Battery Protective Electric Vehicle Charging Management in Renewable Energy System

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***Abstract*—The adoption of grid-connected electric vehicles (GEVs) brings a bright prospect for promoting renewable energy. An efficient vehicle-to-grid (V2G) scheduling scheme that can deal with renewable energy volatility and protect vehicle batteries from fast aging is indispensable to enable this benefit. This paper develops a novel V2G scheduling method for consuming local renewable energy in microgrids by using a mixed learning framework. It is the first attempt to integrate battery protective targets in GEVs charging management in renewable energy systems. Battery safeguard strategies are derived via an offline soft-run scheduling process, where V2G management is modeled as a constrained optimization problem based on estimated microgrid and GEVs states. Meanwhile, an online V2G regulator is built to facilitate the real-time scheduling of GEVs' charging. The extreme learning machine (ELM) algorithm is used to train the established online regulator by learning rules from soft-run strategies. The online charging coordination of GEVs is realized by the ELM regulator based on real-time sampled microgrid frequency. The effectiveness of the developed models is verified on a UK microgrid with actual energy generation and consumption data. This work can effectively enable V2G to promote local renewable energy with battery aging mitigated, thus economically benefiting EV owns and microgrid operators, and facilitating decarbonization at low costs.**

***Index Terms*—Electric vehicle, microgrid, artificial intelligence, renewable energy, battery aging mitigation, vehicle to grid.**

ABBREVIATIONS

GEVs	Grid-connected EVs.
V2G	Vehicle-to-grid.
ELM	Extreme learning machine.
SoC	State of Charge.
NOC	Number of cycles.
DOD	Depth of discharge.
RCC	Rain-flow cycle counting.
CU	Charging urgency.
BLS	Broad learning system.
REA	Renewable energy absorption.
SD	Standard deviation.
CCD	Charging complete degree.

NOMENCLATURE

$\hat{\mathbf{P}}_{wind}$	Estimated wind power generation.
$\hat{\mathbf{P}}_{solar}$	Estimated solar power generation.
$\hat{\mathbf{P}}_{load}$	Estimated microgrid load consumption.
$\hat{P}_{wind,k}$	Estimated wind power generation at k.
$\hat{P}_{solar,k}$	Estimated solar power generation at k.
$\hat{P}_{load,k}$	Estimated microgrid load consumption at k.
$\mathbf{P}_{v,i}$	V2G power and strategy of EV_i.
$\mathbf{P}_{v}$	Optimization variable in soft-run scheduling.
$P_{i,k}$	V2G power of EV_i at k.
C_i^{total}	Total lifetime capacity of the battery.
N_i^{total}	Total lifetime cycles of the battery.
D_i^{cycle}	DOD of the battery in V2G strategy.
N_i^{cycle}	NOC of the battery in V2G strategy.
λ_i	Cost of per battery degradation unit.
$COST_i$	Battery aging cost of EV_i.
P_{ge}	Sum of power generation of the MG.
P_{tg}	Traditional power generation.
ΔP_k	microgrid unbalanced power at k.
$SoC_{\min}$	Minimum limit of battery SoC value.
$SoC_{\max}$	Maximum limit of battery SoC value.
$P_{i,dis}^{\max}$	Maximum V2G discharging power of EV_i.
$P_{i,ch}^{\max}$	Maximum V2G charging power of EV_i.
SoC_i^{end}	Final SoC value of EV_i before departure.
SoC_i^{set}	Preset charging requirements of EV_i.
$\mathrm{SoC}_{i,k}$	Battery SoC state of EV_i at k.
Δf	Frequency deviation of the MG.
ΔP_{efr}	Calculated V2G compensation power.
$\mathbf{MG}$	Microgrid characteristic parameter set.
f_{EFR}	Frequency to power transfer function.
$CU_{i,k}$	Charging urgency of GEV_i at k.
T_k	Remained charging period before departure.
$\mathbf{HS}_k$	Previous five extreme points in SoC profile.
$\mathbf{X}_k$	ELM model training input.
$\mathbf{Y}_k$	ELM model training output.
PE_k	Real-time V2G power.
$\boldsymbol{W}$	Weight matrix of ELM.
C	Regularization coefficient.

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I. Introduction

THE adoption of grid-connected electric vehicles (GEVs) brings a bright prospect for the promotion of renewable energy. However, an efficient vehicle-to-grid (V2G) scheduling scheme that can deal with the volatility of renewable energy and protect vehicle batteries from fast aging is indispensable to enable this benefit [1]. Many studies have investigated V2G management under local renewable energy penetrations. The real-time online decision-making model is one of the most commonly used V2G scheduling methods for its merits in dealing with the volatility of renewable resources [2, 3]. In online V2G scheduling, the behaviors of GEVs are scheduled based on real-time sampled grid status instead of predictions or historical information. A fuzzy-logic algorithm was used in [4] to manage the penetration of GEVs by real-time sampled grid voltage and battery energy states. Experiment results indicated that the established regulator could schedule the V2G behaviors of GEVs in real-time to improve power quality. In [5] and [6], an intelligent optimization approach is developed for the optimal vehicle charging/discharging scheduling in a grid-connected charging station and a smart building based on multi-modal approximate dynamic programming. The proposed strategy exhibits a robust behavior in the presence of stochastic arrival and departure times as well as different pricing models and renewable energy production. Literature [7] proposed an online V2G coordination method using a two-stage rule-based decision-making model.

In online methods, the charging behaviors of each GEV can be dynamically scheduled because the established control models are free of complex optimization processes [8, 9]. The rapidity makes it possible to respond to the volatility of renewable energy. However, predictive information and GEVs cooperative optimization mechanism are not employed in most online methods, and batteries may undergo extra aging cycles because of uncoordinated scheduling [10]. According to [11], without properly designed safeguard scheduling mechanisms, V2G service may rapidly exhaust vehicle battery life. In a quantitative study [12], battery useful life could be decreased to 65% after participating in bi-directional V2G management. The concerns with accelerated battery aging have become the main reason that keeps GEV customers from participating in V2G services.

The studies carried out by the University of Oxford [13] and the University of Washington [14] indicate that battery aging occurs with its operation but can only be detected and mitigated on a large time scale. With the development of communication and computation technologies in recent years, many efforts have been made to reduce battery aging by using optimization-based scheduling methods [15, 16]. A heuristic algorithm-based V2G scheduling method is developed in [17] to schedule the charging behavior of GEVs in the microgrid. The V2G scheduling is modeled as a multi-objective optimization problem under a 24-hour time scale, and the battery aging is mitigated by constraining the number of cycles (NOC) and depth of discharge (DOD). In [18], V2G scheduling is modeled as a stochastic optimization problem, and the mitigation of battery aging is realized by setting NOC constraints. Simulation results indicated that the total economy of the integrated transportation-energy system could be significantly improved. The optimization-based V2G behavior management model achieves optimal scheduling but is not able to be deployed online [19]. The scheduling period is as long as 5 minutes even the most advanced computing equipment is adopted [20]. Literature [6] points out that grid demand and renewable energy sources consist of dynamical external disturbances and with strong transience and unpredictability, making the optimization-based scheduling even more challenging.

The recently developed computationally efficient approaches bring a bright perspective for ensuring V2G scheme optimality and real-time performance. The broad learning system (BLS) [21] and extreme learning machine (ELM) [22], are both least-squares-based supervised learning algorithms with fast learning and strong generalization ability. The broad learning system (BLS) [21] paradigm has recently emerged as a computationally efficient approach in big-data scenarios to supervised learning. The ELM algorithm mainly focuses on dealing with common regression problems with relatively small datasets. Compared with BLS, ELM has better computational efficiency and stability for conventional regression problems. It has been widely used in engineering applications, including industrial processes [23], complex system modeling [24], and fault diagnosis [25]. In this study, the proposed V2G scheme can be simplified to a multiple-input and single-output system. Therefore, the most basic and commonly used supervised learning method: ELM, is employed to solve the learning problem.

Based on the above discussions, this paper develops a novel battery safeguard V2G scheduling method for absorbing local renewable power generation in microgrids based on a mixed learning framework. Battery protective strategy is derived via an offline soft-run scheduling process, where the V2G management is modeled as a mathematical optimization problem by utilizing the estimated microgrid and GEVs state information. Meanwhile, an online V2G regulator is built to enable the real-time GEV charging behavior scheduling. The dynamic extreme learning machine (ELM) algorithm [22] is used to train the established online regulator by learning rules from soft-run strategies. Online GEV charging behavior coordination of individual GEVs is realized by the ELM regulator based on the real-time sampled microgrid frequency state information. The developed methods are verified on a UK microgrid system with real power generation and consumption data. Results indicate that the developed methods can schedule GEVs charging online to absorb local renewable power generation while effectively mitigating battery life loss.

The key contributions of this paper are as follows:

- It is the first attempt to consider vehicle battery safeguard in V2G scheduling in the microgrid with local renewable energy penetration.
- A novel mixed learning framework is established for V2G behavior management. Compared to existing online and offline scheduling methods, V2G scheduling optimality and real-time performance can be simultaneously guaranteed.
- It proposes a novel soft-run mechanism to establish the rule

base for guiding online V2G management. With the developed soft-run optimization model, optimal battery safeguard strategies can be derived for guiding online V2G scheduling.

- It for the first time considers battery safeguard in online V2G regulator by using a supervised learning method. By learning rules from the soft-run strategy, both battery aging mitigation and renewable energy consumption targets can be realized in V2G scheduling.

The rest of the paper is organized as follows: The mixed learning framework is developed in Section II. Sections III and IV establish the battery safeguard soft-run optimization model and online V2G power regulator. The performance of the developed method is evaluated in Section V, followed by concluding remarks in Section VI.

II. Mixed Learning Framework for Online V2G Scheduling

This section proposes a novel mixed learning framework to realize optimal battery safeguard V2G management in microgrid with local renewable energy penetration. As shown in Fig. 1, in the developed mixed learning method, online V2G strategies are cooperatively derived by a soft-run optimization model and a real-time regulator.

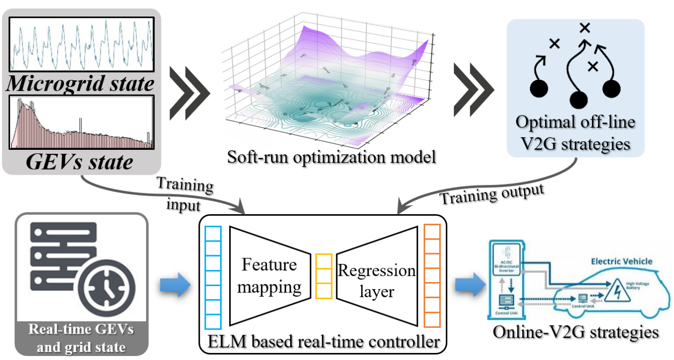

Fig. 1. The established mixed learning framework for online V2G scheduling.

In the first stage, optimal V2G strategies are derived by an offline soft-run optimization model, which operates in a 'virtual' mode. In soft-run operation mode, all the derived strategies are stored in a rule base but not be used to schedule the charging behavior of GEVs directly. V2G scheduling is modeled as a mathematical optimization problem in this stage to guarantee the optimality of the derived strategy. As shown in Fig. 1, microgrid power balance and GEVs battery state information are used as the input variable of the model to reflect microgrid power balancing requirement and vehicle charging requirement comprehensively. GEVs charging behaviors are synergistically scheduled with battery aging mitigation as optimization target and grid power balance state sustaining as constraints. With the established soft-run optimization model, optimal battery safeguard V2G strategy that can provide power balancing service to the microgrid can be derived. The scheduled charging behavior of GEVs under different microgrid power consumption, renewable generation, and battery states are stored in a rule base to direct the establishment of real-time V2G scheduling.

An online V2G power regulator is further established in this study based on a supervised learning method to deal with the volatility of renewable energy. As shown in Fig. 1, to realize battery safeguard schedule, the optimal V2G strategies derived in the soft-run optimization model are used to train the real-time regulator based on the ELM algorithm. Based on the real-time sampled grid and GEVs state information, the trained online regulator directly schedules the charging power of GEVs in real-time for absorbing renewable power generation. Meanwhile, with the V2G scheduling system operation, the ELM model parameters are dynamically updated and trained by the derived soft-run strategies to guarantee its optimal performance.

With the cooperation between the soft-run optimization model and the online regulator, GEVs energy storage capacity can be better utilized to provide power balancing service to the microgrid while mitigating its aging. The rest of the paper mainly focuses on presenting the mathematical principle in the established soft-run optimization model, online power regulator, and the corresponding rules learning method.

III. Battery Safeguard V2G Management: A Soft-Run Scheduling Model

This section proposes an offline soft-run V2G behavior optimization model to derive optimal battery safeguard strategies for guiding real-time V2G management. The prediction of microgrid renewable power generations, power consumption, and GEVs charging behaviors have been well studied in previous literature. Therefore, this section mainly focuses on establishing a mathematical model for deriving the optimal V2G management strategies.

A. Optimization environment and variables

In the developed soft-run V2G scheduling scheme, the optimization target is designed to absorb renewable energy by GEVs energy storage capacity while mitigating battery aging. The absorption of renewable energy can be realized by setting constraints based on the predicted renewable power generations and power consumption. The predicted solar, wind, and grid load consumption can be represented by the following vectors:

$$\hat{\mathbf{P}}_{wind} = \begin{bmatrix} \hat{P}_{wind,0} & \hat{P}_{wind,1} & \cdots & \hat{P}_{wind,k} & \cdots & \hat{P}_{wind,k+n} \end{bmatrix} \quad (1)$$

$$\hat{\mathbf{P}}_{solar} = \begin{bmatrix} \hat{P}_{solar,0} & \hat{P}_{solar,1} & \cdots & \hat{P}_{solar,k} & \cdots & \hat{P}_{solar,k+n} \end{bmatrix} \quad (2)$$

$$\hat{\mathbf{P}}_{load} = \begin{bmatrix} \hat{P}_{load,0} & \hat{P}_{load,1} & \cdots & \hat{P}_{load,k} & \cdots & \hat{P}_{load,k+n} \end{bmatrix} \quad (3)$$

Where: $\hat{P}_{wind,k}$, $\hat{P}_{solar,k}$, and $\hat{P}_{load,k}$ are the estimated wind generation, solar generation, and load consumption at k. In this study, the rolling prediction technology [26] and deep long short-term memory algorithm [27], which has been widely used in microgrid power generation and consumption prediction issues, are used here to provide the prediction information for the soft-run optimization model.

The availability constraints of GEVs is reflected in optimization variables in the designed soft-run optimization model, the V2G strategy of GEV_i can be represented as:

$$\mathbf{P}_{v,i} = \begin{bmatrix} 0 & \cdots & P_{i,c_i} & \cdots & P_{i,k} & \cdots & P_{i,d_i} & \cdots & 0 \end{bmatrix} \quad (4)$$

Where: c_i and d_i are the grid-connected and departure time of GEV_i, which is used to reflect vehicle availability constraints. When GEVs are off-grid, the corresponding V2G power is set as 0. The optimization variable in the established soft-run optimization model is designed as the detailed charging and discharging power of all GEVs:

$$\mathbf{P}_v = \left[\mathbf{P}_{v,0} \quad \cdots \quad \mathbf{P}_{v,i} \quad \cdots \quad \mathbf{P}_{v,n}\right]^T \tag{5}$$

Where: $P_{i,k}$ represents the V2G power of GEV_i at k.

B. Optimization objective

In this study, the objective function is simplified to minimize the battery degradation for all GEVs. To mitigate battery degradation during providing power balancing services, the cycle times and depth of discharge (DoD) of the battery should be constrained. The rain-flow cycle counting (RCC) algorithm has been proved effective in extracting and analyzing the aging cycles of metal material, mechanical systems, and energy storage systems [28, 29]. Therefore, this paper uses the RCC algorithm to extract the aging cycles of GEV batteries during participating in V2G service. Based on the extracted battery cycles and corresponding DoD, the following equation is used to calculate battery equivalent degradation cost:

$$COST_i = \frac{\lambda_i}{2} \bullet \left(\frac{N_i^{cycle}}{N_i^{total}} + \frac{D_i^{cycle}}{C_i^{total}} \right) \tag{6}$$

Where: C_i^{total} and N_i^{total} are the total lifetime capacity and total lifetime cycles throughput of GEV_i battery, D_i^{cycle} and N_i^{cycle} are DoD and aging cycles under current V2G strategy, λ_i is the cost of per battery degradation unit. According to [13], the cycle loss and capacity loss contribute the same in battery aging. Therefore, as described in (5), the vehicle battery aging cost is calculated by averaging the cycle loss and capacity loss. The battery degradation cost of GEVs are computed during optimization process, and the aging costs of all V2G participants are summed up as the objective function:

$$J_{obj} = \sum_{i=1}^{n} \left(\frac{N_i^{cycle}}{N_i^{total}} + \frac{C_i^{cycle}}{C_i^{total}} \right) \bullet \frac{\lambda_i}{2} \tag{7}$$

C. Optimization constraints

In the designed soft-run optimization model, the following constraints are set to satisfy the charging requirement of GEVs and absorb volatile renewable energy in microgrid:

$$S.T. \begin{cases} a. \begin{cases} \hat{P}_{ge,k} = \hat{P}_{wind,k} + \hat{P}_{solar,k} \\ \Delta P_k = \hat{P}_{ge,k} + P_{tg,k} - \hat{P}_{load,k} \\ \sum_{i=1}^{n} P_{i,k} - \Delta P_k \geq 0 \end{cases} \\ b. \begin{cases} -P_{i,\mathrm{dis}}^{\max} \leq P_{i,k} \leq P_{i,\,\mathrm{ch}}^{\max} \\ -\mathrm{SoC}_{\min} \leq \mathrm{SoC}_{i,k} \leq \mathrm{SoC}_{\max} \\ SoC_i^{\mathrm{end}} \geq SoC_i^{\mathrm{set}} \end{cases} \end{cases} \tag{8}$$

- Constraint ***a*** reflects microgrid power balance requirement: power generation $\hat{P}_{ge,k}$ of the microgrid, including wind power $\hat{P}_{\mathrm{wind}}$, solar power $\hat{P}_{\mathrm{solar}}$, and traditional generator power $P_{tg,k}$, should be absorbed by GEV charging power $\sum_{i=1}^{n} P_{i,k}$ and grid load consumption $\hat{P}_{\mathrm{load}}$ as more as possible.
- Constraint ***b*** reflects the charging requirements of V2G participants, including the constraint of battery maximum discharging $P_{i,\mathrm{dis}}^{\max}$ and charging power $P_{i,\,\mathrm{ch}}^{\max}$, permitted minimum and maximum battery state of charge (SoC) value, and final charging requirement SoC_i^{set}.

D. Model solving method

This study uses the established soft-run optimization model to derive the optimal strategies for establishing the rule base. The global optimality but not the algorithm real-time performance is emphasized in this step. Therefore, the cooperative differential evolution algorithm [42], which has been widely used in smart grid energy resource management, V2G scheduling, and smart home energy management, is used to solve the defined optimization model in this study.

IV. Online V2G power regulator for absorbing volatile renewable energy

This section develops an online deployment method for the soft-run V2G management strategy. Firstly, an enhanced frequency response based microgrid state estimation model is introduced to calculate the required V2G compensation power. Then a V2G power regulator is built to online schedule the charging behavior of GEVs.

A. Enhanced frequency response based microgrid state estimation model

This part estimates the power balancing state of the microgrid based on the enhanced frequency response method. Microgrid power balancing can be realized by monitoring its frequency state. The droop control is the commonly used method in frequency regulation issues to improve microgrid energy quality and stability [30, 31]. In the droop control method, the operation of distributed generators and battery energy storage devices are scheduled by the inverter only based on the real-time sampled microgrid frequency state information. However, because of lacking long-term (at least 12 hours) scheduling mechanism, GEVs aging can hardly be actively mitigated by the droop control-based V2G scheme [32]. Therefore, this study establishes an online regulator to schedule the charging behavior of GEVs, where the required V2G compensation power is calculated by utilizing real-time sampled microgrid frequency state information based on the enhanced frequency response method [33].

The V2G compensation power can be calculated by the following equation:

$$\Delta P_{EFR} = f_{EFR}(\Delta f, \mathbf{MG}) \tag{9}$$

Where: Δf and ΔP_{EFR} are frequency deviation and V2G compensation power. $\mathbf{MG}$ is the characteristic parameter set of microgrid, f_{EFR} is system frequency deviation to power fluctuation transfer function [33].

The frequency deviations and the calculated V2G power requirement profile by the enhanced frequency response model are shown in Fig. 2. In Zone A, the microgrid frequency is lower than 50Hz, indicating that renewable generation is not enough to cover consumption. Therefore, the V2G compensation power is negative to guide GEVs to discharge for providing auxiliary power. Conversely, when power generation is higher than consumption, microgrid frequency is higher than 50 Hz. As shown in Zone B, the estimated V2G consumption power is all positive, guiding GEVs to charge for absorbing renewable generation as much as possible. When grid frequency slightly fluctuates around 50 Hz in Zone C, the V2G compensation power is kept at 0 to prevent vehicle batteries from undergoing shallow cycles. In the established online V2G regulator, the value of V2G compensation power is calculated based on the frequency fluctuation of the microgrid. The more violent the frequency deviations, the higher the absolute value of the calculated V2G compensation power.

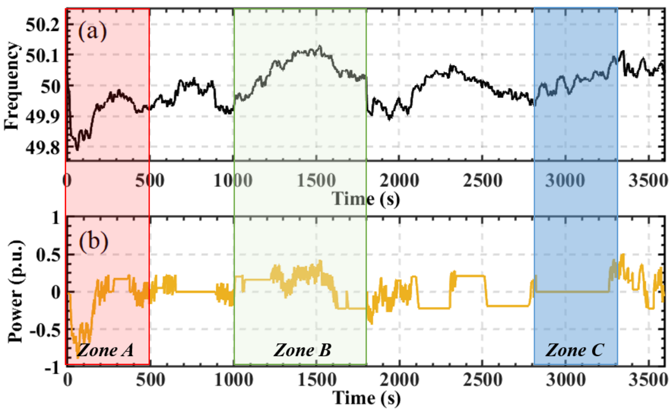

Fig. 2. Calculated V2G power requirement by the enhanced frequency response model. (a) Frequency deviations; (b) estimated V2G compensation power profile.

B. Supervised learning based V2G power regulator

This part establishes an online V2G power regulator by supervised learning the rules in the soft-run optimization model. Instead of the whole fleet, the charging and discharging behavior of individual GEVs are selected as the scheduling output variable to simplify rules learning process and regulator deployment. To ensure the online power regulator can satisfy the charging requirement of GEVs, the concept of charging urgency (CU) is further defined here to describe the dynamic battery state of V2G participants:

$$CU_{i,k} = \frac{Q_i \bullet (SoC_{i,k} - SoC_i^{set})}{P_{i,ch}^{\max} \bullet T_{i,k}} \times 100\% \tag{10}$$

Where: $CU_{i,k}$ is the quantified charging urgency of GEV_i at k, $T_{i,k}$ is the remained charging period before departure.

The value of CU is limited within 0% to 100% when system operation is normal. The higher the value of CU, the more the charging urgency is required for GEV, the less the available V2G energy storage capacity for grid power balancing. In real-time V2G regulator, $CU_{i,k}$ is used as an input to ensure that the charging requirement of GEVs can be timely satisfied. Meanwhile, to mitigate battery aging in providing V2G services, historical charging and discharging behaviors of GEVs in the previous scheduling period are also considered in the established regulator. The previous five extreme points [29], which reflect battery number of cycles and depth of discharge information, are extracted from GEVs SoC profile:

$$\mathbf{HS}_k = \begin{bmatrix} S1_k & S2_k & \cdots & S5_k \end{bmatrix} \tag{11}$$

The training objective of the real-time regulator is to calculate V2G power for an individual GEV based on its charging requirement, battery state, and grid power balance state. Accordingly, model input X and output Y are constructed as:

$$\mathbf{X}_k = \left\{ CU_k \quad \mathbf{HS}_k \quad \Delta P_{EFR,k} \right\} \tag{12}$$

$$\mathbf{Y}_k = \left\{ PE_k \right\} \tag{13}$$

Where: PE_k is calculated the real-time V2G power for individual GEV.

The training of the ELM algorithm-based online V2G power regulator can be depicted by:

$$\min_{\beta \in \mathbb{R}_{L\times m}} \frac{1}{2} \| \boldsymbol{W} \|^2 + \frac{C}{2} \| \bar{\boldsymbol{Y}} \boldsymbol{W} - \boldsymbol{Y} \|^2 \tag{14}$$

Where: $\boldsymbol{W}$ and $\bar{\boldsymbol{Y}}$ are the weight and output matrix of ELM, C is the regularization coefficient. The Tikhonov regularization [34] method is used in this study to update the parameters of ELM:

$$\boldsymbol{W}^* = \left(\bar{\boldsymbol{Y}}^T \bar{\boldsymbol{Y}} + \frac{1}{C} \right)^{-1} \bar{\boldsymbol{Y}}^\top \boldsymbol{Y} \tag{15}$$

The parameter of the real-time regulator should be dynamically updated by learning the latest rules in the soft-run model to ensure the optimal performance. The online sequential dynamic training method is used here to enable dynamic parameter updating in ELM model, which can be realized by the following equations:

$$\boldsymbol{W}_{k+1} = \boldsymbol{W}_k + \mathbf{K}_{k+1} \bar{\boldsymbol{Y}}_{k+1}^\top \left(\boldsymbol{Y}_{k+1} - \bar{\boldsymbol{Y}}_{k+1} \boldsymbol{W}_k \right) \tag{16}$$

$$\mathbf{K}_{k+1} = \mathbf{K}_k - \mathbf{K}_k \bar{\boldsymbol{Y}}_{k+1}^\top \left(\boldsymbol{I} + \bar{\boldsymbol{Y}}_{k-1} \mathbf{K} \bar{\boldsymbol{Y}}_{k+1}^\top \right)^{-1} \bar{\boldsymbol{Y}}_{k+1} \mathbf{K}_k \tag{17}$$

Where: $\mathbf{K}_0 = (\bar{\mathbf{Y}}_0^T \bar{\mathbf{Y}}_0)^{-1}$ is the algorithm gain initialized by (14). When the latest V2G strategies $\boldsymbol{Y}_{k+1}$ from the optimization-based model are generated, the parameters in the online regulator are dynamically updated with (16) ~ (17) to achieve the best performance. With the dynamic training, the established real-time regulator can accurately reproduce the derived V2G strategies in the optimization-based method.

V. Simulation Environment and Results Analysis

In this section, the configuration and the data sources of the studied microgrid and renewable power generation system are described firstly. Then, the qualitative and quantitative analyses are carried out to evaluate the power balancing and battery anti-aging performances of the developed V2G scheduling methods.

A. Data set and simulation environment

A microgrid that consists of local renewable, conventional generator, GEVs, and domestic load is employed to verify the developed V2G scheduling method. As shown in Fig. 3, photovoltaic (PV) array and wind generator are connected to the microgrid AC bus through inverters, while household loads and conventional generators are connected to AC bus directly to sustain power balance states. Based on the real-time sampled microgrid frequency state information, the charging and discharging behavior of GEVs are coordinated by the V2G scheduling system. The corresponding V2G strategies are realized by the smart charging pile between GEVs and microgrids. In this study, targets of V2G scheduling are assumed to absorb local renewable generation and mitigate vehicle battery aging. Therefore, the effect of the power purchase from the main grid is not considered and the microgrid is assumed to operate under off-grid mode.

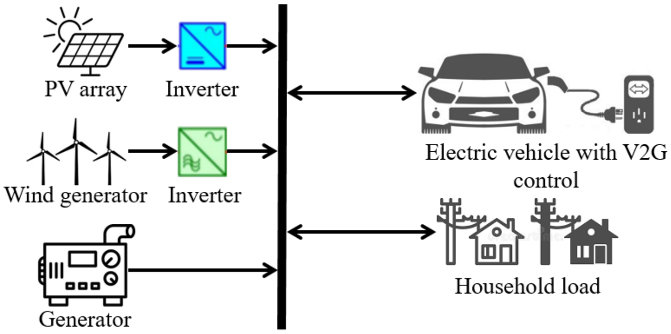

Fig. 3. The topology of the studied microgrid with renewable energy resources and GEVs.

The detailed parameters and characteristics of the tested microgrid system are further illustrated in Table I. The characteristic of conventional power plants is simulated by the dynamic model presented in [35], and the generators are modeled by linearized swing equations. The energy consumption and renewable power generation states of the microgrid are simulated based on the open-access power system operation data [36] provided by Western Power Distribution, UK. The national household travel survey data [37] is employed to simulate the charging behavior of V2G participants, and the Monte Carlo simulation model [38] is used to simulate GEVs availability states. The power conversions processes between the energy generation, consumption, and storage devices are modeled as a steady-state conversion model described in [39]. The power flows between different sectors in the microgrid are simulated to verify the effectiveness of the developed V2G management method.

TABLE I. CONFIGURATION OF THE STUDIED MICROGRID SYSTEM.

Category	Parameters	Value
GEVs and battery	Number of vehicles	300
	Battery capacity	60 kWh
	Minimum battery SoC value	20%
	Maximum battery SoC value	95%
	Maximum Crate	1 C
Microgrid	Demand peak	4.6 MW
	Wind farm rated capacity	6 MW
	PV array rated power	5 MW
	Conventional generator rated power	5.5 MW

The proposed work is implemented on a high-performance workstation equipped with 2×E5-2690v4 processors. The soft-run model and the training of the online regulator are programmed with MATLAB, and the real-time V2G regulation is realized in Simulink to facilitate its hardware deployment.

B. Power balancing and battery anti-aging performance of V2G scheduling

Grid load, solar generation, and wind generation power profiles within 30 working days in the studied microgrid system are shown in Fig. 4. The first peak appears in the period of 08:00 to 10:00, and the maximum grid load level reaches 3.5 MW at around 09:00 because of the rise of commercial power consumption, as shown in (a). The second peak is from 17:00 to 20:00 because of the aggregated use of cooking and heating appliance in households. Without energy storage capacity, microgrid needs to trade with the main grid frequently to satisfy the power requirement of consumers. The solar generation profiles are shown in (b), most of which peak in the period of 11:00 to 12:00 when the valley of grid load profile appears. Without GEVs penetration, the generated power cannot be fully consumed by the grid and the abundant power will be wasted. The wind profile is not as regular as solar profiles, as shown in (c); however, the power generation value in the evening is generally higher than that of in the daytime. However, grid power consumption valleys also appear in this period, and the minimum load is only 1 MW in the early morning. The uncoordinated charging behavior of GEVs makes the situation worse: grid peak load will be further raised in the period of 08:00 to 10:00 and 17:00 to 20:00 after the connection of GEVs, while after 24:00 most GEVs will be fully charged.

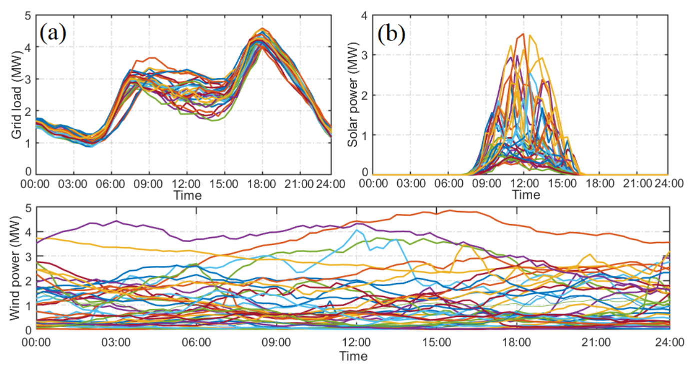

Fig. 4. Microgrid (a) load, (b) solar generation, and (c) wind generation power profiles within 30 working days.

Based on the above microgrid topology, renewable generation, power consumption, and availability of GEVs, V2G scheduling is carried out to improve energy utilization efficiency. Performances of three different V2G schemes, including conventional rule-based method [4] (Case 1), optimization-based [17] method (Case 2), and the developed mixed learning method (Case 3), are compared in this section.

The objective of V2G management is to maximize the renewable energy absorption (REA) rate in the scheduling period. Fig. 5 (a) compares REA rates under different scenarios of renewable power generation and fleet scales. Fluctuation of renewable power generation impacts of scheduling algorithm performance directly. REA rate of the developed mixed learning method is compared with conventional optimization-based method under different renewable generation forecasting error states. Both the optimization-based and mixed learning models achieve satisfactory performance with accurate prediction information. The REA rates reach 98.4% and 97.2%, indicating the effectiveness of V2G scheduling. The optimization-based model and mixed learning model can keep stable before the forecasting error reaches 4%, and the REA rates are generally kept above 92%. However, with the prediction error further increasing, the REA rate decreases dramatically. When forecasting error reaches 10%, the REA rate in the optimization-based method is only 60.7%. The microgrid REA rate can still be kept to 90.2% in the mixed learning method, validating its robustness under uncertain renewable generations and power consumption.

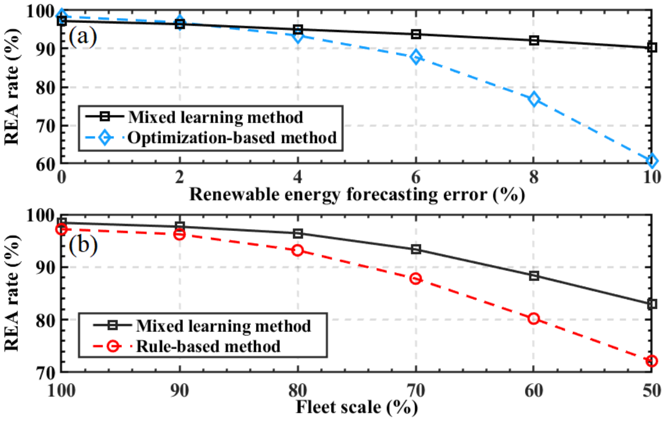

Fig. 5. V2G renewable energy absorption rates under different (a) renewable power generation states and (b) fleet scales.

REA rate of the developed mixed learning method is compared with conventional rule-based method under different fleet scales in Fig. 5 (b). With the decrease of fleet scale, the microgrid REA rate gradually declines because the available energy storage capacity is limited. After fleet scale decreases by 20%, energy storage capacity cannot fully absorb renewable power generation. Therefore, V2G scheduling REA rate dramatically decreases in the simulation. Compared to the conventional rule-based method, the mixed learning method can better adapt to the change of fleet scale. The reason is that regulator hyper-parameter can be updated by the optimization and rules learning processes flexibly. When fleet scale decreases by 50%, REA rate in the rule-based method is only 72.1%. While with the mixed learning method, the above number can be improved to 83.7%, which validates its robustness under the change of fleet scale.

Battery aging cycles of GEV fleet under different DoD ranges in V2G services under three cases are compared in Fig. 6. GEVs are un-coordinately scheduled to respond to renewable energy and grid demand fluctuations in the rule-based method. Vehicle batteries undergo around 2325 and 1352 shallow cycles under 0%~5% and 5%~15% DoDs. Compared to the rule-based method, shallow battery cycles can be reduced by 74.3% and 64.1% in optimization-based and mixed learning methods, which validate the battery protective performance. Optimization-based and mixed learning methods also reduce battery cycles with high (25%~35% and higher than 35%) DoDs. More than 57.2% and 39.3% deep battery cycles can be avoided after the optimization-based and mixed learning methods are deployed, which validates the effectiveness of the battery anti-aging mechanism. The developed mixed learning method achieves a similar battery protective performance compared with the optimization-based method. It should be figured out that vehicle batteries still experience 12.8% more cycles in the mixed learning method. The reason is that the improvement of REA rates is also emphasized in the developed scheme.

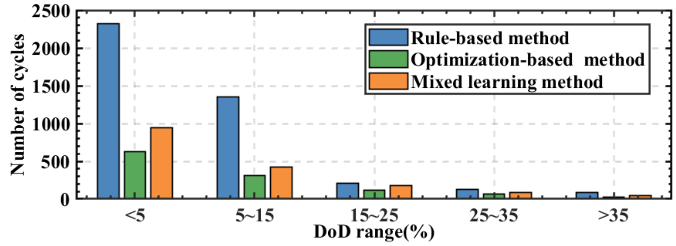

Fig. 6. Battery aging cycles of GEV fleet under different DoD ranges in V2G services.

Table II summarizes the average power balancing and battery aging mitigation performance of three cases in 30 working days. The wind, solar, and load average prediction error in the simulation period can be generally limited to 8.15%, 6.57%, and 9.74%, respectively. In this study, to guarantee system stability, the scheduling interval in Case 1 to 3 are set as 1 s, 300 s, and 1 s, respectively. In terms of algorithm computation speed, the average simulation time of the optimization-based method is as long as 232.7 s due to the complex optimization mechanism. GEVs charging behavior can be directly scheduled based on the rules but free of optimization processes in the rule-based method. Therefore, the simulation time in Case 1 can be shortened to 0.12 s. The simulation time of the soft-run optimization model is 665.5 s, much longer than in Case 2. The reason is that a shorter scheduling interval is adopted to better deal with the volatility of renewable power generation. It should be figured out that the strategies derived by the soft-run optimization model are used to train the ELM-based regulator but not to schedule the charging behavior of GEVs directly. Therefore, the developed mixed learning method achieves a similar calculation speed as the fuzzy logic method by realizing online V2G scheduling through the online regulator.

The rule-based approach can respond to the microgrid power fluctuation in real-time, its REA rate reaches 97.5%, and netload standard deviation (SD) can be limited to 0.42 on average within the simulation period. However, batteries undergo 5265 cycles because lacking collaborative scheduling mechanisms between different GEVs. Compared with the rule-based method, battery aging cycles are reduced to 1512 in the optimization-based method. However, because of the large scheduling intervals, only 73.2% of renewable generation can be absorbed and microgrid net load SD reaches 0.86. The developed mixed learning method can improve both the power balancing and battery anti-aging performance. As shown in Table II, more than 94.6% renewable power generation can be absorbed while battery cycles can be limited to 2295, highlighting the effectiveness of the established online coordinator. The aging model in [13] is further used here to quantify average battery life loss GEVs in different V2G methods. Compared to the rule-based method, the average battery life loss of each V2G participant can be reduced by 50.5% in the optimization-based method. The developed mixed learning method achieves a similar battery safeguard performance compared with the optimization-based method. Vehicle battery life loss can be limited to 4.57×10^{-2}, which validates the battery anti-aging performance of the developed methods. Meanwhile, it should be figured out that the developed mixed learning method can strictly satisfy the charging requirement of V2G participants. Compared to the rule-based method, the charging complete degree (CCD) can be improved from -4.2% to 3.7% with the defined charging urgency concept in the training process of the online regulator.

Table II. Quantitative performance comparison of different V2G scheduling methods in 30 working days.

Scenario	Case 1: Rule-based method	Case 2: Optimization-based model	Case 3: Mixed learning method
Scheduling interval	1s	300s	1s
Calculation time	0.12s	232.7s	665.5s/0.16s
REA rate (%)	97.5	73.2	94.6
Netload SD	0.42	0.68	0.51
Battery cycles	5265	1512	2295
Average life loss (%)	8.33×10^{-2}	4.12×10^{-2}	4.57×10^{-2}
CCD rate (%)	-4.2	2.5	3.7

It should be noted that this paper focuses on the consumption of local renewable energy by GEVs in microgrids but ignores the power purchase from the main grid. Both the V2G scheduling model and microgrid operation mechanism are designed and simulated by assuming that the microgrid is in off-grid mode. However, large-scale wind and solar power plants connected to transmission networks are also of great significance to improving microgrid security and efficiency. Future work will be conducted on V2G scheduling that considers energy mobility and trading between the microgrid and the main grid.

VI. Conclusion

A battery safeguard V2G scheduling method is developed for managing GEVs charging in microgrids with local renewable energy penetrations in this paper. The consumption of volatile renewable energy and the mitigation of battery aging are addressed by establishing a mixed learning V2G scheduling framework. The optimal online GEVs charging strategies are derived from the cooperation between the soft-run optimization model and online V2G power regulator. Through extensive simulations on a microgrid system with real power generation and consumption data, the key findings are:

- Benefiting from the cooperative optimization mechanism, the battery anti-aging strategy can be derived from the soft-run V2G behavior management model. The established ELM algorithm-based regulator can accurately reproduce the derived strategies in the soft-run model. Compared to the conventional online scheduling method, battery aging cycles can be effectively mitigated in V2G service.
- The built online V2G power regulator can schedule the charging power of GEVs in real-time for responding to the volatility of renewable power generation. Compared to the optimization-based method, the REA rate can be significantly improved.
- The supervised learning model has strong extrapolation capability, which makes it possible to respond to uncertain input beyond the training dataset. Owing to the extrapolation capability of the ELM model, the established online regulator can better deal with the uncertainty of renewable energies.

To summarize, the developed behavior learning framework inherits the merit of optimization-based and rule-based methods. The online strategies can effectively guide GEVs to provide battery safeguard power balancing V2G services to microgrids. In this way, they can economically benefit EV owns and microgrid operators, and facilitate decarbonization at low costs.

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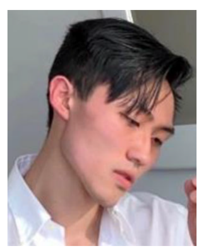

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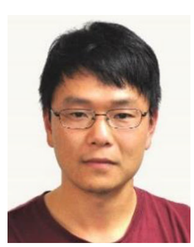

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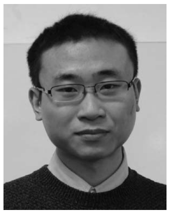

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