

Bidding Strategy for Aggregators of Electric Vehicles in Day-Ahead Electricity Markets

Authors:

Yunpeng Guo, Weijia Liu, Fushuan Wen, Abdus Salam, Jianwei Mao, Liang Li

Date Submitted: 2019-07-26

Keywords: economic dispatch, bidding strategy, electric vehicle aggregator, electric vehicle (EV), electricity market

Abstract:

To make full use of the flexible charging and discharging capabilities of the growing number of electric vehicles (EVs), a bidding strategy for EV aggregators to participate in a day-ahead electricity energy market is proposed in this work. The proposed bidding strategy is able to reduce the operating cost of the EV aggregators and to handle the uncertainties of day-ahead market prices properly at the same time. Agreements between the EV owners and the aggregators are discussed, and a hierarchical market structure is proposed. While assuming the aggregators as economic rational entities, the bidding strategy is established based on the market prices, extra battery charging/discharging costs and the expected profits. The bidding clearing system will display the current/temporal market clearance results of the day-ahead market before the final clearance, and hence the market participants can revise their bids and mitigate the risks, to some extent, of forecasted market price forecast errors. Numerical results with a modified IEEE 30-bus system have demonstrated the feasibility and effectiveness of the proposed strategy.

Record Type: Published Article

Submitted To: LAPSE (Living Archive for Process Systems Engineering)

Citation (overall record, always the latest version):

LAPSE:2019.0806

Citation (this specific file, latest version):

LAPSE:2019.0806-1

Citation (this specific file, this version):

LAPSE:2019.0806-1v1

DOI of Published Version: <https://doi.org/10.3390/en10010144>

License: Creative Commons Attribution 4.0 International (CC BY 4.0)

Article

Bidding Strategy for Aggregators of Electric Vehicles in Day-Ahead Electricity Markets

Yunpeng Guo ¹, Weijia Liu ², Fushuan Wen ^{3,*}, Abdus Salam ³, Jianwei Mao ⁴ and Liang Li ⁴

¹ School of Electrical and Electronic Engineering, North China Electric Power University, Beijing 102206, China; guo_yunpeng@zj.sgcc.com.cn

² School of Electrical Engineering, Zhejiang University, Hangzhou 310027, China; liuweijiamarcel@gmail.com

³ Department of Electrical and Electronic Engineering, Universiti Teknologi Brunei, Bandar Seri Begawan BE1410, Brunei; abdu.salam@utb.edu.bn

⁴ Division of Electric Vehicle Service, State Grid Zhejiang Electric Power Company, Hangzhou 310007, China; mao_jianwei@zj.sgcc.com.cn (J.M.); liiliang@foxmail.com (L.L.)

* Correspondence: fushuan.wen@gmail.com; Tel.: +673-2-461020 (ext. 1316); Fax: +673-2-461035

Academic Editor: Chunhua Liu

Received: 6 November 2016; Accepted: 17 January 2017; Published: 23 January 2017

Abstract: To make full use of the flexible charging and discharging capabilities of the growing number of electric vehicles (EVs), a bidding strategy for EV aggregators to participate in a day-ahead electricity energy market is proposed in this work. The proposed bidding strategy is able to reduce the operating cost of the EV aggregators and to handle the uncertainties of day-ahead market prices properly at the same time. Agreements between the EV owners and the aggregators are discussed, and a hierarchical market structure is proposed. While assuming the aggregators as economic rational entities, the bidding strategy is established based on the market prices, extra battery charging/discharging costs and the expected profits. The bidding clearing system will display the current/temporal market clearance results of the day-ahead market before the final clearance, and hence the market participants can revise their bids and mitigate the risks, to some extent, of forecasted market price forecast errors. Numerical results with a modified IEEE 30-bus system have demonstrated the feasibility and effectiveness of the proposed strategy.

Keywords: electricity market; electric vehicle (EV); electric vehicle aggregator; economic dispatch; bidding strategy

1. Introduction

As a promising means of transportation to replace conventional petroleum fuel vehicles and reduce greenhouse gas emissions, electric vehicles (EVs) have become increasingly popular around the world in recent years [1–3]. In addition to their transportation function, the integration of EVs will also introduce additional electricity consumption into the affected power system. It has been demonstrated by existing research that EV charging and discharging behaviors can have both positive and negative impacts on the power system [4–7]. Thus, suitable mechanisms are required to integrate and handle EVs to accommodate their charging requirements and improve the efficiency of power system operation at the same time.

Some research has already been done on the optimal dispatching and control strategies of EVs to make the best use of the charging/discharging flexibilities of EV batteries and to mitigate possible negative impacts on power systems. For example, optimal dispatch and control approaches for EVs are discussed in [8–11]; the vehicle-to-grid (V2G) potentials of EVs in energy trading and ancillary services are studied in [12–16]; the coordination of EVs and the volatile renewable energy sources are examined in [17–20]; the impacts of flexible EVs on generation expansion planning [21,22]; the EV

charging control in the electricity market environment is investigated in [23]; EVs are considered as price responsive demands, and their flexibilities and impacts on the power system concerned are examined in [24].

Generally, each EV owner is unlikely to respond to the control/market signals and shift the charging load or provide the V2G service individually. Thus, a hierarchical or decentralized structure by introducing EV aggregators or retailers appears necessary for dispatching the charging and discharging of EVs in power system operation [8]. Each aggregator with a certain number of EVs can act as a unique flexible power demand or an energy storage unit. To encourage cooperation between the EV aggregators and the power system operators in power system dispatch, economic incentives appear necessary as aggregators are generally rational economic entities. Thus, market mechanisms are more promising for scheduling the EVs, as the EV aggregators will be automatically motivated to maximize their profits based on the price signals in the concerned electricity market.

Given this background, a bidding strategy for EV aggregators to participate the day-ahead electricity energy market is proposed in this paper. The aggregators are authorized to control the EVs through signing contracts with the EV owners. The bids of the aggregators will be formulated based on their preferred charging/discharging schedules, the market price profiles, and their capabilities and costs to adjust their charging plans. However, certain uncertainties exist in the day-ahead electricity market, and could result in financial risks in the decision-making of the aggregators. Some existing research, such as [25–29], depends on the price predictions, which are not always accurate and reliable. A robust optimization model-based optimal scheduling strategy for EV charging/discharging behaviors is presented in [30] to deal with the price uncertainties, while the results might be conservative due to the nature of robust optimization. The behaviors of plug-in EVs in electricity market environment is analyzed in [31] based on game theory, and the result is affected by the accuracy of market price forecasting.

In this work, a bidding strategy for electric vehicle aggregators in a day-ahead electricity market is investigated. It is assumed that both the EV aggregators and other market participants such as generating companies are permitted to revise their day-ahead market bids/offers any time before the electricity market is cleared, and this market mechanism is employed in some practically operating electricity markets, such as the well-known California electricity market in USA [32], and the National Electricity Market (NEM) in Australia [33]. Besides, this market mechanism was also employed in Zhejiang Province (China) during the power industry restructuring in early 2000s. The bidding clearing system displays the current/temporary market clearance results periodically based on the received bid/offers, which will serve as references for aggregators and generating companies to adjust their optimal bidding strategies/schedules. Once the day-ahead market closes for bids/offers, no market entities can modify their bids/offers anymore, and the final day-ahead market clearing results will be obtained based on the latest updated bids/offers before the day-ahead market is cleared. The temporary market clearance results will not affect the final results. As a result, the market provides equal opportunities to all bidding participants, and the uncertainties of market prices can be handled in this procedure. In general, the time window for day-ahead electricity energy market bidding lasts for at least 2 h, and market participants are entitled to revise their bids/offers if the market provides temporary market clearance results every 30 min.

The major contributions of this paper mainly include the following two points: (1) the interactions between EVs and EV aggregators are examined based on the stochastic characteristics and charging requirements of EVs; (2) a bidding strategy is presented for EV aggregators participating in the day-ahead electricity market without requiring accurate price predictions, and hence can be utilized to alleviate the financial risks caused by the uncertainties of market clearing prices. The remainder of this paper is organized as follows: the EV charging and discharging models and the contracts between the EV owners and the aggregators are developed in Section 2. In Section 3, the day-ahead electricity market clearance mechanism is presented. In Section 4, the market clearing procedure is described, and

the bidding strategy of EV aggregators established. Numerical results with a modified IEEE 30-bus system are given in Section 5, and conclusions presented in Section 6.

2. Electric Vehicle (EV) Charging and Discharging Models

2.1. EV charging and Discharging Behaviors

For private EVs, the charging requirements of EV batteries generally depend on the following factors: battery performance, driving distances, users' driving patterns, driving/parking periods, users' charging preferences and seasonal impacts. The EV charging demands are determined by all these factors together.

For a specific EV, the influences can be attributed to four indexes as the battery capacity can be regarded as a constant: (1) the time when EV connected to the grid, denoted as T_{st} ; (2) the time when EV disconnected from the grid, denoted as T_{en} ; (3) the State-of-Charge (SoC) level at T_{st} , denoted as S_{E0} ; (4) the desired SoC level at T_{en} , denoted as S_E^\oplus .

If the SoC level of the EV battery at time t , denoted as $S_E(t)$, is selected to represent the charging status of the battery, its relationship with the charging power $P_{ch}(\tau)$ and the feedback power $P_{dis}(\tau)$ to the power system concerned in the V2G mode can be formulated as ($\forall t \geq T_{st}$):

$$S_E(t) = S_{E0} + \frac{1}{B_E} \int_{T_{st}}^t (\kappa_{ch} P_{ch}(\tau) - \frac{P_{dis}(\tau)}{\kappa_{dis}}) d\tau \quad (1)$$

Since each EV owner expects to charge its battery to a desired level S_E^\oplus at T_{en} to meet its driving requirements, the EV charging and discharging constraint at T_{en} can be formulated as:

$$S_E(T_{en}) = S_{E0} + \frac{1}{B_E} \int_{T_{st}}^{T_{en}} (\kappa_{ch} P_{ch}(t) - \frac{P_{dis}(t)}{\kappa_{dis}}) dt \geq S_E^\oplus \quad (2)$$

It has been confirmed that battery discharging has a negative impact on the battery life [34,35], and this means that the EV customer will suffer from extra economic loss than in the ordinary charging mode without V2G, if no compensation is provided. The degradation process of EV batteries are modeled in detail and analyzed based on factors such as the driving patterns of EVs, impacts of the depth-of-discharge and ambient temperatures in [35,36]. In this paper, a simplified equation is employed to model the EV battery degradation cost due to battery discharging [37] as:

$$c_{dis} = \frac{C_{PB}}{B_E L_B D_{od}} \quad (3)$$

In (3), the battery life loss is assumed to be affected by the depth-of-discharge D_{od} , the battery purchase cost C_{PB} , the capacity of the battery B_E and its designed life cycles L_B . The calculated c_{dis} denotes the economic cost per unit discharging energy, and can be used to approximately estimate the cost for providing V2G services.

2.2. Interactions between the EVs and the Aggregators

In this work, a hierarchical structure is employed, and the EV aggregators are assumed to act as the third entity between the power system and the EV customers. The aggregators can be the operators in charging stations, charging service providers, or others. Each aggregator schedules the charging and discharging statuses of all EVs concerned, and further participates in the electricity market on behalf of these EV users. As a practical way to protect the customers' privacies, the usage information of the EVs will be encapsulated between the users and the aggregators concerned, while the system operator (SO) can only get the overall load profiles from the aggregators other than the detailed charging and discharging behaviors of each EV [38].

Through an EV charging contract, each aggregator is able to control the charging schedules of the EV batteries concerned, and agrees with the EV customers on certain terms, such as the charging prices. Besides, the EV charging contract should also contain the charging requirements and characteristics of the EVs. For simplicity of presentation, each EV aggregator is assumed to provide local charging services for all the EVs at the same bus of the transmission system concerned. Although the EVs may choose to charge at different distribution feeders, the aggregators will not have to consider the uncertainties associated with the charging locations of the EVs if all the distribution transformers and feeders have sufficient capacities [39].

T_{st} , T_{en} , S_{E0} and S_E^\oplus are stochastic parameters, as the user's driving behavior may change based on his/her willingness, thus the EV charging requirements may vary from day to day. While in the EV charging contract, the expected values of these indexes can be settled through negotiations. For example, the contents of an EV charging contract may include the following terms:

- (1) The EV charging price λ_{ch} . λ_{ch} can be either fixed price or time-of-use (TOU) prices. In a perfectly competitive market, it is likely that each aggregator will provide a competitive charging price to attract more EV customers.
- (2) The expected T_{st} , T_{en} and S_E^\oplus . Each aggregator will guarantee that the EV battery concerned will be charged above the S_E^\oplus by T_{en} , if the EV is plugged in no later than T_{st} . Otherwise, the aggregator is subject to a certain penalty. However, if the EV customer cannot hand over the EV to the aggregator by T_{st} , or the customer has to use the EV before T_{en} , then the aggregator will not be punished even if the $S_E(T_{en})$ is lower than S_E^\oplus .
- (3) The battery charging/discharging limits. To reduce the battery life losses, the SoC level of the battery should be kept within S_E^{\max} and S_E^{\min} during the plugged-in period, and the maximum charging/discharging power should not exceed P_{ch}^{\max} and P_{dis}^{\max} , respectively. It should be noted that if the customer is not willing to discharge its battery, P_{dis}^{\max} must be set to zero.
- (4) The estimated battery discharging cost c_{dis} and expected discharging revenue r_{dis} for EV owners. If an EV discharged a certain amount of power during the plugged-in period, the aggregator has to compensate the EV owner with the extra battery loss, as well as to offer economic rewards to the customer for providing the V2G service.

Apart from the contents mentioned above, other terms may also be included if both the entities consider them necessary and reasonable. For example, to encourage EV owners to extend the length of their plugged-in periods, the EV owners with longer available periods (i.e., larger T_{en} and smaller T_{st}) will receive lower charging prices. However, only the listed four terms are considered in this paper, although the developed methodological framework could be extended to accommodate other terms.

2.3. Aggregated EV Charging and Discharging Model

By controlling the charging and discharging behaviors of EV batteries, the aggregators can schedule the controllable EV demand in response to market price signals to maximize their revenues. The profit of the aggregators mainly depends on the power purchasing costs in the electricity energy markets and the power supply incomes through EV charging contracts. Without loss of generality, the objective of aggregator a with $N_E(a)$ EVs can be expressed to maximize its profit, as shown in (4):

$$\text{Maximize}(R_{CI}(a) + R_{DI}(a)) - (R_{CC}(a) + R_{DC}(a)) \quad (4)$$

where $R_{CI}(a)$, $R_{DI}(a)$, $R_{CC}(a)$ and $R_{DC}(a)$ denote the income for providing EV charging services, discharging services of aggregator a , the cost for providing EV charging services and discharging services of aggregator a , respectively. It should be noted that the EV charging prices also contain other costs such as distribution fees and various kinds of tariffs, apart from the energy prices, while the discharging incomes only depend on the market prices. In this paper, the summation of distribution

fees and tariffs, which is denoted as w , is assumed to have a positive correlation with the amount of the charging power. Equation (4) can be calculated through (5)–(8).

$$R_{CI}(a) = \sum_{t=1}^T \sum_{e=1}^{N_E(a)} \lambda_{ch}(a, e, t) P_{ch}(a, e, t) \quad (5)$$

$$R_{DI}(a) = \sum_{t=1}^T \rho(t) \sum_{e=1}^{N_E(a)} P_{dis}(a, e, t) \quad (6)$$

$$R_{CC}(a) = \sum_{t=1}^T (\rho(t) + w) \sum_{e=1}^{N_E(a)} P_{ch}(a, e, t) \quad (7)$$

$$R_{DC}(a) = \sum_{t=1}^T \sum_{e=1}^{N_E(a)} (c_{dis}(a, e) + r_{dis}(a, e)) P_{dis}(a, e, t) \quad (8)$$

In this work, λ_{ch} is assumed to be a fixed charging price, thus the charging price $\lambda_{ch}(a, e, t)$ in (5) can be rewritten as $\lambda_{ch}(a, e)$. Besides, the EV user has to pay the market price and distribution tariff for the excessive charged energy in case that $S_E(T_{en})$ is greater than S_E^{\oplus} , and this means that the profit of this aggregator is breakeven if the battery is charged between S_E^{\oplus} and its full capacity. $c_{dis}(a, e)$ and $r_{dis}(a, e)$ denote c_{dis} and r_{dis} of the e -th EV from the a -th aggregator per unit discharging power, respectively.

Moreover, in the EV charging contract, some constraints must be respected for aggregator a , as shown in (9)–(13);

$$0 \leq P_{ch}(a, e, t) \leq u_{ch}(a, e, t) P_{ch}^{\max}(a, e) \quad \forall t \in [T_{st}(a, e), T_{en}(a, e)] \quad (9)$$

$$0 \leq P_{dis}(a, e, t) \leq (1 - u_{ch}(a, e, t)) P_{dis}^{\max}(a, e) \quad \forall t \in [T_{st}(a, e), T_{en}(a, e)] \quad (10)$$

$$S_E^{\min}(a, e) \leq S_E(a, e, t) \leq S_E^{\max}(a, e) \quad \forall t \in [T_{st}(a, e), T_{en}(a, e)] \quad (11)$$

$$S_E(a, e, T_{en}) \geq S_E^{\oplus}(a, e) \quad (12)$$

$$u_{ch}(a, e, t) \in \{0, 1\} \quad \forall t \in [T_{st}(a, e), T_{en}(a, e)] \quad (13)$$

where (9) and (10) respectively represent the EV charging and discharging power constraints, (11) represents the battery SoC constraints, (12) represents the EV charging requirements, and the binary variable $u_{ch}(a, e, t)$ constrains that an EV cannot charge and discharge power at the same time, as shown in (9), (10) and (13). $T_{st}(a, e)$ and $T_{en}(a, e)$ denote T_{st} and T_{en} of the e -th EV per unit discharging power from the a -th aggregator, respectively.

It should be noted that the uniform market clearing price $\rho(t)$ is employed to calculate the costs of local EV aggregators with the impact of congestion ignored. However, the proposed model can be modified by introducing locational marginal prices (node prices) in (6) and (7) before applying to large regional aggregators who provide charging services at multiple buses of the transmission system concerned.

3. Day-Ahead Market Clearing Model

With more and more EVs being integrated into the power system, their charging and discharging behaviors will have more significant impacts on the power demand characteristics and the power system operation efficiency. Considered as market participants, the EV aggregators are asked to submit their bids for charging and discharging power to the SO. The bidding clearance problem can be formulated as an optimization of maximizing the social welfare associated. Certain power system security constraints must be accommodated as well. In realistic cases, the market clearing model should consider a series of constraints such as the AC power flow equations, the unit commitment and

generator ramping limits. In this paper, the DC optimal power flow model that only considers the capacity limits of transmission lines is employed for simplicity, since the study of this paper focuses on the bidding strategy formulation for EV aggregators. The simplified DC optimal power flow model is also able to demonstrate the full characteristics of market bidding and clearing process.

If the conventional power demands in the system are considered as inelastic, the objective function of the day-ahead market clearance model with EVs can be described as:

$$\text{Maximize } \Gamma_{EV}(\Phi_{CH}^{bid}) - \Lambda_{EV}(\Phi_{DIS}^{bid}) - \Lambda_G(\Phi_G^{bid}) \quad (14)$$

$$\Gamma_{EV}(\Phi_{CH}^{bid}) = \sum_{t=1}^T \sum_{a=1}^{N_A} f_1(\Phi_{CH}^{bid}(a, t), P_{CH}(a, t)) \quad (15)$$

$$\Lambda_{EV}(\Phi_{DIS}^{bid}) = \sum_{t=1}^T \sum_{a=1}^{N_A} f_2(\Phi_{DIS}^{bid}(a, t), P_{DIS}(a, t)) \quad (16)$$

$$\Lambda_G(\Phi_G^{bid}) = \sum_{t=1}^T \sum_{g=1}^{N_G} f_3(\Phi_G^{bid}(g, t), P_G(g, t)) \quad (17)$$

where $\Lambda_G(\Phi_G^{bid})$ denotes the surpluses of generating companies, $\Gamma_{EV}(\Phi_{CH}^{bid})$ and $\Lambda_{EV}(\Phi_{DIS}^{bid})$ represent the surpluses of EV charging and discharging, respectively. Φ_G^{bid} , Φ_{CH}^{bid} and Φ_{DIS}^{bid} denote the bid curves of generating companies, charging and discharging bids of EV aggregators, respectively. The payoff function f_1 and the cost function f_2 depend on the characteristics of Φ_{CH}^{bid} and Φ_{DIS}^{bid} of the a -th aggregator at time slot t , denoted as $\Phi_{CH}^{bid}(a, t)$ and $\Phi_{DIS}^{bid}(a, t)$ respectively. The payoff function f_3 generally depends on Φ_G^{bid} of the g -th generation company at time t , denoted as $\Phi_G^{bid}(g, t)$.

Both the conventional constraints such as generator output limits and the capacities of the EV aggregators have to be accommodated in the market clearing model, as shown in (18)–(23):

$$\sum_{g=1}^{N_G} P_G(g, t) - \sum_{i=1}^{N_B} P_D(i, t) - \sum_{a=1}^{N_A} (P_{CH}(a, t) - P_{DIS}(a, t)) = 0 \quad (18)$$

$$\sum_{g=1}^{N_G} \psi_i(g) P_G(g, t) - \sum_{a=1}^{N_A} \varphi_i(a) (P_{CH}(a, t) - P_{DIS}(a, t)) - P_D(i, t) = \sum_{j=1}^{N_B} B_{ij} \delta_{ij}(t) \quad (19)$$

$$-PF_{ij}^{\max} \leq B_{ij} \delta_{ij}(t) \leq PF_{ij}^{\max} \quad (20)$$

$$P_G^{\min}(g) \leq P_G(g, t) \leq P_G^{\max}(g) \quad (21)$$

$$P_{CH}^{\min}(a, t) \leq P_{CH}(a, t) \leq P_{CH}^{\max}(a, t) \quad (22)$$

$$P_{DIS}^{\min}(a, t) \leq P_{DIS}(a, t) \leq P_{DIS}^{\max}(a, t) \quad (23)$$

where (18) represents the balance constraint between power supply and load demand; Equation (19) denotes the DC power flow equations, and $\delta_{ij}(t)$ denotes the voltage angle difference between bus i and j at time t ; Equation (20) represents the transmission capacity constraints based on DC power flow; Equations (21)–(23) represent the power output limits of the generating units, charging and discharging power limits of the aggregators, respectively. $\psi_i(g)$ and $\varphi_i(a)$ are binary parameters; if the generating unit g or the aggregator a is located at bus i , then $\psi_i(g)$ or $\varphi_i(a)$ equals to 1, respectively.

In the above day-ahead market clearing model, both the EV aggregators and generating companies are exposed to potential risks introduced by unexpected day-ahead market clearing price profiles. Generally, the market clearing price fluctuations have more influences on the revenue of EV aggregators, as they do not have specific cost functions, while generating companies have more clear cost functions. The issue of mitigating negative impacts of uncertain market prices will be addressed in the next section.

4. Market Clearing Procedure and Bidding Strategy for EV Aggregators

4.1. Market Clearing Procedure

It is assumed that the day-ahead market opens for bids/offers from time T_1 to T_2 ahead of the operating day, and the procedures are detailed as follows. In the aforementioned bidding strategy model, the market price $\rho(t)$ is included and deemed known. Take the day-ahead electricity market as an example, the actual $\rho(t)$ profiles will remain unknown to all the market participants before market clearing. As a result, the aggregators normally have to predict $\rho(t)$ in determining the EV charging and discharging schedules. Since prediction error always exists, some economic risks will be inevitable. To mitigate such risks, a multi-auction based bidding strategy is introduced here, and the procedures are detailed as follows:

- (1) Both generating companies and EV aggregators are able to submit their bids/offers for the next trading day during the period from T_1 to T_2 . The bidding clearing system displays the current/temporary market clearing results based on the received bids/offers at T_1 and the maximum social welfare model discussed in Section 3.
- (2) Based on the current/temporary market clear results and market price $\rho^{\otimes}(T_1)$, generating companies and EV aggregators can then update their bids/offers $\{\Phi_{CH}^{bid}(a, t), \Phi_{DIS}^{bid}(a, t)\}$ or $\Phi_G^{bid}(g, t)$ if necessary.
- (3) The bidding clearing system displays the current/temporary results based on the updated bids/offers from market participants periodically before T_2 . Similarly, EV aggregators and generating companies can revise their bids/offers before T_2 , when the day-ahead market eventually clears.
- (4) The bidding clearing system clears the day-ahead market after T_2 , and publishes the final market clearing results. The EV aggregators will formulate the detailed charging and discharging schedules, denoted as $\{P_{ch}^*(a, e, t), P_{dis}^*(a, e, t)\}$, for each EV concerned based on the final successful bids.

The flowchart of the market clearing procedure is demonstrated in Figure 1. Many papers have developed bidding strategies for generating companies [40–42]. Due to space limitations, the generating companies are assumed to submit supply offers that are based on their actual cost functions and expected profit margin. It is also assumed that the generating companies prefer to exaggerate their supply offers at first, and gradually lower their bid prices if their provisional cleared results have not reached their full capacities. The bidding strategy for EV aggregators will be discussed in the following sections.

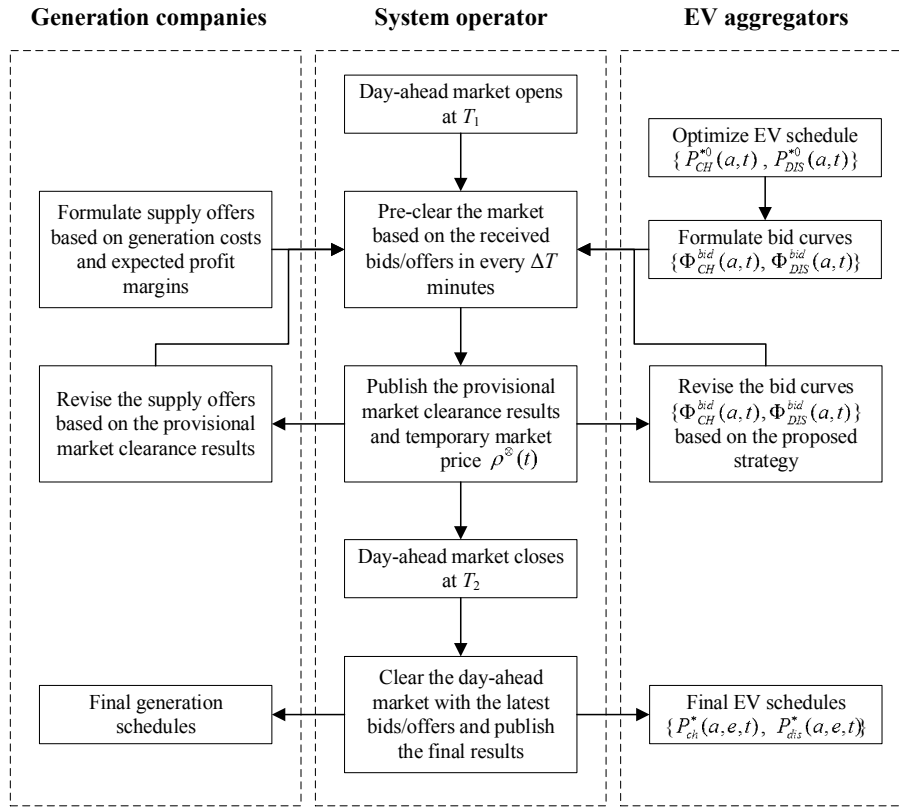


Figure 1. The flowchart of the market clearing procedure.

4.2. Bidding Constraints for EV Aggregators

Each aggregator’s bids for EV charging and discharging schedules are always limited by the availabilities, capabilities and statuses of the EVs concerned. For the e -th EV from the a -th aggregator with an initial optimal schedule of $\{P_{ch}^*(a, e, t), P_{dis}^*(a, e, t), S_E^*(a, e, t)\}$, its flexibility throughout the trading period can be formulated as:

$$\overline{P_{ch}^{up}}(a, e, t) = \min\left\{\frac{B_E(S_E^{\max}(a, e) - S_E^*(a, e, t))}{\kappa_{ch}\Delta t}, P_{ch}^{\max}(a, e) - P_{ch}^*(a, e, t)\right\} \quad (24)$$

$$\overline{P_{ch}^{dw}}(a, e, t) = \min\left\{\frac{B_E(S_E^*(a, e, t) - S_E^{\min}(a, e))}{\kappa_{ch}\Delta t}, P_{ch}^*(a, e, t)\right\} \quad (25)$$

$$\overline{P_{dis}^{up}}(a, e, t) = \min\left\{\frac{\kappa_{dis}B_E(S_E^*(a, e, t) - S_E^{\min}(a, e))}{\Delta t}, P_{dis}^{\max}(a, e) - P_{dis}^*(a, e, t)\right\} \quad (26)$$

$$\overline{P_{dis}^{dw}}(a, e, t) = \min\left\{\frac{\kappa_{dis}B_E(S_E^{\max}(a, e) - S_E^*(a, e, t))}{\Delta t}, P_{dis}^*(a, e, t)\right\} \quad (27)$$

where Δt denotes the specified time interval.

Equations (24)–(27) can be used to calculate the schedulable capacities of the EV. However, in these equations the inter-temporal characteristics of the EV charging process are not taken into account. Thus, the results obtained by (24)–(27) can be seen as optimistic estimations.

The optimal schedule of aggregator a can be obtained through (28) and (29):

$$P_{CH}^*(a, t) = \sum_{e=1}^{N_E(a)} P_{ch}^*(a, e, t) \quad (28)$$

$$P_{DIS}^*(a, t) = \sum_{e=1}^{N_E(a)} P_{dis}^*(a, e, t) \quad (29)$$

Nevertheless, the schedulable charging and discharging power of a fleet of EVs is much harder to estimate than that of a single EV. Even with the EV charging contracts, T_{st} and S_{E0} are still flexible parameters. In this work, these two parameters are assumed to follow normal distributions, and their mean values will be employed by the aggregators in bidding to the market. An adaptive estimation can be done through (30) and (31), while the risk factors χ_{CH}^{up} , χ_{CH}^{dw} , χ_{DIS}^{up} and χ_{DIS}^{dw} with ranges from 0 to 1 can be introduced based on the aggregator's risk preference:

$$\overline{P_{CH}^{up}}(a, t) = \chi_{CH}^{up} \sum_{e=1}^{N_E(a)} \overline{P_{ch}^{up}}(a, e, t), \overline{P_{CH}^{dw}}(a, t) = \chi_{CH}^{dw} \sum_{e=1}^{N_E(a)} \overline{P_{ch}^{dw}}(a, e, t) \quad (30)$$

$$\overline{P_{DIS}^{up}}(a, t) = \chi_{DIS}^{up} \sum_{e=1}^{N_E(a)} \overline{P_{dis}^{up}}(a, e, t), \overline{P_{DIS}^{dw}}(a, t) = \chi_{DIS}^{dw} \sum_{e=1}^{N_E(a)} \overline{P_{dis}^{dw}}(a, e, t) \quad (31)$$

4.3. Bidding Strategy

For any given electricity market price $\rho(t)$, each EV aggregator could attain its optimal EV charging and discharging schedule based on the model demonstrated in (4)–(13). Thus, different $\rho(t)$ profiles will result in various optimal EV charging schedules that significantly differ from one another. An appropriate strategy is vital for the aggregators to adjust bidding prices and EV charging and discharging schedules so as to cover the possible fluctuations of $\rho(t)$.

With the optimal schedule $\{P_{CH}^*(a, t), P_{DIS}^*(a, t)\}$ of aggregator a , the bidding curves demonstrated in Figure 2 can be employed by this aggregator to attain its optimal solution. Generally, two cases are likely to occur:

Case 1: $P_{CH}^*(a, t) \geq 0, P_{DIS}^*(a, t) = 0$. This means that aggregator a prefers to purchase power from the market to charge its EVs. A bidding block with the optimal charging power of $P_{CH}^*(a, t)$ and the bid price higher than $\rho(t)$ will be employed so as to win the bid. At the same time, aggregator a also has the capability to increase its charging power by $\overline{P_{CH}^{up}}(a, t)$ if the price is lower than $\rho(t)$. If the price is high enough for compensating the discharging cost, the aggregator may also discharge power to the power system with a maximum power output of $\overline{P_{DIS}^{up}}(a, t)$.

Case 2: $P_{DIS}^*(a, t) \geq 0, P_{CH}^*(a, t) = 0$. This means aggregator a prefers to sell power to the market by discharging its EVs. Similarly, a bidding block with the discharging power of $P_{DIS}^*(a, t)$ and a bid price lower than $\rho(t)$ will be employed. The discharging power may be added up by $\overline{P_{DIS}^{up}}(a, t)$ with a bid price higher than $\rho(t)$. If the price is lower than the bid price for discharging $\overline{P_{DIS}^{up}}(a, t)$, the aggregator may instead purchase power from the system with a maximum capacity of $\overline{P_{CH}^{up}}(t)$.

The next step is to determine the bid price of each power block. To accommodate the charging requirement of EV customers, the total needed energy of an aggregator is approximately a fixed value. Consequently, the increase/decrease of charging power at one time slot implies the decrease/increase of charging power at another time slot. In this work, the bid prices are derived from $\rho(t)$ at the 'marginal' period T_{mar} . Define $T_{mar}(a)$ as the set of the marginal time slots for aggregator a , and $T_{mar}(a) \subseteq T$, and (32) must be respected for $\forall t \in T_{mar}$:

$$\overline{P_{CH}^{up}}(a, t) \overline{P_{CH}^{dw}}(a, t) + \overline{P_{DIS}^{up}}(a, t) \overline{P_{DIS}^{dw}}(a, t) > 0 \quad (32)$$

Equation (32) represents that at any given time slot t , if the aggregator a has the possibility to increase/decrease its original charging/discharging schedules without violating the requirements of its customers, t will be seen as a marginal time slot, and vice versa. For example, the time periods that the aggregator has to fully charge their EVs to accommodate the demand of EV owners, and

the periods that not a single EV is parked for charging/ discharging services, will not be considered as marginal time periods. Thus, the price data at these non-marginal period will be ignored by the aggregators, as they will not influence the shifting of EV charging/ discharging schedules.

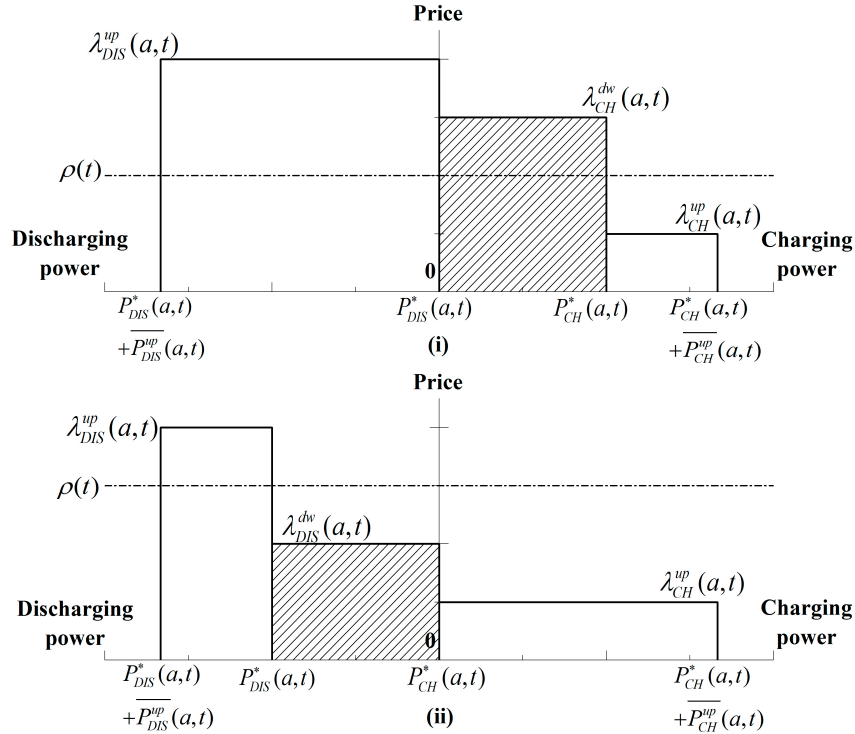


Figure 2. Bidding curves for the a -th aggregator with given market prices of electricity: (i) bids to charge the EVs; (ii) bids to discharge the EVs.

The bid prices for the charging demand can be calculated as:

$$\begin{cases} \lambda_{CH}^{up}(a, t) = \min\{\rho(t) \mid t \in T_{mar}(a)\} \\ \lambda_{CH}^{dw}(a, t) = \max\{\rho(t) \mid t \in T_{mar}(a)\} \end{cases} \quad (33)$$

As mentioned before, battery discharging will incur extra cost to the aggregator, hence in the bid prices for the discharging power this extra cost should be considered and further the bid prices can be calculated as follows:

$$\begin{cases} \lambda_{DIS}^{up}(a, t) = \max\{\rho(t) + c_{dis} + r_{dis} \mid t \in T_{mar}(a)\} \\ \lambda_{DIS}^{dw}(a, t) = \min\{\rho(t) + c_{dis} + r_{dis} \mid t \in T_{mar}(a)\} \end{cases} \quad (34)$$

However, the bid prices in (34) underestimate the cost for providing or scheduling V2G power. If aggregator a increases its discharging power by $\Delta P_{DIS}(a, t)$, it will have to purchase an additional charging power of $\Delta P_{CH}(a, t)$ to meet the customers' charging requirement, as shown in (35):

$$\Delta P_{CH}(a, t) = \frac{1}{\kappa_{ch}\kappa_{dis}} \Delta P_{DIS}(a, t) \quad (35)$$

Besides, w in (7) should also be considered in determining the discharging bid prices, then (34) can be modified as:

$$\begin{cases} \lambda_{DIS}^{up}(a, t) = \frac{\max\{\rho(t) \mid t \in T_{mar}(a)\} + w}{\kappa_{ch}\kappa_{dis}} + c_{dis} + r_{dis} \\ \lambda_{DIS}^{dw}(a, t) = \frac{\min\{\rho(t) \mid t \in T_{mar}(a)\} + w}{\kappa_{ch}\kappa_{dis}} + c_{dis} + r_{dis} \end{cases} \quad (36)$$

Thus, $\Phi_{CH}^{bid}(a, t)$ and $\Phi_{DIS}^{bid}(a, t)$ can be obtained through (33) and (36), as well as Figure 2. c_{dis} and w are very expensive compared with the average day-ahead energy prices, and this makes the bid prices for discharging much higher than that for charging. In general, it is only possible for the EV owners to discharge their batteries in real-time, balancing or ancillary service markets for high prices to compensate the discharging costs. Nonetheless, the bid prices in (33) and (36) are applicable not only in day-ahead market, but also in real-time and ancillary service markets.

If the aggregators do not get enough power supply from the day-ahead electricity market or bilateral contract market to supply their EV charging demands, they will have to purchase in the real-time market or balancing market with high and volatile electricity prices, and hence more cost will be incurred for the aggregators. Thus, the accommodation of the constraint shown in (37) is desirable in the bidding procedure so as to meet the total energy requirements of the aggregators:

$$\sum_{t=1}^T (\kappa_{ch} P_{CH}^*(a, t) - \frac{P_{DIS}^*(a, t)}{\kappa_{dis}}) = \sum_{t=1}^T (\kappa_{ch} P_{CH}^{*0}(a, t) - \frac{P_{DIS}^{*0}(a, t)}{\kappa_{dis}}) \quad (37)$$

However, (37) cannot be automatically guaranteed during the market clearing process. Thus, correction terms that consider the successful bids in the previous published market clearance results are introduced to revise the bids in (33) and (36). Binary variables $\mu_o(a, k)$ and $\mu_u(a, k)$ are assumed to have positive values if the k -th provisional cleared total EV charging energy of the a -th EV aggregator is higher or lower than the estimated daily energy requirement. Equation (33) can be modified as:

$$\begin{cases} \lambda_{CH}^{up}(a, t) = \min\{\rho(t) \mid t \in T_{mar}(a)\} \times (1 + \mu_u(a, k)(1 - \frac{k+1}{K_{max}})\vartheta) \\ \lambda_{CH}^{dw}(a, t) = \max\{\rho(t) \mid t \in T_{mar}(a)\} \times (1 - \mu_o(a, k)(1 - \frac{k+1}{K_{max}})\vartheta) \end{cases} \quad (38)$$

where K_{max} denotes the maximum rounds that the bidding clearing system will display provisional market clearing results, ϑ denotes the correction coefficient. If $\mu_o(a, k) = 1$, $\lambda_{CH}^{dw}(a, t)$ will be decreased to reduce the successful EV charging energy; If $\mu_u(a, k) = 1$, $\lambda_{CH}^{up}(a, t)$ will be increased so that more charging power is likely to be cleared. The bid prices in (37) can be handled similarly.

4.4. Bidding Procedures of EV Aggregators

Based on the market clearing process discussed in Section 4.1 and the bidding strategy proposed in Section 4.3, the bidding procedure of the a -th EV aggregator in day-ahead market can be summarized as follows.

- (1) Aggregator optimizes its initial energy schedules $\{P_{CH}^{*0}(a, t), P_{DIS}^{*0}(a, t)\}$ for the next operating day based on the forecast day-ahead market price and the estimated behaviors of EVs based on (5)–(13).
- (2) Formulate the energy bids/offers $\{\Phi_{CH}^{bid}(a, t), \Phi_{DIS}^{bid}(a, t)\}$ based on the calculated $\{P_{CH}^{*0}(a, t), P_{DIS}^{*0}(a, t)\}$ and bidding strategy shown in (33)–(38), and submit the bids/offers to the system operator when the day-ahead market opens at T_1 .
- (3) Revise the energy bids/offers based on the temporary market clearing price based on (33)–(38), until the day-ahead market closes at T_2 . It should be noted that the modification of $\{\Phi_{CH}^{bid}(a, t), \Phi_{DIS}^{bid}(a, t)\}$ does not require solving the model (5)–(13), which reduce the computational burdens.

5. Numerical Results

A modified version of the IEEE 30-bus system with six generating units is used for demonstrating the proposed model and method. The data of generating units are listed in Table 1, and MU stands for the monetary unit associated. Several assumptions are adopted in the simulation:

- (1) There are three EV aggregators, respectively, located at buses 7, 17 and 26, and each aggregator has 5000 registered EVs.

- (2) For all EVs registered with an aggregator, T_{en} and S_E^\oplus follow the normal distributions of $N(7 \text{ a.m.}, 1 \text{ h})$ and $N(80\%, 3\%)$, respectively. T_{st} and S_{E0} follow the normal distributions of $N(6.5 \text{ p.m.}, 1 \text{ h})$ and $N(30\%, 5\%)$, respectively. T_{en} and S_E^\oplus are fixed values in the EV charging contracts, while T_{st} and S_{E0} are estimated by each aggregator.
- (3) It is assumed that all EVs are the same, and share same parameters as well as charging and discharging limits. Detailed EV data are listed in Table 2.
- (4) All generating companies will exaggerate their bid prices by 10% at first. The exaggerated parts will be lowered to 0 during the market clearing process, if their full capacities have not been reached.

The proposed bidding strategy of EV aggregators and the day-ahead market clearing model are solved by the commercial solver AMPL/CPLEX [8]. The estimated travel pattern data of EVs are sampled based on the abovementioned normal distributions before optimizing the day-ahead energy schedules. The actual data of EVs at the operating day will be separately sampled, and used by the aggregators to allocate their successful day-ahead bids.

Table 1. Data of generating units.

Generator No.	Bus No.	a_g (MU)	b_g (MU/MW)	c_g (MU/MW ²)	P_G^{\min} (MW)	P_G^{\max} (MW)	Expected Profit Margin (%)
1	1	4650	216	4.48	30	80	10
2	2	4400	198	5.12	30	80	10
3	13	3550	192	4.8	10	50	8
4	22	3220	172	6.48	15	45	7
5	23	2830	240	4.2	10	30	5
6	27	2670	233	4.88	10	40	5

Table 2. Data of EV parameters.

P_{ch}^{\max} (kW)	3.3	S_E^{\max}	100%
P_{dis}^{\max} (kW)	3.3	S_E^{\min}	10%
κ_{ch}	93%	$c_{dis} + r_{dis}$ (MU/kWh)	0.90
κ_{dis}	90%	w (MU/kWh)	0.30
B_E (kWh)	28		

5.1. Simulation Results

A typical load curve with an afternoon peak of 245.1 MW and a night valley of 152.3 MW is selected as the uncontrollable load profile. The maximum charging load of all EVs is 49.5 MW, and is around 20% of the maximum uncontrollable load. χ_{CH}^{up} , χ_{CH}^{dw} , χ_{DIS}^{up} and χ_{DIS}^{dw} in (30) and (31) are all set to 1 (the most optimistic value). The day-ahead market opens for bids/offers during 08:00~12:00, and the bidding clearing system publishes the provisional market clearance results in every half hour. The system load profiles during the bidding process are demonstrated in Figure 3. The error between the final cleared results and the provisional market clearing results at 11:00 is less than 1.0%, which means that the bidding process converges in six iterations. Three EV aggregators are assumed to have different market forecasts at the beginning of the day-ahead market bidding period, and are demonstrated in Figure 4 with the final day-ahead market clearing price. Their temporary cleared energy bids at 08:00 and final cleared bids after 12:00 are shown in Figure 5. The average SoC profile of each EV aggregator based on the final cleared day-ahead market bids is demonstrated in Figure 6.

The SoC profiles of four EVs of the third EV aggregator are demonstrated in Figure 7. The EV charging will be scheduled based not only on the stochastic parameters such as T_{st} and T_{en} , but also on the proposed strategies considering the market bidding process and clearing prices. In Figure 7, EV-2 started charging its battery as soon as it plugged into the grid, while EV-1 waited for a couple of hours before the charging finally started. On the other hand, EV-2 will be charged to S_E^\oplus hours ahead of T_{en} , thus the charger will stay idle in the early morning.

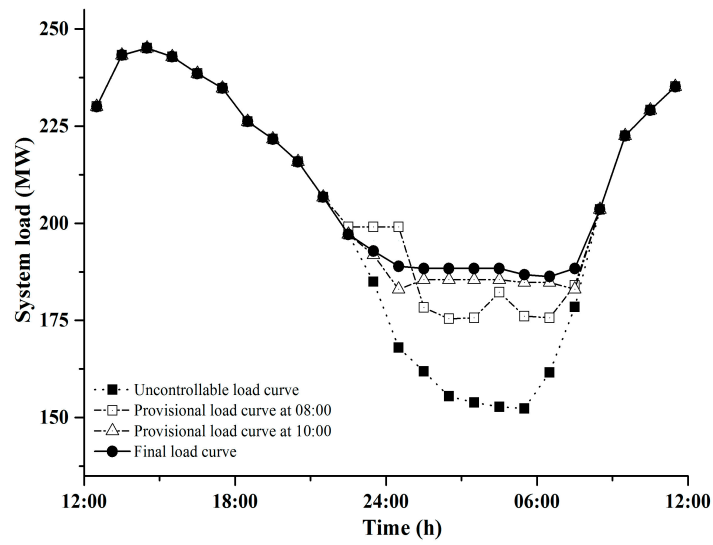


Figure 3. System load profiles during the market clearing process.

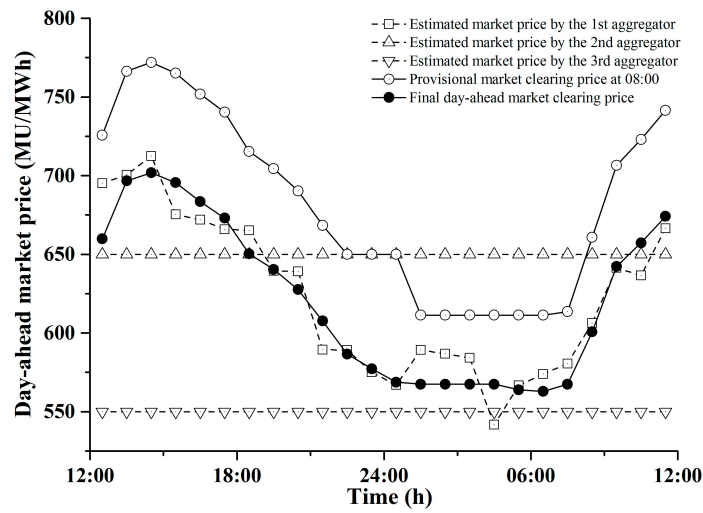


Figure 4. Price forecasts of EV aggregators and final market clearing price.

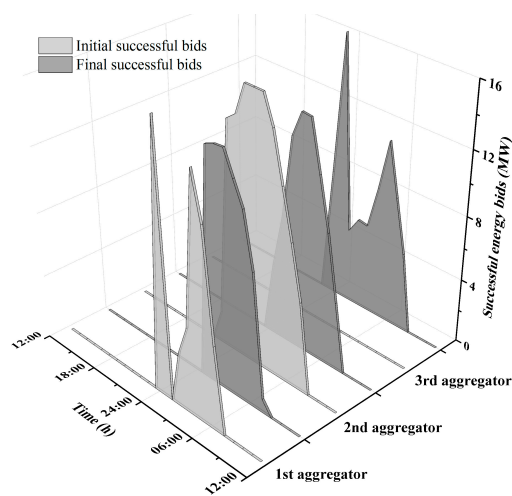


Figure 5. Initial and final successful energy bids of EV aggregators.

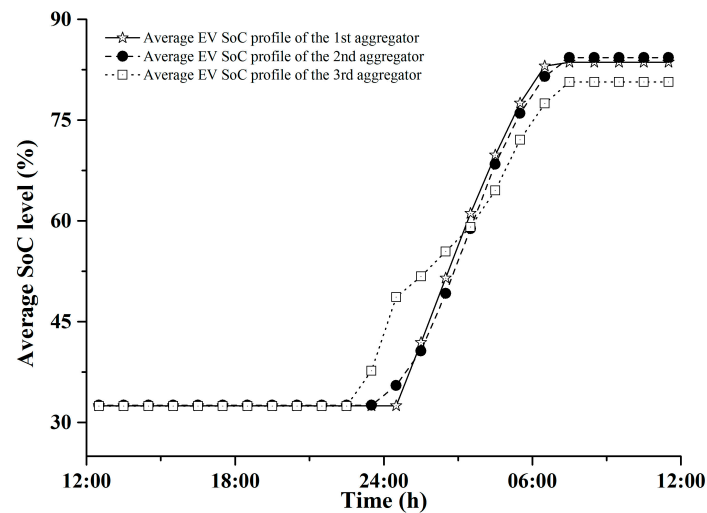


Figure 6. Aggregators' SoC profiles based on the final cleared day-ahead market bids.

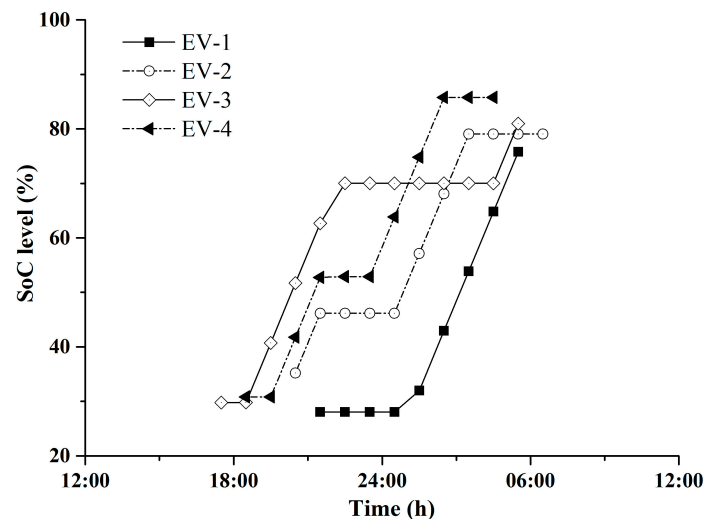


Figure 7. Individual SoC profiles of four selected EVs from the 3rd aggregator.

As can be clearly observed from Figure 7, the charging behaviors of EVs have been scheduled and shifted through the proposed strategies.

5.2. Analysis of Simulation Results

Statistics of the simulation results are demonstrated in Table 3, where the social welfare is calculated assuming that the inelastic loads will bid at a fixed price of 1000 (MU/MWh). In the test cases, three EV aggregators have different forecasts of the day-ahead market prices in determining their initial EV charging schedules. Thus, their initial successful bids vary significantly from one another, as shown in Figure 5. However, their final cleared energy bids are more similar in Table 3. The current/temporary bidding clearing results are helpful for the aggregators to formulate reasonable market bids/offers with the absence of perfect market price estimation. At the same time, the social welfare will be improved as well. The daily charging requirements of EV aggregators can be mostly accommodated, with an average error of 2.8%. In Table 3, the cleared energy for the 3rd aggregator is less than its daily requirement, thus its average SoC profile is lower than the other aggregators at the end of the charging period in Figure 6. As a result, it has to make additional purchase in other markets such as the real-time market to fulfill the charging demand of its EVs.

Table 3. Statistics of the simulation results.

	EV Aggregator	Required Daily Energy (MWh)	Cleared Daily Energy (MWh)	Total Charging Cost (MU)	Social Welfare (MU)
Provisional market clearance at 08:00	1st aggregator	75.50	57.17	3.55×10^4	9.97×10^5
	2nd aggregator	75.34	121.13	7.52×10^4	
	3rd aggregator	75.15	0.00	0.00	
Final market clearance after 12:00	1st aggregator	75.50	76.96	4.36×10^4	1.30×10^6
	2nd aggregator	75.34	77.86	4.41×10^4	
	3rd aggregator	75.15	72.60	4.12×10^4	

As shown in Figure 5 and Table 3, the daily energy demands of all the aggregators are satisfied practically based on proposed bidding strategy, despite the fact that their forecasted day-ahead market prices before have great differences. In this case study, both the 2nd and the 3rd aggregator have extremely bad predictions on the shape of market clearing price, thus their initial cleared energy bids are either way above or below their required daily energy demand for EV charging services. The 1st aggregator, on the other hand, only clears 76% of its daily energy demand with its good knowledge of the final market clearing prices. Through the proposed bidding strategy, the successful energy bids of EV aggregators become much closer to their actual daily demand, which are irrelevant to their forecast accuracies of market clearing prices. Several conclusions can be drawn based on the results in Figure 5 and Table 3:

- (1) Market clearing prices are influenced synthetically by the behaviors of generation companies and users, and their volatilities and uncertainties make it difficult for EV aggregators to make perfect estimation of. As a result, even the aggregators with near-perfect price estimations are not guaranteed to fulfill their energy demand due to the uncertainties of market clearing prices.
- (2) The proposed bidding strategy enables the EV aggregators and other market participants to modify their bids/offers through updated market information, so that EV aggregators are capable to get their desirable energy bids in the market without the necessity to predict market clearing prices. In this way, the aggregators are freed from the consideration of market price uncertainties and the accompanied financial risks, like the 2nd and 3rd EV aggregators in the case study.

With the clearing results in the day-ahead electricity market, the aggregators will try to follow their successful bids. On the other hand, as the aggregators submit their bids based on the overall capacities of the EVs, it is possible that they are not able to strictly follow their cleared charging or discharging bids. This can be explain from two aspects: (1) the predictions in (30) and (31) are too optimistic; (2) the cleared day-ahead market bids may not be sufficient for the EV aggregators to charge all their EVs to the agreed level based on the contracts. Thus, aggregators may have to deviate from their successful day-ahead market bids to compensate the charging energy vacancy as well as the unachievable EV charging/discharging power. In the test case, the maximum error between the load curve in the situation with market clearing and the final load curve that the aggregators can achieve is about 0.88MW. If the values of χ_{CH}^{up} , χ_{CH}^{dw} , χ_{DIS}^{up} and χ_{DIS}^{dw} are set to 0.8, the daily charging requirements can be met for all three EV aggregators, while the maximum error can be reduced to 0.32 MW as well.

The results in Section 5.1 show that all the three EV aggregators will not discharge their batteries in the day-ahead market, as the battery discharging cost ($c_{dis} + r_{dis}$) as well as all the distribution fees and tariffs play important roles in determining the final bidding results of the EV aggregators. In this test case, the day-ahead market price profile is relatively smooth, with the highest and lowest clearing prices at 701.8 (MU/MWh) and 562.9 (MU/MWh), respectively. According to the battery discharging bids shown in (36), the discharging of EV batteries is very economic-inefficient. Figure 8 demonstrates two ideal cases where the overall battery discharging costs and distribution fees are considerably lower than those in Table 2. As can be seen in Figure 8, with lowered discharging costs and distribution fees, the system load during peak hours (16:00–20:00) will be decreased due to the EV battery discharging

behaviors, and the discharged energy will be compensated at late night. Thus, the EV aggregators may have incentives to discharge their batteries if the discharging costs and grid tariffs are significantly lowered. However, EV aggregators generally are not willing to providing discharging services in day-ahead energy markets considering c_{dis} , r_{dis} and w , as discussed in Section 4.3. Nonetheless, the simulation results also illustrate that the battery discharging cost and the distribution tariffs must be respected to attain an appropriate level of revenue for the aggregators and EV owners in deregulated electricity markets.

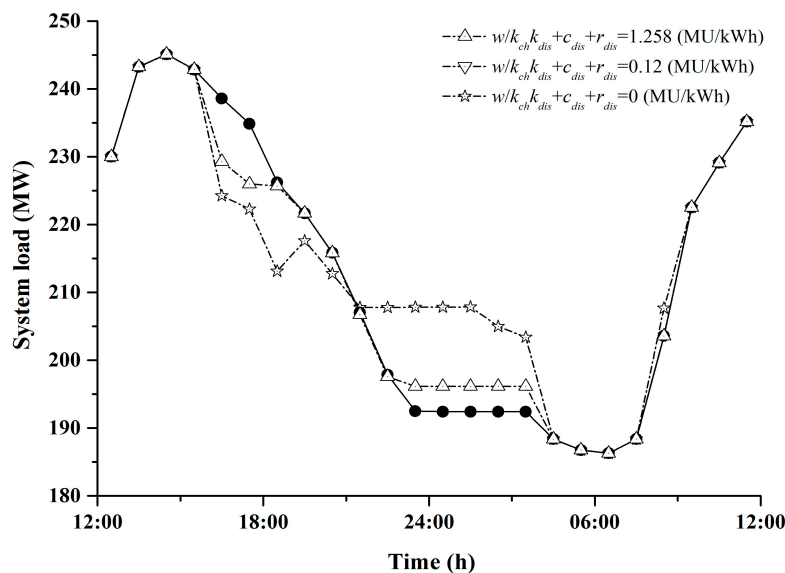


Figure 8. System load profiles with different discharging costs and distribution fees.

Moreover, two benchmark methods are introduced here to make comparisons with the proposed bidding strategy:

Benchmark I: A traditional economic dispatch model minimizing the total system operating cost, where the generating companies are paid by their true generating costs;

Benchmark II: Day-ahead market clearing without the proposed bidding clearing display procedure, while each EV aggregator bids with the information of the final market price as described in Figure 4. The optimal energy schedules of aggregators are obtained based on the final market price, and the single block bid price for the optimized charging power is set to 1000 MU/MWh.

The schedule results of EVs attained by different methods and market frameworks are listed in Table 4, where M_1 , M_2 , M_3 and M_4 represent the results of the provisional market clearing at 08:00, final market clearing after 12:00, the results of Benchmark I, and II, respectively. The charging price λ_{ch} that EV aggregators offers their EV customers is set to 1000 MU/MWh.

Table 4. Comparisons of the EV schedule efficiencies with different strategies.

Strategy	M_1	M_2	M_3	M_4
Total generated energy (MWh)	5040.1	5089.3	5087.9	5091.0
Total generating cost (MU)	2.463×10^6	2.487×10^6	2.486×10^6	2.489×10^6
Total generating income (MU)	3.979×10^6	3.702×10^6	2.486×10^6	3.706×10^6
Total generating profit (MU)	1.516×10^6	1.215×10^6	0.0	1.217×10^6
Total EV charging energy (MWh)	178.30	227.42	225.99	229.08
Total EV charging cost (MU)	1.11×10^5	1.29×10^5	1.19×10^5	1.33×10^6
Average EV charging price (MU/MWh)	622.55	567.23	526.57	578.67
Total EV charging income (MU)	1.78×10^5	2.27×10^5	2.26×10^5	2.29×10^5
Aggregators' total profit (MU)	0.67×10^5	0.98×10^5	1.07×10^5	0.96×10^5
Computational time (s)	17.44	30.17	1059.04	16.92

From Table 4, the following several points are noted:

- (1) EV aggregators in M_1 employ their estimated market prices in optimizing their energy schedules and market bids, and the cleared results are generally much worse than the other strategies due to price forecast errors. Nonetheless, the total generating profit is the highest, as the generating companies tend to exaggerate their bids at first. Generating companies will prefer to decrease their bidding prices in order to increase their cleared capacities at certain periods, which will result in lower generating income in M_2 eventually.
- (2) The total EV charging energy with the strategy M_2 is slightly higher than that with M_3 , since the constraint (37) cannot be guaranteed through market bidding. Moreover, the results of M_2 is comparable to the benchmark results of M_3 , which is an ideal case without the consideration of deregulated market environments. As a consequence, the effectiveness of proposed market bidding strategy demonstrates has been validated.
- (3) M_3 is considered the best strategy among all the strategies, in terms of the total generating cost, total EV charging cost and the average EV charging price. It is reasonable since the SO in strategy M_3 will have perfect information of generating cost functions and EV driving behavior. However, the centralized control structure ignores the surpluses of both the generating companies and the EV aggregators, and the privacy of the EV customers cannot be protected at the same time. Besides, it is also the most time consuming strategy, and more time will be required if even more EVs are integrated into the power system. In comparison, the computational demand of the proposed strategy M_2 is significantly lower, as multiple small problems are solved instead of a large problem.
- (4) The result of M_4 is quite similar to M_2 by the proposed strategy. As the proposed market clearing procedure proceed, the provisional market clearing prices will be stabilized, thus the reference price of M_2 is generally very close to the final market clearing price used for M_4 . It should be noted that it is impractical that market participants are able to make perfect market price predictions. The price forecast of the 1st EV aggregator is quite accurate, as shown in Figure 4. However, its initial cleared bids can hardly be regarded satisfactory, as the daily charging demand haven't been met. As a result, the proposed market clearing procedure and bidding strategy is feasible in helping EV aggregators and other market participants to alleviate financial risks caused by market price forecast errors.

6. Conclusions

The problem of developing optimal bidding strategies for EV aggregators in a day-ahead electricity energy market is addressed in this paper. The possible losses for scheduling EV charging and discharging loads as well as the extra cost of EV battery life cycle losses are taken into account in the proposed strategy. Simulation results with a revised version of the IEEE 30-bus system have demonstrated the feasibility and effectiveness of the proposed bidding strategies in a decentralized market structure, and the results are almost as good as those of the centralized structure with perfect information. Thus, the proposed bidding strategies are effective in helping market participants such as EV aggregators to handle the risks in day-ahead electricity energy markets.

The V2G function by discharging EV batteries does not make economic sense for EVs and their aggregators in the electricity energy market considering the high discharging costs and distribution tariffs. On the other hand, simulation results also show that V2G is economically feasible if discharging costs and distribution tariff become considerably lower. Another promising business for EV battery discharging is to participate in ancillary markets, where charging/discharging behaviors may bring extra profits for the aggregators and the EV owners.

Acknowledgments: This work is jointly supported by the National Basic Research Program (973 Program) (No. 2013CB228202), the National Natural Science Foundation of China (No. 51477151), and a project from State Grid Zhejiang Electric Power Company (5211DF150007).

Author Contributions: Yunpeng Guo conceived the project, proposed the methodological framework and implementation roadmap; Weijia Liu designed the implementation algorithm, performed the simulations; Fushuan Wen organized the research team, reviewed and improved the methodological framework and implementation algorithm; Abdus Salam, Jianwei Mao, Liang Li reviewed and polished the manuscript. All authors discussed the simulation results and approved the assessment methodology.

Conflicts of Interest: The authors declare no conflict of interest.

Nomenclatures

B_E	Battery capacity of a single electric vehicle (EV)
B_{ij}	Element i - j of the susceptance matrix
C_{PB}	Battery purchase cost of a single EV
D_{od}	Permitted battery discharging depth of each EV
L_B	Designed EV battery life cycles
N_A	Number of EV aggregators
N_B	Number of buses in the studied power system
$N_E(a)$	Number of EVs of aggregator a
N_G	Number of generating companies
$P_{CH}(a, t), P_{DIS}(a, t)$	EV charging and discharging schedule of aggregator a
$P_{CH}^*(a, t), P_{DIS}^*(a, t)$	Optimal EV schedule of aggregator a in the bidding process
$P_{CH}^0(a, t), P_{DIS}^0(a, t)$	Optimal EV schedule of aggregator a before the bidding process starts
$P_{CH}^{\max}(a, t), P_{CH}^{\min}(a, t)$	Maximum and minimum charging power of aggregator a at time t , respectively
$\overline{P_{CH}^{up}}(a, t), \overline{P_{CH}^{dw}}(a, t)$	Maximum increasable and reducible EV charging loads of aggregator a at time t , respectively
$P_{DIS}^{\max}(a, t), P_{DIS}^{\min}(a, t)$	Maximum and minimum discharging power of aggregator a at time t , respectively
$\overline{P_{DIS}^{up}}(a, t), \overline{P_{DIS}^{dw}}(a, t)$	Maximum increasable and reducible EV discharging loads of aggregator a at time t , respectively
$P_D(i, t)$	Uncontrollable load of bus i at time t
PF_{ij}^{\max}	Maximum power flow limit of line i - j
$P_G(g, t)$	Active power output of generator g at time t
$P_G^{\max}(g), P_G^{\min}(g)$	Maximum and minimum power output limits of generator g , respectively
$P_{ch}(a, e, t), P_{dis}(a, e, t)$	Charging and discharging power of EV e under aggregator a at time t , respectively
$P_{ch}^*(a, e, t), P_{dis}^*(a, e, t)$	Optimal EV charging and discharging schedule of EV e under aggregator a
$P_{ch}^{\max}(a, e), P_{dis}^{\max}(a, e)$	Maximum charging and discharging power of EV e under aggregator a , respectively
$\overline{P_{ch}^{up}}(a, e, t), \overline{P_{ch}^{dw}}(a, e, t)$	Maximum increasable and reducible EV charging loads of EV e under aggregator a at time t , respectively
$\overline{P_{dis}^{up}}(a, e, t), \overline{P_{dis}^{dw}}(a, e, t)$	Maximum increasable and reducible EV discharging loads of EV e under aggregator a at time t , respectively
$S_E(a, e, t)$	State-of-Charge (SoC) level of EV e under aggregator a at time t
$S_E^*(a, e, t)$	SoC profiles of EV e under aggregator a in its optimal schedule
$S_E^{\max}(a, e), S_E^{\min}(a, e)$	Maximum and minimum acceptable SoC levels of EV e under aggregator a , respectively
T	Time horizon considered
c_{dis}	Battery life cycle loss cost per unit discharging power
r_{dis}	Expected revenue per unit discharging power
$u_{ch}(a, e, t)$	Binary variable denoting the charging/discharging status of EV e of aggregator a at time t
$\lambda_{CH}^{up}(a, t), \lambda_{CH}^{dw}(a, t)$	Bid prices to increase and decrease EV charging loads of aggregator a at time t , respectively
$\lambda_{DIS}^{up}(a, t), \lambda_{DIS}^{dw}(a, t)$	Bid prices to increase and decrease EV discharging loads of aggregator a at time t , respectively
$\kappa_{ch}, \kappa_{dis}$	EV battery efficiencies for charging and discharging, respectively
$\rho(t)$	Day-ahead market price at time t
$\rho^{\otimes}(t)$	Temporary day-ahead market clearing price during the bidding process

References

1. Boulanger, A.G.; Chu, A.C.; Maxx, S.; Waltz, D.L. Vehicle electrification: Status and issues. *Proc. IEEE* **2011**, *99*, 1116–1138. [[CrossRef](#)]
2. Ipakchi, A.; Albuyeh, F. Grid of the future. *IEEE Power Energy Mag.* **2009**, *7*, 52–62. [[CrossRef](#)]
3. Lopes, J.A.P.; Soares, F.J.; Almeida, P.M.R. Integration of electric vehicles in the electric power system. *Proc. IEEE* **2011**, *99*, 168–183. [[CrossRef](#)]
4. Ma, Y.; Houghton, T.; Cruden, A.; Infield, D. Modeling the benefits of vehicle-to-grid technology to a power system. *IEEE Trans. Power Syst.* **2012**, *27*, 1012–1020. [[CrossRef](#)]
5. Schneider, K.; Gerkenmeyer, C.; Kintner-Meyer, M.; Fletcher, R. Impact assessment of plug-in hybrid vehicles on pacific northwest distribution systems. In Proceedings of the IEEE Power and Energy Society 2008 General Meeting, Pittsburgh, PA, USA, 20–24 July 2008.
6. Zhou, L.; Li, F.; Gu, C.; Hu, Z.; Blond, S.L. Cost/benefit assessment of a smart distribution system with intelligent electric vehicle charging. *IEEE Trans. Smart Grid* **2014**, *5*, 839–847. [[CrossRef](#)]
7. Das, R.; Thirugnanam, K.; Kumar, P.; Lavudiya, R. Mathematical modeling for economic evaluation of electric vehicle to smart grid interaction. *IEEE Trans. Smart Grid* **2014**, *5*, 712–721. [[CrossRef](#)]
8. Yao, W.; Zhao, J.; Wen, F.; Xue, Y.; Ledwich, G. A hierarchical decomposition approach for coordinated dispatch of plug-in electric vehicles. *IEEE Trans. Power Syst.* **2013**, *28*, 2768–2778. [[CrossRef](#)]
9. He, Y.; Venkatesh, B.; Guan, L. Optimal scheduling for charging and discharging of electric vehicles. *IEEE Trans. Smart Grid* **2012**, *3*, 1095–1105. [[CrossRef](#)]
10. Pudjianto, D.; Djapic, P.; Aunedi, M.; Gan, C.K.; Strbac, G.; Huang, S.; Infield, D. Smart control for minimizing distribution network reinforcement cost due to electrification. *Energy Policy* **2013**, *52*, 76–84. [[CrossRef](#)]
11. Ortega-Vazquez, M.A.; Bouffard, F.; Silva, V. Electric vehicle aggregator/system operator coordination for charging scheduling and services procurement. *IEEE Trans. Power Syst.* **2013**, *28*, 1806–1815. [[CrossRef](#)]
12. Schuller, A.; Dietz, B.; Flath, C.M.; Weinhardt, C. Charging strategies for battery electric vehicles: Economic benchmark and V2G potential. *IEEE Trans. Power Syst.* **2014**, *29*, 2014–2022. [[CrossRef](#)]
13. Al-Awami, A.T.; Sortomme, E. Coordinating vehicle-to-grid services with energy trading. *IEEE Trans. Smart Grid* **2012**, *3*, 453–462. [[CrossRef](#)]
14. Yang, H.; Chung, C.Y.; Zhao, J. Application of plug-in electric vehicles to frequency regulation based on distributed signal acquisition via limited communication. *IEEE Trans. Power Syst.* **2013**, *28*, 1017–1026. [[CrossRef](#)]
15. Sortomme, E.; El-sharkawi, M.A. Optimal scheduling of vehicle-to-grid energy and ancillary services. *IEEE Trans. Smart Grid* **2012**, *3*, 351–359. [[CrossRef](#)]
16. Sortomme, E.; El-Sharkawi, M.A. Optimal combined bidding of vehicle-to-grid ancillary services. *IEEE Trans. Smart Grid* **2012**, *3*, 70–79. [[CrossRef](#)]
17. Kempton, W.; Tomić, J. Vehicle-to-grid power implementation: From stabilizing the grid to supporting large-scale renewable energy. *J. Power Sources* **2005**, *144*, 280–294. [[CrossRef](#)]
18. Hu, W.; Su, C.; Chen, Z.; Bak-Jensen, B. Optimal operation of plug-in electric vehicles in power systems with high wind power penetrations. *IEEE Trans. Sustain. Energy* **2013**, *4*, 577–585.
19. Tan, Z.; Yang, P.; Nehorai, A. An optimal and distributed demand response strategy with electric vehicles in the smart grid. *IEEE Trans. Smart Grid* **2014**, *5*, 861–869. [[CrossRef](#)]
20. Aunedi, M.; Strbac, G. Efficient system integration of wind generation through smart charging of electric vehicles. In Proceedings of the International Conference and Exhibition on Ecological Vehicles and Renewable Energies (EVER), Monte Carlo, Monaco, 27–30 March 2013.
21. Ramírez, P.J.; Papadaskalopoulos, D.; Strbac, G. Co-optimization of generation expansion planning and electric vehicles flexibility. *IEEE Trans. Smart Grid* **2016**, *7*, 1609–1619. [[CrossRef](#)]
22. Ramírez, P.; Papadaskalopoulos, D.; Strbac, G. Impact of electric vehicles flexibility on generation expansion planning. In Proceedings of the IEEE Power Engineering Society (PES) Innovative Smart Grid Technologies Europe (ISGT Europe), Copenhagen, Denmark, 6–9 October 2013.
23. Rotering, N.; Ilic, M. Optimal charge control of plug-in hybrid electric vehicles in deregulated electricity markets. *IEEE Trans. Power Syst.* **2011**, *26*, 1021–1029. [[CrossRef](#)]

24. Papadaskalopoulos, D.; Strbac, G.; Mancarella, P.; Aunedi, M.; Stanojevic, V. Decentralized participation of flexible demand in electricity markets—Part II: Application with electric vehicles and heat pump systems. *IEEE Trans. Power Syst.* **2013**, *28*, 3667–3674. [[CrossRef](#)]
25. Gonzalez Vaya, M.; Andersson, G. Optimal bidding strategy of a plug-in electric vehicle aggregator in day-ahead electricity markets under uncertainty. *IEEE Trans. Power Syst.* **2015**, *30*, 2375–2385. [[CrossRef](#)]
26. Vagropoulos, S.I.; Bakirtzis, A.G. Optimal bidding strategy for electric vehicle aggregators in electricity markets. *IEEE Trans. Power Syst.* **2013**, *28*, 4031–4041. [[CrossRef](#)]
27. Bessa, R.J.; Matos, M.A.; Soares, F.J.; Lopes, J.A.P. Optimized bidding of an EV aggregation agent in the electricity market. *IEEE Trans. Smart Grid* **2012**, *3*, 443–452. [[CrossRef](#)]
28. Nguyen, D.T.; Le, L.B. Optimal bidding strategy for microgrids considering renewable energy and building thermal dynamics. *IEEE Trans. Smart Grid* **2014**, *5*, 1608–1620. [[CrossRef](#)]
29. Conejo, A.J.; Nogales, F.J.; Arroyo, J.M. Price-taker bidding strategy under price uncertainty. *IEEE Trans. Power Syst.* **2002**, *17*, 1081–1088. [[CrossRef](#)]
30. Ortega-Vazquez, M.A. Optimal scheduling of electric vehicle charging and vehicle-to-grid services at household level including battery degradation and price uncertainty. *IET Gener. Transm. Distrib.* **2014**, *8*, 1007–1016. [[CrossRef](#)]
31. Shafie-khah, M.; Moghaddam, M.P.; Sheikh-El-Eslami, M.K.; Rahmani-Andebili, M. Modeling of interactions between market regulations and behavior of plug-in electric vehicle aggregators in a virtual power market environment. *Energy* **2012**, *40*, 139–150. [[CrossRef](#)]
32. Albuyeh, F.; Alaywan, Z. Implementation of the California independent system operator. In Proceedings of the 21st power industry computer applications, Santa Clara, CA, USA, 16–21 May 1999; pp. 233–238.
33. Contreras, J.; Candiles, O.; de la Fuente, J.I.; Gomez, T. Auction design in day-ahead electricity markets. *IEEE Trans. Power Syst.* **2001**, *16*, 88–96. [[CrossRef](#)]
34. Guenther, C.; Schott, B.; Hennings, W.; Waldowski, P.; Danzer, M.A. Model-based investigation of electric vehicle battery aging by means of vehicle-to-grid scenario simulations. *J. Power Sources* **2013**, *239*, 604–610. [[CrossRef](#)]
35. Zhou, C.; Qian, K.; Allan, M.; Zhou, W. Modeling of the cost of EV battery wear due to V2G application in power systems. *IEEE Trans. Energy Convers.* **2011**, *26*, 1041–1050. [[CrossRef](#)]
36. Peterson, S.B.; Apt, J.; Whitacre, J.F. Lithium-ion battery cell degradation resulting from realistic vehicle and vehicle-to-grid utilization. *J. Power Sources* **2010**, *195*, 2385–2392. [[CrossRef](#)]
37. Andersson, S.L.; Elofsson, A.K.; Galus, M.D.; Goransson, L.; Karlsson, S.; Johnsson, F.; Andersson, G. Plug-in hybrid electric vehicles as regulating power providers: Case studies of Sweden and Germany. *Energy Policy* **2010**, *38*, 2751–2762. [[CrossRef](#)]
38. Shao, S.; Pipattanasomporn, M.; Rahman, S. Demand response as a load shaping tool in an intelligent grid with electric vehicles. *IEEE Trans. Smart Grid* **2011**, *2*, 624–631. [[CrossRef](#)]
39. Muñoz, E.R.; Razeghi, G.; Zhang, L.; Jabbari, F. Electric vehicle charging algorithm for coordination of the grid and distribution transformer levels. *Energy* **2016**, *113*, 930–942. [[CrossRef](#)]
40. Li, T.; Shahidehpour, M. Strategic bidding of transmission-constrained GENCOs with incomplete information. *IEEE Trans. Power Syst.* **2005**, *20*, 437–447. [[CrossRef](#)]
41. Plazas, M.A.; Conejo, A.J.; Prieto, F.J. Multimarket optimal bidding for a power producer. *IEEE Trans. Power Syst.* **2005**, *20*, 2041–2050. [[CrossRef](#)]
42. Gountis, V.P.; Bakirtzis, A.G. Bidding strategies for electricity producers in a competitive electricity marketplace. *IEEE Trans. Power Syst.* **2004**, *19*, 356–365. [[CrossRef](#)]

