Optimization of Aggregate Capacity of PEVs for Frequency Regulation Service in Day-ahead Market

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Abstract*—An aggregator can coordinate plug-in electric vehicles (PEVs) to provide frequency regulation service to an independent system operator (ISO). The aggregator can participate in the electricity markets of ISOs which provide economic incentives for PEV frequency regulation service. While the ISOs typically use forward market (e.g., day-ahead market (DAM)) to trade frequency regulation service, the available regulation capacity of an aggregator is subject to the random arrival and departure of the PEVs. In the DAM, the aggregator submits a bid to indicate its available capacity on the next day. This motivates us to study the problem of how an aggregator determines its bid in the DAM, given the uncertainty of the available regulation capacity of the PEVs. The DAM is used to trade the frequency regulation capacity in California ISO (CAISO) and New York ISO (NYISO). We consider two types of DAMs based on the market rules of CAISO and NYISO. For the first type, the exact amount of regulation capacity submitted in the DAM needs to be fulfilled on the next day. For the second type, a market participant can settle a shortage of capacity by paying a penalty to the ISO. In both cases, the aggregator can participate in the real-time market (RTM) to sell extra capacity on the next day. We formulate the problem for determining the bid using stochastic programming. As PEVs have uncertain arrival and departure times, our problem formulation incorporates risk management using the conditional value at risk. Efficient algorithms are proposed for solving the formulated problem. PEV charging data collected in Vancouver, Canada, is used in our simulations. We compare the profit of the aggregator when it participates in the markets of CAISO and NYISO. Our simulation results show that the uncertainty of the PEVs' available capacity has less effect on the profit and financial risk as the number of PEVs increases.

***Keywords*—Plug-in electric vehicles, aggregator, frequency regulation, conditional value at risk.**

I. Introduction

In recent years, there have been significant efforts to replace the combustion engine vehicles with plug-in electric vehicles (PEVs). The yearly sales of PEVs in the United States (U.S.) have increased from 17,763 to 118,882 from year 2011 to 2014 [1]. The surge in PEV sales can be partially attributed to the rapidly falling cost of batteries. From year 2007 to 2014, the cost of battery in PEVs has reduced from \$1000 per kWh to \$500 per kWh [2]. Most PEVs (pure battery electric vehicles and plug-in hybrid electric vehicles) use the electricity drawn from the power grid to reduce the consumption of fossil fuels.

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PEVs can provide frequency regulation service when they are parked and connected with the power grid. The power grid needs this service to compensate the mismatch between generation and load, and to maintain the utility frequency around a nominal value (e.g., 60 Hertz) [3]. In the current power grid of the U.S., independent system operators (ISOs) monitor the real-time utility frequency deviation and issue a frequency regulation signal every few seconds to some of the power generators. Those generators adjust their output power according to the signal. On the other hand, by exploiting the bidirectional communication systems of the emerging smart grid, PEVs have the potential to provide frequency regulation service by changing their real-time charging rate rapidly.

PEVs can provide frequency regulation service with either bidirectional or unidirectional chargers. A framework for unidirectional PEV frequency regulation service is proposed in [4] and can prevent battery degradation due to discharging. Since most of the current PEV chargers only support charging but not discharging, we consider the PEV frequency regulation service with unidirectional chargers in this paper.

The available regulation capacity of a PEV depends on its allowed charging rate. Alternating current (AC) charging is usually used for residential users. The typical charging specification in a household in the U.S. is 110V 12A/16A for the power socket (or 220V 32A for a dryer socket). The allowed charging rate of a PEV depends on both the socket and the charger. The chargers of PEVs are classified according to their maximum allowed charging rate into level 1 (≤ 1.9 kW), level 2 ($1.9-19.2$ kW), and level 3 (≥ 19.2 kW) [5]. In most cases, the charging rate of a PEV is less than 7.2 kW when it is charged at a household since a charging infrastructure which can provide higher charging rates is typically unavailable in households.

The PEV frequency regulation service is demonstrated in [6], where PEVs are able to follow the regulation signal from Pensylvania Jersey Maryland Interconnection. A model predictive control algorithm for coordinating the PEVs to track the regulation signal is proposed in [7] and the results show that PEVs can provide a substantial amount of regulation capacity. The economic analyses in [6], [8] show that PEV owners can make a profit by selling the regulation capacity of their PEVs to ISOs. The authors in [9] provide a survey on economical evaluations of PEV frequency regulation service. The analysis in [10] estimates that the daily profit of a PEV can be \$1.71 for providing frequency regulation service. The estimation of the revenue in the German market [11] is $30-80$ Euro per PEV in one month. The battery wear cost of EV frequency regulation service is evaluated in [12].

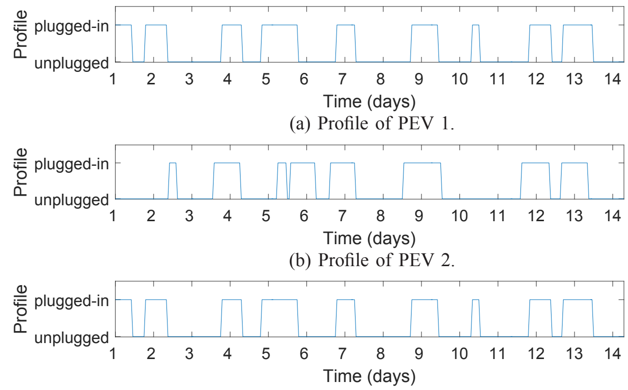
PEVs are intrinsically dispersed and each PEV has limited regulation capacity. An *aggregator* can be used to coordinate a fleet of PEVs in order to satisfy the minimum capacity (e.g., 0.1 MW [13, p. 48]) required to enter the wholesale market of an ISO. In [14], the role of the aggregator in market participation is discussed and several business models are proposed. As the hourly regulation capacity is the commodity traded in the market, it is necessary to schedule the hourly regulation capacity of the PEVs. The uncertainty of the regulation signal is taken into account in the scheduling algorithm proposed in [15]. In [16], an algorithm based on robust optimization to schedule the hourly regulation capacity is proposed. References [4], [15], [16] focus on the operation of each PEV while the uncertainty of the regulation capacity of PEVs is not fully addressed.

The available regulation capacity from a fleet of PEVs is time-varying and subject to the random times when the PEVs are plugged-in and unplugged. In [17], a stochastic model for the PEVs' regulation capacity is developed based on the hourly probability that a PEV is connected with the power grid. An algorithm to assign regulation tasks to PEVs with dynamic arrival and departure times is proposed in [18]. In [19], an algorithm to estimate the regulation capacity based on queuing theory is proposed. An online algorithm is used to handle the unknown arrival and departure time for PEV charging scheduling in [20]. The authors in [21] analyze the effect of PEV charging by taking into account the uncertainty of the PEVs' charging periods. On the other hand, the market participation of the aggregator for selling the regulation capacity has been less explored in the literature.

A. Market System

The terminology and market systems of frequency control services are different in different countries and states. The frequency control services consist of the primary, secondary, and tertiary services [11]. For ISOs in North America [22]–[24], the term frequency regulation service basically refers to the secondary frequency control service, where the ISO issues a regulation signal to service providers to restore the utility frequency. The surveys in [25], [26] compare the terminology and market systems in Europe and North America. In Germany and Sweden, monthly and weekly markets are used to trade the frequency regulation service, respectively [11]. On the other hand, the day-ahead market (DAM) and real-time market (RTM) (i.e., the two-settlement market system) are used by the ISOs in the U.S. to trade energy, frequency regulation service, and other ancillary services (i.e., the services to help the ISO to operate the electricity grid reliably) [22]–[24]. In this paper, we consider an aggregator which provides frequency regulation service and participates in the two-settlement market system.

In the two-settlement market system, on the day before the operation hours, the market participants (e.g., power plants) submit their bids in the DAM to indicate their available capacity and asking prices. For example, for California ISO (CAISO), the participants need to submit bids before 10 am on the day prior to the operation hours. The participants can bid on services which they are able to provide, including energy and various types of ancillary services. After 10 am, CAISO will close the market, perform a co-optimization of energy and ancillary services [27, p. 183], and announce the results.



(a) Profile of PEV 1.

(b) Profile of PEV 2.

(c) Profile of PEV 3.

Fig. 1. Sample profiles of PEVs' connection with the power grid. At each time instant, a PEV is either plugged-in or unplugged to the power grid. The data was collected in Vancouver, Canada in Jan. 2015 [33].

The ISO awards a contract to each winner in the DAM. For the frequency regulation service, it is interesting to note that ISOs have different market rules for this contract and we consider here two types of DAMs. For the first type of DAM, the amount of frequency regulation capacity specified in the contract awarded in the DAM needs to be exactly fulfilled on the next day. This is the case for the CAISO [22, p. 87]. On the other hand, for the second type of DAM, a market participant can settle a shortage of frequency regulation capacity and honor the contract by paying a penalty to the ISO, if necessary. This is the case for the New York ISO (NYISO) [23, p. 53]. Note that this difference in contract between DAMs is for the frequency regulation service rather than the energy.

The aggregator can sell its extra capacity in the RTM on the next day, if any. The RTM is used to trade the frequency regulation service on the basis of short time intervals. In CAISO, the RTM closes 75 minutes prior to the operating hour and the services are traded on the basis of 15 minutes.

The aggregator can participate in both the DAM and the RTM. The survey in [28] compares the market rules of the ISOs in the U.S., especially the recent progress in supporting energy storage systems to provide frequency regulation service. The participation of an aggregator in the Iberian market is analyzed in [29]. In [30], an algorithm is proposed to leverage an energy storage system for PEV charging and participate in the DAM and RTM. The bidding algorithm proposed in [31] takes into account the uncertainty of the regulation signal and the market clearing prices. The contract awarded in the DAM is considered in [32]. However, as mentioned above, in practice, there are two types of DAMs, which require different methods to determine the bid. In this paper, we are interested in the following question: *How should an aggregator determine the capacity it submits in the bid for the frequency regulation service in the DAM?*

B. Motivations and Contributions

The regulation capacity of an aggregator is made up of the scattered, uncertain, and small-scale capacities of many PEVs which makes the aggregator different from other market participants. Fig. 1 shows sample profiles of the stochastic connection periods of PEVs with the power grid. As can be observed from Fig. 1, the PEV charging sessions are stochastic and different PEVs tend to have different charging periods. Thus, it is necessary to account for the uncertainty of the arrival and departure times of the PEVs in the bid. Moreover, financial risk may arise from the randomness of the available capacity of the PEVs. The risk is the uncertainty that the profit is lower than the expected value or even becomes negative. Note that the profit can be negative when the aggregator needs to pay a penalty to honor the contract. Hence, as a market participant, it is desirable to consider the financial risk and an effective measure of the financial risk is the conditional value at risk (CVaR) [34], [35]. In summary, the aggregator is a new type of market participant with unique characteristics and requires novel algorithms to determine its bid for the frequency regulation service. The main contributions of this paper are summarized as follows:

- We model the market participation of an aggregator which coordinates the PEVs to provide frequency regulation service to an ISO. Thereby, we take into account two types of DAMs based on the market rules of CAISO and NYISO.
- We formulate the problem of determining the bid of the aggregator in the DAM using stochastic programming. Our formulation incorporates the CVaR to account for the financial risk caused by the uncertain capacity of the PEVs. Efficient algorithms for solving the formulated problem are provided.
- We evaluate the performance of the proposed algorithm using simulations based on real PEV charging data, collected in Vancouver, Canada. The historical prices for the frequency regulation service of CAISO and NYISO are used to study the two considered types of DAMs. We compare the profit and financial risk of the aggregator when it participates in the markets of CAISO and NYISO. Our results show that the impact of the uncertainty of the available capacity on the profit decreases as the number of PEVs increases.

Different from the existing works on optimal charging control of PEVs [4], [15], [16], our work focuses on the market participation of the aggregator. Our work is also different from [28]–[30] since we use a more realistic model to determine the bid in the DAM. Moreover, we study the effect of the uncertain capacity on the market participation under two types of the DAMs via analytical modeling and simulations.

This paper is organized as follows. The system model is introduced in Section II. In Section III, we present the problem formulation and develop efficient algorithms for tackling the considered problem. Simulation results are presented in Section IV, and conclusions are drawn in Section V.

II. System Model

The PEVs can provide frequency regulation service to an ISO and participate in the DAM and RTM via an aggregator. Fig. 2 illustrates the operation of the aggregator which aggregates the regulation capacity of PEVs and sells the capacity to an ISO. The aggregator first participates in the DAM and submits a bid to the ISO. A contract will be awarded by the ISO to the aggregator if the aggregator is one of the winners. According to the contract, the aggregator will provide a certain amount of regulation capacity in each hour of the next day and the ISO will reimburse the aggregator for the capacity. As the PEVs' regulation capacity is uncertain and can be different from the amount specified in the contract, in the RTM on the next day, the aggregator may sell extra capacity beyond the amount submitted in the DAM. Finally, the ISO issues a real-time frequency regulation signal to the aggregator. The aggregator sends a control signal to the PEVs by dividing the regulation signal proportionally according to the capacity of each PEV. Then, the PEVs provide the frequency regulation service by changing their real-time charging rate according to the received signal.

A. Bid of the Aggregator

In the DAM, the aggregator submits a bid to indicate its available capacity on the next day and its asking price. In particular, the aggregator needs to specify its regulation up and regulation down capacities in the bid, i.e., the amount by which the EVs' real-time charging power can be decreased and increased, respectively. We use $\mathcal{T} = \{1, \ldots, T\}$ to denote the set of operating hours on the next day. Let control variables $v^{\mathrm{up}}(t)$ and $v^{\mathrm{dn}}(t)$ denote the amount of regulation up capacity and regulation down capacity for hour $t \in \mathcal{T}$ in the bid of the aggregator, respectively. Note that the aggregator needs to submit both the capacity and the asking prices in the DAM in practice. In this paper, we assume the available capacity of the aggregator is relatively small compared to the traded capacity in the market. That is, we assume the aggregator is a price taker which accepts the market clearing prices announced by the ISO and does not try to influence the market by strategically setting its asking prices. Hence, we focus on determining the capacity $v^{\mathrm{up}}(t)$ and $v^{\mathrm{dn}}(t)$ in the DAM. We assume that the aggregator wins the bid and the ISO awards the aggregator a contract where the contract size is the same as the capacity in the bid. The contract specifies that the aggregator is responsible to provide $v^{\mathrm{up}}(t)$ regulation up capacity and $v^{\mathrm{dn}}(t)$ regulation down capacity at hour $t \in \mathcal{T}$ on the next day. We denote the set of the PEVs by $\mathcal{N} = \{1, \ldots, N\}$. The regulation up capacity and regulation down capacity of PEV $i \in \mathcal{N}$ at hour $t \in \mathcal{T}$ are denoted by $v_i^{\mathrm{up}}(t)$ and $v_i^{\mathrm{dn}}(t)$, respectively. The values of $v_i^{\mathrm{up}}(t)$ and $v_i^{\mathrm{dn}}(t)$ are uncertain when the aggregator submits its bid in the DAM. In other words, the contract requires that the aggregator provides a *certain* amount of capacity on the next day while the available capacity of the PEVs is *uncertain*.

B. The DAM and RTM

We study two types of DAMs and use a binary parameter $\theta \in \{0, 1\}$ to distinguish between them. For the first type

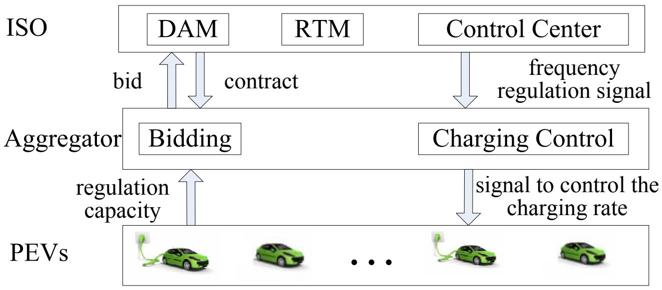


Fig. 2. The aggregator coordinates the PEVs to participate in the DAM and RTM, and provides frequency regulation service to the ISO. The aggregator needs to submit a bid to obtain a contract from the ISO in the DAM.

$(\theta=0)$, the aggregator is obliged to provide the amount of capacity specified in the contract with a probability close to one. We introduce the following chance constraints:

$$\mathbb{P}\Big(v^{\text{up}}(t) \le \sum_{i\in\mathcal{N}} v_i^{\text{up}}(t)\Big) \ge \gamma^{\text{up}}(1-\theta), \quad t\in\mathcal{T}, \tag{1}$$

$$\mathbb{P}\Big(v^{\text{dn}}(t) \le \sum_{i\in\mathcal{N}} v_i^{\text{dn}}(t)\Big) \ge \gamma^{\text{dn}}(1-\theta), \quad t\in\mathcal{T}, \tag{2}$$

where $\mathbb{P}(A)$ denotes the probability of event A. Parameters $\gamma^{\text{up}}, \gamma^{\text{dn}} \in (0,1)$ are the required confidence levels with which the PEVs can provide the capacity specified in the contract. γ^{up} and γ^{dn} take values close to one. Note that if an aggregator repeatedly fails to honor its contract, then it may not be able to participate in the market anymore, [22, p. 87]. As the participants in electricity markets are usually assessed based on their reliability [36], we use chance constraints (1) and (2) to ensure that the PEVs can provide the capacity specified in the contract with a probability close to one when $\theta=0$. In contrast, for the second type of DAM $(\theta=1)$, a shortage of the available capacity (i.e., a positive value of $v^{\text{up}}(t)-\sum_{i\in\mathcal{N}} v_i^{\text{up}}(t)$ or $v^{\text{dn}}(t)-\sum_{i\in\mathcal{N}} v_i^{\text{dn}}(t)$) is allowed and the aggregator can honor the contract by paying a penalty to the ISO according to the amount of shortage. In this case, constraints (1) and (2) are always satisfied as $\theta=1$. Note that the difference between the two types of DAMs can be explained with economic theory [37]. The contract awarded by the ISO in the DAM can be regarded as a forward contract in economics because the commodity (i.e., the regulation capacity) is delivered in the future (i.e., the next day). A forward contract can be settled in two ways, namely physical delivery and financial settlement [37]. The key difference between the two types of considered DAMs is that the contract awarded in the first type of DAM can only be settled with physical delivery while financial settlement is allowed in the second type of DAM.

The aggregator may sell extra capacity (beyond the amount submitted in the DAM) in the RTM, regardless of the type of DAM of the ISO [22], [23]. Note that ISOs typically purchase capacity in the DAM according to their estimated demand on the next day, which may deviate from their real demand. Hence, ISOs purchase additional regulation capacity occasionally in the RTM.

On the other hand, for the second type of DAM, the aggregator may pay a penalty for a shortage of capacity. This penalty is used by the ISO to purchase regulation capacity from other market participants. In fact, this penalty is calculated based on the market clearing prices in the RTM [23, p. 53], [38, p. 9]. Hence, the aggregator may have either an additional revenue or a penalty in the RTM, which needs to be considered to calculate its profit.

C. Profit of the Aggregator

The profit of the aggregator has three components. The first component is the revenue earned in the DAM. Let $p_{\text{dam}}^{\text{up}}(t)$ and $p_{\text{dam}}^{\text{dn}}(t)$ denote the prices of the regulation up capacity and regulation down capacity at hour $t\in\mathcal{T}$ in the DAM, respectively. The second component of the aggregator's profit is the revenue or penalty in the RTM. We denote the average prices of the regulation up capacity and the regulation down capacity at hour t in the RTM by $p_{\text{rtm}}^{\text{up}}(t)$ and $p_{\text{rtm}}^{\text{dn}}(t)$, respectively. Note that a short time interval is typically used in the RTM, such as five minutes. Prices $p_{\text{rtm}}^{\text{up}}(t)$ and $p_{\text{rtm}}^{\text{dn}}(t)$ can be obtained by averaging the market clearing prices in the RTM over the time intervals within hour t. We assume the aggregator is able to sell its capacity in the RTM when $p_{\text{rtm}}^{\text{up}}(t), p_{\text{rtm}}^{\text{dn}}(t) > 0$. On the other hand, if the ISO has no demand for regulation capacity in the RTM in hour t, then $p_{\text{rtm}}^{\text{up}}(t), p_{\text{rtm}}^{\text{dn}}(t) = 0$ and the revenue in the RTM is zero. The third component of the aggregator's profit are the payments by the aggregator to the PEVs. We use $p_{\text{ev}}^{\text{up}}(t)$ and $p_{\text{ev}}^{\text{dn}}(t)$ to denote the prices that the aggregator pays for the regulation up capacity and regulation down capacity of a PEV at hour t, respectively. The values of $p_{\text{ev}}^{\text{up}}(t)$ and $p_{\text{ev}}^{\text{dn}}(t)$ depend on the agreement between the aggregator and the PEVs. We assume that each PEV receives a payment according to its available capacity. Let r denote the profit of the aggregator, which is given by

$$\begin{aligned} r = \sum_{t\in\mathcal{T}} \Bigg(& p_{\text{dam}}^{\text{up}}(t) v^{\text{up}}(t) + p_{\text{dam}}^{\text{dn}}(t) v^{\text{dn}}(t) \\ & + (1-\theta)\Big(p_{\text{rtm}}^{\text{up}}(t)\Big(\sum_{i\in\mathcal{N}} v_i^{\text{up}}(t) - v^{\text{up}}(t)\Big)^+ \\ & \qquad + p_{\text{rtm}}^{\text{dn}}(t)\Big(\sum_{i\in\mathcal{N}} v_i^{\text{dn}}(t) - v^{\text{dn}}(t)\Big)^+ \Big) \\ & + \theta\Big(p_{\text{rtm}}^{\text{up}}(t)\Big(\sum_{i\in\mathcal{N}} v_i^{\text{up}}(t) - v^{\text{up}}(t)\Big) \\ & \qquad + p_{\text{rtm}}^{\text{dn}}(t)\Big(\sum_{i\in\mathcal{N}} v_i^{\text{dn}}(t) - v^{\text{dn}}(t)\Big)\Big) \\ & - \Big(p_{\text{ev}}^{\text{up}}(t) \sum_{i\in\mathcal{N}} v_i^{\text{up}}(t) + p_{\text{ev}}^{\text{dn}}(t) \sum_{i\in\mathcal{N}} v_i^{\text{dn}}(t)\Big)\Bigg), \end{aligned} \tag{3}$$

where $(x)^+ = \max\{x,0\}$. The first line in (3) is the revenue earned in the DAM. The second and third lines in (3) denote the revenue in the RTM for the first type of DAM $(\theta=0)$. On the other hand, for the second type of DAM $(\theta=1)$, the revenue or penalty in the RTM is given by the fourth and fifth lines in (3). The sixth line is the payment from the aggregator to the PEVs. The capacities $v^{\text{up}}(t)$ and $v^{\text{dn}}(t)$ are control variables for the aggregator. The prices $(p^{\text{up}}_{\text{dam}}(t), p^{\text{dn}}_{\text{dam}}(t))$ and $(p^{\text{up}}_{\text{rtm}}(t), p^{\text{dn}}_{\text{rtm}}(t))$ are announced by the ISO in the DAM and the RTM, respectively. Hence, $p^{\text{up}}_{\text{dam}}(t)$, $p^{\text{dn}}_{\text{dam}}(t)$, $p^{\text{up}}_{\text{rtm}}(t)$, and $p^{\text{dn}}_{\text{rtm}}(t)$ are uncertain input parameters for the aggregator.

III. Problem Formulation and Algorithm

In this section, we formulate an optimization problem for the aggregator to determine its bid in the DAM based on an optimality criterion regarding its profit. Thereby, we consider two metrics for the profit, namely the expected profit and the financial risk, where the risk is measured by the CVaR. In practice, the market participants not only consider their expected profit but also tend to choose an option which leads to a lower financial risk compared to other options. In economics, risk aversion is used to model the attitude of market participants who are reluctant to financial risk and prefer a steady payoff. Therefore, risk aversion is accounted for in our problem formulation. Our formulation also takes into account the random arrival and departure times of the PEVs, and the uncertainty of the prices.

A. Risk-Averse Bid of the Aggregator

We consider an aggregator with risk aversion. Hence, both the expected profit and the CVaR are included in the objective function. Let $\alpha \in (0,1)$ denote an arbitrary confidence level. The *value at risk* (VaR_α) is the largest value of an auxiliary variable η for which the probability that the profit in (3) is less than η is less than or equal to 1–α, i.e., $\text{VaR}_\alpha = \max\{\eta \mid \mathbb{P}(r < \eta) \leq 1-\alpha\}$. The CVaR_α is defined based on VaR_α as the expected profit for the cases when the profit is not more than VaR_α [34]. That is,

$$\text{CVaR}_\alpha = \underset{r \leq \text{VaR}_\alpha}{\mathbb{E}}(r), \tag{4}$$

where $\mathbb{E}$ denotes expectation with respect to random variables $p^{\text{up}}_{\text{dam}}(t)$, $p^{\text{dn}}_{\text{dam}}(t)$, $p^{\text{up}}_{\text{rtm}}(t)$, $p^{\text{dn}}_{\text{rtm}}(t)$, $\sum_{i\in\mathcal{N}} v_i^{\text{up}}(t)$, and $\sum_{i\in\mathcal{N}} v_i^{\text{dn}}(t)$, $t \in \mathcal{T}$. Note that both VaR_α and CVaR_α are metrics for the financial risk and we use CVaR_α in this paper because it accounts for the profit beyond the confidence level α. In the DAM, the aggregator submits a bid which contains the capacity of the 24 hours of the next day. The problem for determining the bid is formulated as follows

$$\begin{aligned}
&\underset{v^{\text{up}}(t),\, v^{\text{dn}}(t),\, t\in\mathcal{T}}{\text{maximize}} && (1-\beta)\,\mathbb{E}(r) + \beta\,\text{CVaR}_\alpha && \text{(5a)}\\
&\text{subject to} && v^{\text{up}}(t), v^{\text{dn}}(t) \geq 0, \quad t \in \mathcal{T}, && \text{(5b)}\\
& && \text{constraints (1) and (2).} && \text{(5c)}
\end{aligned}$$

Note that we use the approach in [34] where CVaR_α represents the tail profit. We aim to maximize the weighted sum of the expected profit and CVaR_α in the objective function in (5a). Parameter $\beta \in [0,1]$ is a tunable parameter which adjusts the weight of the expected profit $\mathbb{E}(r)$ and CVaR_α. Increasing β puts more weight on CVaR_α and improves the profit in unfavorable cases (the cases where the profit is low). Decreasing β puts more weight on the expected profit and less weight on CVaR_α. When $\beta = 0$, the aggregator aims to maximize the expected profit and neglects the financial risk. This special case can be used to model a risk-neutral aggregator.

Problem (5) has CVaR_α in its objective function. CVaR_α is typically calculated in a scenario-based manner [34], [35]. A scenario is a possible realization of the random input parameters from the ISO ($p^{\text{up}}_{\text{dam}}(t)$, $p^{\text{dn}}_{\text{dam}}(t)$, $p^{\text{up}}_{\text{rtm}}(t)$, $p^{\text{dn}}_{\text{rtm}}(t)$) and the PEVs ($\sum_{i\in\mathcal{N}} v_i^{\text{up}}(t)$, $\sum_{i\in\mathcal{N}} v_i^{\text{dn}}(t)$). The historical prices of the ISO from the past days [39] can be used to generate the values of $p^{\text{up}}_{\text{dam}}(t)$, $p^{\text{dn}}_{\text{dam}}(t)$, $p^{\text{up}}_{\text{rtm}}(t)$, and $p^{\text{dn}}_{\text{rtm}}(t)$ in different scenarios. On the other hand, the aggregator needs to estimate the available capacity of the PEVs on the next day. In particular, possible values of the regulation capacity of a PEV can be obtained based on its historical charging session records. Then, the aggregate capacities $\sum_{i\in\mathcal{N}} v_i^{\text{up}}(t)$ and $\sum_{i\in\mathcal{N}} v_i^{\text{dn}}(t)$ for different scenarios can be generated accordingly (c.f. Section III-B). Let $\mathcal{K}$ denote the set of scenarios and $|\mathcal{K}|$ its cardinality. Let $\mathbb{P}(\boldsymbol{\omega}_k)$ denote the probability of scenario $\boldsymbol{\omega}_k$. We use $\boldsymbol{\omega}_k$, $k \in \mathcal{K}$, to denote the kth scenario. $r(\boldsymbol{\omega}_k)$ denotes the profit under scenario $\boldsymbol{\omega}_k$. We rewrite problem (5) as follows [34]

$$\begin{aligned}
&\underset{\substack{\eta,\, v^{\text{up}}(t),\\ v^{\text{dn}}(t),\, t\in\mathcal{T}}}{\text{maximize}} && \Big((1-\beta)\,\mathbb{P}(\boldsymbol{\omega}_k)\sum_{k\in\mathcal{K}} r(\boldsymbol{\omega}_k) \\
& && + \beta\big(\eta - \frac{\mathbb{P}(\boldsymbol{\omega}_k)}{1-\alpha}\sum_{k\in\mathcal{K}}(\eta - r(\boldsymbol{\omega}_k))^+\big)\Big) && \text{(6a)}\\
&\text{subject to} && \text{constraints (1), (2), and (5b),} && \text{(6b)}
\end{aligned}$$

where the expression $\eta - \frac{\mathbb{P}(\boldsymbol{\omega}_k)}{1-\alpha}\big(\sum_{k\in\mathcal{K}}(\eta - r(\boldsymbol{\omega}_k))^+\big)$ is used as a scenario-based estimate of CVaR_α [34]. We introduce auxiliary variables $\phi(\boldsymbol{\omega}_k), k \in \mathcal{K}$, to denote the value of $(\eta - r(\boldsymbol{\omega}_k))^+$. Problem (6) can be rewritten as

$$\begin{aligned}
&\underset{\substack{\eta,\, \phi(\boldsymbol{\omega}_k),\, k\in\mathcal{K},\\ v^{\text{up}}(t),\, v^{\text{dn}}(t),\\ t\in\mathcal{T}}}{\text{maximize}} && \Big((1-\beta)\,\mathbb{P}(\boldsymbol{\omega}_k)\sum_{k\in\mathcal{K}} r(\boldsymbol{\omega}_k) \\
& && + \beta\big(\eta - \frac{\mathbb{P}(\boldsymbol{\omega}_k)}{1-\alpha}\sum_{k\in\mathcal{K}}\phi(\boldsymbol{\omega}_k)\big)\Big) && \text{(7a)}\\
&\text{subject to} && \phi(\boldsymbol{\omega}_k) \geq \eta - r(\boldsymbol{\omega}_k), \quad k\in\mathcal{K}, && \text{(7b)}\\
& && \phi(\boldsymbol{\omega}_k) \geq 0, \quad k\in\mathcal{K}, && \text{(7c)}\\
& && \text{constraints (1), (2), and (5b).} && \text{(7d)}
\end{aligned}$$

Constraints (7b) and (7c) ensure that $\phi(\boldsymbol{\omega}_k) \geq (\eta - r(\boldsymbol{\omega}_k))^+$. As the objective function (7a) is decreasing with respect to $\phi(\boldsymbol{\omega}_k)$, the optimal solution of problem (7) is obtained only if either $\phi(\boldsymbol{\omega}_k) = \eta - r(\boldsymbol{\omega}_k)$ or $\phi(\boldsymbol{\omega}_k) = 0$. We study two cases for problem (7) and its chance constraints (1) and (2). First, when $\theta = 1$, the right hand side of constraints (1) and (2) become 0 and the constraints are always satisfied. However, when $\theta = 0$, i.e., for the first type of DAM, chance constraints (1) and (2) make problem (7) difficult to solve. The probabilities in constraints (1) and (2) are not amenable to an efficient solution and it is even difficult to validate whether a solution is feasible for chance constraints. In the literature, chance constraints are usually tackled using approximation methods [40]–[44]. The Bernstein approximation is used to tackle chance constraints in [40], [41]. It requires knowledge of the moment generating functions of the unknown parameters and these functions are hard to obtain for problem (7). In this paper, we use the framework in [42]–[44] to handle the chance constraints. The basic idea is to generate independent samples of the unknown parameters and then find a solution which satisfies the chance constraints in these scenarios. Using the framework in [42]–[44], we obtain the following problem:

$$\underset{\substack{\eta,\,\phi(\boldsymbol{\omega}_k),\,k\in\mathcal{K},\\ v^{\text{up}}(t),\,v^{\text{dn}}(t),\\ t\in\mathcal{T}}}{\text{maximize}} \quad \Big((1-\beta)\,\mathbb{P}(\boldsymbol{\omega}_k)\sum_{k\in\mathcal{K}} r(\boldsymbol{\omega}_k) + \beta\big(\eta - \frac{\mathbb{P}(\boldsymbol{\omega}_k)}{1-\alpha}\sum_{k\in\mathcal{K}}\phi(\boldsymbol{\omega}_k)\big)\Big) \tag{8a}$$

$$\text{subject to} \quad v^{\text{up}}(t) \le \sum_{i\in\mathcal{N}} v^{\text{up}}_{i,k}(t), \quad t\in\mathcal{T}, \quad k\in\mathcal{K}, \tag{8b}$$

$$v^{\text{dn}}(t) \le \sum_{i\in\mathcal{N}} v^{\text{dn}}_{i,k}(t), \quad t\in\mathcal{T}, \quad k\in\mathcal{K}, \tag{8c}$$

$$\text{constraints (5b), (7b), and (7c),} \tag{8d}$$

where $v^{\text{up}}_{i,k}(t)$ and $v^{\text{dn}}_{i,k}(t)$ are the regulation up capacity and regulation down capacity of PEV i at hour t under scenario k. Problem (8) is a linear programming problem which approximates chance constraints (1) and (2) using scenario-based constraints (8b) and (8c), respectively. An interesting problem is how many scenarios are needed in order to approximate the chance constraints. According to [42]–[44], if $\mathbb{P}(\boldsymbol{\omega}_k) = \frac{1}{|\mathcal{K}|}$, we can select the number of scenarios as

$$|\mathcal{K}| \ge \left\lceil \frac{1}{1-\gamma}\left(B-1+\ln\frac{1}{\delta}+\sqrt{2(B-1)\ln\frac{1}{\delta}+\ln^2\frac{1}{\delta}}\right)\right\rceil, \tag{9}$$

where B is the number of variables in the chance constraint and $\gamma = \max\{\gamma^{\text{up}}, \gamma^{\text{dn}}\}$. $\delta\in(0,1]$ is a constant. If we select the number of scenarios according to (9), then the solution obtained in problem (8) will satisfy chance constraints (1) and (2) with a probability which is not less than $1-\delta$. We can set $\gamma^{\text{up}} = \gamma^{\text{dn}} = 0.95$, $\delta = 0.01$ and generate 185 scenarios such that chance constraints (1) and (2) are satisfied with a probability which is not less than 99%.

B. Aggregate Regulation Capacity of PEVs

The regulation capacity of an aggregator is the sum of the uncertain capacities of many PEVs. Possible values of the uncertain capacity of an individual PEV can be derived based on the historical records of its charging sessions. Let $\mathcal{L}_i$ denote the set of recent records for PEV $i\in\mathcal{N}$ in the past J days. A record of charging session $l\in\mathcal{L}_i$ contains the time $\hat{t}^a_{i,l}$ when the PEV charger is plugged-in, the time $\hat{t}^d_{i,l}$ when the charger is unplugged, the initial state of charge (SOC) $s^a_{i,l}$, and the SOC $s^d_{i,l}$ when it departs.

For simplicity of notation, we use term $\hat{t}$ to denote the index of hour during J days whereas t is the index of hour in one day. That is, $\hat{t}\in\{1,\dots,24\times J\}$ and $t\in\{1,\dots,24\}$. Let $p^e(\hat{t})$ denote the prices of charged energy at hour $\hat{t}$. We denote the regulation up component and the regulation down component of the regulation signal at hour $\hat{t}$ by $f^{\text{up}}(\hat{t}) = \frac{1}{|\Phi|}\sum_{\tau\in\Phi}\max\{q(\hat{t},\tau),0\}$ and $f^{\text{dn}}(\hat{t}) = \frac{1}{|\Phi|}\sum_{\tau\in\Phi}\max\{-q(\hat{t},\tau),0\}$, respectively, where $q(\hat{t},\tau)\in[-1,1]$ denotes the regulation signal at time slot $\tau\in\Phi$ at hour $\hat{t}$ under record l. Here, Φ is the set of time slots within one hour. On the other hand, the maximum hourly charged energy of PEV i, the battery capacity of PEV i, the SOC of PEV i, and the price of the charged energy at hour $\hat{t}$ are denoted by $e^{\max}_i$, b_i, $s_i(\hat{t})$, and $p^e(\hat{t})$, respectively.

Let $\hat{v}^{\text{up}}_{i,l}(\hat{t})$ and $\hat{v}^{\text{dn}}_{i,l}(\hat{t})$ denote the regulation up capacity and the regulation down capacity of PEV i at hour $\hat{t}$ given record l, respectively. Constant $\mu>0$ denotes a coefficient weighing the SOC at departure time, compared to the monetary profit. The regulation capacity of PEV $i\in\mathcal{N}$ for record $l\in\mathcal{J}_i$ can be obtained as

$$(\hat{v}^{\text{up}}_{i,l}(\hat{t}),\hat{v}^{\text{dn}}_{i,l}(\hat{t}),\hat{t}\in[\hat{t}^a_{i,l},\hat{t}^d_{i,l}])^* = \underset{\substack{\hat{v}^{\text{up}}_{i,l}(\hat{t}),\,\hat{v}^{\text{dn}}_{i,l}(\hat{t}),\\ \hat{t}\in[\hat{t}^a_{i,l},\hat{t}^d_{i,l}]}}{\text{argmax}} \sum_{\hat{t}\in[\hat{t}^a_{i,l},\hat{t}^d_{i,l}]} \Big(\hat{v}^{\text{up}}_{i,l}(\hat{t})p^{\text{up}}_{\text{ev}}(\hat{t}) + \hat{v}^{\text{dn}}_{i,l}(\hat{t})p^{\text{dn}}_{\text{ev}}(\hat{t}) - p^e(\hat{t})(x_{i,l}(\hat{t}) - f^{\text{up}}(\hat{t})\hat{v}^{\text{up}}_{i,l}(\hat{t}) + f^{\text{dn}}(\hat{t})\hat{v}^{\text{dn}}_{i,l}(\hat{t}))\Big) + \mu\, s(\hat{t}^d_{i,l}) \tag{10a}$$

$$\text{subject to} \quad x_{i,l}(\hat{t}) + \hat{v}^{\text{dn}}_{i,l}(\hat{t}) \le e^{\max}_i, \quad \hat{t}\in[\hat{t}^a_{i,l},\hat{t}^d_{i,l}], \tag{10b}$$

$$x_{i,l}(\hat{t}) - \hat{v}^{\text{up}}_{i,l}(\hat{t}) \ge 0, \quad \hat{t}\in[\hat{t}^a_{i,l},\hat{t}^d_{i,l}], \tag{10c}$$

$$\hat{v}^{\text{up}}_{i,l}(\hat{t}),\ \hat{v}^{\text{dn}}_{i,l}(\hat{t}) \ge 0, \quad \hat{t}\in[\hat{t}^a_{i,l},\hat{t}^d_{i,l}], \tag{10d}$$

$$s_i(\hat{t}^a_{i,l}) = s^a_{i,l}, \tag{10e}$$

$$s_i(\hat{t}+1) = s_i(\hat{t}) + \tfrac{1}{b_i}\Big(x_{i,l}(\hat{t}) - \hat{v}^{\text{up}}_{i,l}(\hat{t})f^{\text{up}}(\hat{t}) + \hat{v}^{\text{dn}}_{i,l}(\hat{t})f^{\text{dn}}(\hat{t})\Big), \quad \hat{t}\in[\hat{t}^a_{i,l},\hat{t}^d_{i,l}), \tag{10f}$$

$$s(\hat{t}^d_{i,l}) \ge s^d_{i,l}, \tag{10g}$$

where $x_{i,l}(\hat{t})$ is the baseline charging rate of PEV i at hour $\hat{t}$ under record l. $f^{\text{up}}(\hat{t})\hat{v}^{\text{up}}_{i,l}(\hat{t})$ and $f^{\text{dn}}(\hat{t})\hat{v}^{\text{dn}}_{i,l}(\hat{t})$ are the decrease and increase of the charged energy within hour $\hat{t}$ due to the regulation up service and the regulation down service, respectively. Hence, $x_{i,l}(\hat{t}) - f^{\text{up}}(\hat{t})\hat{v}^{\text{up}}_{i,l}(\hat{t}) + f^{\text{dn}}(\hat{t})\hat{v}^{\text{dn}}_{i,l}(\hat{t})$ denotes the charged energy in hour $\hat{t}$ of PEV i. The term $\mu s(\hat{t}^d_{i,l})$ is introduced to model the effect of charging during the interval $[\hat{t}^a_{i,l},\hat{t}^d_{i,l}]$ in the future. Constraints (10b) and (10c) ensure that the regulation capacity of the PEVs are within their maximum and minimum charging rate. Constraint (10f) models the hourly update of the SOC of PEVs. Constraint (10g) ensures that the PEV has charged sufficient energy at its departure. Note that problem (10) is formulated on an hourly basis because the hourly regulation capacity is traded in the DAM. Problem (10) can be solved as a stochastic program [45] to obtain possible values of the regulation capacity of PEV i for each scenario.

A PEV may have multiple or zero records in one day. Let $\mathcal{J} = \{1,\dots,J\}$ denote the set of J days during which the records were obtained. We introduce term $j\in\mathcal{J}$ to denote the index of day. Let $v^{\text{up}}_{i,j}(t)$ and $v^{\text{dn}}_{i,j}(t)$ denote the regulation up capacity and regulation down capacity at day $j\in\{1,\dots,J\}$. Now, we need to map the capacity for each record $(\hat{v}^{\text{up}}_{i,l}(\hat{t}),\hat{v}^{\text{dn}}_{i,l}(\hat{t}))$ to the capacity for each day

Algorithm 1 Bidding algorithm executed by the aggregator on the day before the operation hours

Initialize θ, γ^{up}, γ^{dn}, α, β, μ, $\mathcal{T}$, $\mathcal{N}$, and $\mathcal{K}$
Call cloud servers to execute Algorithm 2 for each PEV and obtain matrices $\mathbf{G}_i, i \in \mathcal{N}$
Construct scenarios $\boldsymbol{\omega}_k, k \in \mathcal{K}$, based on matrices $\mathbf{G}_i, i \in \mathcal{N}$, and the historical prices in the past days from the ISO
Solve problem (8) as a stochastic program to obtain $v^{\text{up}}(t)$ and $v^{\text{dn}}(t)$, $t \in \mathcal{T}$
Submit $v^{\text{up}}(t)$ and $v^{\text{dn}}(t), t \in \mathcal{T}$, to the ISO

Algorithm 2 EV capacity scheduling algorithm executed in cloud servers for PEV $i \in \mathcal{N}$ when called by the aggregator

Initialize $e_i^{\max}$ and b_i
Generate values of $\hat{t}^a_{i,l}$, $\hat{t}^d_{i,l}$, $s^a_{i,l}$, $s^d_{i,l}$, $p^e(\hat{t})$, $f^{\text{up}}(\hat{t})$, and $f^{\text{dn}}(\hat{t})$, $l \in \mathcal{L}_i$, based on the historical records of the charging sessions of PEV i
for all $l \in \mathcal{L}_i$ **do**
    Solve problem (10) as a stochastic program to obtain $v^{\text{up}}_{i,l}(\hat{t})$ and $v^{\text{dn}}_{i,l}(\hat{t})$, $\hat{t} \in [\hat{t}^a_{i,l}, \hat{t}^d_{i,l}]$
end for
Calculate $\mathbf{G}_i$ according to (12) and report $\mathbf{G}_i$ to the aggregator

$(v^{\text{up}}_{i,j}(t), v^{\text{dn}}_{i,j}(t))$:

$$(v^{\text{up}}_{i,j}(t), v^{\text{dn}}_{i,j}(t)) = \begin{cases} (\hat{v}^{\text{up}}_{i,l}(t+24(j-1)), \hat{v}^{\text{dn}}_{i,l}(t+24(j-1))), \\ \qquad\qquad \text{if } t+24(j-1) \in [\hat{t}^a_{i,l}, \hat{t}^d_{i,l}], \\ \qquad\qquad \text{for } j \in \{1, \ldots, J\}, \quad l \in \mathcal{L}_i, \\ (0,0), \qquad \text{otherwise}. \end{cases} \tag{11}$$

We use a $J \times 48$ matrix $\mathbf{G}_i$ to collect the values of the regulation capacity of PEV i for each hour in the past J days, i.e.,

$$\mathbf{G}_i = \begin{bmatrix} v^{\text{up}}_{i,1}(1) & v^{\text{dn}}_{i,1}(1) & \cdots & v^{\text{dn}}_{i,1}(24) \\ \vdots & \vdots & \vdots & \vdots \\ v^{\text{up}}_{i,J}(1) & v^{\text{dn}}_{i,J}(1) & \cdots & v^{\text{dn}}_{i,J}(24) \end{bmatrix}. \tag{12}$$

When the aggregator has received matrices $\mathbf{G}_i, i \in \mathcal{N}$, it generates scenarios for problem (8) by randomly selecting values of $v^{\text{up}}_i(t)$ and $v^{\text{dn}}_i(t)$ based on matrices $\mathbf{G}_i$.

The algorithms to determine the bid are presented in Algorithms 1 and 2. The aggregator executes Algorithm 1 and calls cloud servers to execute Algorithm 2 to obtain possible values of the regulation capacities of the PEVs (i.e., the matrices $\mathbf{G}_i, i \in \mathcal{N}$). The client-server model can be used for calculation of the possible PEV regulation capacities such that these values are available even when the PEVs are not connected with the power grid. The PEVs report their historical records of charging sessions to the server in the cloud computing infrastructure (e.g., Amazon Web Services [46]) via communication systems and these records are stored in the database of the servers. When called by the aggregator, the cloud servers execute Algorithm 2 for each PEV to obtain matrices $\mathbf{G}_i, i \in \mathcal{N}$, and send the results to the aggregator. Then, the aggregator continues the execution of Algorithm 1, determines the values of $v^{\text{up}}(t)$ and $v^{\text{dn}}(t)$, and submits the values to the ISO. On the other hand, the aggregator may also participate in the RTM on the next day. In the RTM, the aggregator reports $v^{\text{up}}(t) - \sum_{i \in \mathcal{N}} v^{\text{up}}_i(t)$ and $v^{\text{dn}}(t) - \sum_{i \in \mathcal{N}} v^{\text{dn}}_i(t)$ to the ISO. If these values are positive, which means the aggregator has extra capacity, the ISO may purchase this capacity and compensate the aggregator. If these values are negative and $\theta = 1$, the ISO may charge a penalty to the aggregator, according to the market clearing prices in the RTM.

IV. Performance Evaluation

We evaluate the performance of the proposed algorithms with real data collected in Vancouver, Canada [33][1]. There were 2026 records available for our study. Each record contains several tags including the time when the PEV charger was plugged-in, the time when the PEV charger was unplugged, and the amount of charged energy. These records are used in our simulation study to mimic the charging sessions of the PEVs. An empirical probability density function of the charged energy is obtained from the records and shown in Fig. 3. For the charging period, i.e., the length of time that the PEV charger is plugged, the expected value is 14.545 hours while the standard deviation is 6.06 hour. The average arrival time is around 1 pm while the standard deviation is 3.41 hour. Note that the data were collected by the PEVs on campus. These PEVs were used by campus staff to perform their work instead of commuting. In the following, we consider a fleet of 1000 PEVs. Each PEV has a battery capacity of 24 kWh [47]. The maximum hourly charged energy is assumed to be 6 kWh, which is a typical charging rate of a level 2 charger. The prices of the frequency regulation service in the DAM and RTM in CAISO [48] and NYISO [39] are used in our simulations to study the two considered types of DAMs. Fig. 4 shows samples of the prices in Jan. 2015 from CAISO and NYISO. We used the prices from CAISO when $\theta = 0$ and the prices from NYISO when $\theta = 1$, respectively, since CAISO uses the first type of DAM while the second type of DAM is used by NYISO. In our simulations, we assume $p^{\text{up}}_{\text{ev}}(t) = 0.6\mathbb{E}[p^{\text{up}}_{\text{dam}}(t)]$ and $p^{\text{dn}}_{\text{ev}}(t) = 0.6\mathbb{E}[p^{\text{dn}}_{\text{dam}}(t)]$ in (3). We set $\alpha = 0.9$, $\beta = 0.2$, and $\mu = 2$ in our algorithm unless stated otherwise.

We simulated the expected profit and the financial risk of the aggregator when it participates in the markets of CAISO and NYISO. The results are shown in Figs. 5 and 6. The aggregator is able to obtain a higher profit in NYISO compared to the case when it participates in the market of CAISO. In particular, when the maximum hourly charged energy is 6 kWh, the daily profit is \$45.2 and \$21.1 for NYISO and CAISO, respectively. The profit increases as the maximum hourly charged energy increases because a higher charging rate enables PEVs to provide a larger frequency regulation capacity. The profit gradually saturates when the maximum hourly charged energy becomes very large because the frequency regulation capacity

[1] The available data belongs to an "EV cloud" project in the province of British Columbia in Canada. Public PEV charging stations installed in the province are connected with a database via the cellular network. A small subset of detailed data, which were collected on campus, was available for our study.

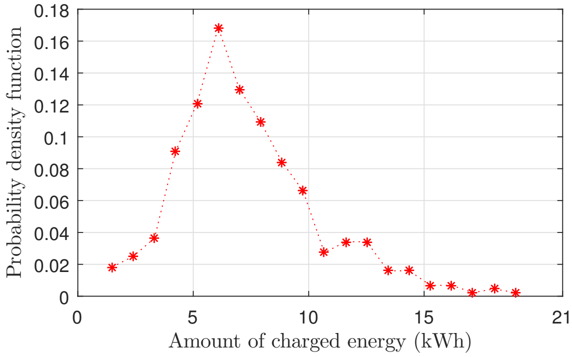
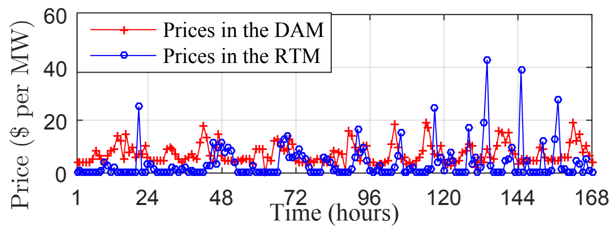
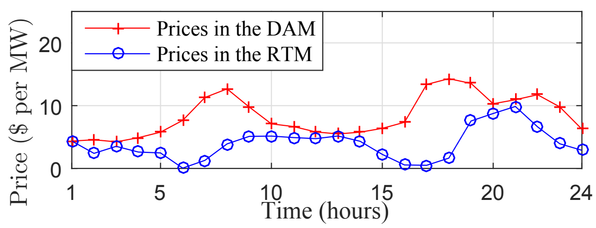


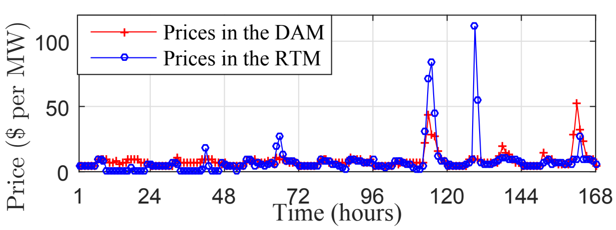
Fig. 3. The empirical probability density function of the energy charged per charging session. The battery capacity of the PEVs which are used to obtain the data is 24 kWh.



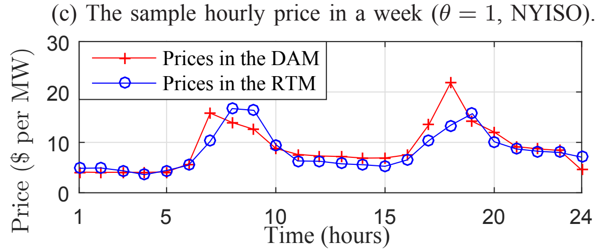
(a) The sample hourly price in a week ($\theta = 0$, CAISO).



(b) The average hourly price in a day ($\theta = 0$, CAISO).



(c) The sample hourly price in a week ($\theta = 1$, NYISO).



(d) The average hourly price in a day ($\theta = 1$, NYISO).

Fig. 4. The prices in the DAM and RTM for the frequency regulation service in CAISO and NYISO. The average hourly price is obtained based on the prices during Jan. 1, 2015 to Jan. 31, 2015. The y-axis is the sum of the prices of the regulation up and regulation down capacities.

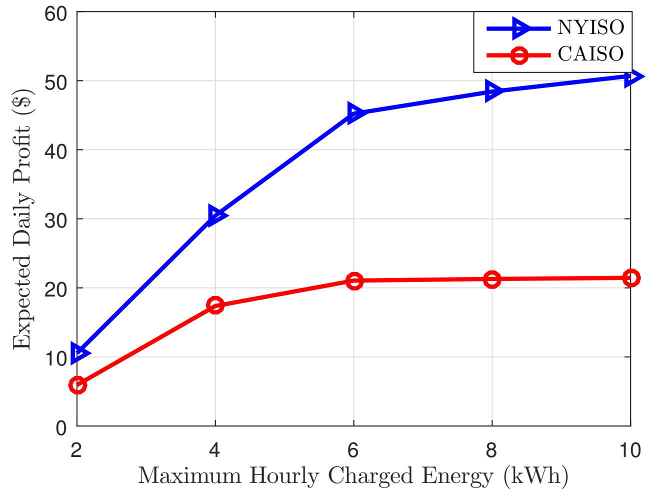


Fig. 5. Expected daily profit versus maximum hourly charged energy.

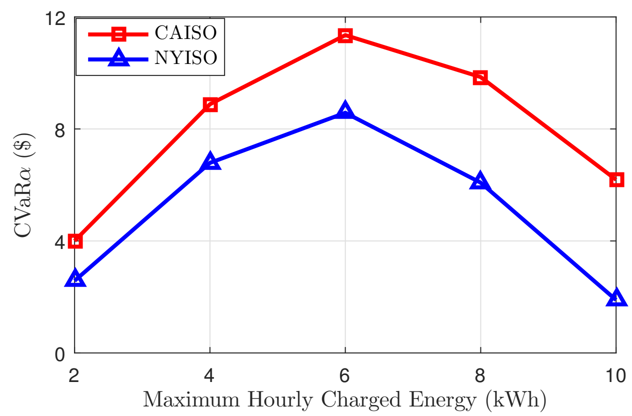


Fig. 6. CVaR$_\alpha$ versus maximum hourly charged energy.

is also limited by the charging demand, when PEVs are using unidirectional chargers. Fig. 6 shows the CVaR$_\alpha$ as a function of the maximum hourly charged energy. When the maximum hourly charged energy is 6 kWh, the CVaR$_\alpha$ of the aggregator is \$11.4 and \$8.6 for NYISO and CAISO, respectively. As the maximum hourly charged energy increases, the CVaR$_\alpha$ first increases and then decreases when the maximum hourly charged energy exceeds 6 kWh. This is because a large maximum hourly charged energy tends to increase both the expected available regulation capacity and the uncertainty of the available regulation capacity. On the other hand, CVaR$_\alpha$ decreases with respect to the uncertainty of the available capacity.

Next, we study the effect of the number of PEVs on the market participation of the aggregator. Fig. 7 shows the expected profit of the aggregator divided by the number of PEVs as a function of the number of PEVs. The CVaR$_\alpha$ of the aggregator divided by number of PEVs is shown in Fig. 8. As can be observed from Figs. 7 and 8, as the number of PEVs increases, both the profit of the aggregator divided by number of PEVs and the CVaR$_\alpha$ of the aggregator divided by number of PEVs increase (i.e., the financial risk decreases). The results in Figs. 7 and 8 show that using an aggregator as an agent to represent a large number of PEVs for market participation can improve the profit and reduce the financial risk. This is because the uncertainty of the available regulation

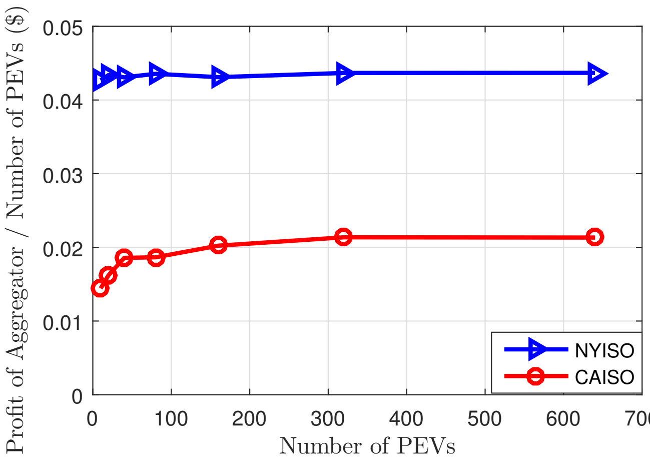


Fig. 7. Expected daily profit of aggregator divided by the number of PEVs versus the number of PEVs.

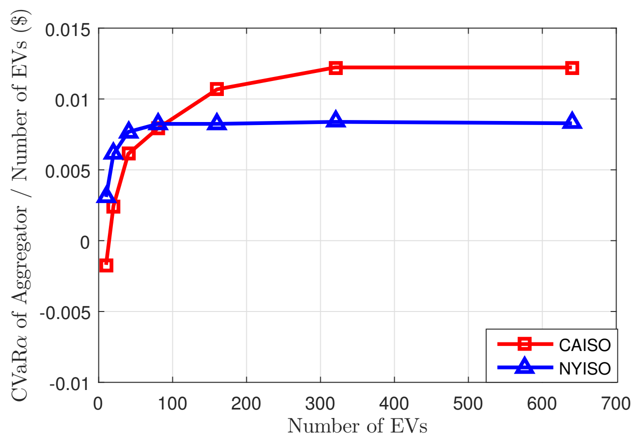
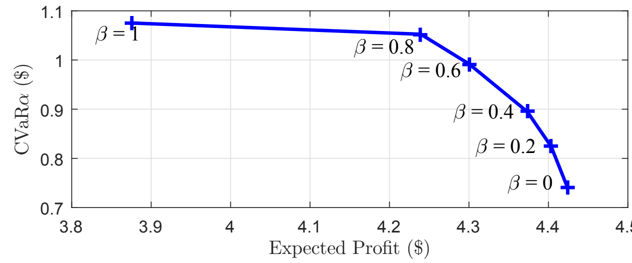


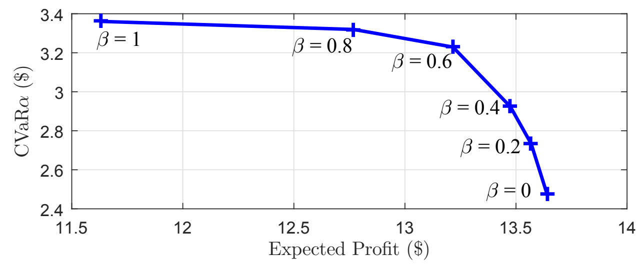
Fig. 8. CVaR_α of aggregator divided by the number of PEVs versus the number of PEVs.

capacity is reduced as the number of PEVs increases. We also observe that the effect of the uncertain capacity of the PEVs on the profit and CVaR_α is larger for an aggregator participating in the markets of CAISO compared to the markets of NYISO. This is because CAISO requires that the aggregator must be able to fulfill the capacity submitted in DAM, which makes the bidding more sensitive to the uncertainty of the available capacity.

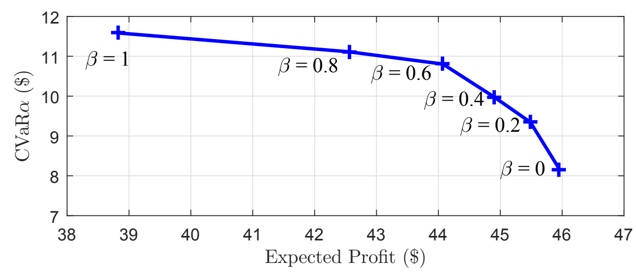
We also analyze the tradeoff between the expected profit and the CVaR_α. The tradeoff can be depicted with an efficient frontier [34], which comprises a set of efficient points. An efficient point is a pair of expected profit and CVaR_α such that it is impossible to improve one of them without reducing the other one [34]. We are able to obtain the efficient frontier when $\theta = 1$ (because the optimal solution of problem (5) can be obtained when $\theta = 1$). The efficient frontier is shown in Fig. 9. As can be observed from Fig. 9, the tradeoff between the expected profit and the CVaR_α can be tuned using parameter β. As β decreases, the expected profit increases while the CVaR_α decreases. Moreover, the efficient frontier depends on the number of the PEVs. The simulation results of the efficient frontier when the number of PEVs is 100, 300, and 1000, are shown in Figs. 9(a), 9(b), and 9(c), respectively. We can select



(a) Number of EVs is 100.



(b) Number of EVs is 300.



(c) Number of EVs is 1000.

Fig. 9. Efficient frontier between the expected profit and CVaR_α. This figure shows the tradeoff between the expected profit and CVaR_α tuned by parameter β.

an appropriate value of β based on Figs. 9(a), 9(b), and 9(c) to achieve a desired tradeoff between expected profit and CVaR_α.

V. Conclusion

In this paper, we studied an aggregator participating in the DAM and RTM to obtain a contract from an ISO for providing frequency regulation service. Two types of DAMs were considered which followed the market rules of CAISO and NYISO, respectively. We formulated a stochastic optimization problem to determine the bid in the DAM. Risk management was taken into account in the formulation using the CVaR. An efficient algorithm was proposed to solve the formulated problem. Numerical experiments were performed based on real PEV charging data collected in Vancouver, Canada. Simulation results showed that an aggregator coordinating a large number of PEVs (more than a few hundreds) is helpful for the market participation of PEVs. As the number of PEVs increases, the uncertainty of the available regulation capacity has less effect on the profit and financial risk. For future work, an interesting extension is to jointly consider the two-settlement market system of the ISOs, the line losses, and the physical topology of the distribution network.

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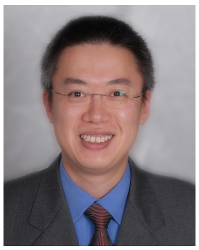

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