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Advanced Battery Management Method for Energy–Transportation Network

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Abstract. Grid-connected Electric Vehicles (GEVs) and the energy-transportation network offer encouraging prospects for boosting the adoption of renewable energy sources and Micro-Grid (MG) economics. However, the complicated battery aging mechanism and unpredictable MG statuses make it difficult to identify the best Vehicle-to-Grid (V2G) options. This study uses a unique Deep Reinforcement Learning (DRL) framework with model-free prediction and control to construct a novel online battery anti-aging energy management solution for the energy-transportation network. By simulating the effects of cycle count, discharge depth and charge and discharge rate, the quantification of aging cost in V2G strategies is accomplished using rain-flow cycle counting technology and battery aging characteristic analysis. The efficiency of agent actions to prevent aging in batteries is assessed using the standard life loss model. A DRL method is used to describe multiobjective learning for GEV charging coordination. Maximizing the use of renewable energy sources while lowering MG power variations and car battery aging expenses is the goal of the training. On an MG in the world countries, the created energy-transportation network energy management approach has been confirmed to be successful in providing optimal power balance and battery anti-aging control. Through the perfect coordination of GEV charging and renewable energy, this paper offers a cost-effective and efficient technique for MG power balancing, hence supporting a low cost decarbonisation transition.

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1. Introduction

According to renewable energy, it offers a promising solution to environmental issues, but power networks face significant obstacles as a result of its widespread use. Micro-grids(MG) can improve the dynamic interactions between load demand and renewable energy sources because of their comparatively low transmission voltage [1]. However, MG's power balance is challenging to maintain because of the intermittent nature of renewable energy and demand fluctuations, and the mismatch may result in sudden, short-term power fluctuation problems. Adding more reserve power generation, energy storage devices, and advanced power management techniques are examples of conventional MG power balancing solutions that, to some extent, fall short in terms of economics, stability, or dependability [2], [3]. A promising solution to MG's power balance issues is provided by the electrification of road vehicles and the energy-transportation nexus idea [4]. By postponing their need in space and time, grid-connected electric vehicle (GEV) onboard batteries can provide a way to increase MG flexibility and achieve continuous operation by serving as mobile storage units. Through vehicle-to-grid (V2G) regulation, GEV batteries are utilized in [5]–[7] to supply peakshaving, voltage regulation, and frequency regulation services. The findings of simulations and experiments show that using the movable energy storage capacity offered by GEVs can greatly improve energy quality and system stability when charging management techniques are implemented effectively. V2G services are also utilized in [8] and [9] to assist with the operation of solar and wind power generating. With the penetration of renewable energy, GEV batteries can be utilized to supply power balancing services and enhance the MG's stability and economy. The cost of GEV battery life loss as a result of delivering V2G service is still a barrier to the widespread usage of vehicle batteries. When MG uses renewable energy and battery energy storage, the situation gets worse since the battery may experience too many short circuit [10]. The development of the life loss analysis model is crucial for grid energy storage systems [13], hybrid powertrains [12], and battery energy management in electric vehicles [11]. In order to guide battery energy management and provide a life-cycle cost analysis tool in the energy-transportation nexus, the quantified battery aging cost can be employed as a benchmark of degradation-oriented mode of operation. Quantifying battery aging costs in energy management has been the subject of numerous studies. One of the most popular techniques for protecting car batteries in the literature currently in publication is the single-factor bucket model [14]. An event-based scheduling approach for optimum GEV charge management is developed in [15]. In order to mitigate the aging of GEVs in V2G services, complex battery aging models have been shown to be both essential and effective [14]. A model of battery aging that incorporates temperature effects, When offering V2G services, C-rate, state of charge (SoC), and DoD are integrated [17] to reduce the anticipated customer's charging cost. The best techniques are derived by stochastic optimization, and simulation results confirm that the battery antiaging performance is excellent. However, the implementation of intricate aging models and extensive optimization techniques complicates the V2Gmodel, further impairing the real-time performance of the scheduling system [18]. Comprehensive battery aging models and heuristic methods are used in [19] and [20] to mitigate aging expenses in V2G services. According to simulation studies, it is possible to effectively lower the expenses associated with battery depreciation. However, even with the most sophisticated computing equipment, the optimization-based V2G scheduling interval is only able to be reduced to 5 minutes, making it difficult to suppress oscillations in renewable energy and transitory MG demand. Using a DRL framework, this paper creates a unique online battery protective energy management technique for the energy-transportation nexus. First, the degradation cost in V2G scheduling is designed as a function of battery NoC, DoD, and C-rate using rain-flow cycle counting technology and battery deterioration characteristic analysis. The battery anti-aging efficacy of V2G techniques in DRL is assessed using the well-established aging cost model. Next, using the DRL framework, multiobjective learning is used to model the coordination of GEV charging. Maximizing renewable penetration while lowering vehicle battery aging costs is the DRL model's training goal. An experience pool is created using historical MG power balance and GEV battery conditions, and the trained DRL model is used to schedule the online charging and discharging procedures. With the established technique to absorb renewable energy while minimizing the phenomenon of vehicle battery aging in V2G service, the energy storage capacity of GEVs may be scheduled online.

2. ADVANCED MODEL FOR QUANTIFICATION OF ATTERY ENERGY STORAGE SYSTEM LIFE LOSS

Some of Numerous factors affecting battery health are identified in related research and can be broadly categorized into calendar and cycle aging [25]. All aging processes that are included in calendar aging cause a battery cell to degrade without regard to charge-discharge cycling [26]. Calendar aging is inevitable, according to literature [13], which also demonstrates that it has no effect on battery life in energy management. Rather, the primary source of GEV life loss is cycle aging, which is brought on by battery cycles [27]. Thus, this article only takes into account the cycle of aging. Cycles with varying Crates and DoDs affect battery life in a variety of ways and to varying degrees, per the findings of the battery degradation modes analysis obtained in [28]. Based on the discussion above, this section analyzes battery NoC, DoD, and C-rate data in SoC and GEV discharging power profiles to create a battery aging quantification model that measures battery life loss in V2G methods.

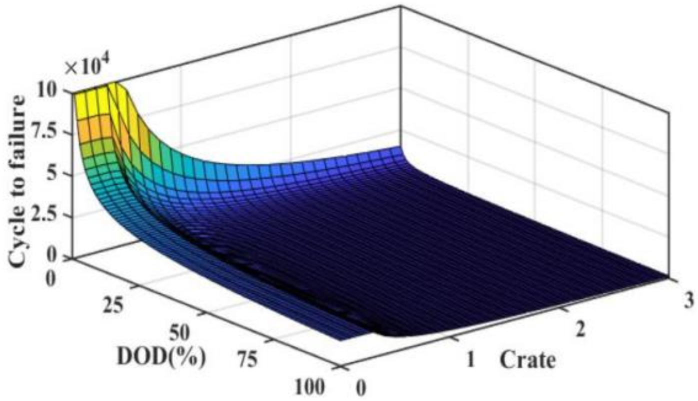

Figure 1. Constructed battery CTF responding profile

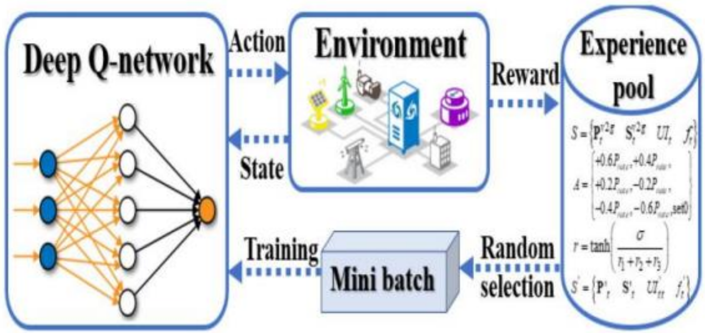

Figure 2. Designed deep-reinforcement-learningbased V2G behavior management framework.

Battery-rated cycle life under various operating situations is described in the CTF profile. In order to measure the effect of cycles with varying DoDs and C-rates on battery life loss in V2G scheduling, the notion of cycle-to-aging (CTA) is further described in this article.

3. V2G BEHAVIOR MANAGEMENT FRAMEWORK BASED ON DEEP REINFORCEMENT AND LEARNING WITH MODEL – FREE PREDICTION AND CONTROL

This method uses the DRL algorithm to address dynamic V2G behavior management and find the best power exchange between MG and GEVs. The four components of the DRLVM framework are the agent, environment, experience pool, and deep Qnetwork, as illustrated in Figuer 2. The decision variable in the established DRLVM framework is the charging behavior of GEVs, and the agent is chosen as an individual V2G participant. Three Markov decision processes are used to model the coordination of GEV charging at various points during the scheduling period: 1) state s, 2) action a, and 3) reward r are necessary components. The environment state variables in V2G scheduling are all continuous variables, in contrast to traditional decision-making. In the meanwhile, the battery SoC and historical V2G power should be taken into account in order to facilitate battery anti-aging scheduling, which makes the Q-value computation burden even more difficult. As a result, this paper uses a deep neural networkbased state continuous V2G scheduling technique. As illustrated in Figure 2, Q-values under continuous system state change in the decision system are estimated using a deep network. Reinforcement learning is the science of learing to make decision which affect the reward, the agent state, and environment state. The following formula can be used to represent the estimated Q-value:

$$Q(s, a) \approx \psi(s, a; \omega, b) \text{ ---------------------- } (1)$$

where w and b stand for the weights and biases of the trained deep neural network, respectively, and ψ is the transfer function. In the real world, GEV charging is coordinated using the trained deep Qnetwork. The action with the highest Q-value, which is represented as follows, is used to derive the corresponding V2G scheduling strategies:

$$\pi = \arg\max Q(s, a \mid \omega Q, b Q) \text{ ----------------- } (2)$$

where π is Reinforcement learning strategy

4. MULTIOBJECTIVE LEARNING MODEL IN V2G BEHAVIOR MANAGEMENT

A. Multiobjective Reward Function Design

To considering the reward function's definition should align with the goal of V2G scheduling since it directs agents to make the right choices. This section creates a multi-objective incentive system to reduce battery life losses and MGload fluctuations in DRLVM. The initial goal is to reduce battery deterioration. As explained in (10) and (11) the charging power and SoC trajectory of GEVs are taken from the historical V2G strategy base and reorganized in a time series. Battery life loss in V2G methods can be computed using the life loss quantification model that was defined.

$$D = \eta\ (Pt\ v2g, St\ v2g) \text{ ------------------- } (3)$$

To increase the MG's stability and economics, DRLVM's training objectives also include reducing load fluctuations and absorbing renewable energy sources. The second reward function is chosen to be the MG's uneven power with GEV penetration.

$$G=Pload+m.PV2g-Psolar+Pwind \text{ ------------- } (4)$$

Where, m- the aggregation impact in V2G service is reflected by the number of GEVs and the internal structure of the control circuit. The control scheme consists of Fuzzy controller, limiter, and three phase sine wave generator for reference current generation and generation of switching signals. The peak value of reference currents is estimated by regulating the DC link voltage. The actual capacitor voltage is compared with a set reference value. The error signal is then processed through a Fuzzy controller, which contributes to zero steady error in tracking the reference current signal.The learning model for the DRLVM framework is established in this part along with the mathematical premise. The first step in implementing V2G behavior learning is creating a multiobjective reward system that can accurately represent the needs for battery antiaging and MG power balance. The deep-Qnetwork's architecture and model training methodology are then explained in detail.

B. STRUCTURE AND TRAINING METHOD OF THE DEEP-Q-NETWORK

To guide the charging behavior of GEVs, the Qvalue of various activities should be evaluated in the designed DRLVM. One way to think about the Qvalue estimate in DRLVM is as a multi-input to multi-output regression problem. It is challenging to understand the regularity between the decision system's state and the Q-value of actions due to the intricate mapping relationship between the inputs and outputs. One of the most widely used artificial intelligence systems is the neural network, which uses numerous nodes and abstract mathematical models to mimic how neurons in the human brain function. Neurons in several layers of a neural network carry out actions in accordance with various functions, neural network can theoretically map any relationship as long as the network parameters and reasonable network structure are appropriately built. In order to improve the generalization ability of the learning process, better handle continuous grid and GEV state variables, and enhance the optimization effect of the constructed V2G coordinator, this study fits the estimated Qvalue using a multilayer deep neural network.

C= 1 2n ∑ ∑ (YQt,i(Xst) − YQt, i(Xst)) 8 2 x=1 n i=1 ---> (5)

Where Xst is the training input of the Q-network, which consists of system state variable at t. YQt is the Q-value of different actions, which can be calculated based on [20]. YQt is the output of the Qnetwork. n is the size of the selected mini-batch.

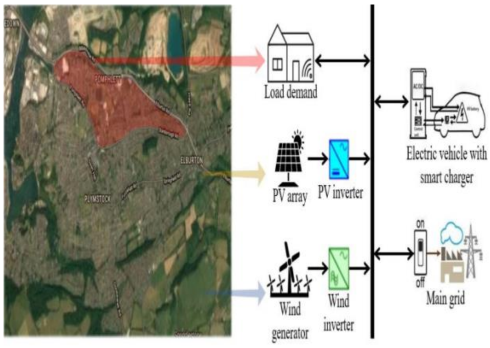

Figure 3. Configuration of the studied MG system with renewable energy penetration

Table 1. Battery characteristic parameters of the simulated GEVs fleet

Parameters	Value
Battery cell type	Lithium-ion 18650
Number of cells	444
Battery Module capacity	232Ah,5.3kWh
Voltage nominal	3.8V/Cell, 22.8V/Module
Charging voltage cut-off	4.2V/Cell, 25.2V/Module
Discharging voltage cut-off	3.3V/Cell, 19.8V/Module
Rated discharging current	500A
Battery pack configuration	2p5s
Battery pack capacity	53 kWh

5. CASE STUDY

The performance of the created DRLVM approach is demonstrated in this section. After presenting the topology and specifications of the MG system under study, the power balancing and anti-aging capabilities of the car batteries are assessed. The performance of the created DRLVM approach is demonstrated in this section. After presenting the topology and specifications of the MG system under study, the power balancing and anti-aging capabilities of the car batteries are assessed.

A. Microgrid System Test

In order to give the MG power balancing services, the charging behaviors of 350 GEVs are simulated in this paper. Table I shows the specific battery characteristic parameter for the GEVs under study. Each GEV's battery pack has a rated capacity of 53 kWh and is made up of 10 modules coupled in a 2p5s arrangement. The 444 lithiumion cells that make up the battery module have a rated capacity of 3400 mAh, a nominal voltage of 3.8 V, and a rated discharge current of up to 500A. The battery cell's cutoff voltages for charging and discharging are 4.2 and 3.3 V, respectively.

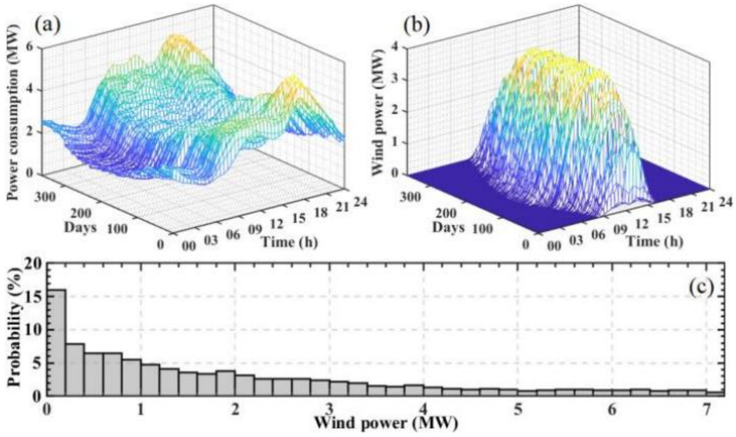

Figure 4. DRL model training data. (a) MG demand profiles. (b) Solar power generation profiles. (c) Wind power generation states distribution.

B. PERFORMANCE ASSESSMENT OF POWER BALANCING

The performance of four distinct V2G scheduling algorithms—the DRLVM method (Case 4), the peak-shaving oriented scheduling (PSOS) method [40] (Case 2), the Q-learning method [41] (Case 3), and the conventional fuzzy logic method [39] (Case 1)—is quantitatively compared in this section based on the power system configuration mentioned above. Figure. 5 analyzes the power balancing performance of several V2G scheduling techniques over a span of 250 working days. Because of the intricate optimization mechanism, the PSOS method's average simulation duration, in terms of algorithm computing speed, is as long as 265.4 s. In contrast to the PSOS approach, the charging behavior of GEVs can be immediately planned according to the rules, but the fuzzy logic method does not require any optimization steps.

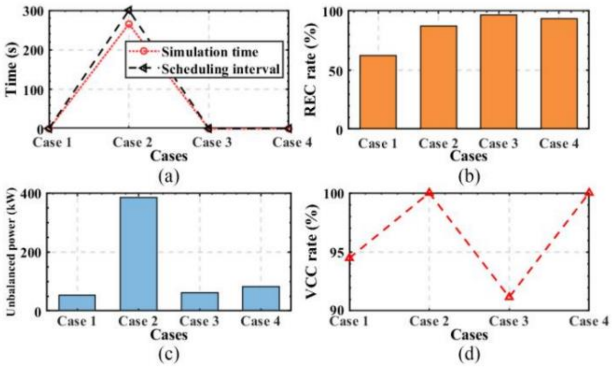

Figure 5. Power balancing performance comparison of different cases:(a) simulation time; (b) V2G renewable energy consumption rate; (c)system unbalanced power; and (d) vehicle charging completion rate.

Consequently, Case 2's simulation duration can be lowered to 0.13 seconds. Because of the offline training process, the simulation time can be kept to 0.25 and 0.27 seconds, and the Q-learning and DRLVM approaches calculate at a rate comparable to the fuzzy logic method. Therefore, in comparison to the optimization-based PSOS method, online scheduling techniques are better suited to handle variations in renewable power generation and demand fluctuations. In this article, the scheduling intervals in Cases 1–4 are set to 1, 300, 1, and 1 s, respectively, to ensure system stability. Fig. 7 displays the battery SoC profiles of a GEV using fuzzy logic and DRLVM techniques on a typical workday. Battery NoC in the V2G scheme using the DRLVM method is much lower than with the fuzzy logic method. Fuzzy logic is used to arrange GEVs to use as much renewable energy as possible. As a result, as Zone C illustrates, the battery experiences a significant number of shallow cycles when handling variable wind power supply in the evening. By modifying the battery working power, the V2G scheduling system can absorb renewable power generation via the DRLVM approach rather than flipping the battery charging state.

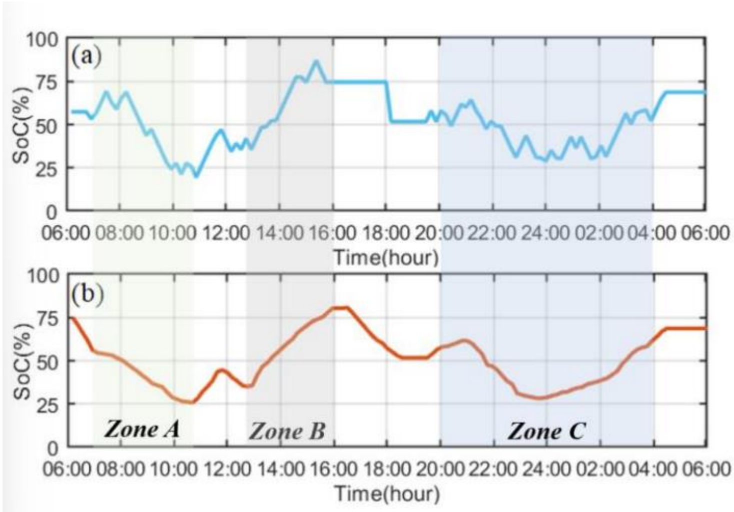

Figure 7. Battery SoC profiles of a GEV in a regular working day in (a)fuzzy logic method and (b) developed DRLVM method.

Table 2. Quantitative performance evaluation of different v2g scheduling methods

Scenario	Case 1: fuzzy logic method	Case2: psos method	Case3: q-learning method	Case 4: drlvm method
Number of cycles	2552	1954	2434	1875
Average C-rate	1.78	1.46	1.74	1.24
Battery life loss(%)	15.75	8.29	12.85	6.27

Table 2. provides a quantitative analysis of the battery anti-aging performance of various V2G scheduling techniques over the course of the simulation. The PSOS method's cooperative optimization approach allows for greater coordination of GEV charging behavior. Compared to the fuzzy logic approach, the battery's NoC and C-rate during the simulation period can be decreased by 23.4% and 17.9%, respectively. When the created aging model and multiobjective learning approach are used, the battery cycles and C-rate can be further decreased to 1875 and 1.24, respectively, yet the Q-learning method performs very similarly to the fuzzy logic method. The created DRLVM approach can reduce battery life loss by 60.2%, 24.4%, and 51.2%, respectively, in comparison to fuzzy logic, PSOS, and Q-learning methods. During the simulation period, battery life loss may be kept to 6.27%, confirming the efficacy of the created DRLVM technique.

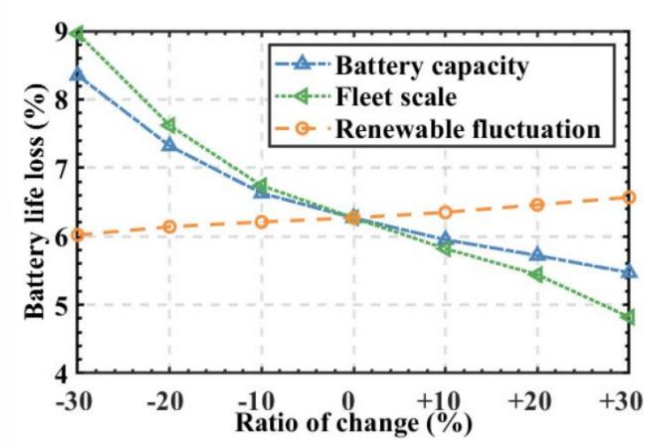

Figure 8. DRLVM method battery protective performance sensitivity analysis

Battery life loss is further examined using sensitivity analysis when fleet size, wind power generation variability, and vehicle battery capacity vary. Figure 8 illustrates that while fleet size and battery capacity have a favorable impact on lowering life loss in V2G services, renewable variation has a negative impact. The designed DRLVM method can function steadily even when the energy storage capacity of GEVs varies. The battery life loss in V2G services may still be kept to 8.37% and 8.94%, respectively, even when fleet scale and battery capacity drop by 30%. Likewise, fleet size has a greater effect on V2G system battery protection performance than battery capacity. Variability in renewable power generation has very little effect on V2G scheduling. Even when the rate of change of wind power fluctuation reaches 30%, battery life loss can be kept to 6.62%, confirming the resilience of the established DRLVM method.

6. Conclusion

This research created a unique battery anti-aging V2G scheduling technique that can use the energy storage capacity of GEVs to provide power balancing services for the MG. A battery deterioration model was used to quantify the aging cost of GEVs V2G scheduling. The DRL framework was used to describe the ideal GEV charging coordination as a multiobjective learning problem. The following are the main conclusions from indepth simulations on an MG system constructed using actual power generation and consumption data in the United Kingdom: 1) The existing aging cost analysis model can more thoroughly model battery aging characteristics than the bucket model. Once the created battery aging quantification model is used, vehicle battery life loss in V2G service can be greatly decreased. 2) The reinforcement-learning-based

V2G scheduling, which takes advantage of offline training, can arrange GEV charging behavior in realtime to reduce the unpredictability of renewable energy. MG imbalanced power and REC rate can be greatly decreased and enhanced as a consequence. Additionally, this article's methodology's application can be summed up as follows: 1) The wellestablished battery life loss analysis model serves as a useful life-cycle cost analysis tool and a baseline for degradation-oriented modes of operation that direct battery energy management. 2) The simulation results in this study and the wellestablished DRL-based V2G scheduling model-free predictive control specify the best vehicle battery utilization plan in smart energy systems taking deterioration into account, which can further increase the efficiency of the energy transport nexus.

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