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An improved vehicle to the grid method with battery longevity management in a microgrid application

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Abstract:

This paper proposed an improved vehicle-to-grid (V2G) scheduling approach for the frequency control with the advantage of protecting the batteries hence saving the battery lifetime during grid connected service. The proposed methodology is improved in two ways. Firstly, to give a prediction of the available electric vehicle (EV) battery capacity in the control time-step for the V2G service, a deep learning based prediction is developed. Secondly, this study advances the previous V2G method by adding the quantitative analysis of the battery cycle life into the V2G optimization. The accurate prediction of the schedulable battery capacity based on the LSTM algorithm is shown very effective in the power system frequency control. Also, compared with the previous method that without battery lifetime control, the proposed method benefits in the reduction of charge/discharge cycles.

Keywords: Electric vehicles; Deep learning; Frequency control; Microgrid; Vehicle to the grid;

Nomenclature:

CTF	Cycle-to-failure
DB	Dead-band
DoD	Depth of discharge
Deep-RNN	Deep recurrent neural networks
EV	Electric vehicle
LSTM	Long-short term memory
PSO	Particle swarm optimization
V2G	Vehicle-to-grid

1. Introduction

The increasingly share of renewable sources integrated to the network, strict set for the reduction of greenhouse gas emissions, and the need for providing clean energy, call for a paradigm shift in energy systems. The efficient power generations and energy consumptions are playing the key factors in this transformation[1-3]. On the one hand, the changes are obvious in the power gird as the generations are moving from the large centralized power plants to the distributed renewable sources [4, 5]. The transport electrification, on the other hand, is playing a vital role in this transformation has been recognized by industry and policy makers [6-8]. The ambitious targets are

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published to promote the transport evolution by many countries[9, 10]. For example, the United Kingdom government has announced a ban on the sale of the traditional diesel and petrol cars and vans after 2040 [11]. Inherently, the EVs or more specifically, the power batteries are regarded as the intruders for the traditional power grid, and with the large-scale adoption of electric vehicles, their uncoordinated charge demands are adding strains on the grid infrastructure [12]. As a result, if electric vehicle charging is left uncoordinated, the adoption of electric vehicles is expected to cause significant system power fluctuations, which will bring significant challenges on both system frequency and voltage stability reported by many researches[13, 14].

Nevertheless, the EV power batteries is regarded as the “moving energy storage” that offer the means to enhance power system flexibility especially for the grid and achieve uninterrupted operation by deferring their demand in time and even space and acting as dynamic storage devices. Therefore, it comes to the concept of vehicle-to-grid that effectively integrates the aggregated EVs into the microgrid as distributed energy resources to act as controllable generations or loads achieving the benefit of frequency regulating, voltage control, techno-economic operating, etc.[15-19]. The increasing penetration of renewable generation, the updated advances in energy storages and the substantial uptake of electrification of transport itself, is incessantly imposing unprecedented complexity and uncertainty on the V2G scheduling. With the increasing penetration of renewable energy resources, the development of high-performance V2G scheduling strategies has attracted much attention in global academic and industry communities[23-25]. Electric vehicles could provide ancillary services for the grid, but to enable this benefit, a key issue that should be addressed first is how to predict the V2G schedulable capacity information to meet different utility demands of power dispatch.

The statistical forecasting is widely used to make the capacity prediction based on historical data [26, 27]. Ref [28] interduces a power management method for integrating the EVs to the gird with fuzzy logic algorithm achieving an excellent operational resource scheduling. In the V2G scheme, the conventional scheduling could hardly address the emerging opportunities regarding to increased system information and complexity. The V2G control need to deal with not only the regular charge behavior under prediction scheme but the short-term uncertainty as well. Deep learning algorithms have been investigated to be used different applications such as fault detection [29, 30], demand side forecasting in power systems [31] and traffic prediction in transportation system [32]. The long short-term memory neural network is good at mining deep structure features in time-series data[33, 34], hence used for the battery capacity prediction.

To mitigate the battery degradation problem, on the one hand, the new V2G method should functionally take the battery degradation into account, and on the other hand, the new V2G scheme should provide the evidences with quantitative analysis of the techno-economic advantages to the customers to encourage their participation. The trade-off between the V2G service and the battery lifetime degradation is very difficult to reach. In addition, the objective function is usually not simple linear or quadratic, so the regular convex optimization method is not suitable in this case [35]. The introducing of a quantitative index of battery degradation makes it much worse that the objective function is non-gradient, which fails the regular gradient descent algorithms [36] and the non-gradient optimisation is normally used to solve this kind of problem. Different methods of none-gradient optimisation can be found with different characteristics in the knowledge field in different kind of applications [37-41]. Liu et al provide an good example by developing a multi-objective optimization strategy to optimize to maximize the fundamental frequency as well as minimize the dynamic displacement simultaneously [42]. The particle swarm optimization (PSO) has been investigated to be used in different applications [43, 44]. Huo et al presents an decomposed hybrid particle swarm method to achieve the optimal operation of interconnected energy hubs[44]. For the multi-objective optimization problem, the study presented by [45] developed a PEV charging coordination method based on fuzzy discrete particle swarm optimization, where several optimization objectives are combined based on fuzzy logic. However, the previous approaches did not consider the battery aging process and the quantitative analysis of the battery aging effect during the V2G services. To solve this problem, this study developed an PSO algorithms combined with the rain-flow cycle counting to reflect the battery aging process in the V2G scheduling. Comparing to the empirical-based or data-driven battery life estimation models, it is easier to quantify the cycles in rain-flow counting algorithm-based battery life estimation model [46]. Therefore, the EV battery charge/discharge cycle number is used in the proposed PSO algorithm.

The proposed EV battery available capacity prediction method and V2G battery anti-aging scheduling approach is verified to be effective by in the power system frequency regulation service. Compared with the previous method that without battery lifetime degradation consideration, the proposed method benefits in the reduction in charge/discharge cycles.

2. System description

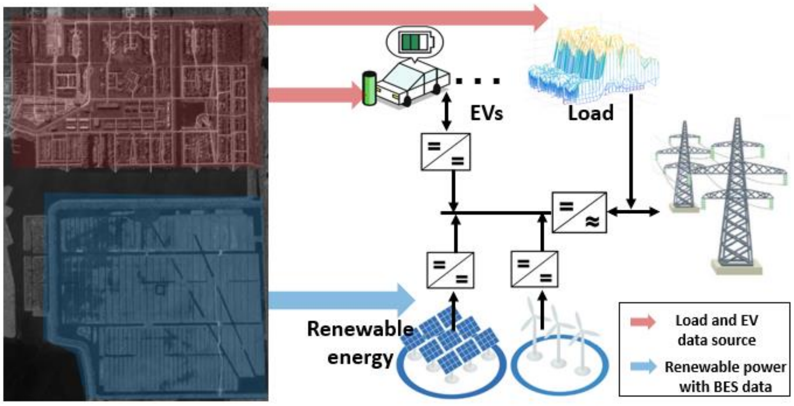

Fig. 1 Schematic of the microgrid system with real data source.

The microgrid system employed in this study is shown in Fig. 1 based on a microgrid data in in Belgium. This grid connected microgrid is built as a demonstration project to enable the large penetration of the renewable energies as well as to make arbitrage trades by contributing power system services. The EV battery anti-aging control is one of the main contributions of the proposed V2G method, whereas the battery lifetime performance should be evaluated availably in a long duration. Therefore, this study takes advantage of the real case of the microgrid in Belgium and builds the long-term V2G simulation model based on the real data in the yearly range. The structure of the long-term microgrid operation model is shown in Fig. 1 including renewable power and electrical vehicles. The onboard batteries participate the grid service via the gird connection and the communication links also exist connecting electric devices in the distributed locations and exchange their status information and control references in the long-term simulation [13, 15]. Aiming at the yearly range of the simulation, the microgrid and the electric devices are implemented by the linearized model and the microgrid is established based on the benchmark scheme [47].

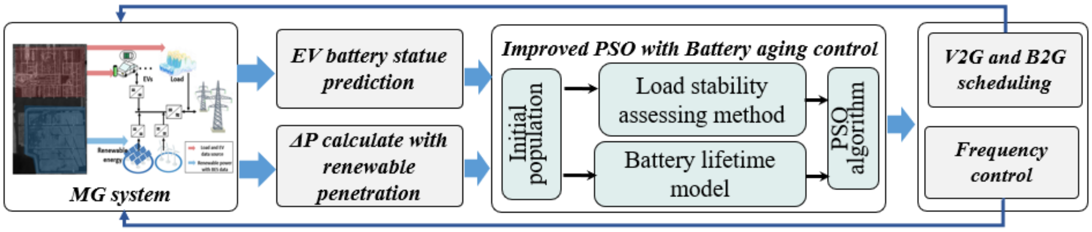

Fig. 2 Architecture of the proposed new V2G scheduling approach for system frequency control.

The logic diagram of the proposed new V2G method with the LSTM based EV capacity prediction and the improved PSO algorithm is shown as Fig. 2. The power system frequency regulation is selected as the target service providing by the EVs. As shown in Fig. 2, the microgrid works as both the real historical data source and the controlled system. The new V2G management module based on the improved PSO algorithm, formulates the V2G charge/discharge schemes for every grid-connected EV with both the information of grid-connected EVs and the prediction result. The optimization objectives are to mitigate power system fluctuation as well as minimize battery degradation. The microgrid model together with the novel V2G algorithm are developed in the Matlab.

3. Methodology

3.1 EV statue prediction

In the residential area, both the EV charge behavior or timing and the EV battery state at start/end points comply with some regular pattern, hence are predictable [48]. This is particularly helpful in the proposed new V2G scheduling method, as the demanding power and available discharging power of the onboard batteries could be predicted in time series. The deep recurrent neural networks (Deep-RNN) which is able to map the input into the corresponding sequential output, and fully expose the time-related features of it [49], is developed in this study. It consists of one input layer, several hidden layers, and one output layer, all of which are fully connected. Also, the timely update of the reference trajectory, here is the EV battery statue, is necessary to main the fast-transient response of the system control. Therefore, in order to avoid gradient blurry in long durations as well as to timely transfer the "just past" to the future prediction, this paper makes active combination of a roiling prediction scheme with LSTM. The LSTM is a specific architecture of Recurrent neural networks (RNN), and the parameters of LSTM are updated based on the Eq. 1 below.

$$
\begin{gathered}
a_1^t = b_{in} + W_1^{sc} h_1^{t-1} + W_{in}^{ic} x^t \\
h_i^t = f_{activation}(a_i^t) \\
a_i^t = b_i + W_i^{sc} h_i^{t-1} + W_{i-1,i}^{ic} h_{i-1}^t \\
o_i^t = b_{out} + W_n^{sc} h_n^{t-1} + W_{out}^{ic} h_n^t
\end{gathered}
\tag{1}
$$

Where x^t is the system data input, o^t is the prediction output, h_i^t is the state of i^{th} network layer, $f_{activation}$ is the activation function, b_i is the bias. W_i^{sc} and $W_{i,i-1}^{ic}$ are the weight of self-connection and inter-connection, respectively. Therefore, the state of the neuron *i* at time step *t* depends on three factors: 1) t^{th} time step input x^t or sharing state h_{i-1}^t at time *t* from $(i\text{-}1)^{th}$ layer, 2) bias b_i, and 3) sharing states h_i^{t-1} at current network layer from last time step *t-1*.

Combining the roiling time scale together with the LSTM algorithm could predict as well as update the EV status dynamically in the V2G services. This comprehensive method is shown in Fig. 3.

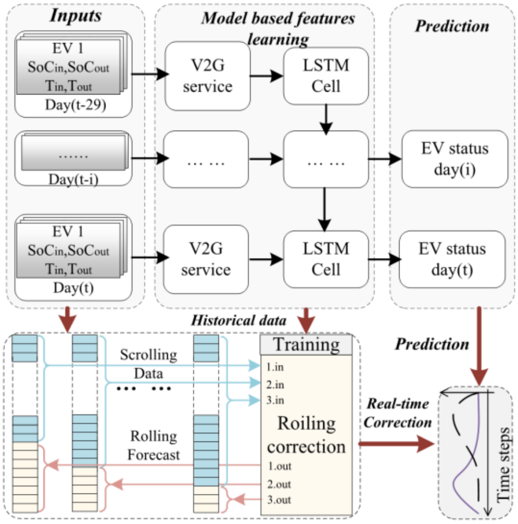

Fig. 3 The principle of the V2G schedulable capacity prediction method using the Deep-LSTM

As it is shown in Fig. 3, the data of all V2G participants in the MG is obtained and stored in a database. The V2G schedulable charging and discharging power based on the V2G service is used to train the prediction model. The LSTM algorithm then is used to obtain the V2G schedulable capacity. Also, within the LSTM cell for the EV status prediction, the rolling prediction process is performed repeatedly based on both the updated historical data and the real-time EV status. The accurate EV status or onboard battery status prediction is the critical reference for the EV batteries using in power system frequency control. History data of the EV in this study is mainly used to predict the available capacity of the battery for the grid service. The proposed method will be implemented easier at the aggregator, since the computational ability of the single charging pile is limited to achieve the prediction. Privacy protocol may be needed between the aggregator and the participant.

3.2 Power requirement prediction

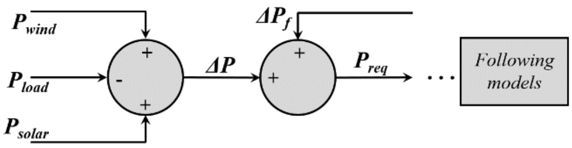

Fig. 4 Power requirement for the V2G service

The complexity of microgrid power forecasting lies in a). the significant volatility and uncertainty; and b), the uncertainty existing in both sides of the renewable generation and power consumption (load demand)[47]. In the proposed microgrid system, the EVs are expected to fulfill main two functions as shown in Fig. 5. First, the EV battery should enable the high penetration of the renewable power as much as possible by mitigating the power fluctuations inside the microgrid. Second, the onboard batteries could also provide frequency response for the main gird by power exchange. For the former function, the net power ΔP see Eq. 2 is the charge/discharge reference for the battery. Therefore, the single parameter ΔP could be set as the forecast target rather than the three predictive variable that wind power P_{wind}, solar power P_{solar} and load demand P_{load}. The power prediction methods have already been studied by many works, so this study does not introduce the prediction method in detail[50, 51]. The pooling-based neural network which could address the over-fitting issue, is used in this study to make the prediction based on the historical data of the net power.

$$\Delta P = P_{wind} + P_{solar} - P_{load} \tag{2}$$
$$P_{req} = \Delta \mathrm{P} + \Delta P_f \tag{3}$$

For the frequency support services, the procurement is normally agreed in advance. For example, there are currently two trials under way in the UK a). reduce the procurement advance period from 1 month to 1 week; b). same day procurement in 4 hourly blocks. Therefore, the power requirement for the frequency control ΔP_f is preset and available as an input for the EV battery. As shown in Eq. 3, the ΔP together with the ΔP_f are the power reequipment P_{req} for the following models.

3.3 Battery lifetime model

In the proposed V2G control, the battery lifetime prediction should meet two key requirements. First, the prediction should be fast enough. Second, the battery lifetime model should be able to quantify the battery lifetime reduction and renew the battery lifetime status to the EV consumer at the end time of daily V2G service. To satisfy the first scenario, the rain-flow cycle-counting algorithm which use less computing resources but been proved to accurate, is introduced in this study. The rain-flow cycle-counting algorithm has been widely used for analyzing the fatigue data and was investigated for battery cycling quantification by many published works[52-55]. With the reference of the cycles to failure chart the rain-flow cycle-counting could also make prediction of battery remaining lifetime. However, the previous rain-flow cycle-counting based approaches could not meet the second criteria that it could only calculate the degradation of the battery at charging pint neglecting the aging effect of the onboard battery in the driving mode. Consequently, prediction of the battery lifetime cannot be correct. To solve this problem, we introduced a Mile-to-Age function by which the battery aging effect during the driving mode is calculated based on the increased mileage [56].

The battery "cycle-to-failure" (CTF) curve (describing Battery cycles to failure vs. depth of discharge) is defined as number of cycles in function of depth of discharge (DoD) before the end of lifetime. In the rain-flow cycle counting algorithm, the "cycle-to-failure" curve works as an important reference to return the quantitative factor of battery degradation of each cycle. The Ref [57] presents an the "cycle-to-failure" curve/characteristic for the battery for an electric vehicle is used in this study to describe the "battery cycles to failure vs. depth of discharge".

For example, a typical "cycle-to-failure" curve is shown in Fig. 5 and at the depth of discharge 80%, the battery has 2500 cycles. Therefore, a very straightforward estimation can be made that if the battery undergoes one cycle with DoD of 50%, the battery lifetime degraded by 0.04% (1/2500=0.0004).

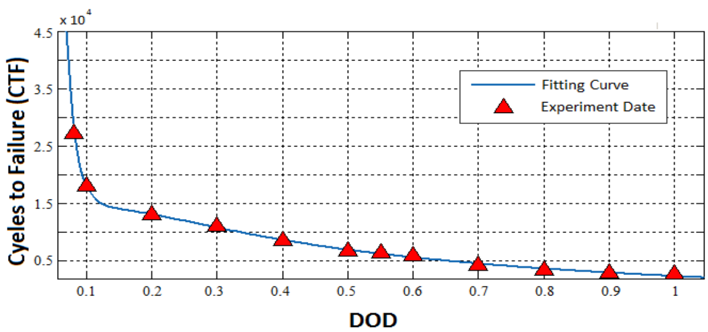

Fig.5 A typical cycle-to-failure curve [58]

The battery lifetime model in V2G service is shown as Algorithm 1.

Algorithm 1: Battery lifetime model in V2MG service

```
Input: Battery SOC trajectory in V2G scheduling and mileage increase
Output: Number or cycles at corresponding DODs
1:    Clone SOC data into A matrix and B matrix, and record the length of the SOC
data with m
2: Part one: Reconstruct SOC data
3:      for i ← 2 to m-1 do
4:          if (A (i-1) - A (i)) * (A (i) - A (i+1)) > 0 then
5:              Eliminate A (i), and store the reconstructed data in the B matrix
6:          end if
7:      end for
8: Part two: Definition the function of judging full cycle and convert the mileage
increase to the equivalent full cycle.
9:      re ← fun (B)
10:     Initialize the value of re (re ← 0), and record the length of the B data with
n
11:     Find the full cycle with four-point counting
12:         for j ← 1 to n-4 do
13:             s1 ← | B (j+1) – B (j+2) |
14:             s2 ← | B (j+3) – B (j) |
15:             if s1 <= s2 do
16:                 Assign 1 to re, and end the current cycle
17:             else
18:                 Assign 0 to re, and start the next round
19:             end if
20:         end for and sum(re) +cycle(mi)
21:     return
22: Part three: Find the amplitude and value of each full cycle and calculate the
degradation factor using the cycle-failure-curve.
23:     Store amplitude, value and number of cycles in the F matrix, J matrix and
X matrix.
24:     while fun (B)==1 or fun(B)==0 do
25:         if fun (B) ==1 do
26:             for j ← 1 to n-4 do
27:                 s1 ← | B (j+1) – B (j+2) |
28:                 s2 ← | B (j+3) – B (j) |
29:                 e3 ← (B (j+2) + B (j+1)) / 2
30:                 if s1 < s2 then
31:     Store S1 and e3 in the F matrix and the J matrix, respectively. Delete point
        B(j+1) data, and recalculate the length of the B data, and end the current
        cycle
32:                 else then
33:                     Start the next round
34:                 end if
35:             end for
36:         elseif fun (B) == 0
37:             End the current cycle
38:         end if
39:     Start the next round
40:     end while
```

3.4 Frequency control

In the frequency control, the EV charger must respond to deviations in nominal frequency (50 Hz) by decreasing or increasing their power output. It should be figured out that in the proposed microgrid, the frequency control function is the defined as frequency service offered by the total microgrid to the main grid rather than the batteries to the microgrid itself. Therefore, the ΔP_f offered by the EV batteries is not required to mitigate all the frequency fluctuations whereas the frequency fluctuation is the reference signal for the charge and discharge commends for the onboard batteries. This means both the actions and depth of the actions have the free ranges for the optimization.

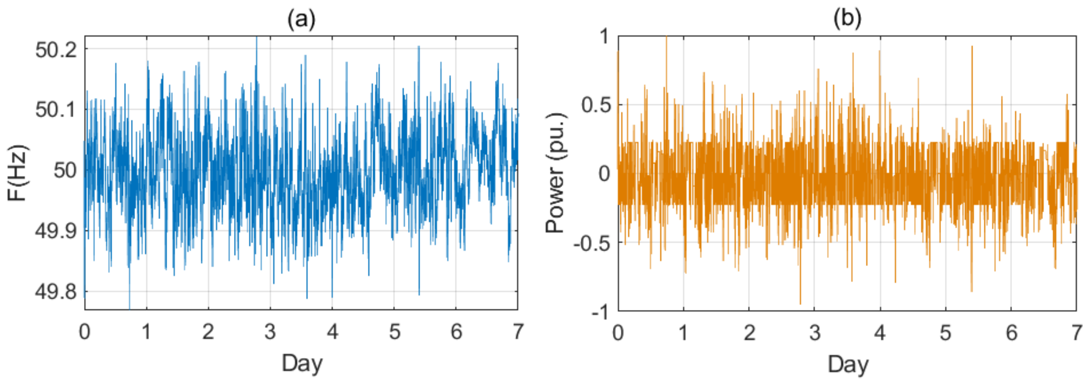

Fig. 6. (a). frequency data; (b) power profile

The real time frequency data is published by the National Grid and used for the case study in this paper. The frequency is converted to the power based on the document published by the National Grid and this document covers the testing requirements for pre-qualification assessment and reproving of the frequency services [59]. Fig. 6 shows an example of converting the real-time frequency to the power demand.

3.5 Battery active anti-aging control.

The essence of V2G scheduling is a decision-making issue, a fast and effective decision algorithm is indispensable for scheduling the charging and discharging behavior of the EVs. On the basis of the rolling time domain prediction-decision principle a multi-objective optimization for the V2G service is developed based on the particle swarm optimization algorithm. The highlight of this section is intelligent V2G scheme with the battery active anti-aging control and the POS works as a tool in this highlight so the POS algorithm will not be introduced in detail. The optimization variable in V2G scheduling is the charge/discharge power of every grid-connected EV. The particle dimension is $(n+1)\times(T_u+T_w)$, where n is the total number of EVs already in the grid, T_w and T_u are the number of decision points in the future and past control step respectively. Given $P_{i,j}$ represents the charge/discharge power of EV_i in time slot *j*. The pending scheduling sequence is obtained by the iteration process. The objective function is a multinomial hybrid function OBJ_p(see Eq. 3) that describes the onboard batteries need to contribute to the gird services

$$OBJ_p = \min\left\{\frac{1}{u+v}\sum_{t=1}^{u+w}\left[\lambda P_{req}(t) + \sum_{i=1}^{n} P_I(t) + \lambda P_p(t) - \lambda \bar{P}_A\right]^2\right\} \tag{4}$$

Where u is the V2G behavior in past intervals that are unmodifiable but have an influence on the system, v is the schedulable V2G behaviors in future intervals. $P_{req}(t)$ is the system power requirement at the interval t, $\bar{P}_A$ is the average power requirement. $\sum_{i=1}^{n} P_I(t)$ is the power exchange of grid-connected EVs, $P_p(t)$is the scheduled charge/discharge power of EVs that will soon access the grid, which reflects the utilization degree of future V2G schedulable capacity. Since not all the EV customers want to take active part in the grid services, so the participation willingness factor λ is introduced ranging from 0 to 1 with the 0.1 interval into the objective function. If λ is zero that means the EV users do not want to the provide gird service and the onboard battery will only be charged during the connected period. The object function will return to a constant power requirement. If λ is one, the EV owners will give 100% access to the control their batteries in the gird services. Therefore, the EV users have the freedom in action in the proposed optimization.

$$OBJ_{bat} = \min\left\{\sum_{i=1}^{n} N_i^{cycle}\right\} \tag{5}$$

The OBJ_{bat} function (see Eq. 5) is developed to minimize battery degradation in V2G, the cycle time is considered in objective function in our work. N_i^{cycle} is the charge/discharge cycles of EV_i based on the proposed approach in Section 3.3. It also should be figured out that, the two objective functions are tested as equal factors in this study. Another level of optimisation could also be designed to achieve a more accurate uniformization of the objectives, but is not considered in this study. The constrains are shown as below in Eq. 6:

$$St. \begin{cases} \boldsymbol{a.} \quad SoC_i^{end} \geq SoC_i^{set} \\ \boldsymbol{b.} \begin{cases} -P_{i,discharg}^{max} \leq P_i \leq P_{i,ch\,arg\,e}^{max} \\ -SoC_{min} \leq SoC_{i,t} \leq SoC_{max} \end{cases} \\ \boldsymbol{c.} \begin{cases} P_{req}(t) = \Delta P(t) + \Delta P_f(t) \\ \Delta P(t) = P_{wind}(t) + P_{solar}(t) - P_{load}(t) \\ \sum_{i=1}^{n} P_I(t) - \Delta P(t) \geq 0 \end{cases} \\ \boldsymbol{d.} \quad DP_{sum}^t \leq P_t^{pre} \leq CP_{sum}^t \\ \boldsymbol{e.} \begin{cases} 0 \leq \lambda \leq 1 \\ 1 \leq n \leq 27 \cdots \end{cases} \end{cases} \tag{6}$$

a. the travel demand of V2G participants should always be satisfied, charging should be completed before departure.
b. DoD and charge/discharge rate are restricted see the Section 3.3 for detail.
c. The power requirement inside the microgrid should be met in real-time whereas freedom is given in the frequency control for the main grid in the opination.
d. DP_{sum}^t and CP_{sum}^t are the predicted maximum schedulable discharging power and charging power boundaries respectively and $P_p(t)$ should be set in the range.
e. Numerical constraints

It should be noted that the total cycle number is indeed an objective variable of the present optimization algorithm ($OBJ_{bat} = \min\{\sum_{i=1}^{n} N_i^{cycle}\}$), of which ($N_i$) the calculation presented in Section 3.3 allows it to be given as integer. The cycle number works as the objective parameter rather than the design variable.

4. Result and discussion

The base load data used in this paper is the measured real data of load demand from the microgrid with 57 households with 27 EV owners with one-year data including vehicle type, return home time, departure time, travel distance, etc... The most active time 16:00-24:00 and 00:00-08:00. Assuming the distribution of the participation factor λ obeys normal distribution. In the uncommitted charging scenario, it is assumed that EV owners would immediately charge their vehicles after arriving home with rated power until the batteries were fully charged.

Based on the proposed deep learning approach in Section 3 and the real EV battery data, we made the prediction of the available capacity for the V2G service. Fig. 7 gives the examples of the two customers with two different sizes of electric vehicles in four and half-hours' prediction. It is obvious that the predictions of the available capacities of the two electric vehicles could track the real EV battery data.

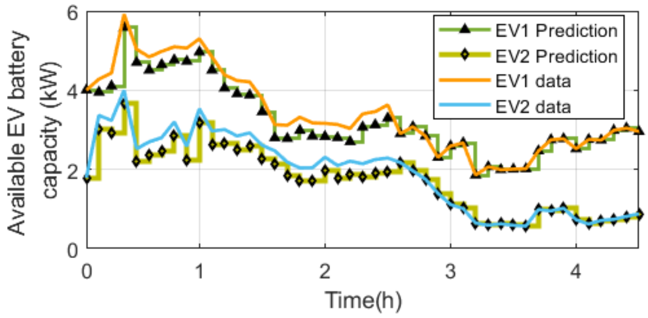

Fig. 7. Predictions of the available capacities of the two electric vehicles

A comparation is also made based on the simulation in 37 days of the battery data during the connection period 16:00 to 08:00 the second day. The results show that the battery undergoes deeper discharge (15% in average) with regular V2G management than that of the new method. Also, the proposed V2G scheduling method considering battery active anti-aging is able to reduce the amounts of full cycles, hence significantly mitigate battery degradation.

Fig. 8 shows the results of the power contribution of the EV batteries in the frequency control. As it illustrated in the Fig. 8, the EV batteries are controlled to charge and discharge power with respect to deviations in the grid frequency and the ramp-rate limits. The ramp-rate limit is made based on the system requirement based on the method described in [60]. The dead-band (DB) in the frequency code is set as ±0.015 Hz around the system frequency 50 Hz. The EV batteries do not need to response to the frequency control, which provide the opportunity within power limits to optimize battery status. For example, as show in the Area A' (see Fig. 8. b), the EV will maintain as charging in the DB, even though there are some points at which the system frequency is less than 50 Hz (see Area A in Fig. 8.a). Also, in the Area B around 19:00, the largest frequency droop can be observed, and correspondingly, the EV batteries provide the maximal power in the Area B'.

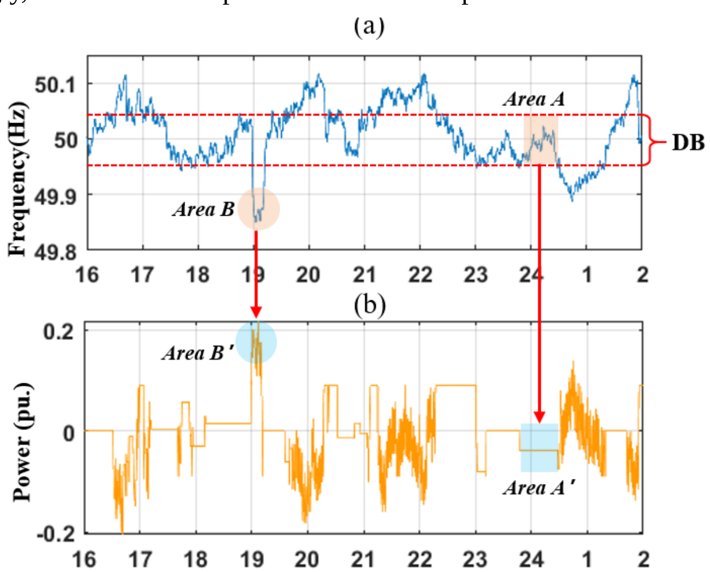

Fig. 8 (a). Main grid frequency fluctuations (b). Power contributions of the connected electric vehicles

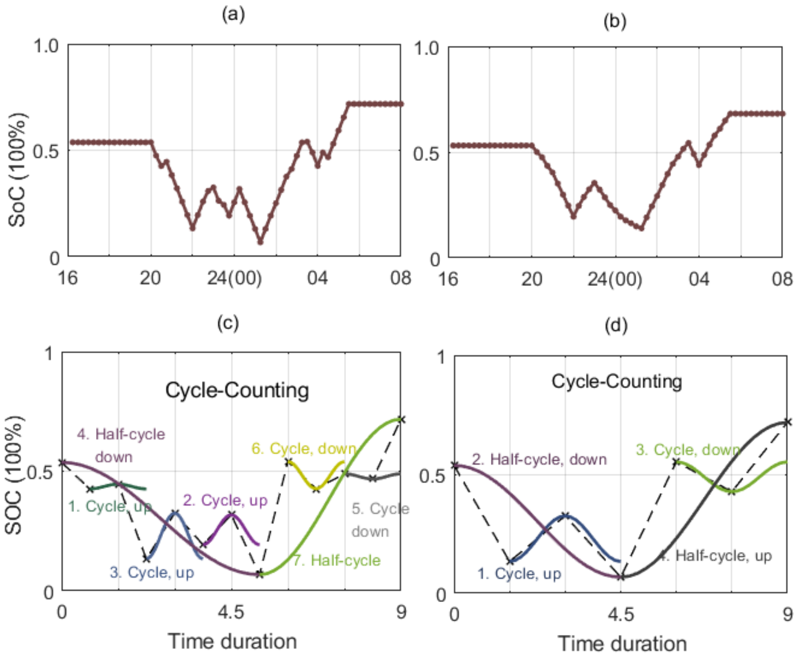

Fig. 9. The comparison of battery cycling performance in the uncommitted V2G scenario (a), (c) and battery cycling performance with the proposed new V2G method (b) and (d).

To avoid rapid battery degradation during participating in V2G, this study proposed the new V2G scheduling method considering battery active anti-aging in section 3. The comparison of battery cycling performance in the uncommitted V2G scenario that with the new V2G method is shown in Fig. 9. The figure is made based on a customer electric vehicle data in a random date. It is apparent that under the control of V2G management method proposed in this paper, the amounts of charge/discharge cycles are effectively restricted.

5. Conclusion

This paper proposed a new V2G scheduling method with the advantage of protecting the onboard battery from overused hence improved the battery lifetime during the V2G service. The methodology is improved in two ways. Firstly, to give an accurate prediction of the available EV battery capacity in the control time-step for the V2G service, the long short-term memory neural network is developed for the V2G scheduling. Secondly, this study advances the V2G scheduling by adding the battery lifetime model in the optimisation. The simulation results highlight that the proposed capacity prediction method could simulate the V2G behavior of aggregate EVs accurately. It is the fact that the EV need to absorb power/energy from the grid. While, EV batteries are also regarded as the “moving energy storage” that offer the means to enhance power system flexibility especially for the grid and achieve uninterrupted operation. This study mainly focuses on the technical part of the V2G scheduling achieving an optimisation that to some extent, satisfies the power requirement from the batteries at the same time to minimize the battery lifetime degradation (to minimize the cycle number). It should be highlighted that the economic analysis is also very important in the knowledge filed of the V2G with regarding to, for example, the charging costs, revenues, emissions, etc., which may be the potential topics in the future research about the V2G.

Acknowledgments

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