Chapter 14

Optimal scheduling with vehicle-to-grid ancillary services

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14.1 Overview

In this chapter, we propose a method for the utility grid operator and aggregators to coordinate multiple grid-connected electric vehicles (EVs) so as to provide electric-power ancillary services accounting for quality-of-service (QoS) guarantees for EV charging in a multilevel vehicle-to-grid (V2G) system. This method includes applying consensus-algorithm-based distributed control, designing the control objective functions and constraints for providing ancillary services, and designing the constraints for charging/discharging power schedules and the individual QoS requirements of EVs. The consensus-algorithm-based distributed control consists of operation protocols for control and communication among the utility grid operator, aggregators, and EVs, calculating the control signals in the utility grid operator and aggregators, determining the optimal charging/discharging power schedules of EVs so as to provide a required type of ancillary services as well as satisfy the QoS requirements of EVs.

14.1.1 Electric vehicles and ancillary services

With the worldwide concerns on climate change due to global warming, many countries have established environmental policies to control the greenhouse gas (GHG) emissions, the primary cause of global warming. For example, California has adopted the Global Warming Solutions Act of 2006 to reduce its GHG emissions to 80% of the 1990 levels by 2050. One way to achieve GHG reduction is wide deployment of EVs. According to Electric Power Research Institute (2013), it is estimated that EVs would account for over 5% of new vehicle sales by 2020. Annual carbon dioxide (CO₂) reductions contributed by transportation electrification are expected to reach beyond 100 million tons by 2025 and 500 million tons by 2050.

The adoption of EVs will bring environmental and economic benefits including reducing GHG emissions, reducing dependence on fossil fuels, improving the

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stability and flexibility of the power system by utilizing the batteries installed in EVs as energy storage. The use of the batteries of grid-connected EVs for the provision of electric-power ancillary services is in the focus of this chapter.

The Federal Energy Regulatory Commission (FERC) defines ancillary services as those “necessary to support the transmission of electric power from seller to purchaser given the obligations of control areas and transmitting utilities within those control areas to maintain reliable operations of the interconnected transmission system.” Hirst and Kirby (1996) outlined seven main types of ancillary services:

- scheduling and dispatch,
- load following,
- reliability,
- supplemental operating,
- energy imbalance,
- real-power loss replacement, and
- voltage control.

The EV fleets are able to provide ancillary services to the power grid by utilizing their batteries as distributed energy storage. Grid-connected EVs can charge or discharge their batteries to absorb or deliver power to the grid. The concept of V2G has been applied to describe such operation mode of EVs. V2G can be both unidirectional when EVs provide ancillary services by modulating their charging rates, and bidirectional when EVs are also allowed to discharge their batteries to inject energy back to the grid. V2G ancillary services can be used to refer to the ancillary services provided by V2G power. The economic benefits of V2G are compelling (Kempton and Tomić, 2005a). V2G can provide fast-response service because of the fast-response characteristics of battery power. It can smooth out the power fluctuations between generation and load, and is important for supporting the integration of renewable energy generation (Kempton and Tomić, 2005b).

14.1.2 Current research

In order to provide V2G ancillary services, the charging/discharging power schedules of EVs should be coordinated or controlled properly. Research on charging/discharging control of EVs can be categorized as centralized control and distributed control. The aggregator of EVs acts as the central controller in centralized control (Han et al., 2010; Sortomme and El-Sharkawi, 2012). The scalability issue is the main drawback of centralized control; the high computational complexity of the centralized control algorithms becomes a burden against efficient and prompt operations of the system as the number of EVs scales up.

Distributed control enjoys the advantage of high scalability over centralized control. It can be classified as fully distributed control and consensus-algorithm-based distributed control. In fully distributed control, no central node is involved in the decision-making process of the distributed EV nodes. For provision of frequency regulation, fully distributed control strategies based on local frequency measurement have been proposed (Ota et al., 2012; Yang et al., 2013). However,
those fully distributed strategies cannot achieve the global optimum among the EV fleet since the control is for a single EV and the discharging/charging schedules of EVs are not coordinated.

In consensus-algorithm-based distributed control, a central node acts as the consensus manager to coordinate the distributed nodes in the decision-making process. Decisions are made locally by the distributed nodes. Consensus has been studied in system control area (Olfati-Saber and Murray, 2004). Consensus-algorithm-based distributed control has been applied to coordinated EV charging (Gan et al., 2013; Ma et al., 2010). However, only a few proposals apply consensus-algorithm-based distributed control to solve the control problem of V2G ancillary services.

The system for providing V2G ancillary services has been structured as a hierarchical or multilevel architecture. However, most existing work on charging/discharging control of V2G ancillary services are designed for a system with only one aggregator to coordinate the schedules of EVs. In existing solutions that consider multiple aggregators, the control algorithms of the solutions can only support one level of aggregators (Yao et al., 2013). Therefore, a method that can support the charging/discharging control for a multilevel V2G system would be of value.

Although EVs can earn rewards for their EV owners/users by providing ancillary services, the fundamental function of EVs is for transportation. The charging needs of EVs must be met when the EVs are plugged in and provide ancillary services. The existing work models the charging needs as a desired value of the state-of-charge (SOC) of the batteries (Ota et al., 2012). However, it would be more realistic to model the charging needs as a desired range of SOC. In addition, other QoS guarantees of the EVs should be taken into account, such as control of the battery degradation due to providing ancillary services.

Based on the discussion above, it is noted that none of the existing solutions are designed for the distributed charging/discharging control based on the consensus algorithm that supports a multilevel V2G system. Our goal is to develop such a system.

### 14.2 System architecture

In this section, we propose a multilevel system architecture, as shown in Figure 14.1, for the provision and operation of bidirectional V2G frequency regulation service. A preliminary proposal of the architecture without the operation protocol design can be found in our prior work (Lin et al., 2013).

The system, consists of three key components: the utility grid operator, aggregators, and many EVs. The V2G system allows bidirectional power flow, namely, EVs can not only consume electric energy from the power grid by charging their batteries but also deliver electric energy back to the grid by discharging their batteries. Allowing discharging of the batteries would increase the number of charging/discharging cycles and therefore shorten the longevity of the batteries. Hence, in practice, some of the EV owners/users may not allow their EVs to provide bidirectional V2G ancillary services. To take this situation into consideration,
a participation ratio of bidirectional V2G, $\theta_{bi} \in \{0, 1\}$, is used to denote the proportion of the EVs that participate in bidirectional V2G in the system. The subscript “bi” of $\theta_{bi}$ is short for “bidirectional.” The system has a hierarchical structure with multiple levels of nodes. The utility grid operator is the root node. The aggregators directly connected to the grid operator are called level-1 aggregators. An aggregator directly connected to a group of level-$(l + 1)$ aggregators is called a level-$l$ aggregator, where $l = 1, 2, \ldots, N_L$ and $N_L$ is the number of aggregator levels in the system. For convenience, the aggregators directly connected to EVs are called aggregators of EVs. Correspondingly, all the other aggregators are called aggregators of aggregators. Each aggregator node can be viewed as the “root node” of a subtree of aggregators and EVs. Each aggregator node is uniquely numbered according to its location in the multilevel architecture. As shown in Figure 14.1, a level-$i$ aggregator that is the $j$-th aggregator of all level-$i$ aggregator (numbered from left to right in Figure 14.1) is labeled as $A_{ij}$, where $1 \leq i \leq N_L$. The aggregators at the same level may have different numbers of sub-levels. The size of a
A subtree is determined by the size of its subordinate EV fleets and other geographical, economic, and/or technical factors, such as the communication radius, delay, and cost between nodes at different levels. For instance, a parking lot or a certain area of a large parking lot can install an aggregator of EVs. A number of such parking areas can be controlled by an aggregator of aggregators.

Three types of operation protocols for control and communication between neighboring levels, namely, operator-aggregator protocol, aggregator-aggregator protocol, and aggregator-EV protocol are designed. Each protocol operates between a node and its immediate subordinate nodes as illustrated in Figure 14.1. The operator-aggregator protocol governs how the grid operator assigns the requests for ancillary services to and coordinates the level-1 aggregators to meet the demand of ancillary services. The requests for ancillary services are the aggregators’ shares for the demand of ancillary services according to their signed contracts for providing ancillary services. The aggregator-aggregator protocol governs how an aggregator of aggregators coordinates its immediate subordinate aggregator to meet requests for ancillary services. The aggregator-EV protocol specifies the process and algorithm for an aggregator of EVs to coordinate its connected EVs to decide their charging/discharging schedules. In other words, the aggregators act as the interface between the utility grid and EV fleets so that the grid operator does not need to care about the individual charging/discharging profiles of EVs. These EVs can collectively form a massive energy storage system to provide ancillary services.

Consensus-algorithm-based distributed control is applied in the three types of operation protocols. Consensus algorithm requires an iterative process to reach the final solution. Figure 14.2 shows a simple example of a consensus-algorithm-based distributed control. In each round of iteration, the consensus manager calculates a consensus result according to the information states or decisions received from the local controllers and broadcasts the result to the local controllers as the control signal. Then, every local controller adjusts its information state or decision based on the consensus result and reports its decision to the consensus manager. The iterative process ends when the predetermined stopping criteria are met.

The three types of operation protocols have a nested relation as shown in Figure 14.3. The operator-aggregator includes processes of aggregator-aggregator protocol.
protocol. The aggregator-aggregator protocol includes processes of aggregator-aggregator protocol or aggregator-EV protocol, which are illustrated in the following subsections.

14.2.1 Operator-aggregator protocol

Figure 14.4 shows the flowchart of the operator-aggregator protocol. The operator-aggregator protocol operates between the utility grid operator and the level-1 aggregators. The overall scheduling process of the multilevel V2G system starts
from the operator-aggregator protocol. In the iterative part of the operator-aggregator protocol, the grid operator should wait for its subordinate node – the level-1 aggregators to run the aggregator-aggregator protocol or the aggregator-EV protocol. The notation of parameters and variables in Figure 14.4 is explained as follows. \( N_0 \) is the number of the level-1 aggregators. The subscript \( j = 1, 2, \ldots, N_0 \) in the assigned share \( R_{ij} \) and the reported commitment \( P_{ij} \) for ancillary services of aggregator \( A_{ij} \) indicates that \( A_{ij} \) is the \( j \)-th level-1 aggregator (numbered from left to right in Figure 14.1). The request signal \( R \), the arrays of the assigned shares \( R_O \), and the reported commitments \( P_O \) are generic formulations, i.e., their actual forms and dimensions are determined by the specific type of ancillary services the system is currently concerned. The function \( f_{OA} \) is for calculating the consensus result or control signal, i.e., the shares \( R_O \) for ancillary services, according to the latest information states or decisions, i.e., the commitments \( P_O \) for ancillary services, reported by the level-1 aggregators. The stopping criteria can be based on the number of iterations performed, and/or the convergence of the control signal \( R_O \) within the convergence tolerance. When the operator-aggregator protocol finishes, the overall scheduling process of the V2G system ends and all the EVs participating in the scheduling process should execute their latest reported charging/discharging schedules so as to provide the specified type of ancillary services AS to the power grid.

14.2.2 Aggregator-aggregator protocol

Figure 14.5 shows the flowchart of the aggregator-aggregator protocol. The aggregator-aggregator protocol operates between an aggregator of aggregators and its immediate subordinate aggregators. Figure 14.5 presents the operation protocol for a level-\( i \) aggregator \( A_{ij} \) and its subordinate level-(\( i + 1 \)) aggregators, where \( 1 \leq i \leq N_L \). As indicated in Figures 14.2–14.5, a (level one) aggregator and its subordinate aggregators start operating the aggregator-aggregator protocol when the grid operator assigns the share for ancillary services to the level-1 aggregator. A level-\( i \) aggregator, where \( 2 \leq i \leq N_L \), and its subordinate aggregators start operating the aggregator-aggregator protocol when the upper level aggregator of the level-\( i \) aggregator assigns the share for ancillary services to the level-\( i \) aggregator in the upper level aggregator-aggregator protocol. For the convenience of notation, the subordinate level-(\( i + 1 \)) aggregators of the level-\( i \) aggregator \( A_{ij} \) are denoted as \( a_{(i+1)k} \), \( k = 1, 2, \ldots, N_{ij} \), in the aggregator-aggregator protocol, where \( N_{ij} \) is the number of the subordinate level-(\( i + 1 \)) aggregators of \( A_{ij} \). The assigned share and the reported commitment for ancillary services of aggregator \( d_{(i+1)k} \), \( k = 1, 2, \ldots, N_{ij} \), are denoted as \( R_{(i+1)k} \) and \( P_{(i+1)k} \), respectively. The function \( f_{AA} \) is for calculating the shares \( R_{A_{ij}} \) according to the latest reported commitment \( P_{A_{ij}} \) for ancillary services of the subordinate level-(\( i + 1 \)) aggregators of \( A_{ij} \). The stopping criteria can be based on the number of iterations performed, and/or the convergence of the control signal \( R_{A_{ij}} \) within the convergence tolerance. By the end of the aggregator-aggregator protocol, \( A_{ij} \) should calculate and report its commitment for ancillary services \( P_{ij} \) to its upper level node (the grid operator or a level-(\( i - 1 \)) aggregator) based on the commitments \( P_{A_{ij}} \) reported by its subordinate level-(\( i + 1 \)) aggregators.
14.2.3 Aggregator-EV protocol

Figure 14.6 shows the flowchart of the aggregator-EV protocol. The aggregator-EV protocol operates between an aggregator of EVs and its subordinate EVs. Figure 14.6 presents the operation protocol for a level-$i$ aggregator $A_{ij}$ and its subordinate EVs, where $1 \leq i \leq N_L$. As indicated in Figures 14.2–14.6, the aggregator-EV protocol is triggered by either the operator-aggregator protocol or the aggregator-aggregator protocol. The aggregator-EV protocol is different from the other two types of operation protocols in that it directly tackles the problem of determining the charging/discharging schedules of the EVs. The subordinate EVs of the aggregator $A_{ij}$ are denoted as $EV_{n}^{(ij)}$, where $N_{ij}$ is the number of $A_{ij}$’s subordinate EVs. $EV_{n}^{(ij)}$’s charging/discharging schedule $Q_n$ refers to the specific values of power, time, and duration that EV will charge or discharge its battery at. The function $f_{AE}$ is for calculation of the consensus result or control signals in the aggregator-EV protocol. The function $f_{AE}$ is a function of the EVs’ aggregate schedule $Q_{A}$ rather than every individual EV’s schedule, since the aggregator only cares about the collective charging/discharging behaviors of the EVs when it coordinates them to meet the assigned share $R_{ij}$ for ancillary services. The individual QoS requirement for battery charging/discharging of EVs should be taken into account when the EVs decide their own schedules. The stopping criteria...
can be based on the number of iteration performed, and/or the convergence of the control signals within the convergence tolerance. By employing the aggregator-EV protocol, $A_{ij}$ can calculate and report its commitment for ancillary services $P_{ij}$ to its upper level node (the grid operator or a level-$(i-1)$ aggregator) based on the schedules $Q$ reported by its subordinate EVs.

**14.2.4 EV requirements**

When an EV is plugged in and operating in the V2G mode, meeting the QoS requirement for battery charging/discharging set by its user, rather than the requests for ancillary services from the utility grid operator, should be the first priority. The QoS requirements should include but are not limited to:

- **Charging needs:** An EV must get charged with adequate amount of electricity specified by its user before it is plugged out.
- **Smart charging/discharging:** An EV’s charging/discharging strategy should consider the SOC of its battery. It should avoid deep discharging and over-charging of...
the battery and should reduce the number of battery charging/discharging cycles while providing ancillary services so as to prolong the battery life.

- Security and privacy: The driving patterns and records of rewards related to the provision of ancillary services by EV users should remain private.

The first requirement in the list above is the primary purpose of EV charging. The provision of ancillary services should never impair the fundamental function, i.e., transporting people or goods, of EVs. Therefore, EV users should be guaranteed that their EVs will be adequately charged before being plugged out. The first requirement can be incorporated into the optimal scheduling process as a constraint. A smart charging/discharging strategy mentioned in the second requirement should be able to achieve better utilization of the battery storage in EVs, e.g., storing electricity in advance to cope with the variability and uncertainty of the demand of ancillary services, and protect the battery life from being severely harmed by charging/discharging frequently. The smart charging/discharging strategy should synthesize the EVs’ capability and availability of power and energy, i.e., the output power limits, capacity, and SOC of the battery, the amount of electricity to charge and planned plug-out time of the EVs, etc., to decide the optimal schedules. The second requirement can be incorporated into the optimal scheduling process by the design of the function $f_{AE}$ and constraints. The driving patterns mentioned in the third requirement include the SOC, charging/discharging power, time and locations of plugging-in and plugging-out of EVs. Three basic principles for security and protection of EV users’ privacy in the V2G system are suggested. First, the collection of user data during V2G activities should ask for the users’ permissions in advance. Second, an authentication mechanism should be established to ensure legal and safe access to the V2G system and the data. Third, the network security system should be robust against cyber-attacks and prevent the data from being intercepted during transmission.

### 14.3 System model and problem formulation

#### 14.3.1 Control objective for V2G regulation service

The existing control schemes (Donadee and Ilic, 2014; Han et al., 2011; Ota et al., 2009, 2012; Shi and Wong, 2011; Wang et al., 2013; Yang et al., 2013) for the V2G regulation service seek to offset the regulation demand with the charging/discharging power of EVs so that the sum of the regulation demand and the aggregate power of EVs is zero. However, since frequency regulation is a zero-energy service (Kirby, 2004), the charging needs of EVs, which consume energy, is unlikely to be met merely by offsetting the regulation demand.

This section generalizes the optimal scheduling method for the aggregator-EV protocol proposed in our prior work (Lin et al., 2014). The imbalance between generation and load originates from their respective uncertainties. Given that such imbalance cannot be fully compensated by EVs, we propose to schedule the charging/discharging power of EVs to absorb the uncertainties of generation and load.
In other words, EVs are employed to smooth out the power imbalance fluctuations of the grid by minimizing the variance of the profile of the total power, which is the sum of the regulation demand and the aggregate power of EVs.

From an economic perspective, the proposed control objective is to minimize the costs for the system to meet the regulation demand and the charging needs of EVs. Without V2G or other storage technologies, conventional generators have to be used to supply frequency regulation at a great expense, including the high ramping costs and the lost opportunity costs of the underutilized regulation capacity (Kirby, 2004). By implementing the proposed control objective, the random fluctuations of the regulation demand are absorbed by EVs. Therefore, the resultant total power of the regulation demand and the powers of EVs can be met by conventional generators with minimal ramping costs, and the required generation reserve for the regulation service is minimized as well.

14.3.2 Models and constraints

The coordinated scheduling, which determines the charging/discharging schedule of EVs, is the core of the aggregator-EV protocol. Consider a scenario in which an aggregator of EVs coordinates NEV EVs to schedule their charging/discharging profiles so as to provide the V2G regulation service over a participation period $[T_{\text{begin}}, T_{\text{end}}]$, which is divided equally into $N_T$ time slots of length $\Delta t$. Let $\mathcal{T} = \{T_k | k = 1, 2, \ldots, N_T\}$ be the set of the slotted participation period, $R(T_k)$ be the assigned share of the actual regulation demand, i.e., the actual regulation request, at time slot $T_k$, and $P_n(T_k)$ be the charging/discharging power of EV $n$ at $T_k$, for $T_k \in \mathcal{T}$ and $n \in \mathcal{N} = \{1, 2, \ldots, NEV\}$. We assume that the share of the regulation demand of an aggregator accounts for a fixed proportion of the total regulation demand in the grid during $\mathcal{T}$. $R(T_k) > 0$ means that the grid calls for regulation up due to generation shortfall. Similarly, when $R(T_k) < 0$, regulation down is required to absorb excessive power from the grid. When $P_n(T_k) > 0$, EV $n$ is charging. When $P_n(T_k) < 0$, it is discharging and delivering power back to the grid. Each EV will provide either unidirectional or bidirectional V2G regulation service according to its contract to the aggregator. Let $\theta_n \in [0, 1]$ denote the proportion of the EVs that participate in bidirectional V2G.

Denote the plug-in time and plug-out time of EV $n$ as $T_{n,\text{in}}$ and $T_{n,\text{out}}$, respectively. When EV $n$ is plugged in, its charging/discharging power should follow:

$$P_{n,\text{discharge}} \leq P_n(t) \leq P_{n,\text{charge}}, t \in [T_{n,\text{in}}, T_{n,\text{out}}],$$

(14.1)

where $P_{n,\text{discharge}} \leq 0$ and $P_{n,\text{charge}} > 0$ denote the limits of discharging power and charging power of EV $n$, respectively.

Denote the profile of the actual regulation requests as $R(\mathcal{T}) = (R(T_1), R(T_2), \ldots, R(T_{N_T}))^T$, where $(\cdot)^T$ denotes transposition. Denote the charging/discharging schedule of EV $n$ as $P_n(\mathcal{T}) = (P_n(T_1), P_n(T_2), \ldots, P_n(T_{N_T}))^T$, and the schedules of all EVs as $P_N(\mathcal{T}) = (P_1(\mathcal{T}), P_2(\mathcal{T}), \ldots, P_{NEV}(\mathcal{T}))$. Then, the profile of the total power, which is the sum of the regulation requests and the
aggregate power of EVs, is defined as follows:

$$P_{\text{total}}(T) = R(T) + P_A(T),$$  \hspace{1cm} (14.2)

where $P_A(T)$ denotes the profile of the aggregate power of EVs defined as:

$$P_A(T) = \sum_{n \in \mathcal{N}} P_n(T).$$  \hspace{1cm} (14.3)

Let $SOC_{n,0}$, $SOC_n(T_k)$, and $C_n$ be the initial SOC, SOC at the end of $T_k$, and capacity of the battery pack of EV $n$, respectively. Considering the energy conversion efficiency between the power grid and the batteries of EVs, $SOC_n(T_k)$ can be calculated as:

$$SOC_n(T_k) = SOC_{n,0} + \frac{\Delta t}{C_n} \sum_{i=1}^{k} \eta(P_n(T_i)) P_n(T_i),$$  \hspace{1cm} (14.4)

where $\eta(x)$ calculates the energy conversion efficiency of a given charging/discharging power $x$ of an EV. Assume that the charging and discharging efficiencies are, respectively, identical among the EVs. Then, $\eta(x)$ is defined as:

$$\eta(x) = \begin{cases} 
\eta_{ch} & \text{if } x \geq 0 \\
\frac{1}{\eta_{dch}} & \text{if } x < 0 
\end{cases}$$  \hspace{1cm} (14.5)

where $\eta_{ch}$ and $\eta_{dch}$ are the charging and discharging efficiencies of the EVs, respectively, and therefore we have:

$$0 < \eta_{ch}, \eta_{dch} \leq 1.$$  \hspace{1cm} (14.6)

Two constraints for the SOC of the battery pack during the plug-in period of EV $n$, where $n \in \mathcal{N}$ are proposed as:

$$SOC_n(T_{N_T}) \geq SOC_{n,\text{MinCh}},$$ \hspace{1cm} (14.7)

$$SOC_{n,\text{min}} \leq SOC_n(T_k) \leq SOC_{n,\text{max}}, T_k \in \mathcal{F}.$$ \hspace{1cm} (14.8)

$SOC_{n,\text{MinCh}}$ denotes the minimum value of SOC that EV $n$ needs to reach before it is plugged out. The constraint represented by (14.7) ensures that EV $n$ will have been charged up with enough energy for the next trip when it is plugged out. $SOC_{n,\text{min}}$ and $SOC_{n,\text{max}}$ denote the lower and upper SOC limits, respectively, of EV $n$ for all $T_k \in \mathcal{F}$. The constraint in (14.8) prevents deep discharging or over-charging of the battery so as to prolong the battery life.

### 14.3.3 Formulation of forecast-based scheduling

Assume that, before the participation period $\mathcal{F}$, the aggregator receives the forecasting profile $R_f(\mathcal{F}) = (R_f(T_1), R_f(T_2), \ldots, R_f(T_{N_T}))^T$ of its actual regulation requests $R(\mathcal{F})$, and is able to communicate with $N_{EV}$ EVs that are going to
participate in the V2G regulation service during \( T \). Then, according to the control objective proposed in Section 14.3.1, it should coordinate these \( N_{EV} \) EVs to determine their optimal charging/discharging schedules \( P_N(\mathcal{T}) \) by the following optimization problem:

\[
\min_{P_N(\mathcal{T})} U_f(P_A(\mathcal{T})) \quad (14.9)
\]

such that \( \forall n \in \mathcal{N} \), (14.1), (14.7), and (14.8) hold, where \( U_f(P_A(\mathcal{T})) \) calculates the variance of the profile of the total power \( P_{total}(\mathcal{T}) \). Therefore, we have:

\[
U_f(P_A(\mathcal{T})) = \text{Var}(P_{total}(\mathcal{T}))
\]

\[
= \frac{1}{N_T} \sum_{T_i \in \mathcal{T}} (R_f(T_i) + P_A(T_i)) - \frac{1}{N_T} \left( \sum_{T_j \in \mathcal{T}} (R_f(T_j) + P_A(T_j)) \right)^2,
\]

where \( \text{Var}(\cdot) \) denotes the function for calculating variance.

**Lemma 1** The objective function (14.10), \( U_f : \mathbb{R}^{N_T} \to \mathbb{R} \) of the optimization problem (14.9) is convex.

**Proof.** \( \forall 1 \leq i,j \leq N_T \), according to the first-order partial derivatives of \( U_f(P_A(\mathcal{T})) \), \( \frac{\partial U_f(P_A(\mathcal{T}))}{\partial P_A(T_i)} \), the second-order derivatives are as follows:

\[
\frac{\partial^2 U_f(P_A(\mathcal{T}))}{\partial P_A(T_i)^2} = \frac{2}{N_T^2} (N_T - 1),
\]

\[
\frac{\partial^2 U_f(P_A(\mathcal{T}))}{\partial P_A(T_i) \partial P_A(T_j)} = -\frac{2}{N_T^2}.
\]

Thus,

\[
\nabla^2 U_f(P_A(\mathcal{T})) = \frac{2}{N_T^2} \begin{bmatrix}
N_T - 1 & -1 & -1 & \cdots & -1 \\
-1 & N_T - 1 & -1 & \cdots & -1 \\
-1 & -1 & \ddots & \ddots & \vdots \\
\vdots & \ddots & \ddots & N_T - 1 & -1 \\
-1 & -1 & \cdots & -1 & N_T - 1
\end{bmatrix}.
\]

Due to the symmetry of \( \nabla^2 U_f(P_A(\mathcal{T})) \), it is obvious that all the principal minors of order \( i \) are equal to the leading principal minor of the same order \( i \), \( i = 1, 2, \ldots, N_T \). Further, by applying mathematical induction, it can be proved that
all the leading principal minors of $\nabla^2 U_f(P_A(\mathcal{T}))$ are non-negative. Hence, $\nabla^2 U_f(P_A(\mathcal{T}))$ is positive semidefinite. In addition, since the domain of $U_f$, $\text{dom}(U_f) = \mathbb{R}^{N_r}$, is convex, it follows from the second-order conditions for convex function (Boyd and Vandenberghe, 2004) that the function $U_f : \mathbb{R}^{N_r} \to \mathbb{R}$ is convex.

**Lemma 2** The feasible set of the optimization problem (14.9) is convex.

**Proof.** The feasible set of (14.9) is defined by the constraints (14.1), (14.7), and (14.8). It is obvious that the region defined by (14.1) is convex. The constraint (14.7) can be transformed into (14.14). The constraint (14.8) can be transformed into (14.15) and (14.16). Thus, $\forall n \in \mathcal{N}$, $k \in \{1, 2, \ldots, N_T\}$ we have:

$$\sum_{i=1}^{N_T} \eta(P_n(T_i))P_n(T_i) \geq \frac{C_n}{\Delta t} (SOC_{n,\text{MinCh}} - SOC_{n,0}),$$  \hspace{1cm} (14.14)

$$\sum_{i=1}^{k} \eta(P_n(T_i))P_n(T_i) \geq \frac{C_n}{\Delta t} (SOC_{n,\text{min}} - SOC_{n,0}),$$  \hspace{1cm} (14.15)

$$\sum_{i=1}^{k} \eta(P_n(T_i))P_n(T_i) \leq \frac{C_n}{\Delta t} (SOC_{n,\text{max}} - SOC_{n,0}).$$  \hspace{1cm} (14.16)

We prove that the region defined by (14.14), which equivalent to (14.7), is convex. Assume that $P_{n,1}(\mathcal{T}), P_{n,2}(\mathcal{T})$ are any two points that satisfy (14.14). $\forall 0 \leq \lambda_1, \lambda_2 \leq 1, \lambda_1 + \lambda_2 = 1$, we denote:

$$P_{n,3}(\mathcal{T}) = \lambda_1 P_{n,1}(\mathcal{T}) + \lambda_2 P_{n,2}(\mathcal{T}).$$  \hspace{1cm} (14.17)

It can be shown that the following inequality holds $\forall T_i \in \mathcal{T}$,

$$\eta(P_{n,3}(T_i))P_{n,3}(T_i) \geq \lambda_1 \eta(P_{n,1}(T_i))P_{n,1}(T_i) + \lambda_2 \eta(P_{n,2}(T_i))P_{n,2}(T_i).$$  \hspace{1cm} (14.18)

It follows from (14.18) that $P_{n,3}(\mathcal{T})$ also satisfies (14.14). Hence, the feasible set defined by (14.14) is convex. Similarly, it can be shown that, $\forall k \in \{1, 2, \ldots, N_T\}$, the feasible set defined by (14.15) is also convex.

When $k = 1$, it is obvious that the region defined by (14.16) is convex. Then, by applying mathematical induction, it can be shown that $\forall k \in \{1, 2, \ldots, N_T\}$, the region defined by (14.16) is also convex.

To conclude, the region defined by each of the constraints (14.1), (14.7), (14.8) is convex. Therefore, the feasible set of (14.9) is convex.

**Theorem 1** The optimization problem in (14.9) is a convex optimization problem.

**Proof.** According to Lemmas 1 and 2, it follows from the definition of convex optimization problem (Boyd and Vandenberghe, 2004) that (14.9) is a convex optimization problem. □
The solution of the forecast-based scheduling problem in (14.9) provides the best possible schedules $P_N(T)$ if and only if the forecasting profile of regulation requests $R_f(T)$ is accurate, i.e., $R_f(T) = R(T)$. However, in reality, the forecast of the regulation demand is highly inaccurate and vulnerable to forecasting errors of generation and load. Hence, the forecast-based scheduling in (14.9) is not practical.

### 14.3.4 Formulation of online scheduling

In practice, the regulation demand is derived from the regulation signals measured in real time. Hence, it is more realistic to adopt online scheduling, which schedules the charging/discharging power of EVs in response to the real-time input of a regulation request. Consider a scenario of online scheduling where at each time slot $T_k \in \mathcal{T}$, the aggregator receives the real-time signal of a regulation request $R(T_k)$ and then coordinates the EVs to update their charging/discharging schedules from $T_k$ to $T_N$, i.e., $\{P_n(T_j) | n \in \mathcal{N}, k \leq j \leq N_T\}$, so that $\text{Var}(P_{\text{total}}(T))$ is minimized. We have:

$$
\text{Var}(P_{\text{total}}(T)) = \frac{1}{N_T} \sum_{i=1}^{N_T} \left( R(T_i) + \sum_{n \in \mathcal{N}} P_n(T_i) - A(P_{\text{total}}(T)) \right)^2 
\quad + \frac{1}{N_T} \sum_{j=k+1}^{N_T} \left( R_f(T_j) + \sum_{n \in \mathcal{N}} P_n(T_j) - A(P_{\text{total}}(T)) \right)^2,
$$

(14.19)

where $A(P_{\text{total}}(T))$ denotes the average of $P_{\text{total}}(T)$ as:

$$
A(P_{\text{total}}(T)) = \frac{1}{N_T} \left( \sum_{i=1}^{k} R(T_i) + \sum_{j=k+1}^{N_T} R_f(T_j) + \sum_{T_j \in \mathcal{T}} \sum_{n \in \mathcal{N}} P_n(T_j) \right).
$$

(14.20)

From (14.19), the forecasts of the future regulation requests $R_f(T_j), j = k+1, k+2, \ldots, T_k$, can be approximated by:

$$
R_f(T_j) = \mathbb{E}(R(T_j)|\{R(T_i)|1 \leq i \leq k\}).
$$

(14.21)

However, the calculation of the conditional expectation in (14.21) requires the distribution of the regulation demand which is not known a priori. Nonetheless, since frequency regulation is a zero-energy service, the expectation of the total energy that the regulation service requires is zero over a long period of time. Therefore, we can make the following assumption:

$$
\mathbb{E}(R_S(T)) = 0,
$$

(14.22)

where

$$
R_S(T) = \sum_{T_i \in \mathcal{T}} R(T_i).
$$

(14.23)
From (14.21) and (14.22), we have:

$$
\sum_{j=k+1}^{N_T} R_f(T_j) = \mathbb{E} \left( \sum_{j=k+1}^{N_T} R(T_j) | \{R(T_i) | 1 \leq i \leq k\} \right) = - \sum_{i=1}^{k} R(T_i). \quad (14.24)
$$

By applying the Cauchy-Schwarz Inequality, we can derive a lower bound of the second summation in (14.19) when $k \leq N_T - 1$ as follows:

$$
\frac{1}{N_T} \sum_{j=k+1}^{N_T} \left( R_f(T_j) + \sum_{n \in \mathcal{V}} P_n(T_j) - A(P_{\text{total}}(\mathcal{F})) \right)^2 \geq \frac{1}{N_T (N_T - k)} \left( \sum_{j=k+1}^{N_T} R_f(T_j) + \sum_{n \in \mathcal{V}} \sum_{j=k+1}^{N_T} P_n(T_j) - (N_T - k) A(P_{\text{total}}(\mathcal{F})) \right)^2.
$$

(14.25)

The equality of (14.25) holds if and only if the following condition is satisfied:

$$
\forall k + 1 \leq j, l \leq N_T, R_f(T_j) + P_A(T_j) = R_f(T_l) + P_A(T_l). \quad (14.26)
$$

The condition (14.26) also minimizes (14.19). Therefore, the lower bound derived in (14.25) can be used to approximate (14.19) since we seek to minimize the variance of $P_{\text{total}}(\mathcal{F})$.

Based on (14.24) and (14.25), an approximation of $\text{Var}(P_{\text{total}}(\mathcal{F}))$ in (14.19) for $k \leq N_T - 1$ is derived and used as the objective function for the online scheduling problem as follows:

$$
U_o(Q_A(T_k)) = \frac{1}{N_T} \sum_{i=1}^{k} \left( R(T_i) + \sum_{n \in \mathcal{V}} P_n(T_i) \right)^2 + \frac{\alpha(k)}{N_T} \left( - \sum_{i=1}^{k} R(T_i) + \sum_{n \in \mathcal{V}} FP_n(T_k) \right)^2 - \frac{1}{N_T^2} \left( \sum_{n \in \mathcal{V}} \left( \sum_{i=1}^{k} P_n(T_i) + FP(T_k) \right) \right)^2,
$$

where

$$
Q_A(T_k) = (P_A(T_k), FP_A(T_k))^T = \sum_{n \in \mathcal{V}} Q_n(T_k), \quad (14.28)
$$

and

$$
\alpha(k) = \begin{cases} 
\frac{1}{N_T - k} & \text{if } 1 \leq k \leq N_T - 1 \\
0 & \text{if } k = N_T
\end{cases} \quad (14.29)
$$
In (14.28), $Q_n(T_k) = (P_n(T_k), FP_n(T_k))^T$ denotes the control variables or schedule of EV $n$, $\forall n \in \mathcal{N}$, at $T_k$, where $FP_n(T_k)$ is the sum of the future charging/discharging powers of EV $n$ as follows:

$$FP_n(T_k) = \sum_{i=k+1}^{N_T} P_n(T_i). \quad (14.30)$$

Note that the charging/discharging powers of the EVs before $T_k$, i.e., $\{P_n(T_i)|n \in \mathcal{N}, 1 \leq i \leq N_T\}$, are not included in the control variables since they are already historical data.

Denote the schedules of all EVs at $T_k$ as $Q_{\mathcal{N}}(T_k) = (Q_1(T_k), Q_2(T_k), \ldots, Q_{NEV}(T_k))$. The online scheduling problem for the V2G regulation service is formulated as follows:

At each $T_k \in \mathcal{T}$,

$$\min_{Q_{\mathcal{N}}(T_k)} U_o(Q_{\mathcal{A}}(T_k)) \quad (14.31)$$

such that for all $n \in \mathcal{N}$,

$$\eta(P_n(T_k))P_n(T_k) + \eta(FP_n(T_k))FP_n(T_k) \geq \frac{C_n}{\Delta t}(SOC_{n,MinCh} + SOC_{n,MOS}(T_k) - SOC_n(T_{k-1})) \quad (14.32)$$

and (14.1), (14.8) hold.

From (14.32), $SOC_{n,MOS}(T_k)$ denotes the SOC “margin of safety” of EV $n \in \mathcal{N}$ defined as follows:

$$SOC_{n,MOS}(T_k) = \begin{cases} 
\mu(SOC_{n,max} - SOC_{n,MinCh}), & T_k \in [T_{n,in}, (1 - \tau)T_{n,in} + \tau T_{n,out}] \\
-SOC_{n,MinCh}, & \text{otherwise} \\
0, & \text{otherwise}
\end{cases} \quad (14.33)$$

where $\mu \in [0, 1]$ quantifies the relative amount of the safety margin, and $\tau \in [0, 1]$ determines the ratio of the time that the safety margin is in effect. The parameters $\mu$ and $\tau$ are identical among the EVs.

The constraint (14.32) is derived from (14.7) with $SOC_{n,MOS}(T_k)$ added to the charging requirement of EV $n$, where $n = 1, 2, \ldots, N_{EV}$, in (14.7). The purpose of introducing the margin of safety for charging is to cope with the uncertainty of the regulation requests. Because the objective function (14.27) for the online scheduling problem in (14.31) approximates $\text{Var}(P_{total}(\mathcal{T}))$ in (14.19) based on the zero-sum assumption in (14.22) of the regulation requests $R(\mathcal{T})$, such approximation may be inaccurate when the assumption stated in (14.22) does not hold in some cases. By introducing the margin of safety for charging in (14.32), the EVs
would buffer some more energy on top of their minimum charging requirements to meet the extra energy needs for regulation up, i.e., \(R_S(T) > 0\).

**Lemma 3** For all \(T_k \in \mathcal{F}\), the objective function (14.27), \(U_o : \mathbb{R}^2 \to \mathbb{R}\) of the optimization problem (14.31) is convex.

**Proof.** \(\forall 1 \leq k \leq N_T - 1\), according to the gradient of \(U_o(Q_A(T_k))\), \(\nabla U_o(Q_A(T_k))\), the Hessian of \(U_o(Q_A(T_k))\) is as follows:

\[
\nabla^2 U_o(Q_A(T_k)) = \frac{2}{N_T^2} \begin{bmatrix}
N_T - 1 & -1 \\
-1 & \frac{N_T}{N_T - k} - 1
\end{bmatrix}.
\]

(14.34)

When \(k = N_T\), the Hessian of \(U_o(Q_A(T_{N_T}))\) is as follows:

\[
\nabla^2 U_o(Q_A(T_{N_T})) = \frac{2}{N_T^2} \begin{bmatrix}
N_T - 1 & 0 \\
0 & 0
\end{bmatrix}.
\]

(14.35)

It can be checked that both (14.34) and (14.35) are positive semidefinite. In addition, since the domain of \(U_o\), \(\text{dom} \{U_o\} = \mathbb{R}^2\), is convex, it follows from the second-order conditions for convex function (Boyd and Vandenberghe, 2004) that the function \(U_o : \mathbb{R}^2 \to \mathbb{R}\) is convex. □

**Lemma 4** For all \(T_k \in \mathcal{F}\), the feasible set of the optimization problem (14.31) is convex.

**Proof.** The feasible set of (14.31) is defined by the constraints (14.1), (14.8), and (14.32). Similar to the proof of the convexity of the region defined by (14.14) in Lemma 2, it can be shown that, for all \(T_k \in \mathcal{F}\), the region defined by (14.32) is convex. In addition, it is obvious that the region defined by each of the constraints (14.1) and (14.8) is convex. Therefore, for all \(T_k \in \mathcal{F}\), the feasible set of (14.31) is convex. □

**Theorem 2** For all \(T_k \in \mathcal{F}\), the optimization problem in (14.31) is a convex optimization problem.

**Proof.** According to Lemmas 3 and 4, it follows from the definition of convex optimization problem (Boyd and Vandenberghe, 2004) that (14.31) is a convex optimization problem. □

Although the proposed online scheduling problem in (14.31) only optimizes an approximation of (14.19), it is more practical than the forecast-based scheduling problem in (14.9) because it does not require the forecasts of the regulation requests. In addition, (14.31) incurs much lower computational complexity than (14.9) since it reduces the number of control variables significantly.
14.4 Decentralized scheduling algorithm

In this section, two classes of decentralized algorithms, namely, Algorithms 14.1 and 14.2, and Algorithms 14.3 and 14.4, are proposed to solve the forecast-based scheduling problem in (14.9) and the online scheduling problem in (14.31), respectively. They are inspired by the decentralized algorithm proposed for optimal EV charging control (Gan et al., 2013) and based on the gradient projection method (Bertsekas and Tsitsiklis, 1989).

Since Algorithms 14.1 and 14.2 distribute the computational efforts to EVs, the aggregator only needs to perform simple arithmetic for calculating the control signals with a computational complexity equal to $O(N_{EV})$. In each round of the iterations, every EV should update its own schedule by solving an optimization problem. The computational complexity of an EV is $O(1)$ in terms of the scale of the set of EVs. Therefore, Algorithms 14.1 and 14.2 are highly scalable.

Lemma 5 \( \forall m \geq 1 \), the following inequality holds:

\[
\langle \nabla U_f(P_A^{m-1}(\mathcal{T}))) - \nabla U_f(P_A^{m}(\mathcal{T})), P_A^{m-1}(\mathcal{T}) - P_A^{m}(\mathcal{T}) \rangle \\
\leq \frac{2}{N_T} \|P_A^{m-1}(\mathcal{T}) - P_A^{m}(\mathcal{T})\|^2.
\]  

(14.36)

**Proof.** According to the first-order partial derivatives of $U_f(P_A(\mathcal{T}))$ derived in (14.44), we have,

\[
\langle \nabla U_f(P_A^{m-1}(\mathcal{T}))) - \nabla U_f(P_A^{m}(\mathcal{T})), P_A^{m-1}(\mathcal{T}) - P_A^{m}(\mathcal{T}) \rangle \\
= \frac{2}{N_T} \sum_{T_k \in \mathcal{T}} (P_A^{m-1}(T_k) - P_A^{m}(T_k))^2 - \frac{2}{N_T} \left( \sum_{T_j \in \mathcal{T}} (P_A^{m-1}(T_j) - P_A^{m}(T_j))^2 \right)^2 \\
\leq \frac{2}{N_T} \sum_{T_k \in \mathcal{T}} (P_A^{m-1}(T_k) - P_A^{m}(T_k))^2 \\
= \frac{2}{N_T} \|P_A^{m-1}(\mathcal{T}) - P_A^{m}(\mathcal{T})\|^2. 
\]

(14.37)

**Lemma 6** \( \forall n \in \mathcal{N}, m \geq 1 \), the following inequality holds:

\[
\langle s_f^n(\mathcal{T}), P_n^m(\mathcal{T}) - P_n^{m-1}(\mathcal{T}) \rangle \geq -\|P_n^m(\mathcal{T}) - P_n^{m-1}(\mathcal{T})\|^2. 
\]  

(14.38)

**Proof.** See the proof of Lemma 1 of Gan et al. (2013). \( \square \)
Theorem 3 In Algorithms 14.1 and 14.2, the schedules $P_m^N(T)$ converge to one of the optimal solutions for the forecast-based scheduling problem in (14.9) as $m \to \infty$.

Proof. \forall m \geq 1,

$$U_f(P_m^N(T))$$

$$\leq U_f(P_m^{n-1}(T)) - \langle \nabla U_f(P_m^N(T)), P_m^N(T) - P_m^N(T) \rangle$$

$$\leq U_f(P_m^{n-1}(T)) - \langle \nabla U_f(P_m^N(T)), P_m^N(T) - P_m^N(T) \rangle$$

$$+ \frac{2}{N_T} \|P_m^{n-1}(T) - P_m^N(T)\|^2$$

$$= U_f(P_m^{n-1}(T)) - \frac{1}{\beta} \sum_{n \in V} \langle s_f^n(T), P_m^{n-1}(T) - P_m^N(T) \rangle$$

$$+ \frac{2}{N_T} \|P_m^{n-1}(T) - P_m^N(T)\|^2$$

$$\leq U_f(P_m^{n-1}(T)) - \frac{1}{\beta} \sum_{n \in V} \|P_m^{n-1}(T) - P_m^N(T)\|^2$$

$$+ \frac{2}{N_T} \|P_m^{n-1}(T) - P_m^N(T)\|^2$$

$$\leq U_f(P_m^{n-1}(T)) + \left( \frac{2}{N_T} - \frac{1}{\beta N_E V} \right) \|P_m^{n-1}(T) - P_m^N(T)\|^2$$

$$\leq U_f(P_m^{n-1}(T)). \quad (14.39)$$

The first inequality holds due to the first-order condition (Boyd and Vandenberghe, 2004) of the convex function $U_f$. The second inequality is due to Lemma 5, the third inequality is due to Lemma 6, the fourth inequality is due to the Cauchy-Schwarz inequality, and the fifth inequality is due to $0 < \beta < \frac{N_T}{2N_E V}$.

According to (14.39), $U_f(P_m^N(T))$ is nonincreasing as $m$ increases. Further, it is easy to check that $U_f(P_m^N(T)) = U_f(P_m^{n-1}(T))$ if and only if $P_m^N(T) = P_m^{n-1}(T)$. If $P_m^N(T) = P_m^{n-1}(T)$, it follows from the proof of Theorem 3 of Gan et al., (2013) that $P_m^N(T)$ minimizes $U_f$. To conclude, $P_m^N(T)$ minimizes $U_f$ as $m \to \infty$. \[ \Box \]

Lemma 7 \forall m \geq 1, $T_k \in T$, the following inequality holds:

$$\langle \nabla U_o(Q_m^{n-1}(T_k)) - \nabla U_o(Q_m^N(T_k)), Q_m^{n-1}(T_k) - Q_m^N(T_k) \rangle$$

$$\leq \frac{2}{N_T} \|Q_m^{n-1}(T_k) - Q_m^N(T_k)\|^2. \quad (14.40)$$

Proof. Similar to the proof of Lemma 5, the inequality (14.40) can be proved by simple derivation.
∀m ≥ 1, T_k ∈ ℋ, according to the gradient of U_o(Q_A(T_k)), ∇U_o(Q_A(T_k)), derived in (14.48), we have,

$$
\langle \nabla U_o(Q_A^{m-1}(T_k)) - \nabla U_o(Q_A^m(T_k)), Q_A^m(T_k) - Q_A^{m-1}(T_k) \rangle
$$

$$
= \frac{2}{N_T} (P_A^{m-1}(T_k) - P_A^m(T_k))^2 + \alpha(k) \frac{2}{N_T} (FP_A^{m-1}(T_k) - FP_A^m(T_k))^2
$$

$$
- FP_A^m(T_k))^2 - \frac{2}{N_T} (P_A^{m-1}(T_k) - P_A^m(T_k) + FP_A^{m-1}(T_k) - FP_A^m(T_k))^2
$$

$$
\leq \frac{2}{N_T} ((P_A^{m-1}(T_k) - P_A^m(T_k))^2 + (FP_A^{m-1}(T_k) - FP_A^m(T_k))^2)
$$

$$
(1 - \alpha(k)) \frac{2}{N_T} (FP_A^{m-1}(T_k) - FP_A^m(T_k))^2
$$

$$
\leq \frac{2}{N_T} ||Q_A^{m-1}(T_k) - Q_A^m(T_k)||^2.
$$

(14.41)

The second equality is due to α(k) ≤ 1. □

**Lemma 8** ∀n ∈ ℳ, m ≥ 1, T_k ∈ ℋ, the following inequality holds:

$$
\langle s_o^m(T_k), Q_A^m(T_k) - Q_A^{m-1}(T_k) \rangle \geq -||Q_A^m(T_k) - Q_A^{m-1}(T_k)||^2
$$

(14.42)

**Proof.** See the proof of Lemma 1 of Gan et al. (2013). □

**Theorem 4** In Algorithms 14.3 and 14.4, at any time slot T_k ∈ ℋ, the schedules Q_A^m(T_k) converge to one of the optimal solutions for the online scheduling problem in (14.31) as m → ∞.

**Proof.** Similar to the proof of Theorem 3, by applying the first-order condition of the convex function U_o, Lemmas 7 and 8, and the Cauchy-Schwarz inequality, successively, it can be shown that, ∀T_k ∈ ℋ, U_o(Q_A^m(T_k)) is nonincreasing as m increases. It can be checked that U_o(Q_A^m(T_k)) = U_o(Q_A^{m-1}(T_k)) if and only if Q_A^m(T_k) = Q_A^{m-1}(T_k), and such Q_A^m(T_k) minimizes U_o. To conclude, Q_A^m(T_k) minimizes U_o as m → ∞. □

In Algorithms 14.1 and 14.2, ⟨·, ·⟩ represents the dot product operation and || · || denotes the Euclidean norm.

**Algorithm 14.1** Forecast-based scheduling for aggregator

**Input:** The participation period ℋ. Before the participation period ℋ starts, the aggregator receives the forecasting profile of the regulation requests R_f(ℋ) and knows the number of EVs N_EV.

**Output:** The charging/discharging schedules of EVs P_A(ℋ) = (P_1(ℋ), P_2(ℋ), ..., P_N_EV(ℋ)).
Choose a parameter $\beta$ such that $0 < \beta < \frac{N_T}{2N_{EV}}$.

Wait for the initial schedule $P_n^0(\mathcal{T})$ of every $EV$ $n \in \mathcal{N}$.

Set the iteration number $m \leftarrow 1$, repeat Steps 1–3.

1. Calculate the control signal $s_f^m(\mathcal{T}) = (s_f^m(T_1), s_f^m(T_2), \ldots, s_f^m(T_{N_T}))^T$ as follows:

$$s_f^m(\mathcal{T}) = \beta \nabla U_f(P_{A}^{m-1}(\mathcal{T}))$$

(14.43)

Therefore $\forall T_k \in \mathcal{T}$,

$$s_f^m(T_k) = \beta \frac{\partial U_f(P_{A}^{m-1}(\mathcal{T}))}{\partial P_A(T_k)} = \frac{2\beta}{N_T} (R_f(T_k) + \sum_{n \in \mathcal{N}} P_n^{m-1}(T_k))$$

$$- \frac{2\beta}{N_T^2} \left( \sum_{T_j \in \mathcal{T}} (R_f(T_j) + \sum_{n \in \mathcal{N}} P_n^{m-1}(T_j)) \right)$$

(14.44)

Broadcast the control signal $s_f^m(\mathcal{T})$ to all $EV$.

2. Wait for the updated schedule $P_n^m(\mathcal{T})$ reported by every $EV$ $n \in \mathcal{N}$.

3. If the stopping criteria are not met, set $m \leftarrow m + 1$ and go to Step 1. Otherwise, broadcast the message that the iteration process ends to all $EV$.

**Return** $P_n^m(\mathcal{T}) = P_n^m(\mathcal{T})$.

**Algorithm 14.2** Forecast-based scheduling for each $EV$ $n \in \mathcal{N}$

**Input:** The participation period $\mathcal{T}$. $EV$ $n \in \mathcal{N}$ knows its own constraints (14.1), (14.7), and (14.8).

**Output:** The charging/discharging schedule of $EV$ $n$, $P_n(\mathcal{T})$.

Initialize the schedule $P_n^0(\mathcal{T})$ such that $P_n^0(\mathcal{T})$ lies in the boundary of the region defined by the constraint (14.7). Then report $P_n^0(\mathcal{T})$ to the aggregator. Set the iteration number $m \leftarrow 1$, repeat Steps 1–3.

1. Wait for the updated control signal $s_f^m(\mathcal{T})$ broadcast by the aggregator.

2. Calculate a new schedule $P_n^m(\mathcal{T})$ as:

$$P_n^m(\mathcal{T}) = \arg \min_{P_n(\mathcal{T})} \left( (s_f^m(\mathcal{T}), P_n(\mathcal{T})) + \frac{1}{2} \| P_n(\mathcal{T}) - P_n^{m-1}(\mathcal{T}) \|^2 \right),$$

(14.45)

such that (14.1), (14.7), and (14.8) hold.

Report $P_n^m(\mathcal{T})$ to the aggregator.

3. If the aggregator has not announced that the iteration process has ended, set $m \leftarrow m + 1$ and go to Step 1.

**Return** $P_n(\mathcal{T}) = P_n^m(\mathcal{T})$. 
### 14.4.1 Forecast-based scheduling

For the forecast-based scheduling, it is assumed that all \(N_{EV}\) EVs are available to run Algorithms 14.1 and 14.2 under the coordination of the aggregator before the participation period \(T\) starts. Since the forecasting inputs of the regulation requests over such a long time horizon \(T\) (a span of hours in our context), are highly unreliable, forecast-based scheduling is not practical in the real world. Nonetheless, Algorithms 14.1 and 14.2 can still be useful to obtain the best possible scheduling results as the performance bound when we assume that \(R_f(\mathcal{F})\) is accurate in the simulation.

The stopping criteria of Algorithms 14.1–14.4 can be based on the number of iterations performed, i.e., \(m = M_f\), where \(M_f\) is the maximum number of iterations, and/or the convergence of the control signal \(s_f^m(\mathcal{F})\) within the convergence tolerance, i.e. \(\|s_f^m(\mathcal{F}) - s_f^{m-1}(\mathcal{F})\| \leq \epsilon_f\), where \(\epsilon_f > 0\) is the convergence tolerance.

The forecast-based scheduling problem in (14.9) minimizes the variance of \(P_{total}(T)\). Therefore, without considering the constraints of (14.9), the optimal solutions of (14.9) should follow:

\[
\forall T_i \in \mathcal{F}, P_{total}(T_i) = A(P_{total}(\mathcal{F}))
\]  

(14.46)

The value of \(A(P_{total}(\mathcal{F}))\) does not affect the optimality of (14.9) as long as (14.46) is satisfied. Since the constraints (14.7) and (14.8) allow the final SOC of an EV \(n \in \mathcal{N}\) to be within a given range, i.e., \(SOC_n(T_k) \in [SOC_{n,MinCh}, SOC_{n,max}]\), the total energy consumption of EVs, \(\sum_{T_k \in \mathcal{F}} P_A(T_k)\), is not fixed. The proposed Algorithms 14.1 and 14.2 does not determine the value of \(A(P_{total}(\mathcal{F}))\). Nevertheless, the value of \(A(P_{total}(\mathcal{F}))\) in the optimization result is related to the schedules \(P^0_n(\mathcal{F})\) in the initialization step, since the searching for the optimal schedules \(P^0_n(\mathcal{F})\) starts from \(P^0_n(\mathcal{F})\).

In each round of the iterations of Algorithms 14.1 and 14.2, the aggregator calculates and broadcasts the control signal \(s_f^m(\mathcal{F}) \in \mathbb{R}^{N_T \times 1}\) from the schedules \(P^m_{n^-1}(\mathcal{F}) \in \mathbb{R}^{N_T \times N_{EV}}\) received from the EVs. Every EV \(n \in \mathcal{N}\) needs to solve the optimization problem (14.46) to obtain its updated schedule \(P^m_n(\mathcal{F}) \in \mathbb{R}^{N_T \times 1}\) and reports \(P^m_n(\mathcal{F})\) to the aggregator. Therefore, the total communication overheads \(CO_f\) of Algorithms 14.1 and 14.2 are calculated as:

\[
CO_f = D \cdot m_f \cdot N_T \cdot (N_{EV} + 1)
\]  

(14.47)

where \(D\) and \(m_f\) denote the size of a one-dimensional control variable, e.g. \(P_n(T_k)\), and the number of iterations performed, respectively.

**Algorithm 14.3 Online scheduling for aggregator**

**Input:** At any time slot \(T_k \in \mathcal{F}\), the aggregator knows the total number of time slots \(N_T\), and the number of EVs \(N_{EV}\), and has received the regulation requests \(\{R(T_i)\}_{1 \leq i \leq k}\).

**Output:** The charging/discharging schedules of EVs at \(T_k\), \(Q_n(T_k) = (Q_1(T_k), Q_2(T_k), \ldots, Q_{N_{EV}}(T_k))\).
Choose a parameter $\beta$ such that $0 < \beta < \frac{N_T}{2N_{EV}}$.

Wait for the initial schedule $Q^0_n(T_k)$ of every EV $n \in \mathcal{N}$.

Set the iteration number $m \leftarrow 1$, repeat Steps 1–3.

1. Calculate the control signal $s^m_o(T_k) \in \mathbb{R}^{2 \times 1}$ as follows:

\[
s^m_o(T_k) = \beta \nabla U_o(Q^{m-1}_A(T_k)) = \beta \left( \frac{\partial U_o(Q^{m-1}_A(T_k))}{\partial P_A(T_k)}, \frac{\partial U_o(Q^{m-1}_A(T_k))}{\partial F_P A(T_k)} \right)^T
\]

\[
= \frac{2\beta}{N_T} \begin{pmatrix}
R(T_k) + P^{m-1}_A(T_k) \\
\alpha(k) \left( -\sum_{i=1}^k R(T_i) + F P^{m-1}_A(T_k) \right)
\end{pmatrix}
\]

\[
- \left( \frac{2\beta}{N_T^2} \right) \begin{pmatrix}
\sum_{i=1}^{k-1} P_A(T_i) + P^{m-1}_A(T_k) + F P^{m-1}_A(T_k)
\end{pmatrix}
\]

(14.48)

Broadcast the control signal $s^m_o(T_k)$ to all EVs.

2. Wait for the updated schedule $Q^m_n(T_k)$ reported by every EV $n \in \mathcal{N}$.

3. If the stopping criteria are not met, set $m \leftarrow m + 1$ and go to Step 1. Otherwise, broadcast the message that the iteration process ends to all EVs.

Return $Q^m_n(T_k) = Q^m_n(T_k)$.

Algorithm 14.4 Online scheduling for each EV $n \in \mathcal{N}$

Input: At any time slot $T_k \in \mathcal{T}$, $n \in \mathcal{N}$ knows its own constraints (14.1), (14.8), and (14.32).

Output: The charging/discharging schedules of EV $n$ at $T_k$, $Q^m_n(T_k)$.

Initialize the schedule $Q^0_n(T_k)$ as:

\[
Q^0_n(T_k) = \begin{cases}
\text{a point at the boundary of the region defined by (14.32)} & k = 1 \\
\frac{F P(T_{k-1})}{T_{n, out} - T_{k-1}} (\Delta t, T_{n, out} - T_k)^T & \text{otherwise}
\end{cases}
\]

and report $Q^0_n(T_k)$ to the aggregator.

Set the iteration number $m \leftarrow 1$, repeat Steps 1–3.

1. Wait for the updated control signal $s^m_o(T_k)$ broadcast by the aggregator.
2. Calculate a new schedule $Q^m_n(T_k)$ as:

$$Q^m_n(T_k) = \arg\min_{Q_n(T_k)} \left( \langle s^n_n(T_k), Q_n(T_k) \rangle + \frac{1}{2} \|Q_n(T_k) - Q^{m-1}_n(T_k)\|^2 \right),$$

(14.50)

such that (14.1), (14.8), and (14.32) hold. Report $Q^m_n(T_k)$ to the aggregator.

If the aggregator has not announced that the iteration process has ended, set $m \leftarrow m + 1$ and go to Step 1).

Return $Q_n(T_k) = Q^m_n(T_k)$.

### 14.4.2 Online scheduling

For the online scheduling, Algorithms 14.3 and 14.4 are performed at every slot $T_k \in T$ to update the schedules of EVs according to the newly received regulation request $R(T_k)$.

Similar to those of Algorithms 14.1 and 14.2, the stopping criteria of Algorithms 14.3 and 14.4 can be $m = M_o$ where $M_o$ is the maximum number of iterations, and/or $\|s^n_o(T) - s^{m-1}_o(T)\| \leq \varepsilon_o$, where $\varepsilon_o > 0$ is the convergence tolerance.

At every slot $T_k \in T$, the optimization results $Q^{o_i}(T_k)$ are influenced by the profiles of the current and past regulation requests $\{R(T_i)\}_{1 \leq i \leq k}$ and the historical charging/discharging power of the EVs $\{P_n(T_k)\}_{n \in N, 1 \leq i < k}$.

In each round of the iterations of Algorithms 14.3 and 14.4, the aggregator calculates and broadcasts the control signal $s^m_o(T_k) \in \mathbb{R}^{2 \times 1}$ from the schedules $Q^{m-1}_n(T_k) \in \mathbb{R}^{2 \times N_{EV}}$ received from the EVs. Every EV $n \in N$ needs to solve the optimization problem (14.45) to obtain its updated schedule $Q^m_n(T_k) \in \mathbb{R}^{2 \times 1}$ and reports $Q^m_n(T_k)$ to the aggregator. Therefore, the total communication overhead $CO_o$ of Algorithms 14.3 and 14.4 at each time slot is calculated as:

$$CO_o = D \cdot m_o \cdot 2 \cdot (N_{EV} + 1)$$

(14.51)

where $m_o$ denotes the number of iterations performed.

### 14.5 Case studies

This section synthesizes and presents the simulation results reported in our prior works (Lin et al., 2013, 2014).

#### 14.5.1 V2G scheduling algorithms

The scheduling algorithms, namely, Algorithms 14.1 and 14.2 for the forecast-based scheduling problem in (14.9), Algorithms 14.3 and 14.4 for the online scheduling problem in (14.31), and an extended version, which is introduced below, of the optimal decentralized charging (ODC) algorithm proposed in Gan et al. (2013), will be investigated by computer simulation.
Since the ODC algorithm proposed in Gan et al. (2013) does not consider discharging of EV batteries, we extend ODC by enabling discharging to fit in our context. Hence, the optimization problem of ODC with discharging (ODCD) is discussed as follows:

\[
\min_{P_j(T_j) \in \mathcal{T}} \sum_{T_i \in \mathcal{T}} u \left( R_f(T_i) + \sum_{n \in \mathcal{N}} P_n(T_i) \right)
\]

such that for all \( n \in \mathcal{N} \), (14.1) holds, and

\[
SOC_n(T_{NT}) = SOC_{n, MinCh}, \quad (14.52)
\]

where \( u : \mathbb{R} \to \mathbb{R} \) is strictly convex. According to Theorem 2 of Gan et al. (2013), the optimal total power profile obtained by (14.52) is independent on the choice of \( u \).

According to Property 1 of Gan et al. (2013), ODC is able to obtain a flat total power profile by scheduling the charging activities of EVs. However, when discharging is introduced and ODC is extended to ODCD, such valley-filling property of ODC may not be inherited by ODCD. It will be studied in the simulation.

14.5.2 Performance metric

According to the proposed control objective for the V2G regulation service, the variance of the profile of the total power, \( \text{Var}(P_{\text{total}}) \), is used as the performance metric.

A smaller \( \text{Var}(P_{\text{total}}) \) implies a more flattened profile of the total power, indicating that the fluctuations of the regulation requests are better absorbed by the aggregated EV power, and therefore a better performance.

14.5.3 Simulation setup

The simulation scenario is an aggregator coordinating \( N_{EV} = 1,000 \) EVs to decide their charging/discharging schedules from 19:00 in the evening to 7:00 on the next morning. This 12-hour period of time is divided equally into \( N_T = 144 \) slots of length \( \Delta t = 5 \) minutes.

The hypothetic EV group consists of four models of EVs currently on the market: Chevrolet Volt with a 16.5-kWh battery pack (Che, 2014), Ford C-MAX Energi with a 7.6-kWh battery pack (For, 2014), Nissan Leaf SV with a 24-kWh battery pack (Nis, 2014), and Tesla Model S with a 60-kWh battery pack (Tes, 2014). Each of the four models accounts for 25% of the 1000 EVs. All EVs are assumed to have been contracted to provide the V2G regulation service, either unidirectionally or bidirectionally. According to the standard Level 2 charging in the US, we assume that the charging power of Chevrolet Volt and C-MAX Energi can vary from 0 to 4.0 kW. Nissan Leaf SV and Tesla Model S have their dedicated 240-volt chargers with charging powers of 6.6 kW (Nis, 2014) and 10 kW (Tes, 2014), respectively. Thus, we assume that the charging power of Leaf SV and Model S can vary from 0 to 6.6 kW and from 0 to 10 kW, respectively. Furthermore, the discharging power of all of the four models are assumed to vary from −4 kW to 0 for bidirectional V2G. According to Shao et al. (2012), the distribution of plug-in
time of EVs is close to a normal distribution. Hence, in the simulation, the plug-in
times of EVs are generated based on a normal distribution with the mean at 19:00
and the standard deviation is equal to 1 hour first, and then any plug-in time before
19:00 is set to be 19:00. Similarly, the plug-out times are also generated based on a
normal distribution with the mean at 7:00 and the standard deviation is equal to 1
hour first. Then, any plug-out time after 7:00 is set to be 7:00. The values or
distributions of the parameters for EVs are summarized in Table 14.1.

The fast response regulation signals of the PJM market (Reg, 2013) from
18 December 2012 to 18 January 2013 are used in the simulation. A total of 31 sets
of the 12-hour profiles of regulation signals are extracted from the 32-day period.
According to Rebours et al. (2007), the regulation signal is normalized to be within
the range of [–1,1], and related to the regulation demand linearly. The ratio between
the regulation demand and regulation signal is set by the balancing authority of a
specific control area. Since most of the 1,000 EVs in the hypothetic EV group have
charging and discharging power limits of 4 kW and –4 kW, respectively, and the
regulation service is usually bid on an MW basis (Kempton and Tomić, 2005b), it
is reasonable to assume that the aggregator would receive the assigned regulation
requests within the range of [–2, 2] MW in this case. Hence, the ratio between the
regulation requests and regulation signal would be 2 MW in the simulation.
According to (14.22), the expectation of the sum of the regulation requests over the
12-hour participation period is assumed to be zero. Figure 14.7 shows the histogram
of the sum of the 12-hour regulation requests. The minimum and maximum values of
the sum, $R_S(\mathcal{T})$, are −13.442 MW and 8.161 MW. It can be observed that the total
energy needs of frequency regulation over the specified 12-hour period may be non-
zero although in most cases the total energy needs are close to zero.

Both Algorithms 14.1 and 14.2 for forecast-based scheduling and ODCD require
the forecasting profile of the regulation requests. In the simulation, it is assumed that
the forecasts of the regulation requests are accurate, i.e., $R_f(T_i) = R(T_i), \forall T_i \in \mathcal{T}$.

For the stopping criteria of Algorithms 14.1 and 14.2, $\epsilon_f = 10^{-5}$ and $M_f = 100$.
As for Algorithms 14.3 and 14.4, $\epsilon_o = 10^{-5}$ and $M_o = 50$.

### 14.5.4 Simulation results

The scheduling results of the three algorithms with various values of the participa-
tion ratio of the bidirectional V2G, $\theta_{bi}$, and the sum of the regulation requests,
$R_S(\mathcal{T})$, are studied. Table 14.2 lists the performances of the three algorithms with
$\theta_{bi}$ equal to 1, 0.5, and 0, respectively, in three special cases of $R_S(\mathcal{T})$, namely, the

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Parameter</th>
<th>Distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu$</td>
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<td>$SOC_{n,0}$</td>
<td>$U[0.45,0.55]$</td>
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<td>$\tau$</td>
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<td>$SOC_{n,MinCh}$</td>
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<td>$SOC_{n,max}$</td>
<td>$U[0.9,0.99]$</td>
</tr>
<tr>
<td>$\eta_{dch}$</td>
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<td>$SOC_{n,min}$</td>
<td>$U[0.3,0.4]$</td>
</tr>
</tbody>
</table>
Figure 14.7  Histogram of the sum of the 12-hour regulation signals with 31 samples. © 2014 IEEE. Reprinted with permission from Lin et al. (2014)

Table 14.2 Performances of the three scheduling algorithms with various values of $R_S(\mathcal{F})$ and $\theta_{bi}$: (a) $R_S(\mathcal{F}) = -24.09$ kW; (b) $R_S(\mathcal{F}) = 8.161 \times 10^3$ kW; (c) $R_S(\mathcal{F}) = -1.344 \times 10^4$ kW

(a)

<table>
<thead>
<tr>
<th>$\theta_{bi}$</th>
<th>Forecast-based scheduling</th>
<th>Online scheduling</th>
<th>ODCD</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.023</td>
<td>9.988</td>
<td>$1.858 \times 10^3$</td>
</tr>
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<td>0.5</td>
<td>0.172</td>
<td>11.903</td>
<td>$1.789 \times 10^3$</td>
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<td>0</td>
<td>$2.638 \times 10^3$</td>
<td>4.065 $\times 10^3$</td>
<td>$1.268 \times 10^4$</td>
</tr>
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</table>

(b)

<table>
<thead>
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<th>$\theta_{bi}$</th>
<th>Forecast-based scheduling</th>
<th>Online scheduling</th>
<th>ODCD</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.0038</td>
<td>45.888</td>
<td>$2.095 \times 10^3$</td>
</tr>
<tr>
<td>0.5</td>
<td>0.272</td>
<td>54.215</td>
<td>$2.090 \times 10^3$</td>
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<tr>
<td>0</td>
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<td>1.395 $\times 10^4$</td>
<td>$2.540 \times 10^4$</td>
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</tbody>
</table>

(c)

<table>
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<tr>
<th>$\theta_{bi}$</th>
<th>Forecast-based scheduling</th>
<th>Online scheduling</th>
<th>ODCD</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.114</td>
<td>4.418 $\times 10^2$</td>
<td>$5.139 \times 10^2$</td>
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<tr>
<td>0.5</td>
<td>0.257</td>
<td>4.716 $\times 10^2$</td>
<td>$5.125 \times 10^2$</td>
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<tr>
<td>0</td>
<td>$2.126 \times 10^3$</td>
<td>1.642 $\times 10^3$</td>
<td>$3.967 \times 10^3$</td>
</tr>
</tbody>
</table>

$^2$ The unit of the performance metric $\text{Var}(P_{\text{total}}(\mathcal{F}))$ is (kW)$^2$. 
minimum absolute, maximum, and minimum values of $R_S(\mathcal{T})$, respectively, among the 31 sets of the profiles of the regulation requests.

First, we compare the scheduling results in the ideal case when the sum of the regulation requests is close to zero. Among the 31 sets of profiles of regulation requests, the one with its sum closest to zero has $R_S(\mathcal{T}) = -24.09\ kW$. Figure 14.8

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure14_8a}
\caption{Simulation results of the three algorithms with $\sum_{T_k \in \mathcal{T}} R(T_k) = -24.09\ kW$ and various configurations of $\theta_{bi}$: (a) $\theta_{bi} = 1$; (b) $\theta_{bi} = 0.5$; (c) $\theta_{bi} = 0$. ©2014 IEEE. Reprinted with permission from Lin et al.(2014)}
\end{figure}
presents the results of the three scheduling algorithms when $\theta_{bi}$ is equal to 1, 0.5, and 0, respectively.

As shown in Figure 14.8(a) with $\theta_{bi} = 1$, i.e., all EVs participate in the bidirectional V2G, the total power profile of the proposed forecast-based scheduling (the dashed curve) is flat, indicating that the power fluctuations represented by the profile of the regulation requests are smoothed out under the assumption of accurate forecasts of the regulation requests. The total power profile of the proposed online scheduling (the dash-dotted curve) is almost as flat as the dashed curve. Note that the dashed curve and the dash-dotted curve are close to two constant positive loads of about 731 kW and 874 kW, respectively. As indicated in Section 14.3.1, the constant loads are approximately equal to the power consumptions for satisfying the charging needs of EVs since the sum of the regulation requests is close to zero. The dash-dotted curve is higher than the dashed curve because the safety margin for charging stated in (14.33) of online scheduling entails a higher energy consumption of EVs.

As shown in Figure 14.8 with $\theta_{bi} = 0.5$, the power profiles of forecast-based scheduling and online scheduling are still flat although 50% of EVs participate in the unidirectional V2G for which discharging is not allowed. However, when all EVs participate in unidirectional V2G, as shown in Figure 14.8 with $\theta_{bi} = 0$, the performances of the two scheduling algorithms deteriorate since the EVs are unable to discharge their batteries to maintain a flat profile of the total power when the regulation requests are large. The results of online scheduling at different values of $\theta_{bi}$ imply that there exists a minimum $\theta_{bi}$ for a given upper bound of $\text{Var}(P_{\text{total}}(T))$. In other words, it may not always be necessary to have all EVs enabled with the bidirectional V2G.

The reliability and resilience of the proposed online scheduling in some extreme cases when $R_S(T)$ is far beyond zero are also investigated. Figure 14.9 presents the
simulation results of the three scheduling algorithms when the sum of the regulation requests $R_S(T)$ is the maximum and the minimum, respectively, among the 31 sets of the profiles of the regulation requests. The total power profiles of online scheduling (the dash-dotted curves) are still nearly as flat as those of forecast-based
scheduling (the dash curves) even when the zero-energy assumption specified in (14.22) is seriously violated and $R_S(\mathcal{T})$ takes large absolute values. Although the safety margin of online scheduling results in a total load a bit higher than that of forecast-based scheduling, it makes online scheduling resilient to different regulation requests. In addition, since the total power profile is flattened by online scheduling, such total load can be economically met by load following or even generation dispatch. Therefore, online scheduling will not impair the stability of the grid.

The proposed forecast-based scheduling and online scheduling outperform ODCD. As shown in Figures 14.8 and 14.9, ODCD fails to produce flat total power profiles even though the forecasts of the regulation requests have been assumed to be accurate. There are obvious spikes in the total power profiles, shown by the dots and solid curves, corresponding to ODCD when the power demands of the regulation-up requests are so high that the EV fleet should collectively provide discharging power to the grid. This is because ODCD does not account for the effect of the round-trip efficiency of a battery. It indicates that the method proposed in Gan et al. (2013) is not suitable to deal with the discharging control of EVs. Moreover, ODCD is impractical for the scheduling control of the regulation service since it requires the forecasting profile of regulation requests.

To summarize, the simulation results further corroborate our statements in Sections 14.3.3 and 14.3.4 that the optimization result of forecast-based scheduling can serve as a performance bound since it is the best possible schedules when the forecasts of the regulation requests are accurate, but online scheduling is more suitable and practical for real-world implementation because it does not depend on the forecasts of the regulation requests, determines the schedules in real time, and has a comparable performance to forecast-based scheduling.

### 14.5.5 Convergence rates

The convergence rates of Algorithms 14.1 and 14.2 for forecast-based scheduling for various values of the ratio of the bidirectional V2G $\theta_{bi}$ and the convergence tolerance $\varepsilon_f$ are presented in Table 14.3. The numbers of iterations shown in Table 14.3 are averaged over the 31 sets of the profiles of the regulation requests. It can be observed that given $\varepsilon_f$, the number of iterations increases as $\theta_{bi}$ decreases. This is because as $\theta_{bi}$ decreases, the number of EVs that are allowed to discharge their batteries decreases, and hence it becomes more difficult for EVs to suppress the peaks of the regulation requests and flatten the total power profile. According to

<table>
<thead>
<tr>
<th>$\theta_{bi}$</th>
<th>$\varepsilon_f$</th>
<th>$10^{-4}$</th>
<th>$10^{-5}$</th>
<th>$10^{-6}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>6.0</td>
<td>7.3</td>
<td>8.3</td>
<td></td>
</tr>
<tr>
<td>0.5</td>
<td>9.0</td>
<td>11.0</td>
<td>13.7</td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>18.0</td>
<td>42.3</td>
<td>88.7</td>
<td></td>
</tr>
</tbody>
</table>
(14.47) and Table 14.3, the communication overheads of Algorithms 14.1 and 14.2 can be obtained. For instance, when $\theta_{bi} = 1$ and $\epsilon_f = 10^{-5}$, the average number of iterations is 7.3. Suppose the size of a one-dimensional control variable $D = 8$ bytes. Then, the average communication overhead $CO_f$ in this case is about 8.028 MB according to (14.47). Forecast-based scheduling is performed one time to determine the schedules of all EVs during the participation period $\mathcal{T}$.

The convergence rates of Algorithms 14.3 and 14.4 for online scheduling in various values of $\theta_{bi}$ and $\epsilon_o$ are presented in Table 14.4. The numbers of iterations in Table 14.4 are averaged over the $N_T = 144$ time slots and the 31 sets of regulation requests. It can be observed that, different from the convergence rate of Algorithms 14.1 and 14.2, the ratio of the bidirectional V2G $\theta_{bi}$ does not have a significant effect on the number of iterations performed in Algorithms 14.3 and 14.4. This can be explained by the much lower dimension of the control variables for online scheduling compared to that for forecast-based scheduling. In online scheduling, at each time slot, an EV should only determine a two-dimensional schedule. Therefore, the schedules of EVs can soon converge to the best-effort ones to minimize the variance of the total power profile. According to (14.51) and Table 14.4, the communication overheads of Algorithms 14.3 and 14.4 can be obtained. For instance, when $\theta_{bi} = 1$ and $\epsilon_o = 10^{-5}$, the average number of iterations at each time slot is 5.2. Thus, the average communication overhead per slot $CO_o$ in this case is about 81.331 kB according to (14.51). Since Algorithms 14.3 and 14.4 should be performed $N_T = 144$ times during the participation period $\mathcal{T}$, the total overhead throughout $\mathcal{T}$ is about 11.437 MB.

### 14.6 Conclusion

The optimal scheduling for an aggregator coordinating its EVs to provide the V2G regulation service is studied. Based on the zero-energy characteristics of frequency regulation, we propose an online scheduling method which depends on the forecast of the regulation demand and allows each EV to determine its own schedule in real time. Our method jointly guarantees adequate charging of EVs and optimizes the quality of the regulation service. A simulation study of 1,000 hypothetical EVs shows that the proposed online scheduling algorithm performs nearly as well as the forecast-based scheduling algorithm, demonstrating the practicability of online...
charging/discharging control for the provision of the V2G regulation service. Future work will extend the methods and models proposed in this chapter to solve the inter-level control in a multilevel V2G system.

Acknowledgements

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