy system configuration optimization. In [16], an equivalent charge cycle estimation method is built based on RFCC to evaluate battery life loss in providing power balancing services. Simulation results validate model significance for investigating BESS optimal configuration in microgrids. Further, battery aging cost is quantified by analyzing battery cycles and DoD extracted from BESS operation profiles in [17]. The anti-aging BESS operation in day-ahead energy and frequency regulation markets is carried out by minimizing battery aging costs. The RFCC is able to quantify the influence of various aging factors on battery degradation. Based on battery life loss quantification results, anti-aging BESS configuration and energy management optimization can be realized offline.

Nevertheless, the essence of RFCC is an abstract function without any analytical mathematical expression, which seriously burdens energy management optimization model solving [18, 19]. In recent years, many efforts have been made to simplify the RFCC algorithm to analytical expression. Literature [20] decomposes the RFCC-based battery degradation model and optimizes BESS operation iteratively. This method yields efficient dispatch results in mitigating battery aging cycles but shows limited effectiveness in reducing DoD and Crate. The reason is that it mainly focuses on suppressing battery aging on a large time-scale. Most important, the simplified aging model is still too complicated to be incorporated into online vehicle BESS management. As an improvement, a piecewise linearization method is further proposed in [21] to quantify aging costs. The cycle depth is simplified to BESS energy output within each control time interval by analyzing battery charging and discharging transitions. It enables the incorporation of DoD and Crate in the optimization of BESS operation but shows limited effectiveness in reducing aging cycles. Supervised learning methods, particularly extreme learning machine (ELM), bring a bright perspective to accurately approximate battery cycle aging mechanisms. Further, it is a strict linear-in-the-parameter model, which can be easily incorporated into online vehicle BESS

energy management. However, to the best of our knowledge, no research has been reported regarding this issue.

To address the above research gap, this paper establishes a two-stage model-data-driven BESS aging quantification and health-aware energy management method for reducing the vehicle battery aging cost. In the first stage, a battery aging state calibration model is established by comprehensively analyzing the impact of battery cycles with various Crates and DoDs. The established model is linearized by learning the relationship between aging features and quantified battery life loss in BESS operation profiles based on the ELM algorithm. In the second stage, with the established linear battery life loss quantification model, a neural hybrid optimization-based energy management method is developed for mitigating vehicle BESS aging. The battery aging cost function is formulated as a linear combination of system states, which simplifies model solving and reduces computation cost. The case studies on an aggregated GEVs peak-shaving scenario and a PHEV with an engine-battery hybrid powertrain demonstrate the effectiveness of the developed method in reducing vehicle battery aging costs and improving vehicle total economy.

The novelty and technical contribution of this paper can be summarized as follows:

- This paper proposes an integrated battery aging quantification and mitigation energy management scheme based on a novel model-data-driven method. From an engineering point of view, it provides a practical solution for reducing the degradation costs of BESS in both V2G services and PHEVs.
- It establishes a cycle life calibration model to label battery aging states in BESS operation profiles. Compared to the bucket model, battery life loss states can be accurately quantified by analyzing accumulative aging behaviors.
- It proposes a novel linearization method for the RFCC algorithm that provides a close approximation of battery cycle aging cost. The quantification of BESS life loss can be represented as a linear cost function of battery working states, which facilitates the model deployment in online vehicle energy management. Compared to conventional simplification methods, the developed method yields more accurate aging quantification results that comprehensively reflect the impact of cycle number, cycle depth, and Crate.
- It proposes a neural hybrid optimization-based anti-aging energy management method for vehicle BESS, where the cost function is formulated as a linear combination of power system working states. Compared to the conventional RFCC optimization method, the neural hybrid method simplifies model solving and reduces the computation cost of BESS management, which facilitates the deployment of anti-aging energy strategies.
- The developed methods are deployed to the two most common vehicle BESS management scenarios: V2G services and PHEV power distribution. V2G coordinator and BESS management unit can incorporate this model in battery management to reduce battery aging costs and improve vehicle total economy.

The remainder of this paper is organized as follows. Section

II presents the developed model-data-driven BESS aging quantification and health-aware management framework. Section III establishes a model-data-driven linear battery life loss quantification model. The proposed neural hybrid optimization-based BESS anti-aging operation scheduling method is presented in Section IV. Section V validates the effectiveness of the developed method in V2G services and PHEV energy management. The conclusions are drawn in Section VI.

II. MODEL-DATA-DRIVEN BESS AGING QUANTIFICATION AND HEALTH-AWARE MANAGEMENT FRAMEWORK

This section proposes a model-data-driven BESS aging quantification and health-aware management framework for reducing the vehicle battery aging cost. As shown in Fig. 1, a linear battery life loss quantification model is established in the first stage. Then, data-driven BESS energy management is realized in the second stage by utilizing a neural hybrid optimization model.

In the first stage, a model-data-driven linear battery life loss quantification model is established to quantify BESS aging costs in energy management strategies. Firstly, the state of battery life loss in BESS operation data is quantified and calibrated by a semi-empirical battery aging model by comprehensively analyzing battery cycle information, including Crate and DoD. Meanwhile, Battery SoC and working power trajectories are extracted to construct an aging feature matrix. With the BESS aging feature matrix and battery life loss in the observation window as training input and output, an ELM learning model is further established in a data-driven learning process. After the training, the mapping relationship between the aging feature matrixes and the quantified battery life loss states is learned by the ELM model. In this way, the ELM model can provide a close approximation of the cycle aging mechanism of BESS in vehicles. Meanwhile, it describes battery aging characteristics with linear equations, which simplify BESS life loss quantification in online vehicle energy management.

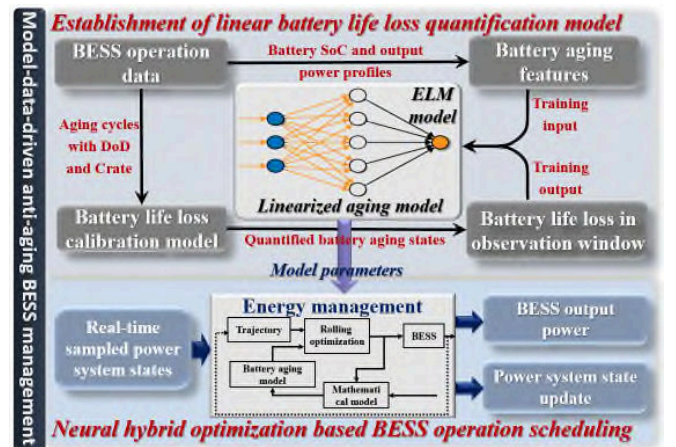


Fig. 1. Model-data-driven BESS aging quantification and health-aware management framework.

In the second stage, a neural hybrid optimization-based BESS operation scheduling model is established to realize data-

driven battery anti-aging energy management. The hyper-parameters in the ELM battery aging model are extracted to quantify BESS aging cost in energy management strategies. Battery anti-aging energy management can be modeled as a mathematical optimization problem by following real-time sampled system power requirements and minimizing battery aging costs. With the hyper-parameters extracted from the ELM model, battery life loss quantification can be modeled as a linear combination of BESS working states (SoC and output power). The anti-aging BESS management target can be realized by minimizing the value of the linear cost function, which simplifies model solving and reduces computing costs. In this study, the linear programming algorithm is used to solve optimal BESS management strategies online for satisfying the power requirements of PHEV and V2G services.

III. ESTABLISHMENT OF MODEL-DATA-DRIVEN LINEAR BATTERY LIFE LOSS QUANTIFICATION MODEL

This section establishes a linear battery aging model based on a model-data-driven method to quantify BESS life loss in energy management strategies. Firstly, a battery cycle life calibration model is established to label battery aging states in BESS operation profiles. Then, a linear battery life loss quantification model is built by learning the mapping relationship between aging features and quantified battery life loss states.

A. BESS cycle life calibration model

Battery aging is a slow and accumulative process that happens with the operation of BESS. To accurately quantify battery aging, BESS operation behavior should be globally and comprehensively analyzed. This part establishes a semi-empirical battery aging model to quantify and calibrate the state of battery life loss in BESS operation data by comprehensively analyzing battery cycle information, including Crate and DoD.

BESS output power and SoC states are used as observation variables of the established aging calibration model to analyze battery cycle life loss. The following vector is constructed to reflect BESS working states:

$$\mathbf{S}_k = [\text{SoC}_k \quad P_k]^T \quad (1)$$

Where: SoC_k and P_k are BESS energy and working power states at k . Model input is designed as BESS states in the whole operation period:

$$\mathbf{RI} = [\mathbf{S}_0 \quad \mathbf{S}_1 \quad \cdots \quad \mathbf{S}_k] \quad (2)$$

Two most significant aging characteristic parameters: DoD and Crate are used to quantify BESS life loss in this study. The RFCC method is employed here to analyze battery aging cycles from BESS working state profiles. The extracted battery aging characteristic parameter matrix $\mathbf{RO}$ can be represented as:

$$\mathbf{RO} = [\mathbf{C}_1 \quad \mathbf{C}_2 \quad \cdots \quad \mathbf{C}_i \quad \cdots \quad \mathbf{C}_n] = f_{\text{rainflow}}(\mathbf{RI}) \quad (3)$$

Where: $\mathbf{C}_i = [\text{DoD}_i \quad \text{Crate}_i]^T$ are the extracted battery DoD and Crate states in i^{th} cycle. f_{rainflow} is RFCC function for extracting battery aging cycles.

DoD and Crate are the common degradation parameters that characterize battery aging. In qualitative analysis, they impact

battery packs with different cell types to a similar degree: the higher the value of DoD and Crate, the more the battery life will be depleted [22]. The 'cycle-to-failure' method uses an empirical cycle depth stress function to quantify the impact of DoD and Crate on battery life. It has been proven effective in inferring the aging characteristics of BESS in energy bidding [20], renewable energy systems [22, 23], and electric vehicles [24] under different 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 [25] and [26], battery packs consisting of cells produced by the same manufacturer have extremely similar aging characteristics. Cell manufacturers usually provide an open-access experimental database as well as an empirical cycle depth stress function to facilitate the quantification and mitigation of battery aging in commercial applications [25, 27, 28]. Therefore, this study uses the empirical cycle depth stress function provided by the cell manufacturer to quantify the impact of cycles with various DoDs and Crates on vehicle BESS aging, which can be depicted by the following equations [29]:

$$\Phi(\text{DoD}) = 1 / (535.8 \cdot \text{DoD}^{-1.259} + 925.9) \times 100\% \quad (4)$$

$$\Psi(\text{Crate}) = 0.8943 \cdot \text{Crate}^{-0.494} + 0.1258 \quad (5)$$

In (4) and (5), Φ calculates percentage battery cycle life loss under different DoDs, while Ψ quantifying the influence of Crate on battery aging. Battery cycle loss in the i^{th} cycle can be derived by calculating the product of two functions:

$$\zeta_i = \Phi(\text{DoD}_i) \cdot \Psi(\text{Crate}_i) \quad (6)$$

Where: ζ_i is the calculated battery cycle life loss contributed by i^{th} cycle. Battery life loss in the whole simulation period $\mathbf{RI}$ can be calculated by accumulating ζ_i in different cycles:

$$L = f_{\text{loss}}(\mathbf{RI}) = \sum_{i=1}^n \zeta_i \quad (7)$$

Where: L and f_{loss} are the quantified battery life loss state and the corresponding quantification function.

B. Model linearization by extreme learning machine

Based on the BESS life loss assessment result, this part establishes a linear aging model by learning the mapping relationship between battery operation behaviors and the corresponding life loss states.

The aging feature matrix $\mathbf{F}^{\text{ag}}$ in the established linear aging quantification model is constructed as:

$$\mathbf{F}_{m,n}^{\text{ag}} = [\mathbf{BS}_{m,n} \quad \mathbf{BP}_{m,n}] \quad (8)$$

Where: $\mathbf{BS}_{m,n}$ and $\mathbf{BP}_{m,n}$ represent the collection of battery SoC and power states in the period $n-m$.

Based on the established battery aging calibration model, battery aging states at m and n are calculated independently, and their difference is used to reflect BESS life loss in this period:

$$D_{m,n} = L_n - L_m = f_{\text{loss}}(\mathbf{RI}_n) - f_{\text{loss}}(\mathbf{RI}_m) \quad (9)$$

Where: L_n , L_m , and $D_{m,n}$ are battery life loss states at m , n , and in the period of $n-m$.

In this study, the ELM algorithm, which has been commonly used in system identification [30] and regression analysis [31],

is further used to model the aging characteristics of BESS. Compared to conventional neural network algorithms, ELM is a naive linear model. It can simulate complex mapping relationships by only using linear functions but free of nonlinear activation functions, which facilitate model deployment in energy management algorithms. Based on the constructed aging features matrix and quantified battery life loss in (8) and (9), the establishment of the ELM model is realized by the following equation:

$$\min_{\beta \in \mathbb{R}^p} \|\mathbf{H} \cdot \mathbf{F}^{ag} - \mathbf{D}\|^2 \quad (10)$$

Where: $\mathbf{H}$ is the ELM network weight matrix, which is solved by the ridge regression in [32] by minimizing the value of (10).

After being trained by the constructed calibration dataset, battery aging characteristics can be learned and reflected by the weight matrix $\mathbf{H}$. Battery life loss quantification in energy management is realized by the following linear transformation:

$$\hat{L} = f_{linear}(\mathbf{F}^{ag}) = \sum_{j=1}^p H_j F_j = \mathbf{H} \mathbf{F}^{ag} \quad (11)$$

Where: f_{linear} is the constructed linear battery aging quantification function.

IV. NEURAL HYBRID OPTIMIZATION-BASED BESS ANTI-AGING OPERATION SCHEDULING METHOD

Based on the established linear battery life loss quantification model, this section further proposes a neural hybrid optimization-based anti-aging energy management method. System objectives and constraints are formulated into a time-windowed optimal control problem to facilitate data driven online vehicle BESS operation scheduling. A general linear time-varying discrete-time system shown in Eq. (12) and (13) subjecting to the time-varying constraints is introduced as the fundamental model of BESS energy management:

$$\mathbf{x}_{k+1} = \mathbf{A}_k \mathbf{x}_k + \mathbf{B}_k \mathbf{u}_k + \mathbf{B}_k \mathbf{d}_k \quad (12)$$

$$\mathbf{y}_k = \mathbf{C}_k \mathbf{x}_k + \mathbf{D}_k \mathbf{u}_k + \mathbf{D}_k \mathbf{d}_k \quad (13)$$

Where, the $\mathbf{x}_k$, $\mathbf{y}_k$, $\mathbf{u}_k$ and $\mathbf{d}_k$ are the system state vector with $\mathbf{x}_k^{\min} \leq \mathbf{x}_k \leq \mathbf{x}_k^{\max}$, $\mathbf{x} \in \mathbb{R}^n$, system output vector with $\mathbf{y}_k^{\min} \leq \mathbf{y}_k \leq \mathbf{y}_k^{\max}$, $\mathbf{y} \in \mathbb{R}^n$, system input vector with $\mathbf{u}_k^{\min} \leq \mathbf{u}_k \leq \mathbf{u}_k^{\max}$, $\mathbf{u} \in \mathbb{R}^n$, and the system disturbance vector, respectively. At each k , a set of system states are updated, and the battery anti-aging control problem is dynamically solved based on real-time sampled BESS states information by the linear optimization model.

A. Battery anti-aging V2G behavior management

In V2G scheduling, BESS in GEVs is used to provide power balancing services. Based on the power balance principle, the continuous-time system power management equation can be obtained as:

$$\dot{\mathbf{x}}_G = \mathbf{A}_G \mathbf{x}_G + \mathbf{B}_G \dot{\mathbf{u}}_G + \mathbf{B}_G \mathbf{d}_G \quad (14)$$

$$\mathbf{x}_G = [\mathbf{S}_{EV_0} \cdots \mathbf{S}_{EV_n}, \mathbf{P}_{EV_0} \cdots \mathbf{P}_{EV_n}]^T \quad (15)$$

Where: $\mathbf{A}_G$ and $\mathbf{B}_G$ are power system state transfer matrix, $\mathbf{B}_{d_G}$ and $\mathbf{d}_G$ are used to reflect power disturbance inside energy generation and consumption sectors because of the loss,

the form of which can be found in [33]. $\mathbf{S}_{EV_i}$ represents the energy state of BESS in GEV_i ; $\mathbf{P}_{EV_i}$ is the auxiliary power provided by V2G services of GEV_i . Aggregated V2G power $\sum_{i=1}^n \mathbf{P}_{EV_i}$ is scheduled by following the peak-shaving tutorial signal provided by the network operator [33, 34].

The quantification of BESS aging cost can be realized by using the following linear function based on the aging model established in Section III. B:

$$\hat{L}_{bat,i} = f_{linear}(\mathbf{F}^{ag}) = \mathbf{H} \cdot [\mathbf{S}_{EV_i} \quad \mathbf{P}_{EV_i}] \quad (16)$$

Where: $\mathbf{S}_{EV_i}$ and $\mathbf{P}_{EV_i}$ are the vectors consisting of the collection of battery SoC and V2G power states in the scheduling period. $\hat{L}_{bat,i}$ is the quantified BESS life loss of GEV_i . In this study, the mitigation of battery aging cost of GEVs is designed as the objective of V2G behavior management. The V2G strategy of GEVs can be derived by the following programming problem:

$$\pi_V = \arg \min_{\mathbf{P}_{EV}} J_{vag} = \sum_{i=1}^n C_{bat,i} \cdot Q_{bat,i} \cdot \hat{L}_{bat,i} \quad (17)$$

$C_{bat,i}$ and $Q_{bat,i}$ are the unit cost and rated capacity of the battery pack in GEV_i , respectively.

B. Battery anti-aging PHEV energy management

Similar to V2G scheduling, the mitigation of BESS aging cost is also of great significance in PHEV energy management. In this study, it is modeled as a data-driven linear optimization problem under a time-discrete system, and the state equation can be described as:

$$\begin{cases} SoC(k+1) = f_{phev}(SoC(k), u(k)) \\ x(0) = SoC_0 \end{cases} \quad (18)$$

Where: f_{phev} is PHEV power system transfer function. The definition of PHEV power and dynamic system models and constraints has been well studied in [35], here we mainly focus on formulating energy management objectives. Similar to the V2G scheduling scenario, BESS aging cost is calculated by the following linear equation based on the established online battery model:

$$C_{aging}(x(k), u(k)) = C_{bat} \cdot Q_{bat} \cdot \hat{L}_{bat} \quad (19)$$

The optimal balance between fuel consumption, electricity consumption, and battery aging cost is modeled as a multi-objective optimization problem. The optimal PHEV energy management strategy is derived by solving the following optimization problem:

$$\pi_B = \arg \min_{\mathbf{P}_B} J_{eco} = \sum_{k=1}^{k+T} [C_{fuel}(x(k), u(k)) + C_{elec}(x(k), u(k)) + C_{aging}(x(k), u(k))] \quad (20)$$

Where: C_{fuel} and C_{elec} are functions to evaluate fuel and electricity cost of PHEV energy management strategy, which can be calculated by the PHEV mathematical model in [29].

V. CASE STUDY

In this section, the effectiveness of the established linear battery life loss quantification model and the designed neural hybrid optimization-based energy management method are

verified by the two most commonly used BESS deployment scenarios in Energy-transportation Nexus: V2G behavior management and PHEV power distribution.

A. Battery anti-aging vehicle charging management

The established linear battery life loss quantification model and neural hybrid optimization-based BESS anti-aging management method can be used to guide the charging behavior of GEVs in various V2G scenarios, such as residential EVs, commercial EVs, and industrial EV fleets. This study mainly focuses on mitigating vehicle aging costs and a most basic and simple V2G mode: aggregated GEVs oriented peak-shaving, is employed to verify the effectiveness.

In this study, the charging behavior of 50 GEVs is simulated to provide peak-shaving services. The configuration of the studied V2G scheduling scenario is illustrated in Table I. The battery pack of the studied GEVs consists of Lithium-Ion cells with 3400 mAh rated capacity and 3.8 V nominal voltage. The rated capacity of the battery pack reaches 53 kWh, which consists of 10 modules (each with 444 Lithium Ion cells) with a 2p5s configuration. The minimum SoC value is set as 10% to protect the battery from over-discharge. Grid demand data comes from the Stentaway Primary substation near Plymouth, which is provided by Western Power Distribution in the UK [36]. The peak-shaving reference value is set as 2 MW in the simulation period according to the BESS operation scheme carried out by Western Power Distribution. In this study, V2G scheduling is carried out as a case study for aggregators at the charging station and residential area, where GEVs can be regarded as fixed energy storage devices in a specific timeframe. The national household travel survey data [37] is employed to characterize the trip behavior of GEVs, and the Monte Carlo simulation model is used to simulate GEVs' grid-connected timeframe.

TABLE I. CONFIGURATION OF THE STUDIED V2G SCHEDULING SCENARIO.

Category	Parameters	Value
Battery parameters	Battery cell type	Lithium-Ion 18650
	Battery cell capacity	3400 mAh
	Voltage nominal	3.8V/Cell, 22.8V/Module
	Number of cells	444
	Battery pack configuration	2p5s
	Battery pack capacity	53 kWh
V2G simulation	Number of vehicles	50
	Minimum battery SoC value	10%
	Peak-shaving reference value	2 MW

Grid demand and V2G power profiles on a regular day within the simulation period are shown in Fig. 2. In this study, the proposed neural hybrid optimization scheme is carried out in

the period of 16:00–24:00 and 00:00–08:00 on the next day that with the most active V2G behaviors and stable GEVs availability. As shown in (a), the demand peak appears in the period of 18:00 to 21:00, and the maximum grid load level reaches 3.3 MW because of the aggregated use of cooking and heating appliance in households. Grid power consumption valleys appear in the evening, and the minimum load is only 0.95 MW in the early morning. Without reasonable V2G schemes, grid peak load will be further raised in the evening peak because of the uncoordinated charging of GEVs, while most of them will be fully charged after 24:00 when the valley peak appears.

With the proposed neural hybrid optimization-based V2G scheme, more than 3.75 MWh of auxiliary energy can be provided for the grid to reduce peak demand. As a result, grid peak power can be reduced by 21.4% on average. It should be noted that the energy feedback is limited after around 22:00 because most batteries are at a low SoC level. The V2G auxiliary power is reduced in this period to protect GEVs from deep discharge, which validates the battery protective effectiveness of the developed V2G scheme. After 24:00, an energy consumption valley appears, and the average demand level is only 1.32 MW. GEVs are scheduled to absorb abundant grid power generation in this period. With the proposed V2G scheme, 6.75 MWh more energy in the valley can be utilized by charging vehicle batteries and the demand level can be elevated to 2.03 MW. As a result, the grid peak-valley difference can be reduced by 68.6% after the V2G services are deployed, which validated the effectiveness of the developed neural hybrid optimization-based V2G behavior management method.

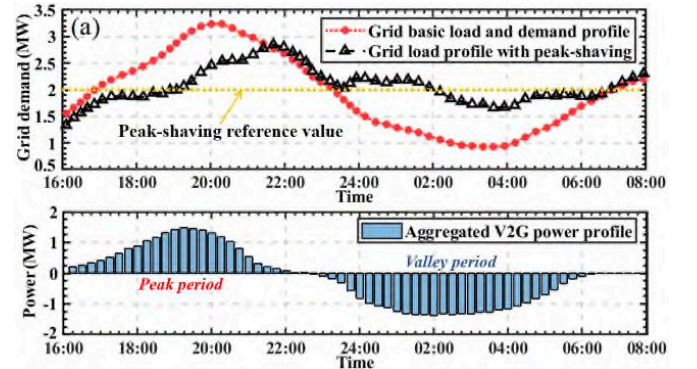


Fig. 2. Peak-shaving performance of the developed V2G behavior management model. (a) Grid load profile; (b) aggregated V2G power profile.

Computation, power balancing, and BESS aging mitigation performances of different V2G schemes are further quantitatively compared in Table II. Firstly, the developed

Table II. Performance comparison of different V2G management methods.

Scenario	Case 1: Rule-based method	Case 2: RFCC optimization method	Case 3: Cycle decomposition method	Case 4: Piecewise linearization method	Case 5: Neural hybrid optimization method
Execution time (s)	0.22	289.71	73.22	9.35	7.64
Load fluctuation (kW)	196.8	315.4	345.8	312.6	294.7
Average battery DoD (%)	112.4	88.1	102.6	94.3	92.5
Average battery cycles	7.91	3.55	3.82	5.44	3.67
Average Crate	0.625	0.367	0.451	0.384	0.397
BESS life loss (%)	3.59×10^{-2}	2.31×10^{-2}	2.92×10^{-2}	2.86×10^{-2}	2.41×10^{-2}

method (Case 5) is compared with conventional V2G schemes with and without anti-aging mechanisms, including the rule-based method [5] (Case 1) and RFCC optimization method [17] (Case 2), to validate its effectiveness. Further, the battery aging mitigation performance of the developed method is also compared with V2G schemes with simplified degradation models, including the cycle decomposition method [20] (Case 3) and the piecewise linearization method [21] (Case 4), to highlight its technical merit.

The rule-based method achieves the best computational performance because its essence is a decision tree. The average algorithm execution time is only 0.22 s. The deployment of the RFCC battery aging model in Case 2 complicates the V2G behavior management dramatically. As a result, its execution time reaches 289.71 s, which obstructs algorithm engineering deployment. The developed linear battery aging model and neural hybrid method simplify anti-aging V2G scheduling to a linear optimization problem. The average algorithm execution time can be shortened to 7.64 s, which validates the computational efficiency.

The battery anti-aging target inevitably impacts V2G peak-shaving performance. As shown in Table II, the load fluctuation increases from 196.8 kW (6.2%) to 315.4 kW (9.8%) and 294.7 kW (9.2%) in the optimization-based and neural hybrid optimization methods, respectively. Nevertheless, with the set of aging mitigation targets, BESS average DoD, cycles, and Crate are reduced by 21.6%, 55%, and 41.3% in Case 2 and 17.7%, 53.6%, and 36.5% in Case 5. With the rule-based method, the daily vehicle battery life loss reaches 0.036% in the simulation period on average. Battery cycles, DoD, and Crates can be significantly reduced by deploying the BESS life loss quantification model through RFCC optimization and neural hybrid optimization methods. The quantified BESS life loss can be reduced by 35.6% and 32.9% on average, which validates the effectiveness of the anti-aging V2G behavior management strategy. In summary, compared to the offline optimization-based method, the developed method can achieve similar peak-shaving and BESS aging mitigation performances but significantly improve the algorithm computation efficiency.

The developed neural hybrid optimization method is also quantitatively compared with two V2G schemes with the simplified degradation model in Table II. The cycle decomposition method in Case 3 can mitigate battery aging cycles but shows limited effectiveness in reducing DoD and Crate. The reason is that it mainly focuses on suppressing battery aging on a large time scale. The piecewise linearization method in Case 3 shows great effectiveness in mitigating battery DoD and Crate in V2G services. However, caused by performance compromise in reducing model complexity, the battery aging cycle increases by 34.7% compared with the RFCC method. With the developed linearized degradation model and neural hybrid optimization method, battery DoD and Crate can be reduced by 9.8% and 12% compared to V2G schemes in Case 3. Meanwhile, battery aging cycles are further reduced by 32.5% compared to Case 4, which validates that it can comprehensively protect vehicle batteries in V2G services. As a result, the quantified daily vehicle BESS life loss can be

reduced further by 17.5% and 15.7%, which highlights the technical merit of the developed method.

B. Hybrid electric vehicle energy management

This part further verifies the effectiveness of the developed BESS energy management method in PHEV power distribution. As shown in Fig. 3, an electric hybrid powertrain consisting of an internal combustion engine (ICE) and a 60 Ah battery pack is investigated. The rated power ICE, integrated starter generator (ISG), and driving motor are 147 kW, 65 kW, and 168 kW, respectively. The battery, ISG motor, and driving motor are connected to the DC bus through three bi-directional converters. Battery works as an energy storage system to provide ancillary service for the vehicle-driven system. On the one hand, by supplying power to the driving motor, BESS operates to reduce the working pressure of ICE and improve the fuel economy of PHEV. On the other hand, BESS is also used to absorb the power generation from the ISG motor and vehicle regenerative braking system. Operation of BESS, ISG, and driving motor are scheduled based on vehicle power requirements by energy management strategies. The detailed parameters of the studied hybrid electric vehicle are provided in [35].

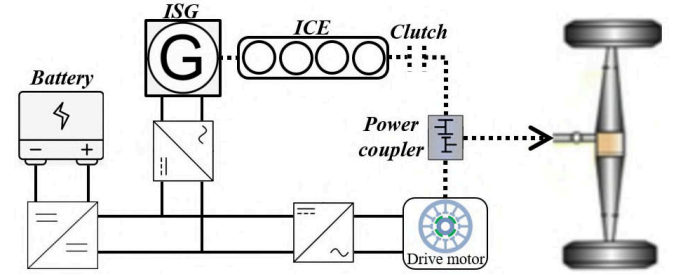


Fig. 3. The power system topology of the studied PHEV.

The Chinese typical urban drive cycle (CTUDC) with a driving range of 5.897 km is used in this study to verify the developed PHEV power distribution model. Vehicle velocity and acceleration profiles in one CTUDC are shown in Fig. 4 (a) and (b) respectively. The PHEV daily operation is simulated under a hybrid working condition consisting of 12 CTUDCs, and we mainly focus on evaluating battery anti-aging performance to verify the proposed health-aware energy management method. In this study, BESS aging is quantified under its whole life cycle, and the average battery aging cycle, Crate, and life loss every day (12 CTUDCs) are used to evaluate algorithm anti-aging performance. Based on the above-defined PHEV power system configuration and vehicle working conditions, battery aging characteristic parameters in five different energy management schemes, including the conventional rule-based method (Case 1) [6], RFCC method (Case 2) [17], cycle decomposition method [20] (Case 3), piecewise linearization method [21] (Case 4), and the developed neural hybrid optimization method (Case 5), are quantitatively compared.

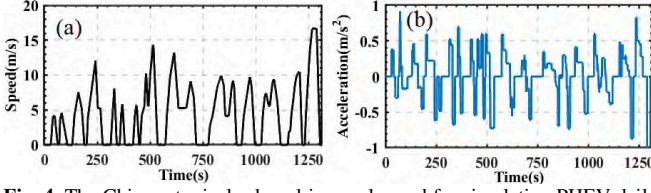


Fig. 4. The Chinese typical urban drive cycle used for simulating PHEV daily operation and verifying energy management strategy. (a) Vehicle velocity profile; (b) acceleration profile.

Fig. 5 compares the battery aging cycle, Crate, and quantified life loss under five different energy management schemes. Battery cycles and Crate reach 584 and 1.94 in Case 1 because BESS anti-aging target is not considered. As a result, battery life loss reaches 0.036% in the conventional rule-based energy management method. BESS aging cycle and Crate are reduced by 37.9% and 26.8% after the RFCC optimization method is employed. Battery life loss can be reduced by 46.8%, but the RFCC method can hardly be deployed in online PHEV energy management because of computational complexity. The performance of PHEV energy management schemes with simplified degradation models is shown in Cases 3 and 4. The cycle decomposition method can significantly mitigate the battery aging cycle but shows limited effectiveness in reducing Crate. Compared to Case 2, battery Crate increases by 23.9% in the simulation period. Similarly, the piecewise linearization method has a significant effect in reducing battery Crate but shows a limited performance in mitigating the aging cycle. Compared with the rule-based method, it mitigates 22.1% battery Crate but can only reduce 22.6% battery cycles (15.3% inferior to the RFCC method). Compared to conventional simplified aging models, the established linearized degradation model and neural hybrid optimization method can mitigate vehicle battery aging cycle and Crate at the same time. Battery Crate and number of cycles can be reduced by 15.3% and 16.7% compared to PHEV energy management schemes in Cases 3 and 4. As a result, BESS life loss is further reduced by 16.9% and 13.2%, which validates the effectiveness of the developed method.

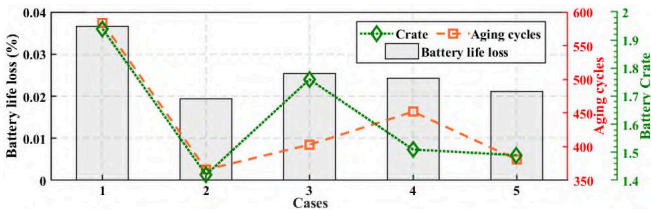


Fig. 5. Comparison of battery aging cycle, Crate, and quantified life loss under different PHEV energy management methods.

This paper focuses on mitigating vehicle BESS aging and thus the elastic navigation and operation scheme is not considered in the proposed V2G and PHEV energy management schemes. It is assumed that vehicle users will strictly follow the scheduled BESS management strategies to facilitate performance verification. However, vehicle users may also override the operation schedules in real-world implementations. Future work can be conducted on deploying the battery life loss quantification model and anti-aging energy management method in human-in-the-loop vehicle BESS

management.

VI. CONCLUSION

A two-stage BESS aging quantification and health-aware management method is proposed in this paper for reducing the battery aging cost in V2G services and PHEV power distribution. A battery aging state calibration model is established by comprehensively analyzing the impact of battery cycles with various Crates and DoDs. The established model is linearized based on a linear-in-the-parameter supervised learning method. With the built linear BESS life loss quantification model, vehicle battery anti-aging energy management is realized by a neural hybrid optimization model. Through extensive case studies and simulations, some key findings are listed as follows:

- The proposed linearization method for the RFCC algorithm provides a close approximation of battery cycle aging cost. Compared to the conventional RFCC optimization method, the computation cost of anti-aging energy management can be significantly reduced.
- The linearized BESS aging model yields more accurate life loss quantification results that comprehensively reflect the impact of cycle number, cycle depth, and Crate on battery aging. It achieves a similar battery anti-aging effectiveness compared to the RFCC optimization method in V2G scheduling and PHEV energy management but significantly reduces algorithm computation complexity.
- In GEVs charging behavior management, battery anti-aging targets are realized by mitigating Crate and DoD. Vehicle batteries can be effectively protected in V2G services with the developed neural hybrid optimization-based BESS management method.
- In vehicle energy management, battery aging cycles and Crate can also be effectively mitigated with the developed neural hybrid optimization method. Vehicle BESS aging can be significantly reduced while providing online power ancillary services to PHEV.

The proposed BESS aging quantification and health-aware management method can be incorporated into aggregated V2G coordinator and onboard PHEV controller. They can help reduce battery aging costs and improve vehicle total economy, thus benefiting the realization of net-zero in the energy-transportation nexus.

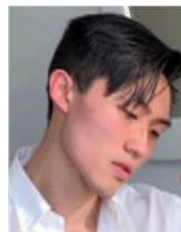
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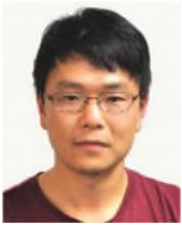
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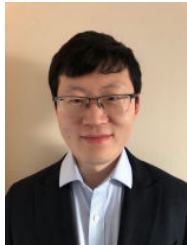


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Linearizing battery degradation for health-aware vehicle energy management

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