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Published in:
Applied Energy

Link to article, DOI:
[10.1016/j.apenergy.2019.02.044](https://doi.org/10.1016/j.apenergy.2019.02.044)

Publication date:
2019

Document Version
Peer reviewed version

[Link back to DTU Orbit](#)

Citation (APA):
Liu, H., Huang, K., Wang, N., Qi, J., Wu, Q., Ma, S., & Li, C. (2019). Optimal dispatch for participation of electric vehicles in frequency regulation based on area control error and area regulation requirement. *Applied Energy*, 240, 46-55. <https://doi.org/10.1016/j.apenergy.2019.02.044>

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Optimal dispatch for participation of electric vehicles in frequency regulation based on area control error and area regulation requirement

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HIGHLIGHTS

- The expected charging of electric vehicles is tracked in real time along with regulation.
 - The regulation is optimally distributed among electric vehicles in charging stations.
 - Area control error and area regulation requirement as signals are compared and analyzed.
 - Two optimal strategies are proposed based on area control error and area regulation requirement.
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ARTICLE INFO

Keywords:

Area control error
Area regulation requirement
Charging demand
Electric vehicle
Optimal dispatch
Vehicle to grid control

ABSTRACT

In this paper, optimal strategies are proposed for electric vehicles in charging stations to participate in the secondary frequency regulation, while considering their charging demands. In order to fairly allocate the dispatch from the control center among electric vehicles according to their charging demands, two optimal real-time strategies are proposed, respectively based on area control error and area regulation requirement. With the proposed strategies, the expected charging of electric vehicles is optimally tracked in real time by using the regulation task from the control center. Simulations on a two-area interconnected power grid show that the proposed two strategies can respectively lead to a 12.66% and 16.78% frequency deviation reduction and a 13.76% and 9.86% generator regulation reduction. At the same time, the charging demands of EVs can also be ensured.

1 Introduction

The crisis of fossil fuel energy and carbon emission has become a considerable concern around the world. Traditional vehicles with internal combustion engines are exacerbating the situation. To deal with this crisis, Electric vehicles (EVs) that can reduce energy consumption and benefit both local and global climates are replacing conventional vehicles [1].

However, the large-scale integration of EVs into the power

grid will make the power system operation and control more challenging [2]. For instance, uncoordinated charging of EVs can increase the peak load level, stress the transmission lines, and damage power system security. Therefore, the orderly charging of EVs comes into being [3]-[5]. As the provision of energy from the vehicle to the grid can compensate the mismatch in generation and load, Kempton *et.al* firstly proposed the concept of Vehicle-to-Grid (V2G) in 1997 [6] and studied the feasibility and benefit of V2G control [7], [8]. V2G

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NOMENCLATURE

Parameters

$\alpha_{i,t}$	Decision parameter for regulation
$\beta_{i,t}^{\text{up}}$	Decision parameters for regulation up
$\beta_{i,t}^{\text{down}}$	Decision parameters for regulation down
$C_{i,t}^{\text{up}}$	Capacity of the i th EV for regulation up at time t
$C_{i,t}^{\text{down}}$	Capacity of the i th EV for regulation down at time t
$d_{i,t}^{\text{min}}$	Minimum plug-in duration of the i th EV at time t
E_i^{rat}	Rated capacity of the i th EV battery
$P_{i,t}^{\text{exp}}$	ECP of the i th EV at time t
P_{max}	Maximum charging/discharging power
$P_{i,t-1}$	V2G power of the i th EV at time $t-1$
$\Delta P_{i,t}^{\text{ARP}}$	ARP of the i th EV at time t
$\Delta P_{i,t}$	Regulation of the i th EV at time t
$\text{SOC}_{i,t}$	Real-time battery SOC of the i th EV at time t
$\text{SOC}_i^{\text{exp}}$	Expected SOC of the i th EV
SOC_{min}	Lower limit of battery SOC
SOC_{max}	Upper limit of battery SOC
S_t^{up}	Regulation task for regulation up at time t
S_t^{Down}	Regulation task for regulation down at time t
T_i^{out}	Plug-out time of the i th EV
t^{real}	Real time
N	The number of EVs at time t

Abbreviations

AA	advanced applications
ACE	area control error
ACE-OA	ACE-based optimal approach
ACE-PA	ACE-based proportional approach
ARP	actual regulation power
ARR	area regulation requirement
ARR-OA	ARR-based optimal approach
ARR-PA	ARR-based proportional approach
DMS	decision and management system
ECP	expected charging power (kW)
EVs	electric vehicles
OA	optimal approach
PA	proportional approach
RMS	root mean square values
RD	real-time database
SFR	secondary frequency regulation
SOC	state of charge
TBC	tie-line frequency bias control
TS	terminal services
V2G	vehicle to grid

control can provide various supports to the power grid, such as voltage regulation [9], spinning reserve [10], [11], load peak shifting [12], [13], and frequency regulation [14], [15]. In particular, participating in frequency regulation has been considered as one of the most promising V2G technologies. In [16], a V2G demonstration project enables EVs to participate in the frequency regulation market of the California Independent Systems Operator.

The frequency regulation compensates the generation-load mismatch and is the key to ensuring the frequency stability of power systems. However, with increasing integration of Renewable Energy Sources (RESs) such as wind and solar photovoltaic, compensating this mismatch becomes more challenging due to the slow response of conventional generators and the uncertainty of RESs. Therefore, fast regulation resources such as EVs are paid much attention to. In [17], an efficient power plant model of EVs was developed for active power regulation considering large-scale wind integration. In [18], a droop-based control was developed to regulate the charging and discharging power of EVs according to the frequency signal. In [19], a decentralized V2G control was proposed for EVs to participate in primary frequency control by adaptively responding to the change of system frequency. In [20], a distributed V2G control was developed to suppress frequency deviation. Besides contributing to primary frequency regulation as in [18]-[20], the V2G control can also participate

in the Secondary Frequency Regulation (SFR) in automatic generation control in power systems. In [21], a V2G control was proposed to participate in SFR considering high frequency regulating signals. In [22], a V2G control strategy was developed to coordinate EVs, battery energy storage stations, and traditional generators to improve frequency stability, while participating in SFR.

As the power provided by an individual EV is too low to be directly dispatched by the control center, the concept of EV aggregators was developed to effectively manage EVs [23]. EV aggregators can enable the aggregation of EVs to participate in SFR implemented in the control center, which is usually called as centralized V2G control. In [24], a V2G control was proposed to coordinate the EV aggregator and traditional power plants while participating in SFR with time-varying delays. For the centralized V2G control to perform SFR in the control center, the capacity and the real-time dispatch strategies are two main concerns that have to be addressed.

The capacity has been discussed from the perspective of energy market [25], [26] and real-time control [27], [28]. In [25], considering the probability distributions of the plug-in time and charging power of EVs, the capacity for regulation was estimated based on historical data. In [26], a queueing network was modeled to estimate the number of EVs for regulation up and regulation down. The capacity in [25] and [26] is based on the number of EVs and a constant charging

power. The capacity of EVs will thus remain unchanged if the number of EVs does not change. However, the capacity for frequency regulation varies with time because the V2G power can change [27], [28].

The real-time dispatch strategy as another concern aims at developing the real-time closed-loop control. The participation of EVs in frequency regulation can yield profits [29]-[31]. In [29], an optimal scheduling was designed to maximize the revenue by controlling the charging according to electricity price and regulation price. In [30], in order to maximize the profits and also satisfy the driving demands, a Markov decision process was used to decide whether an EV should provide frequency regulation. In [31], the potential impact of EVs' participation in the grid regulation on the battery life-time was analyzed to gain high revenue. However, these researches mainly focus on cost and benefits from the energy market but cannot fulfill closed-loop control that performs regulation from the control center. Tracking regulation signals provided in advance can perform frequency regulation and achieve an optimal distribution among EVs [32], [33]. In [32], a welfare-maximizing algorithm was proposed to track regulation signals with EVs' constraints such as the capacity of EVs for regulation and battery energy. In [33], an optimal strategy was proposed to maximize the economic benefits of EV aggregators with the constraints of EV battery energy. Because the driving demands of EVs are only considered inequality constraints, the optimal strategies in [32] and [33] cannot perform the scheduled charging of EVs while participating in regulation. In [27] and [34], real-time closed-loop control strategies were developed for EVs to perform regulation from the control center, but extra charging has to be considered in order to achieve the charging demands. The regulation cannot be achieved because the V2G power of EVs for regulation is reduced by the expected charging to some extent.

In this paper, we focus on optimal real-time dispatch strategies for EVs to participate in SFR. Being different from the existing work, the distinct feature of proposed dispatch strategies is that the regulation task from the control center is fairly allocated among EVs according to the charging demands of EVs. The major contributions of this paper are summarized as follow.

- The charging demands of EVs are tracked in real time by minimizing the expected charging of EVs along with frequency regulation;
- The Area Control Error (ACE) and Area Regulation Requirement (ARR) as regulation signals are carefully compared;
- Two optimal real-time dispatch strategies respectively based on ACE and ARR are proposed to perform the dispatch from the control center in EV charging stations according to the charging demands of EVs;
- The proposed two dispatch strategies are carefully compared in terms of improving frequency quality, reducing generator regulation, and ensuring the expected charging.

The remainder of this paper is organized as follows. In Section 2, the optimal dispatch problem and the regulation

signals on EV dispatch are introduced. In Section 3, a hierarchical structure is presented for EVs to perform regulation in EV charging stations. Optimal dispatch strategies are then proposed in Section 4. In Section 5, the simulation system is introduced. Simulation results are presented in Section 6. Finally, conclusions are drawn in Section 7.

2 Problem description of EV dispatch for regulation in charging stations

2.1 Optimal dispatch problem

For EVs, the key to achieving the dispatch from the control center is to undertake regulation task within their capacity. As illustrated in Fig.1, the capacity of an EV is consisted of the capacity for regulation up and the capacity for regulation down. From Fig. 1, an EV with higher capacity will undertake more regulation task. If the charging demands of EVs are not considered, the dispatch can be implemented according to the capacity of EVs.

Fig. 1. The capacity of an EV for regulation

Due to transport usages, the charging demands of EVs are usually different. While EVs with higher expected charging demands are plugged into the power grid with shorter plug-in durations, more/less power for regulation down/up should be dispatched to EVs to ensure the expected charging. Therefore, the dispatch among EVs should consider the charging demands of EVs.

To express the expected charging of an EV, we define the expected charging power (ECP), $P_{i,t}^{\text{ecp}}$, of an EV as

$$P_{i,t}^{\text{ecp}} = \frac{E_i^{\text{rat}} (\text{SOC}_i^{\text{exp}} - \text{SOC}_{i,t})}{T_i^{\text{out}} - t^{\text{real}}} \quad (1)$$

where $\text{SOC}_i^{\text{exp}}$ is the expected SOC of the i th EV; $\text{SOC}_{i,t}$ is the real-time battery SOC of the i th EV at time t ; T_i^{out} is the plug-out time of the i th EV; E_i^{rat} is the rated capacity of the i th EV battery; t^{real} is real time.

In (1), ECP is decided according to the charging demands and the plug-in duration. $P_{i,t}^{\text{ecp}} > 0$ indicates that an EV has to be charged for high battery SOC level; $P_{i,t}^{\text{ecp}} < 0$ means that the EV owner could sell the electricity to the power grid.

Fig. 2. The relationship among ECP, expected SOC, and plug-in duration

As illustrated in Fig. 2, ECP depends on the charging demand and the remaining plug-in duration of an EV. The greater the deviation of battery SOC from the expected is and the shorter the remaining plug-in duration is, the greater the ECP is. In order to ensure EV charging, the more/less power undertaken for regulation down/up should be. When ECP is equal to zero, the charging demand of an EV is achieved. Therefore, we can reduce ECPs of EVs with the regulation by the following objective.

$$\min f(\Delta P_{i,t}) = \sum_{i=1}^N \left| \frac{\Delta t(P_{i,t-1} + \Delta P_{i,t})}{T_i^{\text{out}} - t^{\text{real}}} - P_{i,t}^{\text{ecp}} \right| \quad (2)$$

where $\Delta P_{i,t}$ is the regulation of the i th EV at time t ; $P_{i,t-1}$ is the V2G power of the i th EV at time $t-1$; Δt is the time step for dispatch.

As shown in (2), when the regulation from the control center is dispatched to EVs, this regulation will be optimally distributed among EVs with the objective of minimizing the difference between V2G power and ECPs, i.e., the regulation is optimally allocated according to the expected charging of EVs. In this context, for an EV, the greater this difference is, the more the regulation undertaken for reducing the difference is. Therefore, the expected charging of EVs can be optimally performed while achieving frequency regulation.

2.2 Regulation signals

In the literature, ACE is usually used as regulation signals for EVs to participate in frequency regulation [19]- [23]. However, ARR used in the SFR system of real power systems is hardly discussed. ACE and ARR can be illustrated in Fig. 3, in which the tie-line frequency bias control (TBC) is considered. ARR is acquired when ACE passes through a Proportional Integral (PI) controller.

Fig. 3. ACE and ARR signals for regulation in a single-area simplified power system

As shown in Fig. 4 (a), ACE almost has a zero-mean distribution [29] and fast switches between positive and

negative values. As a result, following ACE can maintain the capacity of EVs for regulation, because the V2G power of EVs will not be fixed at the maximum value for a long time.

Compared to ACE, ARR will be kept at positive or negative value for a long time, as shown in Fig. 4 (b), because ARR indicates the generation-load mismatch. While responding to ARR, the V2G power of EVs will increase or decrease continuously, and EVs will lose the capacity for regulation. For instance, when the charging power of an EV reaches its maximum value due to the continuous increase of charging power for regulation down, an EV will lose the capability for regulation down.

(a) ACE fluctuation curve

(b) ARR fluctuation curve

Fig. 4. Regulation signals for EVs' participation in frequency regulation with the integration of wind power into the power grid.

3 Hierarchical dispatch in EV charging Stations

3.1 The framework with EV charging stations

EV aggregators can upload the capacity for regulation from EVs and release the regulation task from the control center to EVs. The hierarchical structure consisting of the control center, EV aggregators, charging stations, and EVs can be shown in Fig. 5.

Fig. 5. Hierarchical structure for EVs' participation in frequency regulation

In the control center, the dispatch is made based on ACE or ARR within the capacity of EVs. In EV aggregators, the dispatch from the control center is allocated to EV charging stations. EV charging stations manage many EVs, and the task for regulation is distributed among EVs based on an optimal strategy.

3.2 EV charging stations

In EV charging stations, located in commercial parking lots, residence community, working places, etc., many charging

devices are provided, where EVs can participate in frequency regulation under the supervision of an EV aggregator, because most of EVs park for more than 90% of the whole day [34].

Fig.6. The structure of an EV charging station

The structure of an EV charging station is shown in Fig. 6, which is composed of the decision and management system (DMS), advanced applications (AA), real-time database (RD), and terminal services (TS). DMS uploads the information of EV charging stations such as the capacity for regulation and receives the task from the aggregator, and releases the command to AA. In AA, interactive functions such as peak shaving, load tracking, and frequency regulation are included. RD is responsible for collecting and storing the data from TS in real time.

In TS, the data acquisition and control uploads EVs' information, such as plug-in time, plug-out time, battery SOC level, and expected charging, and control the charger/discharger according to the command from AA.

4 Optimal dispatch in EV charging stations

Note that in this paper we discuss the participation of EVs in secondary frequency regulation, whose goal is to ensure the system frequency to be nominal frequency. This is a different topic from the economic dispatch or unit commitment problem, which focuses on the optimal generation scheduling to minimize the generation cost. Specifically, the economic dispatch aims at obtaining the optimal power output of generating units while the unit commitment is to find the optimal unit commitment of generating units. Different from achieving an economic optimum in the economic dispatch or unit commitment problem, the optimal dispatch we are discussing here means that the dispatch from the control center is optimally (fairly) allocated among EVs based on ACE or ARR, which indicates the difference between generation and load. In the following we will discuss in more detail about the optimization problem formulation and the solving algorithm, including the objective function, equality constraints, and inequality constraints.

4.1 The precondition of an EV for regulation

The primary objective of EV owners is to charge their EVs to satisfy transport usages. The minimum plug-in duration available for achieving charging demands of EV owners can be defined as

$$d_{i,t}^{\min} = \begin{cases} \frac{E_i^{\text{rat}} (\text{SOC}_i^{\text{exp}} - \text{SOC}_{i,t})}{\eta_c \cdot P_{\max}} & \text{SOC}_{i,t} < \text{SOC}_i^{\text{exp}} \\ 0 & \text{SOC}_{i,t} \geq \text{SOC}_i^{\text{exp}} \end{cases} \quad (3)$$

where $P_{\max}$ is the maximum charging/discharging power; η_c is the charging efficiency.

The parameter $\alpha_{i,t}$ shown in (4) can be used to decide whether an EV will participate in frequency regulation.

$$\alpha_{i,t} = \begin{cases} 1 & T_i^{\text{out}} - t^{\text{real}} > d_{i,t}^{\min} \\ 0 & T_i^{\text{out}} - t^{\text{real}} \leq d_{i,t}^{\min} \end{cases} \quad (4)$$

In (4), $\alpha_{i,t}=1$ indicates that an EV can participate in regulation, while $\alpha_{i,t}=0$ means that only charging is considered for an EV to achieve its charging demand. For clarity, whether or not an EV can participate in regulation is illustrated in Fig. 7. As long as the remaining plug-in duration of an EV is above $d_{i,t}^{\min}$ (i.e., $\alpha_{i,t}=1$), an EV can continue to participate in frequency regulation. Otherwise (i.e., $\alpha_{i,t}=0$), only charging is performed. Note that the minimum duration is calculated in real time and thus the expected charging is tracked in real time.

Fig.7. The judgment of an EV for frequency regulation at time t

For EVs, the minimum and maximum battery levels must be considered as the constraints for regulation. For instance, an EV will lose the capability for regulation down, while its EV battery energy reaches the maximum value of the rated capacity; vice versa. Therefore, we define the parameters shown in (5) and (6).

$$\beta_{i,t}^{\text{up}} = \begin{cases} 1 & \text{SOC}_{i,t} > \text{SOC}_{\min} \\ 0 & \text{SOC}_{i,t} \leq \text{SOC}_{\min} \end{cases} \quad (5)$$

$$\beta_{i,t}^{\text{down}} = \begin{cases} 1 & \text{SOC}_{i,t} < \text{SOC}_{\max} \\ 0 & \text{SOC}_{i,t} \geq \text{SOC}_{\max} \end{cases} \quad (6)$$

where, $\text{SOC}_{\max}$ and $\text{SOC}_{\min}$ are the upper and lower limits of the battery SOC.

In (5) and (6), $\beta_{i,t}^{\text{up}}=1$ and $\beta_{i,t}^{\text{down}}=1$ indicate that the EV has capability for regulation up and regulation down; or else, an EV will lose the capability for regulation up or regulation down.

Now, in an EV charging station, the capacity of an EV for regulation can be calculated according to Fig. 1, as follows.

1) The capacity of an EV for regulation up

$$C_{i,t}^{\text{up}} = \alpha_{i,t} \cdot \beta_{i,t}^{\text{up}} \cdot (P_{\max} + P_{i,t-1}) \quad (7)$$

2) The dispatch of an EV for regulation down

$$C_{i,t}^{\text{down}} = \alpha_{i,t} \cdot \beta_{i,t}^{\text{down}} \cdot (P_{\max} - P_{i,t-1}) \quad (8)$$

4.2 Objective function

As discussed in Section 2.1, our objective is to reduce ECP as much as possible. With the constraints in Section 4.1, the objective function in (2) can be rewritten for regulation down and regulation up, respectively.

1) The objective function for regulation up

$$\min f(\Delta P_{i,t}) = \sum_{i=1}^N \alpha_{i,t} \cdot \beta_{i,t}^{\text{up}} \cdot \left| \frac{\Delta t(P_{i,t-1} + \Delta P_{i,t})}{T_i^{\text{out}} - t^{\text{real}}} - P_{i,t}^{\text{ecp}} \right| \quad (9)$$

2) The objective function for regulation down

$$\min f(\Delta P_{i,t}) = \sum_{i=1}^N \alpha_{i,t} \cdot \beta_{i,t}^{\text{down}} \cdot \left| \frac{\Delta t(P_{i,t-1} + \Delta P_{i,t})}{T_i^{\text{out}} - t^{\text{real}}} - P_{i,t}^{\text{ecp}} \right| \quad (10)$$

Note that, (9) and (10) will not work together, because regulation up and regulation down cannot happen

simultaneously.

4.3 Equality constraints

To achieve the dispatch from an EV aggregator, two equality constraints have to be considered for regulation up and regulation down, respectively.

1) The balance for regulation up

$$\sum_N \alpha_{i,t} \cdot \beta_{i,t}^{\text{up}} \cdot \Delta P_{i,t} = S_t^{\text{up}} \quad (11)$$

2) The balance for regulation down

$$\sum_N \alpha_{i,t} \cdot \beta_{i,t}^{\text{down}} \cdot \Delta P_{i,t} = S_t^{\text{down}} \quad (12)$$

Similar to (9) and (10), (11) and (12) cannot co-exist for each regulation.

4.4 Inequality constraints

The regulation that an EV can undertake must be performed within its capacity. Therefore, we have the inequality equations in (13) and (14) for regulation up and regulation down, respectively.

1) The constraint for regulation up

$$0 < \Delta P_{i,t} < C_{i,t}^{\text{up}} \quad (13)$$

2) The constraint for regulation down

$$0 < \Delta P_{i,t} < C_{i,t}^{\text{down}} \quad (14)$$

While considering the charging and discharging efficiency, the charging and discharging power of an EV can be described as follows.

$$P_{i,t}^{\text{EV}} = \begin{cases} (P_{i,t-1} + \Delta P_{i,t}) \eta_c & \text{charging} \\ (P_{i,t-1} + \Delta P_{i,t}) / \eta_d & \text{discharging} \end{cases} \quad (15)$$

4.5 Optimal algorithm

The optimal algorithm for dealing with the optimal model in Section 4.2-4.4 is illustrated in Fig.8. The modern interior point method is used to solve the optimal model in the MATLAB environment, which is implemented with the following steps.

Step 1: Upload system parameters consisting of plug-in time, plug-out time, and the expected charging; update state parameters including real-time SOC level ($\text{SOC}_{i,t}$), real-time V2G power ($P_{i,t}$), and current time (t).

Step 2: Calculate the minimum duration ($d_{i,t}^{\min}$) and the parameter ($\alpha_{i,t}$) according to (3) and (4) to decide whether an EV can participate in regulation; if not, only performing charging.

Step 3: Decide the parameters ($\beta_{i,t}^{\text{up}}$) and ($\beta_{i,t}^{\text{down}}$) according

to (5) and (6); calculate the capacity of EVs ($C_{i,t}^{up}$ and $C_{i,t}^{down}$) according to (7) and (8) and at the same time, upload the capacity to an EV aggregator.

Step 4: If performing the dispatch for regulation up is “Yes”, solve the optimal model consisting of (9), (11), and (13); otherwise, solve the optimal model in (10), (12), and (14).

Step 5: Regulate the V2G power of EVs following the optimal solution; control the charging/discharging of EVs.

Step 6: The dispatch for regulation is finished in this turn.

Fig.8. The flowchart of optimal dispatch algorithm

5 Simulation system

5.1 System and parameters

As shown in Fig. 9, a two-area interconnected power system is used where the “Thermal plants” block is illustrated in Fig. 10, and the parameters are listed in Table 1. Note that this two-area interconnected power system has been extensively used to simulate the participation of EVs in frequency regulation in the literature, e.g., [18], [22], [24], [34]. The load fluctuation illustrated in Fig. 11 follows a normal distribution with zero mean, and wind power output shown in Fig. 12 is from the historical data of real power systems. The EVs are integrated into Area A.

Fig. 9. A two-area interconnected power system

Fig. 10. Thermal power plant for frequency regulation

Fig. 11. Load fluctuation in a time series with 1 second intervals

Fig. 12. Wind power output in a time series with 1 second intervals

Table 1
Parameters of a two-area power system

Parameters	Area-A	Area-B
Maximum load capacity (MW)	20,000	10,000
Proportional and integral gains	1,0.01	1,0.01
Time constant for LFC (s)	4	4
Frequency bias factor (pu/Hz)	0.15	0.075
Inertia constant (pu. s)	0.32	0.16
Load damping coefficient (pu/Hz)	0.04	0.02
Synchronizing torque coefficient (Hz)	0.04	0.04
Dead band of primary frequency detection (s)	0.033	0.033
Time constant for frequency detection (s)	0.1	0.1
Communication delay (s)	1	1
Dead band of ACE (MW)	10	10
Ramp speed (MW/min)	200	100

5.2 Parameters of EVs

In this simulation, we consider an EV aggregator with 100 EV charging stations, each of which manages 1000 EVs, as shown in Table 2. Besides, to describe the random integration of EVs into the power grid, a normal distribution simulated by the Latin Hypercube Sampling method is used to imitate the plug-in time, plug-out time, initial SOC, and the expected SOC. The other parameters of EVs, such as battery capacity, maximum V2G power, and maximum/minimum SOC limitation, are also listed in Table 2.

Table 2
Simulation parameters of EVs

Parameters	
The number of EV Aggregators	1
The number of EV charging stations	100
The number of EVs in each charging station	1,000
Plug-in time (h)	Time $\sim N(10, 0.5)$
Plug-out time (h)	Time $\sim N(14, 0.5)$
Initial SOC at the plug-in time (pu)	SOC $\sim N(0.4, 0.1)$ SOC $\in [0.2, 0.5]$
Expected SOC at the plug-out time (pu)	SOC $\sim N(0.7, 0.1)$ SOC $\in [0.5, 0.8]$
Battery capacity (kWh)	32
Maximum V2G power (kW)	7
Charging/discharging efficiency	0.92
Maximum/minimum SOC limitation (pu)	0.9/0.2

6 Simulation and discussions

The random integration and departure of EVs are considered in EV charging stations. The histogram of the plug-in time and plug-out time of all EVs (i.e., 1,000 EVs) in an EV charging station is shown in Fig. 13. The regulation is dispatched to EVs as much as possible and is distributed among EVs based on the proposed ACE-based optimal approach (ACE-OA) or ARR-based optimal approach (ARR-OA). Following the dispatch performed in proportion according to the capacity [34], the ACE-based proportional approach (ACE-PA) and ARR-based proportional approach (ARR-PA) are used to show the advantages of the proposed ACE-OA and ARR-OA, respectively.

Fig. 13. The integration and departure of all EVs in an EV charging station.

6.1 Optimal distribution among EVs

In order to show the optimal distribution among EVs, we define an actual regulation power (ARP) at time t , $\Delta P_{i,t}^{\text{ARP}}$.

$$\Delta P_{i,t}^{\text{ARP}} = \frac{\Delta t \cdot \Delta P_{i,t}}{T_i^{\text{out}} - t^{\text{real}}} \quad (16)$$

In (16), ARP is used to track the ECP in (1) and can show an optimal distribution among EVs. For clear demonstration, we randomly choose five EVs, which is shown in Fig. 14 and Fig. 15 for regulation down and regulation up, respectively.

Fig. 14. The optimal distribution among EVs for regulation down

Fig. 15. The optimal distribution among EVs for regulation up

While performing PA for frequency regulation, the dispatch is independent to ECP as shown in Figs: 14 and 15, which is not beneficial for tracking the expected battery energy. However, while considering OA for regulation down, as shown in Fig. 14, the larger the ECP is, the more the ARP is, which is beneficial for elevating the EV battery energy. For regulation up, as illustrated in Fig. 15, the larger the ECP is, the less the ARP is. As a result, an EV with higher ECP will release less power to the grid to ensure charging demand.

Therefore, by the proposed approach, an optimal distribution can be achieved among EVs according to the charging demands of EVs.

6.2 The effects of ACE-OA and ARR-OA on the power grid

We here consider the time window between 11:00 and 13:00, because most of EVs are usually integrated into the grid in this time period.

6.2.1 Regulation of ACE-OA and ARR-OA on frequency

To demonstrate the effectiveness of ACE-OA and ARR-OA in improving the quality of frequency and ACE, the root mean

square values (RMS) of frequency deviations and ACE are, respectively, listed in Tables 3 and 4.

Table 3
The quality of frequency in area-A

	RMS of Frequency deviation (Hz)	Decrease (%)
Without EVs	0.0367	--
ACE-PA	0.0322	12.33
ACE-OA	0.0321	12.66
ARR-PA	0.0308	15.99
ARR-OA	0.0305	16.78

Table 4
The quality of ACE in area-A

	RMS of ACE (MW)	Decrease (%)
Without EVs	138.43	--
ACE-PA	99.64	28.02
ACE-OA	98.49	28.85
ARR-PA	97.18	29.80
ARR-OA	96.08	30.59

As shown in Table 3, the RMS of the frequency deviation decreases by 12.33% for ACE-PA and by 15.99% for ARR-PA, while this deviation decreases by 12.66% for ACE-OA and by 16.78% for ARR-OA. On the other hand, the RMS of ACE decreases by 28.85% for ACE-OA and by 30.59% for ARR-OA, compared with the case that the RMS of ACE decreases by 28.02% for ACE-PA and by 29.80% for ARR-PA.

This is because EVs can quickly track ACE and ARR due to their fast charging/discharging characteristics, as shown in Fig. 16(a) and Fig. 17(a). Compared with ACE-PA and ACE-OA, ARR-PA and ARR-OA achieve higher quality of frequency and ACE.

6.2.2 Influences of ACE-OA and ARR-OA on generators

As shown in Table 5, the participation of EVs in frequency regulation can reduce the output of traditional generators. Therefore, traditional generators can be released from regulation to avoid frequent regulating. The RMS of the generator regulation decreases by 9.53% for ARR-PA and by 13.22% for ACE-PA, while this reduction decreases by 9.86% for ARR-OA and by 13.76% for ACE-OA. Compared with PA, OA shows the advantage in reducing generator regulation.

Table 5
The reduction of generator regulation

	RMS of generator regulation (MW)	Decrease (%)
Without EVs	98.28	--
ACE-PA	85.28	13.22
ACE-OA	84.75	13.76
ARR-PA	88.91	9.53
ARR-OA	88.58	9.86

In order to clearly show the reduction of generator regulation while considering ARR-OA and ACE-OA, we choose a 20-minute window for demonstration. When EVs can track ACE

or ARR signal, the generator output will be kept unchanged, i.e., the generator regulation will be equal to zero. If EVs cannot cover ACE or ARR signal, the generator output must be changed to compensate this gap. With the participation of EVs in SFR, the regulation of the generating units can be reduced.

Compared with the case with PA, performing OA shows better performance in tracking ACE or ARR signal, which results in better ACE and frequency quality as shown in Tables 3 and 4. On the other hand, compared with ARR-PA and ARR-OA, the generator regulation is reduced more significantly by ACE-PA and ACE-OA. This is because EVs lose the capacity for regulation more frequently by ARR-PA and ARR-OA than by ACE-PA and ACE-OA.

(a) Tracking ACE signal

(b) The output of generator regulation

Fig. 16. The influence of regulation on generators based on ACE

(a) Tracking ARR signal

(b) The output of generator regulation

Fig. 17. The influence of regulation on generators based on ARR

6.3 Impacts of ACE-OA and ARR-OA on EV battery

One EV is randomly selected to demonstrate the impacts of ACE-PA, ACE-OA, ARR-PA, and ARR-OA on the EV battery energy. The result is shown in Fig. 18.

From Fig.18, ACE-PA, ACE-OA, ARR-PA, and ARR-OA can achieve the charging demand of the selected EV. For ACE-PA, ARR-PA, and ACE-OA, the frequency regulation ends before the plug-out time, because the plug-in duration left is not above its minimum plug-in duration for charging. In contrast, ARR-OA can perform regulation until the plug-out time. Therefore, ARR-OA has advantages over ACE-OA, ACE-PA, and ARR-PA in terms of the plug-in duration for regulation. Compared with PA, OA has longer plug-in duration for regulation, as illustrated in Fig. 18.

Fig. 18. Impacts of PA and OA on an EV Battery

6.4 Sensitivity on battery capacity and SOC distribution

6.4.1 Impacts of battery capacity on regulation

To clearly show the impacts of different EV battery capacities on regulation, we assume that the plug-in time, plug-out time, initial SOC, and expected SOC are the same for all EVs. For different EV batteries, ARR-OA can better improve the frequency quality, while ACE-OA has advantages in reducing generator regulation, as illustrated in Figs: 19 and 20.

Fig. 19. The RMS of frequency deviation with different EV batteries

Fig. 20. The RMS of generator regulation with different EV batteries

From Fig. 19, it is seen that under ACE-OA the frequency quality gets worse with the increase of the EV battery capacity. This is because the greater the battery capacity is, the longer the expected charging is, as shown in Fig. 21. For ARR-OA, the regulation can be maintained almost unchanged as illustrated in Fig. 19, because the expected charging does not run all the time as shown in Fig. 22.

Fig. 21 SOC curves of different battery capacity with ACE-OA

Fig. 22 SOC curves of different battery capacity with ARR-OA

Fig. 23. SOC curves with normal and uniform distributions

6.4.2 Influences of different SOC distribution on regulation

In order to show the influences of different initial SOC distributions of EV batteries on regulation, we consider the normal and uniform distributions with the same mean value to emulate the initial SOC levels. Specially, we assume that SOC follows $\sim N(0.4, 0.1)$ and $\sim U[0.2, 0.6]$ respectively. We also assume that all EVs have with the same expected SOC levels. Although the initial SOC distributions of EVs are different, the regulation is almost the same, as shown in Table 6. Besides, as illustrated in Fig. 23, for both ACE-OA and ARR-OA, the expected charging can always be achieved for different initial battery SOC distributions.

Table 6

The RMS of frequency deviation and generator regulation for normal and uniform distributions

	Normal distribution		Uniform distribution	
	ACE-OA	ARR-OA	ACE-OA	ARR-OA
Frequency deviation (Hz)	0.0301	0.0289	0.0301	0.0289
Generator regulation (MW)	84.83	88.16	84.79	88.18

7 Conclusions

In this paper, with area control error or area regulation requirement respectively as regulation signals, two optimal strategies are proposed to implement an optimal dispatch according to the charging demands of electric vehicles in charging stations. By the proposed approaches, the expected charging of electric vehicles can be tracked in real time while performing frequency regulation. Simulations on a two-area interconnected power system are used to validate the effectiveness of the proposed strategies in improving the quality of frequency, reducing traditional generator outputs, and achieving the charging demands of electric vehicles. The proposed strategies can ensure the charging demands of electric vehicles while achieving the regulation task from the control center. The area-control-error-based strategy can reduce more generator outputs, while the area-regulation-requirement-based strategy can ensure better frequency quality and longer plug-in duration for regulation.

The proposed methods can be applied to implement an optimal dispatch for frequency regulation in electric vehicle charging stations. Our work only focuses on the fair distribution among electric vehicles in charging stations. The extension may be devoted to the optimal coordination among electric vehicle charging stations.

Acknowledgment

This work was supported by the National Natural Science Foundation of China (Grant No. 51577085), by the Guangxi Natural Science Foundation for the Distinguished Young Scholars of Guangxi (Grant No. 2018JJG160007), and by the Scientific Research Foundation of Guangxi University (Grant No. XTZ160522)

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