Article

Vehicle-to-grid Management for Multi-time Scale Grid Power Balancing

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Abstract: The mitigation of peak-valley difference and transient power fluctuation are both of great significance to the economy and stability of the power grid. This paper proposes a novel vehicle-to-grid behavior management method that can provide peak-shaving and fast power balancing service to the grid simultaneously. Firstly, a multi-time scale vehicle-to-grid behavior management framework is designed to enable large-scale optimization and real-time control at the same time in vehicle-to-grid scheduling. Then, the grid peak-shaving requirement is modeled as a mathematical optimization problem in a centralized V2G state coordinator, where the charging behavior of all grid-connected electric vehicles can be synergistically scheduled. The optimization variable is designed as a group of vehicle-to-grid state control signals that can respond to grid peak-shaving requirements. Further, a V2G power controller is designed to manage the vehicle charging power in real-time based on the sampled grid frequency state and discrete state control signal. In the developed scheduling method, the charging power of grid-connected electric vehicles is scheduled by the cooperation between the V2G state coordinator and the power controller. The effectiveness of the proposed methodologies is verified on a microgrid system, and results indicate that the V2G scheduling can achieve multi-time scale grid power balancing.

Keywords: Electric vehicle, multi-time scale scheduling, vehicle to grid, grid energy storage, peak management, power balancing.

Abbreviations

EV	Electric vehicles
GEVs	Grid-connected electric vehicles
V2G	Vehicle to grid
G2V	Grid to vehicle
FLC	Fuzzy logic control
ICT	Information and communications technology
VSC	V2G state control
MSVBM	Multi-time scale V2G behavior management
GA	Genetic algorithm
FLVPC	Fuzzy logic V2G power controller
SD	Standard deviation

I. Introduction

Vehicles and power grids are two important components of the modern energy system. In recent years, the growing concerns with the shortage of fossil fuels and greenhouse gas emissions call for a paradigm shift in power grids [1, 2]. The traditional energy generation devices, including the diesel generator and the coal-fired power plant, are gradually replaced by renewable energies [3, 4]. Different from traditional energy generation sectors, the intermittent nature of renewable energy makes it difficult to maintain the power balance between supply and demand. The unstable power balancing state may cause frequency fluctuation and voltage deviation problems, which can further do harm to the grid economy and stability [5, 6].

Meanwhile, with the electrification of transportation systems, conventional fuel vehicles are replaced by electric vehicles (EVs) due to environmental and economic benefits [7, 8]. Inherently, grid-connected electric vehicles (GEVs), or more specifically, power batteries of GEVs are regarded as the intruder to the power grid, and with the large-scale adoption, their uncoordinated charging adds significant pressure on the power grid [9, 10]. As a result, if GEVs charging is uncoordinated, it can cause significant power fluctuations, bringing significant challenges to both system economy and stability, particularly for power systems with large renewable energy penetration [11]. Fortunately, different from conventional energy consumption equipment, the vehicle battery can also be used as the named “energy storage system” to feed energy back to the grid when necessary. The inclusion of EVs, however, introduces a challenging problem, i.e. how to coordinate the operation of renewable energy systems, domestic loads, and charging behaviors of GEVs.

To improve the economy and stability of the power grid with renewable energy penetrations, a large volume of studies has investigated vehicle to grid (V2G) behavior management techniques in recent years [12-15]. Decentralized scheduling is one of the most popular V2G management methods. In decentralized methods, GEV charging is scheduled independently by distributed controllers and algorithms [16, 17]. A rule-based decentralized V2G control method was proposed in [18] for GEVs to participate in grid frequency regulation service. Simulations on a two-area interconnected power grid showed that the proposed decentralized method can suppress transient grid power fluctuations while meeting GEVs charging requirements. Mukesh Singh et al. [19] proposed a decentralized V2G scheduling method for grid peak demand management using fuzzy logic control (FLC). Experiment results revealed that the charging and discharging power of GEVs can be controlled in real-time to provide grid power balancing service. Grid state information is sampled and used locally in decentralized methods to schedule the charging power of GEVs [20, 21]. Thus, the transient unpredictable load and power generation fluctuation can be efficiently suppressed and grid frequency can be effectively stabilized. However, each GEV is controlled independently in conventional decentralized methods, and there is no centralized long-term planning or information-sharing mechanism [22, 23]. Consequently, the peak-shaving requirement of the grid can hardly be satisfied in most decentralized V2G methods.

To provide large-time scale peak-shaving service to the grid, V2G behavior of all GEVs should be synergistically scheduled [24, 25]. Recently, with the development of information and communications technology (ICT), researchers have begun to develop centralized V2G scheduling methods to improve peak-shaving performance [26-28]. Kristien Clement Nyns et al. [29] proposed a centralized GEV charging coordination approach by using a dynamic programming algorithm, and the optimal charging profile was formulated by minimizing grid power fluctuations. Literature [30] proposed a method to coordinate V2G behavior based on a self-adaptively imperialist competitive algorithm, where each GEV was scheduled to minimize power imbalance cost considering network constraints. Experiment results on a microgrid system indicated that the grid peak-valley difference can be significantly reduced by the proposed method. In the centralized method, GEV charging demand, load, power supply, and grid state information are synthetically utilized to achieve optimal V2G scheduling [31]. However, centralized V2G scheduling is a time-consuming process, and the control time-step is 5 to 10 minutes or even longer [32, 33]. Therefore, transient unpredictable load and power generation fluctuations can hardly be suppressed in centralized methods [34].

The reduction of peak-valley difference and the suppression of transient load fluctuation are both of great significance to grid economy, stability, and power supply quality [35-37]. However, because lacking of information sharing mechanism in decentralized methods and the limitation of calculation speed in the centralized methods, both are not able to provide peak-shaving and transient power balancing services for the grid at the same time [38]. This paper aims to resolve the aforementioned problems by developing a multi-time scale V2G scheduling method. Grid peak-shaving requirement is modeled as a large-scale optimization problem in a centralized GEVs charging state coordinator, where the charging behavior of all GEVs can be synergistically scheduled. The optimization variable is designed as a group of V2G state control signals that can respond to grid peak-shaving requirements. On the basis of the established centralized GEVs charging state coordinator, a V2G power controller is further designed to manage the vehicle charging power in real-time based on the sampled grid frequency state and discrete state control signal. In the developed scheduling method, the charging power of GEVs is scheduled by the cooperation between the V2G state coordinator and real-time power controller. The key contribution of this paper is summarized as follows:

- This paper is the first attempt to investigate a V2G scheduling method that can satisfy the multi-time scale power balancing requirement of the grid. With the proposed scheduling method, both grid peak-valley difference and transient power fluctuation can be reduced significantly.

- A multi-time scale V2G behavior management (MSVBM) framework is designed, which enables the large-scale optimization and real-time control at the same time in V2G scheduling. Under the MSVBM framework, the charging power of GEVs can be scheduled by the cooperation between the centralized V2G state coordinator and real-time power controller.
- It designs the V2G state control (VSC) signals in a centralized V2G state coordinator, which can model the grid peak-shaving requirement as a mathematical optimization problem. With the VSC signals, GEV charging can be synergistically scheduled to respond to grid peak-shaving requirements.
- It designs a novel V2G power controller, which can schedule V2G power for balancing grid transient power fluctuation in real-time. With the designed real-time controller, the transient grid power fluctuation can be suppressed and the power quality can be significantly improved.

The rest of the paper is organized as follows: The developed MSVBM framework is introduced in Section II. Section III presents the centralized GEVs charging state coordinator. The developed real-time V2G power controller is described in Section IV. The simulation platform and the performance of the proposed V2G scheduling method are provided and evaluated in Sections V, followed by concluding remarks in Section VI.

II. Multi-time scale V2G behavior management framework

To improve grid economy and power quality at the same time by better utilizing GEVs resources, a novel MSVBM framework is developed in this section. As shown in Fig. 1, the developed MSVBM framework consists of two parts: the centralized V2G state coordinator and real-time V2G power controller. The peak-shaving and transient power balancing requirements of the grid are processed with the centralized V2G coordinator and real-time V2G power controller, respectively.

To provide peak-shaving service to the grid in V2G scheduling, the charging behavior of all V2G participants should be cooperatively scheduled. In the designed MSVBM framework, the peak-shaving requirement of the grid is modeled as a centralized optimization problem. The predicted grid load profile, renewable generation profile, and GEVs state information are used to estimate grid power peak-valley characteristics, and then the power level of GEVs is scheduled to provide grid peak-shaving service based on the large-scale optimization algorithm. The optimization variable is designed as a set of VSC signal which can respond to the peak-shaving requirement of the grid. The optimization results: peak-shaving oriented V2G control commands are sent to real-time V2G controllers, working as a guidance signal to direct the actual control of V2G power.

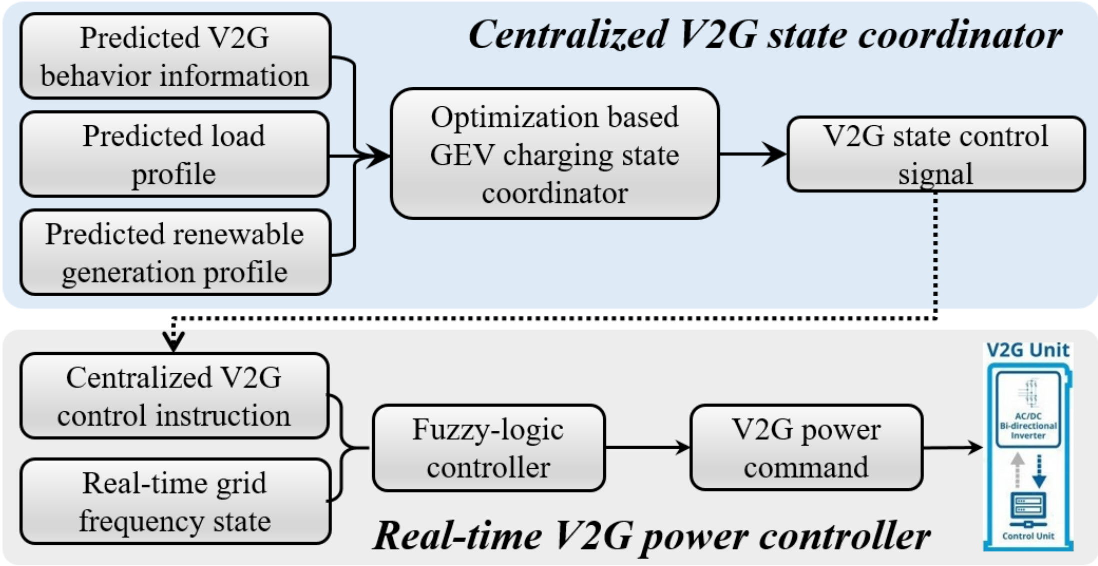

Fig. 1. The developed multi-time scale V2G behavior management framework.

With strong transience and unpredictability, fluctuations of uncertain load and power generation cannot be suppressed by the centralized V2G coordinator. To suppress the transient power fluctuation and improve grid energy quality, a real-time V2G power controller is built to control the GEVs charging power directly. As shown in Fig. 1, with sampled real-time grid frequency state and the VSC commands provided by the centralized coordinator, a fuzzy-logic-based real-time V2G power controller is established to calculate V2G power. The scheduled V2G power command is used to directly control the charging and discharging behavior of GEVs by a smart charger.

In the developed MSVBM framework, GEVs charging power is scheduled by the cooperation between the centralized V2G state coordinator and real-time power controller. V2G state control signal, which is coordinated in the centralized coordinator, is used to respond to peak-shaving requirement and improve grid economy; and the specific V2G power is scheduled by the real-time controller to improve the grid power quality. With the above system operation mechanism, V2G resources can be better mobilized to provide multi-time scale power balancing service to the grid. The rest of the paper will detail the mathematical principle of the centralized V2G coordinator and the real-time V2G power controller

III. Centralized V2G state coordinator

To make better use of GEV resources to provide peak-shaving service, this section develops a GEV charging state coordination model to respond to the large time-scale peak-shaving requirement of the grid. For centralized V2G scheduling, a fast and effective decision algorithm is indispensable for scheduling the charging and discharging power level of GEVs. The heuristic algorithm is one of the most effective ways to solve complex optimization problems. Genetic algorithm (GA) is a typical heuristic algorithm, which has a better adaptability and can usually achieve the global optimal solution, especially in discrete optimization problems [39, 40]. The essential of GEV charging scheduling is a large-scale discrete optimization problem, and thus the GA is used as the core algorithm in the developed centralized V2G state coordination model in this section.

The designed optimization variable is the VSC signal, which is used to reflect the charging/discharging power level of each GEV. To simplify the optimization and facilitate real-time V2G control, the charging and discharging states of each GEV in each time interval are divided into five levels: negative big (NB), negative small (NS), zero (Z), positive small (PS), and positive big (PB). When the load peak appears, the VSC signal is assigned as NB or NS, and the GEVs are scheduled to discharge to reduce the peak-valley difference of the grid. On the contrary, when load valley appears, the VSC signal is changed to PS or PB according to different valley levels, and GEVs are scheduled to charge to satisfy the charging requirement of owners. When the grid load state is relatively stable, the VSC signal is set to Z to protect the vehicle battery from additional cycles. Furthermore, the above five states are further represented with a three-digit binary variable and the encoding rules are as follows

$$S_{i,j} = \begin{cases} NB(111) & \text{Full power discharging} \\ NS(110) & \text{Medium power discharging} \\ Z(000) & \text{No Action} \\ PS(010) & \text{Medium power charging} \\ PB(011) & \text{Full power charging} \end{cases} \tag{1}$$

Where: $S_{i,j}$ is charging state of EV_i at time *j*.

Different from conventional GA algorithms, the individual coding format in the proposed scheduling method is a three-digit binary variable. To improve calculation efficiency, a new chromosome crossover and mutation mechanism is developed. Firstly, in conventional GA, the crossover operation is generally performed in the form of point-to-point, but it is inefficient in large-scale optimization problems, such as V2G scheduling [41, 42]. Therefore, a segment-to-segment crossover approach is applied in our work, shown in Fig. 2(a). The genes in different chromosomes are in 4 units, which can effectively improve the chromosome crossover efficiency. Then, a novel chromosome mutation mechanism is developed to ensure the validity of the optimization. In the proposed coding format, each gene has five states (111, 110, 000, 010, and 011). To simplify chromosome mutation operation and accelerate optimization, it is assumed that each gene mutates in 4 different directions with equal probability, as shown in Fig. 2(b).

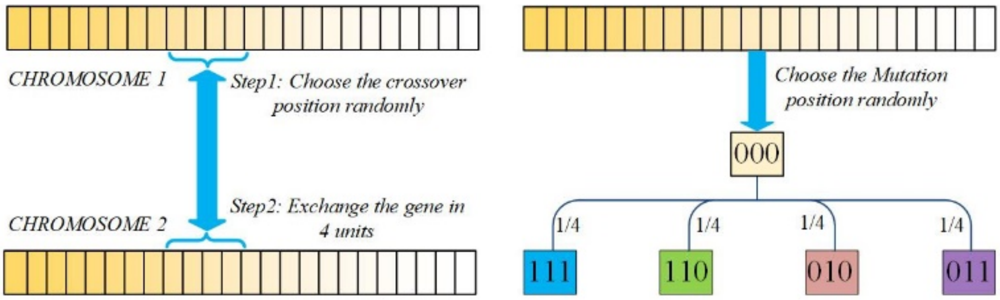

Fig. 2. The designed chromosome crossover and mutation mechanism for three-digit binary variables in V2G scheduling.

The structure of chromosome $\mathbf{S}_I$ in the centralized V2G scheduling model is designed as:

$$\mathbf{S}_\mathbf{I}=\begin{bmatrix} 0 & \cdots & 0 & \cdots & S_{1,u} & S_{1,u+1} & \cdots & S_{1,u+w} \\ \vdots & \ddots & \vdots & \cdots & \vdots & \vdots & \ddots & \vdots \\ 0 & \cdots & 0 & \cdots & S_{m,u} & S_{m,u+1} & \cdots & S_{m,u+w} \\ S_{i,1} & \cdots & S_{i,j} & \cdots & S_{i,u} & S_{i,u+1} & \cdots & S_{i,u+w} \\ \vdots & \ddots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ S_{n,1} & \cdots & S_{n,j} & \cdots & S_{n,u} & S_{n,u+1} & \cdots & S_{n,u+w} \end{bmatrix} \tag{2}$$

The dimension of $\mathbf{S}_I$ is $n\times(u+w)$. Where n is the total number of GEVs; m represents the number of GEVs that has just been connected to the grid and pending V2G scheduling instructions, (n-m) is the number of GEVs that are already connected to the grid. u and w represent historical and future V2G charging states. Historical GEVs V2G behaviors are unchangeable but can affect overall system peak-shaving performance, and therefore, $S_{i,1}\cdots S_{n,u}$ is also designed as part of the optimization variable. Future GEV charging states $S_{1,u+1}\cdots S_{n,u+w}$ are scheduled to provide peak-shaving service for the grid by the optimization process, and the corresponding objective function and constraints are described in the rest of this section. Firstly, the V2G power of EV_i at time j, $P_{i,j}$, is derived by GEV charging state matrix:

$$P_{i,j}=\begin{cases} P_{ed}\times\left| \begin{matrix} 1 \\ \frac{1}{2} \end{matrix} \right. & \begin{matrix} S_{i,j}=NB(111) \\ S_{i,j}=NS(110) \end{matrix} \\ 0 & S_{i,j}=Z(000) \\ P_{ec}\times\left| \begin{matrix} \frac{1}{2} \\ 1 \end{matrix} \right. & \begin{matrix} S_{i,j}=PS(010) \\ S_{i,j}=PB(011) \end{matrix} \end{cases} \tag{3}$$

Where: P_{ed} and P_{ec} are the rated discharging and charging power of the battery. Based on the derived V2G power state, the battery SOC of EV_i can be calculated by the following equation [43]:

$$SoC_{i,j+1}=SoC_{i,j}+\frac{\Delta t\times P_{i,j}\times\eta^i}{C^i}\times 100 \tag{4}$$

Where: Δt is the duration of a dispatch time interval, C^i and η^i are the battery capacity and operation efficiency of EV_i.

The relationship between the scheduled V2G power matrix $\mathbf{P}_I$ and V2G state matrix is:

$$\mathbf{P}_I = f(\mathbf{S}_I) \tag{5}$$

Where: f is V2G state-power transfer function.

The objective function in the centralized V2G scheduling system is to reduce load fluctuation variance:

$$OBJ_p = \min\left\{\frac{1}{u+w}\sum_{t=1}^{u+w}\left[P_{req}(t) - P_{ge}(t) + \sum_{i=1}^{n} f(\mathbf{S}_I(t)) - \overline{P}_{rav}\right]^2\right\} \tag{6}$$

Where: $P_{req}(t)$ and $\overline{P}_{rav}$ are system power requirement at time t and system average power requirement. $P_{ge}(t)$ is the power generation at t in the microgrid. $\sum_{i=1}^{n} f(\mathbf{S}_I(t))$ is the power exchange between GEVs and microgrid.

The defined optimization problem is subjected to the following constraints that reflect the charging requirements of V2G participants:

$$\begin{cases} -P_{i,\text{discharg}}^{\max} \le P_i \le P_{i,\text{ch arg}}^{\max} \\ \text{SoC}_{\min} \le \text{SoC}_{i,t} \le \text{SoC}_{\max} \\ SoC_i^{\text{end}} \ge SoC_i^{\text{set}} \end{cases} \tag{7}$$

Where: $P_{i,\text{discharg}}^{\max}$ and $P_{i,\text{ch arg}}^{\max}$ constraint the maximum battery discharging and charging power of V2G participants to protect the battery for high current; $\text{SoC}_{\min}$ and $\text{SoC}_{\max}$ describe the allowed minimum and maximum battery energy state to avoid over-discharging and over-charging. It is noted that charging should be completed before participants' departure, and therefore, the final battery energy state SoC_i^{end} should be higher than the vehicle charging requirement SoC_i^{set}.

The GA method is used to solve the optimal charging state of GEVs. The focus of this section is to build the mathematical model of the centralized V2G charging state scheme and the GA is the tool to solve the model. Thus, the GA principle will not be introduced in detail. The scheduled optimal GEV charging state command can respond to grid peak-shaving requirement, and it is used as the VSC signal for real-time V2G power controller in the next section.

IV. Real-time V2G power controller

The established centralized GEV charging state coordinator can only satisfy grid peak-shaving requirements but not services to stabilize grid transient power fluctuations. In this section, based on the generated VSC signal in Section III, a real-time V2G power controller that can consider grid multi-time scale grid power balancing requirements is developed to further improve energy quality.

A. Real-time microgrid power balance model

The microgrid is a complex dynamic system with various sources and loads having different characteristics. The power balance of the microgrid influences the energy quality directly: the unbalanced reactive power will result in voltage fluctuation, and the grid frequency fluctuation is contributed by unbalanced active power. In the non-industrial microgrid (family, community, and workplace), the most frequently discussed scenario is the unbalanced active power. Therefore, the power requirement for suppressing transient grid power unbalance is calculated based on the real-time grid frequency state information in this study. The system power balance equation can be obtained as:

$$\Delta P(t) = P_{\text{wind}}(t) + P_{\text{solar}}(t) - P_{\text{load}}(t) \tag{8}$$

ΔP reflects the change of supply and demand balance in the microgrid. The change of ΔP causes the frequency fluctuation, and to improve energy quality, the power balance should be dealt with the power contributions from GEVs. As shown in Fig. 3, in the studied microgrid system, the transient grid power fluctuation caused by the uncertainty of renewable energy and household load will directly impact the frequency state of the grid. Based on the deviations in nominal frequency (50 Hz), the V2G controller schedules the V2G power of GEV batteries directly to provide fast power balancing service for the grid.

B. Real-time V2G power scheduling method

On the basis described microgrid power balance model, to provide peak-shaving service and stabilize the grid transient power fluctuation at the same time by utilizing V2G resources, a fuzzy logic V2G power controller (FLVPC) is developed in this section. The input variables of the FLVPC are chosen as:

1) the frequency deviations of the grid Δf, which reflects the power injection requirements of the grid.
2) the centralized GEV state control command S, which reflects the power requirements for grid peak-shaving service.

The output of the FLVPC is the V2G charging or discharging power P_{real}. To make the output function bounded, the V2G power variable R_{real} with range [-1 ~ 1] is used to describe the V2G output power level. The relationship between P_{real} and S_{real} can be denoted as:

$$P_{real} = R_{real} \times \left| \begin{matrix} P_{ed} & S_{real} < 0 \\ P_{ec} & S_{real} \geq 0 \end{matrix} \right. \tag{9}$$

The membership functions (MFs) of Δf and R_{real} are depicted in Fig. 3. The MFs for input variable Δf is designed as 1) large negative (LN); 2) negative (N); 3) zero (Z); 4) positive (P) and large positive (LP); the 'positive' and 'negative' represent the direction of frequency deviations, 'large' represents the degree of deviation. Similarly, the MFs of the output variable R_{real} are negative big (NB), negative middle (NM), negative small (NS), zero (Z), positive small (PS), positive middle (PM), and positive big (PB). 'Negative' and 'positive' represent grid-to-vehicle (G2V) and V2G mode, respectively. The 'big', 'middle', and 'small' represent the output power degrees.

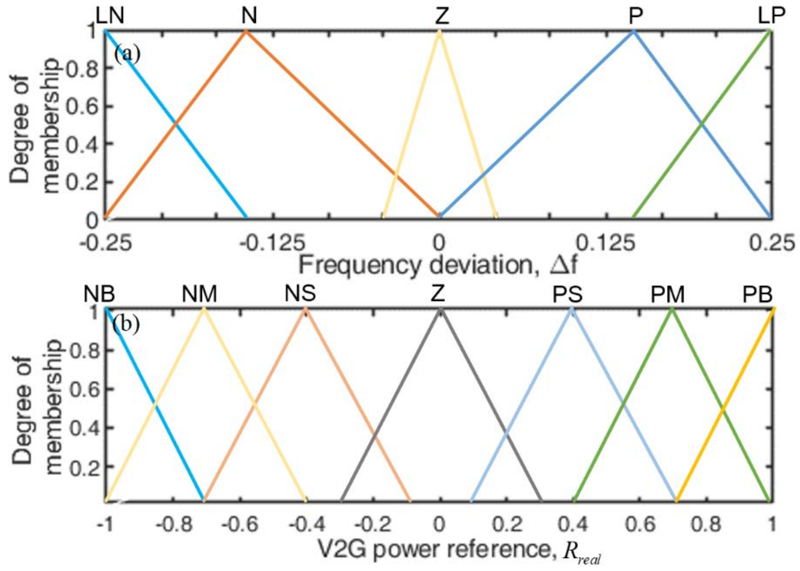

Fig. 3. Membership functions of input and output variables. (a) Input variable Δf , (b) output variable R_{real} .

The V2G power output of GEVs is decided by the rule base of the fuzzy logic control. Each of the outputs implements its rules based on the state of two inputs: the system frequency deviation and the VSC signal. The rules in the proposed FFRVC are shown in Table I. The transient grid load stabilizing performance is emphasized in the designed FFRVC, and thus the charging state of GEVs is mainly decided by the frequency deviation of the grid. When system frequency is lower than the standard value, all GEVs are controlled to discharge power back to suppress the grid transient load fluctuation. In contrast, when the system frequency is higher than the standard, no GEVs are scheduled to discharge. The VSC signal is used to reflect the peak-shaving requirements of the grid in FFRVC. With the same grid frequency state, more system peak-shaving requirements, the higher V2G or G2V power is provided.

Table I. Rule base of the FFRVC to determine the V2G power

Δf \ R_{real} \ *VSC*	**NB**	**NS**	**Z**	**PS**	**PB**
LN	NB	NB	NM	NM	NS
N	NB	NM	NS	NS	Z
Z	NM	NS	Z	PS	PM
P	Z	Z	PS	PM	PB
LP	Z	PS	PM	PB	PB

V. Case study

A. The studied microgrid system

As shown in Fig. 4 (a), a microgrid system [44] that consists of renewable energies, generators, GEVs, and domestic loads is employed to verify the performance of the developed V2G scheduling method. The energy consumptions and power balance state of the grid are simulated based on the open-access power system operation data [45] provided by UK National Grid ESO. The national household travel survey data [46] is employed to simulate the charging behavior of V2G participants, and the Monte Carlo simulation model [47] is used to simulate GEVs usage information. 30 GEVs each with a 16 kWh battery are considered in our research to provide the power balancing service to the grid. The real operation and prediction characteristics of generators and renewable energies from [48] are employed to simulate the power flow between different sectors. In this study, aiming to verify the power balancing performance of GEVs, the smart energy system is simulated in the off-grid mode, the bi-directional power interaction between the main grid and microgrid is not simulated. Therefore, the household load and charging requirements of GEVs will all be satisfied with the energy resources in the microgrid.

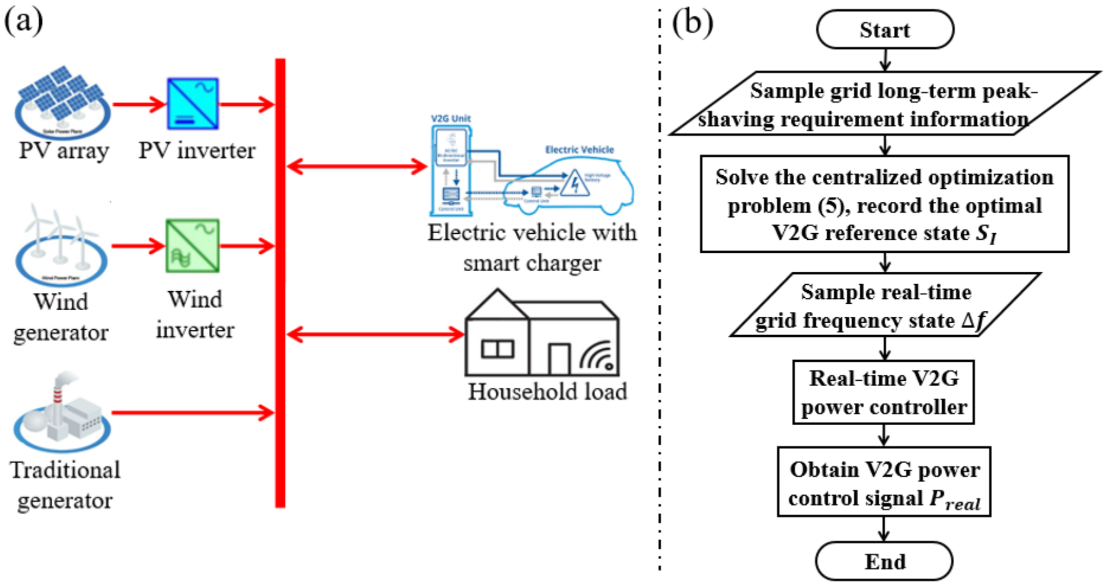

Fig. 4. The verification of the developed V2G scheduling method. (a) Schematic of the studied microgrid system. (b) Flowchart of the simulation process.

In verifying the proposed scheduling method, we assume that the EV usage information, including grid-connected time and battery SOC, departure time, and charging requirement, is known in advance. The most active V2G period (16:00-24:00 and 00:00-08:00) is considered in this study, and the duration of a dispatch time interval is set as 15 minutes. Therefore, the value of u and w in equation (6) are both limited between 0 to 64. Meanwhile, the V2G behavior of 30 GEVs is scheduled, and therefore the maximum value of n is set as 30. The specific simulation process is shown in Fig.

4. (b). First, based on the supply-demand relationship between the generator and household load, the centralized scheduling system solves the optimal power level of GEVs. Then, according to the transient power fluctuation of renewable energies and household load, the real-time V2G power controller calculates the actual V2G power for GEVs.

B. System power balancing performance

Fig. 5 shows the power balancing results of the proposed MSVBM method, where GEV batteries are scheduled to provide long-short term power balancing service to the grid. As shown in (c), In the whole scheduling period (from 16:00 to 24:00 and 00:00 to 08:00), with the FLVPC, the proposed scheduling algorithm can use GEVs batteries to provide power balancing service to the grid according to frequency deviations in real-time. With the fast-auxiliary power provided by vehicle batteries, the short-term power fluctuation of the grid can be suppressed and energy quality can be significantly improved. The V2G capacity can also be scheduled to provide peak-shaving service to the grid with the proposed MSVBM method, the corresponding VSC signal of a GEV from centralized V2G state coordinator is shown in (b). When domestic load peak and valley appear, GEVs are scheduled to discharge or charge to provide peak-shaving service according to the VSC signals in the centralized GEV charging state coordinator. The proposed MSVBM method can deal with the long-term peak-shaving and transient power balancing requirements of the grid at the same time. As shown in Area A, a transient load surge also appears around 21:00. The real-time V2G power controller samples the grid frequency state and controls GEVs to feed power back to the grid to maintain grid stability in real-time. As a result, to suppress this transient power fluctuation, the maximum V2G power in this area is elevated to 0.82p.u. After 00:00, GEV batteries are controlled to be charged. The proposed MSVBM method can also schedule the charging power of GEVs to absorb excess valley power and maintain the transient power balancing of the grid simultaneously, as shown in ***AREA B***. With the cooperation of the centralized V2G state coordinator and real-time V2G power controller, the V2G resources can be reasonably used to improve the grid economy and stability.

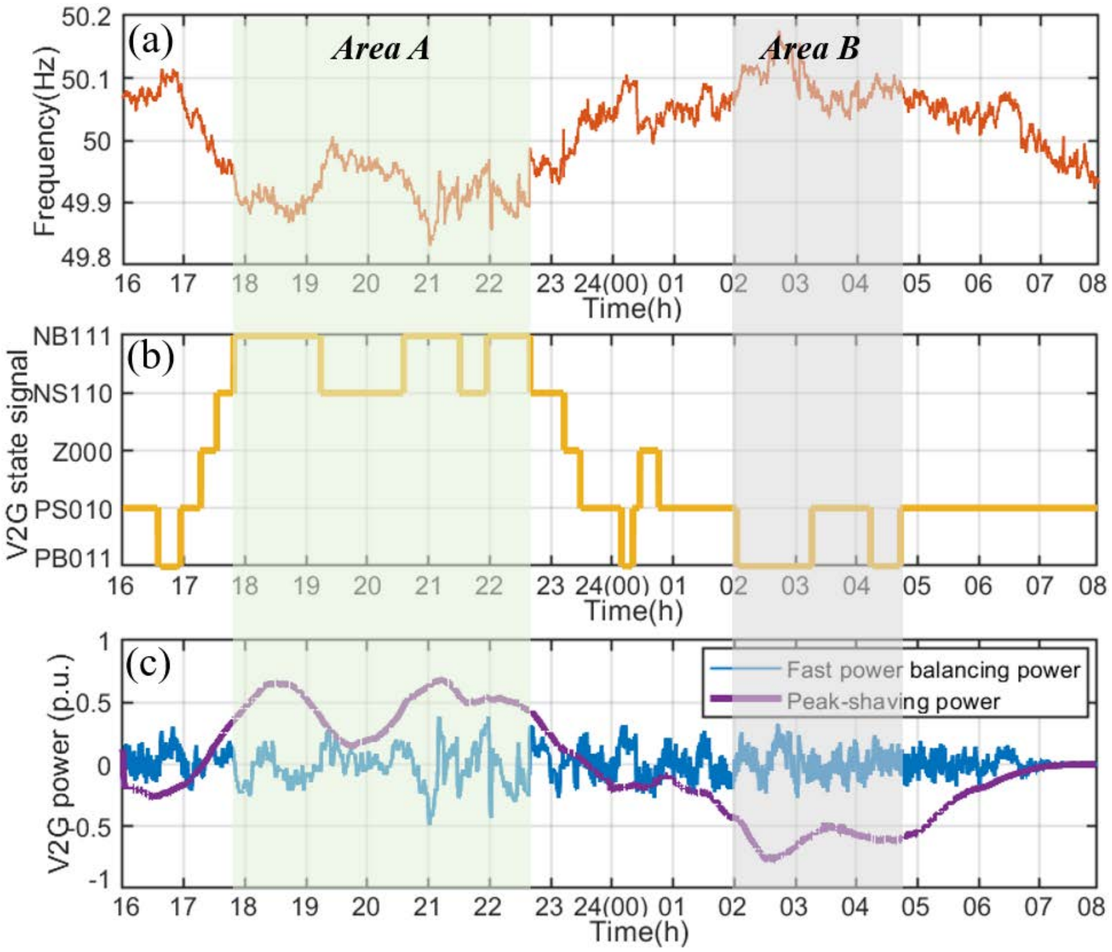

Fig. 5. Power balancing performance of the MSVBM method. (a) Microgrid frequency fluctuations, (b) VSC signal of a GEV from centralized V2G state coordinator, (c) aggregated V2G power of the GEVs.

To verify the effectiveness of the proposed MSVBM method, the V2G power profile of GEVs is compared to the traditional centralized V2G scheduling method [49], as shown in Fig. 6. In the traditional centralized scheduling method, almost all the EVs are scheduled to provide the peak-shaving service for the grid, and the grid economy can be improved. However, as most V2G resources are occupied by the peak-shaving service, the grid transient power fluctuation cannot be suppressed. Comparing to the centralized method, the proposed MSVBM method can utilize V2G resources more reasonably. As shown in (b), the discharging and charging behaviors of GEVs are not as concentrated as that of in the centralized method, more V2G capacity remains for fast power balance regulation service. Within the whole V2G scheduling period, the GEVs V2G power is dynamically controlled by the real-time V2G power controller to balance the grid power state. Meanwhile, during the grid peak hours (19:00~23:00), influenced by centralized GEVs' state control command, most GEVs are still scheduled to provide peak-shaving service.

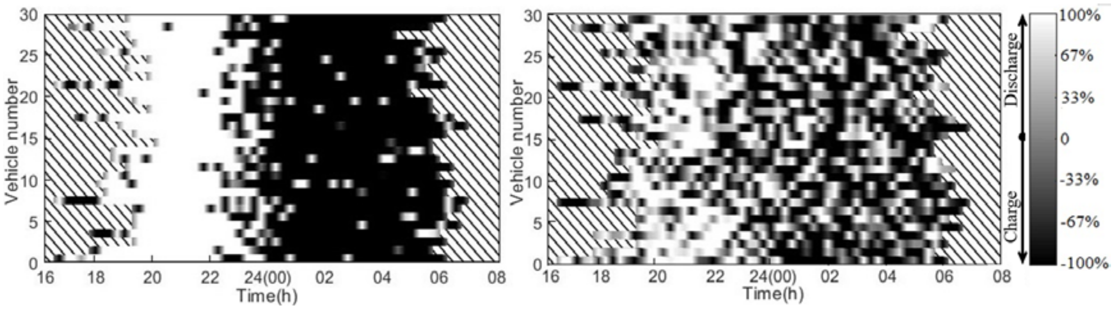

Fig. 6. V2G power profile of 30 GEVs. (a) Conventional centralized V2G scheduling method, (b) the proposed MSVBM method.

The final battery SoC of the 30 GEVs in the developed V2G scheduling method is shown in Fig. 7. The actual battery SoC at departure is 12% higher than the preset value on average, which indicates that the charging requirement of GEVs can always be satisfied. The charging requirements of GEVs are set as a constraint in the centralized V2G scheduling model, and with the optimization, the calculated strategies can always satisfy the corresponding constraints in the defined optimization model. Therefore, charging can always be completed before participant departure with the developed V2G scheduling method.

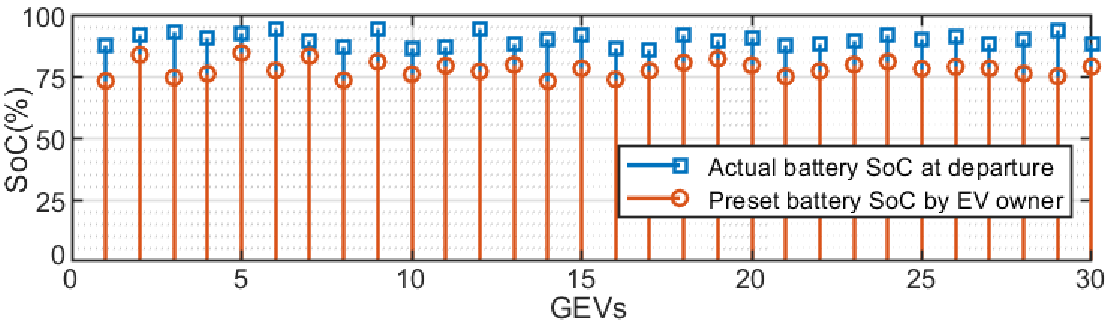

Fig. 7. Actual and preset battery SoC value at departure in the developed MSVBM method.

To better illustrate the improvement, we also quantify the long-term power balancing performance of the proposed scheduling method within 30 days, including 22 workdays and 4 weekends. The performance of all V2G scheduling methods (centralized method [49], fuzzy logic method [50], and the proposed MSVBM method) are compared and summarized in Table II. With 16% and 19.7% overflow of maximum peak and average peak-valley difference, it is obvious that the random charging of GEVs causes additional grid demands. The coordination of GEVs' charging can be realized by the centralized V2G scheduling method. Compared to the random charging scenario, 19.7% peak power is shaved on average and thus the maximum grid peak load and load standard deviation (SD) are reduced by 32.1 % and 50.3%, respectively. However, the unpredictable transient grid power fluctuations cannot be suppressed in the centralized method, which can compromise energy supply quality. In the fuzzy logic-based V2G control method, the power fluctuation is suppressed by the sampled grid frequency state, and the energy supply quality is improved significantly. However, the fuzzy logic method mainly focuses on suppressing the short-term load fluctuation but neglects the long-term peak-shaving, and thus only 7.6% peak load is shaved on average and the peak-valley difference is still as high as 312.4 kW. As a result, the calculated maximum SD is even higher than that of the centralized method. Both peak-shaving and transient power balancing requirements of the grid are considered in the proposed MSVBM method. Therefore, as seen in Table II, the average peak-valley difference is further reduced (205.3 kW, 34.3% lower than the fuzzy logic method and only 6.5% higher than the centralized method). Meanwhile, because of the real-time V2G power controller in the MSVBM method, the grid power supply quality is improved significantly, where the power SD is reduced by 14.3% and 30.7% compared to the centralized method and fuzzy logic method, respectively).

Table II. The long-term power balancing performance of different V2G scheduling methods.

Scenario	Maximum peak power (kW)	Maximum load SD	Average peak shaving (%)	Average peak-valley difference (kW)
Baseload	448.3	105.27	---	336.2
Random charging	533.7	132.55	---	418.7
Centralized method	362.5	65.83	20.7	191.8
Fuzzy logic method	427.4	81.36	7.6	312.4
MSVBM method	385.3	56.42	17.3	205.3

VI. Conclusion

In this paper, a multi-time scale V2G behavior management method is proposed to schedule the charging behavior of GEVs to provide peak-shaving and fast power balancing service for the microgrid. Through extensive demonstrations, the main findings are as follows: served as a power level guidance signal, the VSC signal generated by centralized GEV state coordinator can effectively reflect the peak-shaving requirement of the grid. With the real-time sampled frequency state information, the designed real-time V2G controller can schedule the GEVs to provide fast grid power balance regulation service to the grid. Both the economy and energy quality of the grid can be improved by optimizing the charging power of GEVs through cooperative scheduling between the V2G state coordinator and real-time power controller. The simulation experiment on a real microgrid system showed that the grid load peak can be reduced by 9.8% compared to the fuzzy logic method and the load SD can be reduced by 14.3% compared to the centralized scheduling method, which indicates that the proposed multi-time scale V2G behavior management method can suppress grid transient power fluctuation while providing the same peak-shaving services to the grid as expected.

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