Optimal Bidding Strategy for Electric Vehicle Aggregators in Electricity Markets

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***Abstract*—This paper determines the optimal bidding strategy of an electric vehicle (EV) aggregator participating in day-ahead energy and regulation markets using stochastic optimization. Key sources of uncertainty affecting the bidding strategy are identified and incorporated in the stochastic optimization model. The aggregator portfolio optimization model should include inevitable deviations between day-ahead cleared bids and actual real-time energy purchases as well as uncertainty for the energy content of regulation signals in order to ensure profit maximization and reliable reserve provision. Energy deviations are characterized as "uninstructed" or "instructed" depending on whether or not the responsibility resides with the aggregator. Price deviations and statistical characteristics of regulation signals are also investigated. Finally, a new battery model is proposed for better approximation of the battery charging characteristic. Test results with an EV aggregator representing one thousand EVs are presented and discussed.**

***Index Terms*—Aggregator, ancillary services, batteries, electric vehicles, electricity market, regulation, stochastic optimization.**

NOMENCLATURE

Indices/Sets:

$i\,(I)$ Index (set) of electric vehicles.

$t\,(\mathcal{T})$ Index (set) of hourly time intervals.

τ Index of current dispatch hour.

$k(\mathcal{K})$ Index (set) of sub-hourly time intervals

$$card(\mathcal{K}) = \frac{1}{\Delta t} \cdot card(\mathcal{T}).$$

$\mathcal{K}_t$ Set of sub-hourly time intervals within hour t

$$\mathcal{K}_t = \left\{ k : k \in \left\{ \frac{t-1}{\Delta t} + 1, \frac{t-1}{\Delta t} + 2, \ldots, \frac{t}{\Delta t} \right\} \right\}.$$

$\omega(\Omega)$ Index (set) of scenarios.

Parameters:

Δt Duration of each sub-hourly time interval, in h (i.e., 0.25 for 15 min sub-hourly intervals).

π_ω Scenario ω probability of occurrence.

$\lambda_t^{DA,E}$ Day-ahead forecasted energy price, in \$/MWh.

$\lambda_t^{DA,R+(/-)}$ Day-ahead forecasted regulation up (/down) price, in \$/MW-h.

$\lambda_{k,\omega}^{RT,E}$ Real-time energy price during sub-hourly interval k, in \$/MWh.

$\lambda_{t,\omega}^{RT,E}$ Real-time energy price during hour t (average of sub-houly real-time prices within hour t), in \$/MWh.

$E_i^{bat,\max}$ Battery maximum energy of the ith electric vehicle, in kWh.

$R_{k,\omega}^{dc+(/-)}$ Dispatch to contract ratio—up (/down) reserve.

η_i^c Charging efficiency of the ith electric vehicle (EV).

$T_{i,\omega}^{arr/dep}$ Arrival/departure time of the ith EV.

$SOE_{i,\omega}^{arr}$ Battery state-of-energy of the ith EV at arrival time $\mathrm{T}_{i,\omega}^{arr}$, in pu.

SOE_i^{dep} Desired state-of-energy of the ith EV at departure time $T_{i,\omega}^{dep}$, in pu.

P_i^{chrg} Maximum charger power of the ith EV, in kW.

$SOE_i^{cc,cv}$ State-of-energy for constant current (CC) to constant voltage (CV) charging mode switching, in pu.

$u_{i,k,\omega}$ Parameter which is equal to 1 during the time interval $[\mathrm{T}_{i,\omega}^{arr}, T_{i,\omega}^{dep}]$ that the ith EV is plugged.

M^{fx} Price penalty for energy deviations, in \$/MWh.

dev Threshold, expressed as percentage of DA energy bid, above which energy deviations are penalized.

Variables:

E_t^{DA} Day-ahead energy bid, in MWh.

$R_t^{DA+(/-)}$ Up (/down) day-ahead regulation offer, in MW.

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$R_{t,\omega}^{RT+(/-)}$	Up (/down) regulation offer revised one hour prior to operating hour (real-time regulation offer), in MW.
$E_{k,\omega}^{RT}$	Real-time energy consumption, in MWh.
$E_{k,\omega}^{RT,R+}$	Up reserve deployment in real-time, in MWh.
$E_{k,\omega}^{RT,R-}$	Down reserve deployment in real-time, in MWh.
$\Delta E_{t,\omega}$	Deviation between real-time energy consumption and day-ahead energy bid, in MWh.
$\Delta E_{t,\omega}^{I}$	Instructed deviation between real-time energy consumption and day-ahead energy bid, in MWh.
$\Delta E_{t,\omega}^{U}$	Uninstructed deviation between real-time energy consumption and day-ahead energy bid, in MWh.
$\Delta E_{t,\omega}^{U,Up}$	Up uninstructed deviation, in MWh.
$\Delta E_{t,\omega}^{U,Dn}$	Down uninstructed deviation, in MWh.
$E_{i,k,\omega}^{RT}$	Real-time energy consumption of the ith EV, kWh.
$SOE_{i,k,\omega}$	State-of-energy of the ith EV, in pu.
$P_{i,k,\omega}^{RT\max}$	Maximum real-time charging power capability of the ith EV, in kW.
$Pnlty_{t,\omega}^{U,Up}$	Penalty for up uninstructed energy deviation higher than threshold, $dev \cdot E_t^{DA}$, in \$.
$Pnlty_{t,\omega}^{U,Dn}$	Penalty for down uninstructed energy deviation higher than threshold, $dev \cdot E_t^{DA}$, in \$.

I. Introduction

THE upcoming penetration of electric vehicles (EVs) in the near future commuting drew important research attention targeting at their efficient integration in energy systems. Recent research indicates that a mass, uncontrolled charging of EVs can cause energy shortages, unacceptable voltage fluctuations, transformer overloading and increased energy losses in distribution networks [1]–[3]. A comprehensive review of results from plug-in hybrid electric vehicles (PHEV) impact studies is presented in [4]. On the other hand, the EV battery appears as a new flexible tool for active load participation in electricity markets and if effectively managed a possible threat could become an excellent opportunity for efficient utilization of distributed energy storage and demand response.

The EV battery is a very suitable source for regulation service provision owning to its much faster ramping capability relative to conventional thermal generators. In addition, the EV cost for regulation provision is practically null: while the EV is plugged-in for charging, it can provide regulation service to the grid. Generators incur additional wear costs for participating in ancillary markets, whereas EVs with unidirectional grid interaction do not. Finally, the fixed cost of the battery for regulation provision is zero, since the EV battery investment cost was incurred for the transportation needs of the owner and not for regulation service provision.

Under the smart grid paradigm it is extensively proposed that smart, coordinated charging and fleet participation in ancillary services markets could be implemented by an EV aggregator who acts as a load-serving entity (LSE), bidding in the day-ahead energy and in ancillary services markets on behalf of the EV owners, trying to minimize their charging costs (and maximize his profit) [5]–[7]. The main costs that an aggregator must incur in order to be able to participate in the regulation market are the installation costs of a reliable and fast communication infrastructure with bidirectional data transfer between the aggregator and system operator (SO) and between aggregator's data center and the EV charging stations (wired/wireless solutions) [8]–[10]. Unidirectional participation needs no extra charging hardware, since most EV charger standards include control pins and data carriers in standard charging equipment [11]. Operational costs and costs for identifying and contracting with EV owners with suitable driving patterns and willingness to participate [12] should also be taken into account. A comparative study on costs for the aggregator's essential investments (i.e., ICT, SCADA software, smart meters, etc.) can be found in [13], where the aggregator's cost per charging-point is estimated between 50\$–64\$ in scenarios with large EV penetration.

However, optimal market participation is not an easy task for an EV aggregator who faces specific challenges, mainly related to several sources of uncertainty and the time-coupling introduced by the energy-limited nature of battery storage. Early battery saturation may result in unreliable down regulation provision, while battery undercharging may disappoint EV owners who desire their pre-declared battery state-of-charge (SOC) at departure. Moreover, unpredictable deviations between real-time (RT) and day-ahead (DA) market prices could mean extra debits or credits while uninstructed energy deviations between the day-ahead scheduled and real-time energy consumption could mean extra penalties [14].

EV participation in energy and ancillary services markets has been studied in [5], [15], and [16]. Although a coordinated "smart" charging at hours of low electricity prices is a first step to reduced charging costs, it has been shown that the highest benefits for EV owners are expected through participation in the regulation market. Demonstration projects [17], [18] show the possible ways an EV could respond to automatic generation control (AGC) signal for successful participation in this kind of market.

The EV interaction with the grid can be either bidirectional or unidirectional. The bidirectional mode offers higher flexibility and profits but requires additional hardware, additional protection and leads to increased cycling wear of the battery. The unidirectional mode offers lower flexibility and profits, but it does not face the above challenges and seems as the first step for EV participation in the regulation market. Most important, the unidirectional interaction mode eases concerns about increased battery wear [19]. Although the first research efforts focused on bidirectional (vehicle-to-grid, V2G) interaction [5], [20], [21] recently some models for unidirectional optimal bidding strategy have been proposed. In these models the EV charging rate varies around a set point, the "preferred operating point" (POP) that can take any value between zero and the maximum charging power capability. By reducing (increasing) the charging rate (deviating from POP), an EV can provide up (down) regulation. Deterministic models for unidirectional smart charging with simultaneous participation in energy and regulation markets (both up and down) are proposed in [19] and [22].

Owing to the uncertain nature of market conditions and fleet characteristics, stochastic approaches to the aggregator's optimal bidding problem seem necessary. Another important uncertain parameter is the energy content of the AGC signal. The ratio of dispatched energy to contracted regulation capacity R_t^{dc} can seriously influence the aggregator's reliable regulation market participation [23]. In previous works [5], [6], [16], [22] this ratio was considered very small. However, available AGC data indicate considerable uncertainty in R_t^{dc} [24], [25]. Research including uncertain parameter modeling can be found in [26] where Monte Carlo simulation is used to evaluate optimal bidding in German secondary reserve market, in [27] where uncertainties are considered for optimal coordination of an EV fleet with thermal and wind generation using CVAR risk measure and in [28] where many uncertain parameters are considered using stochastic programming.

This paper develops an optimal bidding strategy model for an EV aggregator who participates in the day-ahead energy and regulation markets. The model is based on two-stage stochastic linear programming (SLP) and takes into account uncertainties related to market conditions and EV fleet characteristics. The main contributions of the paper are:

- The development of an SLP-based optimal bidding strategy model for an EV aggregator participating in the day-ahead energy and regulation markets.
- The systematic treatment of the "instructed" and the "uninstructed" energy deviations (depending on whether responsibility resides with the SO or the EV aggregator) within the optimal bidding model.
- The development of a linear battery charging characteristic model suitable for SLP-based modeling.

Section II describes the EV aggregator and the market framework. Section III presents the mathematical model formulation. Section IV provides case-study results and Section V provides conclusions. Finally, the Appendix presents a linear battery charging model.

II. EV Aggregator and Market Framework

An EV Aggregator, managing a fleet of I EVs, participates in the short-term (DA and RT) wholesale electricity market by submitting energy bids and regulation offers. Unidirectional interaction with the grid is adopted, i.e., the EVs are not capable of discharging energy back to the grid: they can only deviate from POP, by reducing or increasing their charging rate. The Aggregator has RT control on the charging of each individual EV in the fleet: once an EV is plugged in, the Aggregator's algorithm is responsible for modulating the EV charging level. In exchange, the Aggregator offers to the EV owners attractive tariffs through which he shares the profits that he makes in the regulation market with the EV owners. The EV tariff structure is outside the scope of this paper.

The system operator (SO) runs DA energy and regulation (up/down) markets, in which he contracts with market participants DA forward delivery of energy and regulation capacity. The SO also runs a RT balancing energy market, in which he deploys contracted capacity to maintain the system power balance. Uniform pricing rule (UPR) and two-settlement (TSS) system [29] are used for the financial settlement of DA and RT energy deliveries. Under the TSS the Aggregator pays for energy delivery

$$E_t^{DA} \cdot \lambda_t^{DA,E} - \left(E_t^{DA} - E_{t,\omega}^{RT}\right) \cdot \lambda_{t,\omega}^{RT,E} \$$$

where the term in parenthesis is the energy deviation between DA contracted and RT actual energy delivery, $\Delta E_{t,\omega}$, which is traded at the RT energy price, $\lambda_{t,\omega}^{RT,E}$.

A brief description of the assumed short-term (DA and RT) electricity market framework follows:

Day-ahead market: Participants of the DA market (units, load-serving entities) submit supply-offers/demand-bids for energy to the SO in the form of quantity-price pairs (multi-step functions). Participants submit asymmetric supply-offers for regulation capacity in the form of a single quantity-price pair (one pair for regulation up and another pair for regulation down). Based on DA supply-offers for energy and regulation capacity and on demand-bids for energy, the SO clears the DA market by co-optimizing energy and regulation and computes the cleared quantities (DA energy and regulation capacity) system-wide and per participant as well as the DA energy and regulation up/down prices.

Real-time market: Up to one hour prior to the dispatch hour (a) Participants submit RT supply-offers/demand-bids for energy to the SO in the form of quantity-price pairs (multi-step). (b) Participants may submit revised regulation capacity offers with the following restrictions: (i) offer prices may not be changed; they are fixed to their day-ahead values. (ii) Offer quantities may be revised to reflect the most recent operating conditions; however, revised offer quantities may not be higher than day-ahead offer quantities. No penalties are imposed for revising regulation offer quantities. The SO computes dispatch schedules for the next dispatch hour by co-optimizing energy and regulation, issues dispatch schedules to controllable resources and assigns regulation capacity to resources providing regulation. Based on supply-offers, demand-bids and assigned regulation capacities the SO clears the RT market on a rolling basis for every sub-hourly dispatch interval within the dispatch hour.

During *RT System Operation* the SO issues dispatch instructions to controllable resources. Generating units that were selected to provide regulation (units operating under AGC) receive economic base-points every few minutes (e.g., every 5–15 min, depending on the dispatch period) and raise/lower signals every few seconds (e.g., every 2–4 s) automatically from the SO EMS (Energy Management System). Loads providing regulation service (e.g., Aggregated EV charging) are allowed to revise their energy demand quantities one hour prior to the dispatch hour. However, when they do so, they are subject to energy imbalance payments (the deviation of RT from DA quantity is settled at the RT energy price) and possible imbalance penalties (whenever the deviation exceeds a threshold) [14], [30]. The SO EMS can then automatically control the demand of the loads participating in system regulation within the regulation range (revised one hour prior to the dispatch hour) around the energy demand bid quantity (also revised one hour ahead of delivery).

The regulation market is command and control and participating loads must follow AGC signals during real-time operation. A load participant may opt not to participate in this market if he does not submit a regulation offer during the DA market, or if he revises his regulation offer quantity to zero, one hour prior to the dispatch hour. Once a participant submits a regulation offer in the DA market that can be revised up to one hour prior to the dispatch hour and his offer is accepted by the SO, then the participant must follow automatic AGC control signals by the SO EMS within the regulation range assigned by the SO. Otherwise he is subject to non-compliance penalties [31]. Instructed deviations (following either manual or automatic dispatch instructions) are not penalized, since they are not the Aggregator's responsibility.

In order to optimize his participation in the DA and RT markets the Aggregator is assumed to act as price taker, by submitting non-priced (quantity-only) DA energy demand bids (i.e., bids at the market price cap) and non-priced DA regulation capacity offers (i.e., offers at zero price), optimally responding to a deterministic forecast of DA energy and regulation (up/down) prices.

Even ignoring DA price forecast uncertainties, the Aggregator has to factor a number of other uncertainties into his optimal bidding strategy. These uncertainties are due to the stochastic nature of the EV fleet aggregate characteristics and the stochastic nature of the RT deployment of the Aggregator's contracted regulation capacity by the SO (instructed deviations).

Uncertainties in the aggregate fleet characteristics are due to the random behavior of the individual EV drivers. Each EV driver returns home after his last commuting with a certain battery SOC and declares that next morning or at a specific time in the near future he wants the car battery (almost) fully charged. Battery SOC at arrival, arrival and departure times are parameters that should be known in advance, before the Aggregator submits bids in the DA market. This is not an easy task for an individual EV, but for a large fleet the Aggregator could derive statistical patterns, as most of commuting has a daily/weekly repeated pattern [10]. Based on these patterns he can design suitable forecasting approaches for EV fleet behavior [32].

Another source of uncertainty is the energy content of the RT deployment of the contracted regulation capacity, in the form of AGC signals to the Aggregator. The stochastic parameter used to quantify this source of uncertainty is the dispatch-to-contract ratio R_{dc}, defined as the ratio of the RT deployed energy to the contracted regulation capacity of the Aggregator. R_{dc} can be estimated by statistical analysis of the AGC signal to the Aggregator, relative to the respective assigned regulation capacity. In our study, due to the lack of associated data, we assume that the Aggregator's R_{dc} is equal to the System R_{dc}, defined as the ratio of the RT deployed energy to the regulation capacity contracted by the SO system-wide [17]. The energy content of the AGC signal followed by the Aggregator results in instructed energy deviations which are not penalized, since they are not the Aggregator's responsibility. However, owing to the energy limitation imposed by the desired EV battery SOC at departure, instructed energy deviations during a dispatch period may lead to uninstructed energy deviations in other dispatch periods. The latter are subject to deviation penalties.

In our stochastic model uncertainties are modeled in the form of a set of scenarios, $\omega \in \Omega$, created based on past observations. The Aggregator does not know which specific scenario will materialize at the time he decides his DA bidding strategy. Therefore, stochastic optimization with recourse [33] is used in order to devise the optimal bidding strategy. The input parameters of the stochastic bidding strategy model are the deterministic forecast of hourly DA energy and regulation clearing prices, $\{\lambda_t^{DA,E}, \lambda_t^{DA,R+}, \lambda_t^{DA,R-}, \forall t\}$ and sub-hourly (quarter-hour) scenario-based inputs related to RT conditions of the power system $\{\lambda_{k,\omega}^{RT,E}, R_{k,\omega}^{dc+(/-)}, \forall k, \omega\}$ and aggregate fleet characteristics$\{\mathrm{T}_{i,\omega}^{arr}, \mathrm{T}_{i,\omega}^{dep}, SOE_{i,\omega}^{arr}, \forall i, \omega\}$.

III. Mathematical Model Formulation

A. Bidding in the Day-Ahead Energy and Regulation Markets

The problem of the optimal bidding strategy of an EV aggregator in the day-ahead energy and regulation markets is formulated as a two-stage stochastic linear programming problem (SLP) as follows:

$$\begin{aligned}\min \sum_t & \left[\lambda_t^{DA,E} E_t^{DA}\right] \\ & - \sum_\omega \pi_\omega \sum_t \left[\lambda_t^{DA,R+} R_{t,\omega}^{RT+} + \lambda_t^{DA,R-} R_{t,\omega}^{RT-}\right] \\ & + \sum_\omega \pi_\omega \sum_t \Big[-\lambda_{t,\omega}^{RT,E} \Delta E_{t,\omega} \\ & + \left(Pnlty_{t,\omega}^{U,Up} + Pnlty_{t,\omega}^{U,Dn}\right)\Big] \end{aligned} \tag{1}$$

$Subject\ to:$

$$\Delta E_{t,\omega} = E_t^{DA} - \sum_{k \in \mathcal{K}_t} E_{k,\omega}^{RT} \quad \forall \omega, t \tag{2}$$

$$\Delta E_{t,\omega} = \Delta E_{t,\omega}^I + \Delta E_{t,\omega}^U \quad \forall \omega, t \tag{3}$$

$$\Delta E_{t,\omega}^I = \sum_{k \in \mathcal{K}_t} \left(E_{k,\omega}^{RT,R+} - E_{k,\omega}^{RT,R-}\right) \quad \forall \omega, t \tag{4}$$

$$\Delta E_{t,\omega}^U = \Delta E_{t,\omega}^{U,Up} - \Delta E_{t,\omega}^{U,Dn} \quad \forall \omega, t \tag{5}$$

$$E_{k,\omega}^{RT,R+} = R_{k,\omega}^{dc+} \cdot R_{t,\omega}^{RT+} \cdot \Delta t \quad \forall \omega, t, k \in \mathcal{K}_t \tag{6}$$

$$E_{k,\omega}^{RT,R-} = R_{k,\omega}^{dc-} \cdot R_{t,\omega}^{RT-} \cdot \Delta t \quad \forall \omega, t, k \in \mathcal{K}_t \tag{7}$$

$$E_{k,\omega}^{RT} = \sum_i E_{i,k,\omega}^{RT} \quad \forall \omega, k \tag{8}$$

$$E_{i,k,\omega}^{RT} \leq \frac{P_{i,k,\omega}^{RT\max} + P_{i,k+1,\omega}^{RT\max}}{2} \Delta t \quad \forall i, \omega, k \tag{9}$$

$$P_{i,k,\omega}^{RT\max} \leq u_{i,k,\omega} \cdot P_i^{chrg} \quad \forall i, \omega, k \tag{10}$$

$$P_{i,k,\omega}^{RT\max} \leq u_{i,k,\omega} \cdot P_i^{chrg} \cdot \frac{1 - SOE_{i,k,\omega}}{1 - SOE_i^{cc,cv}} \quad \forall i, \omega, k \tag{11}$$

$$SOE_{i,k+1,\omega} = SOE_{i,k,\omega} + \frac{\eta_i^c}{E_i^{bat,\max}} E_{i,k,\omega}^{RT} \ \forall i, \omega, k \tag{12}$$

$$SOE_{i,\mathrm{T}_{i,\omega}^{dep},\omega} = SOE_i^{dep} \quad \forall i, \omega \tag{13}$$

$$R_{t,\omega}^{RT+} \leq \frac{E_t^{DA} - \Delta E_{t,\omega}^U}{1h} \quad \forall \omega, t \tag{14}$$

$$R_{t,\omega}^{RT-} \leq \sum_i \left[u_{i,k,\omega} P_{i,k,\omega}^{RT\max}\right] - \frac{\left(E_t^{DA} - \Delta E_{t,\omega}^U\right)}{1h}$$
$$\forall \omega, t, k \in \left\{\tfrac{t-1}{\Delta t} + 1, \tfrac{t}{\Delta t} + 1\right\} \tag{15}$$

$$R_{t,\omega}^{RT+(/-)} \leq R_t^{DA+(/-)} \quad \forall \omega, t \tag{16}$$

$$Pnlty_{t,\omega}^{U,Up} \geq 0 \quad \forall \omega, t \tag{17}$$

$$Pnlty_{t,\omega}^{U,Up} \geq M^{fx}\left(\Delta E_{t,\omega}^{U,Up} - dev \cdot E_t^{DA}\right) \forall \omega, t \tag{18}$$

$$Pnlty_{t,\omega}^{U,Dn} \geq 0 \quad \forall \omega, t \tag{19}$$

$$Pnlty_{t,\omega}^{U,Dn} \geq M^{fx}\left(\Delta E_{t,\omega}^{U,Dn} - dev \cdot E_t^{DA}\right) \forall \omega, t. \tag{20}$$

The aggregator objective (1) is the minimization of the cost of energy purchased both DA and RT (assuming two settlement system) minus the revenue from regulation market participation. Despite the sub-hourly RT market clearing, hourly settlement of RT deliveries is assumed, i.e., the financial settlement of RT deliveries is carried on an hourly basis, based on the average hourly RT price, a common practice in many electricity markets [34]. Constraint (2) defines the energy deviation between day-ahead and real-time markets, which is characterized as "instructed" and "uninstructed" in (3) and further analyzed in their "up" and "down" components in (4) and (5), respectively. Since hourly average RT prices are used for settlement, there is no need for sub-hourly differentiation of the respective deviations $\Delta \mathrm{E}_{t,\omega}$, $\Delta \mathrm{E}_{t,\omega}^I$, $\Delta \mathrm{E}_{t,\omega}^U$. The instructed deviations due to the energy content of the AGC signal are given in (6) and (7) in terms of the contracted regulation capacity and the corresponding stochastic (scenario-dependent) dispatch-to-contract ratio. The real-time fleet energy consumption is the sum of all individual EV consumptions (8). Here it must be noted that only real-time energy quantities are dispatched to individual EVs. Regulation capacity offer and energy bid are used in forward (DA or hour-ahead) financial contracting and do not need to be assigned to individual EVs. Since $P_{i,k,\omega}^{RT\max}$ refers to the beginning of hour t, $E_{i,k,\omega}^{RT}$ is better approximated by the trapezoidal integration rule in (9). Constraints (10) and (11) define the linear battery charging model presented in the Appendix.

Equation (12) calculates the state-of-energy[1] $SOE_{i,k,\omega}$ and constraint (13) defines the target SOE at departure time T_i^{dep}. In addition, revised up regulation offers should not exceed the possible load reduction capability (14) and down regulation offers should not exceed the possible load increase capability[2] (15). Constraint (16) models the market rule requesting that the revised regulation capacity offer quantities should be less than or equal to the DA offer quantities. Through constraints (10)–(16) the optimum participation of the Aggregator in both the energy and the regulation markets is achieved while satisfying the EV owners' target battery levels at departure, without unnecessarily constraining his bids. The arbitrage between RT and DA markets is exercised through the selection of the uninstructed deviations $\Delta \mathrm{E}_{t,\omega}^U$. It is noted that the numerators of the last terms in (14) and (15) denote the Aggregator "preferred operating point" (POP), which may defer from the actual Aggregator operating point owing to instructed deviations within the regulation range defined by the Aggregator regulation offer, constrained by (14) and (15).

Constraints (17)–(20) define the penalties for energy deviations imposed whenever the deviation exceeds dev% of the day-ahead scheduled quantities. In case energy deviations are not penalized, constraints (17) and (19) are converted to equality (zero penalty for both up and down deviation) and constraints (18) and (20) are omitted.

The first-stage (here and now) decision variables of the proposed two-stage SLP problem are the optimal DA, E_t^{DA}, R_t^{DA+}, R_t^{DA-}.

Uninstructed deviations $\Delta E_{t,\omega}^{U,Up}$, $\Delta E_{t,\omega}^{U,Dn}$ and hour-ahead revised regulation offers, $R_{t,\omega}^{RT+}$, $R_{t,\omega}^{RT-}$, are the key second stage (wait and see) variables driving all remaining second-stage variables (indexed by ω in the model as well as in the "variables" section of the Nomenclature).

B. Bidding in the Day-Ahead Energy Market Only

The objective function is now simplified to (21) because the Aggregator does not participate in regulation market:

$$\min \sum_t \left[\lambda_t^{DA,E} E_t^{DA}\right] + \sum_\omega \pi_\omega \sum_t \left[-\lambda_{t,\omega}^{RT,E} \Delta E_{t,\omega} + \left(Pnlty_{t,\omega}^{U,Up} + Pnlty_{t,\omega}^{U,Dn}\right)\right]. \tag{21}$$

Equation (3) is replaced by

$$\Delta E_{t,\omega} = \Delta E_{t,\omega}^U \quad \forall t, \omega. \tag{22}$$

Constraints (4), (6), (7), (14), (15), and (16) are omitted. All other constraints remain the same.

C. Real-Time Market Participation

As discussed in Section II market rules allow for the revision of the energy bid and regulation offer quantities up to one hour prior to the dispatch hour. Therefore, in addition to the day-ahead market bidding strategy, which is the focus of this paper, the aggregator must also take a sequence of decisions on the real-time (hour-ahead revised) energy bid and regulation offer quantities for all dispatch hours of the dispatch day, based on updated information he receives hour-after-hour during the course of the dispatch day. The aggregator develops his RT market bidding strategy by solving a series of new two-stage stochastic optimization problems on a rolling basis, one for every dispatch hour of the dispatch day. The new problem that determines the

[1] In this work, we use state-of-energy instead of state-of-charge (SOC), as in [35], because of the easy derivation of power and energy quantities in the model, $SOE_{i,k} = (E_{i,k}^{bat}(kWh))/(E_i^{bat,\max}(kWh))$.

SOC is a more accurate variable for describing battery state, as it includes cell voltage variations. However at the aggregator level where the charging power of thousands of EV is estimated, the SOE variable that includes battery characteristic like the one proposed in this work is considered a sufficient approximation.

[2] Using $P_{i,k,\omega}^{RT\max}$ (the maximum real-time charging power capability) at the beginning of hour t and at the beginning of hour $t+1$ in (15), ensures that the full power of the R_t^{RT-} contact can be honored from the beginning of hour t when the maximum charging power trajectory is inclining, or till the end of hour t when the maximum charging power trajectory is declining.

aggregator RT energy bid and regulation offer quantities for dispatch hour τ is

$$\min \sum_{\omega} \pi_{\omega} \left[-\lambda_{\tau,\omega}^{RT,E} \left(\Delta E_{\tau,\omega}^{I} + \Delta E_{\tau}^{U}\right)\right] + \left(Pnlty_{\tau}^{U,Up} + Pnlty_{\tau}^{U,Dn}\right) + \sum_{\omega} \pi_{\omega} \sum_{t=\tau+1}^{T} \left[-\lambda_{t,\omega}^{RT,E} \Delta E_{t,\omega} + \left(Pnlty_{t,\omega}^{U,Up} + Pnlty_{t,\omega}^{U,Dn}\right)\right] \quad (23)$$

subject to constraints (2)–(20), defined only for $t \in [\tau, T]$ and $k \in [(\tau-1)/(\Delta t)+1, (T)/(\Delta t)]$.

In the above two-stage optimization problem, variables ΔE_{τ}^{U}, R_{τ}^{RT+}, R_{τ}^{RT-} representing the uninstructed energy deviation (which determines the RT energy bid quantity[3]). and the RT regulation up/down offer quantities of the dispatch hour τ (the first hour of the optimization horizon) are first-stage (here-and-now) variables, and are scenario-independent. The same variables are second-stage variables for the remaining problem horizon ($\forall t \in [\tau+1, T]$) and are scenario-dependent as in the original stochastic optimization problem (1)–(20). Note that the penalty terms referring to the dispatch hour τ, $Pnlty_{\tau}^{U,Up}$, $Pnlty_{\tau}^{U,Dn}$, in (23) are also scenario independent, since they are functions of the uninstructed deviations, ΔE_{τ}^{U} and the DA bid quantities, which are known parameters in the RT bidding problem (18), (20).

During the solution of the aggregator RT bidding problem (23), (2)–(20) for dispatch hour τ, the DA quantities $\{\lambda_t^{DA,E}, \lambda_t^{DA,R+}, \lambda_t^{DA,R-}, \forall t\}$ are known parameters from the solution of the DA clearing problem, while updated forecasts (data until hour $\tau - 2$) for $\{\lambda_{k,\omega}^{RT,E}, R_{k,\omega}^{dc+(/-)}, \forall \omega, k \geq (\tau-1)/(\Delta t)+1\}$ and $\{\mathrm{T}_{i,\omega}^{arr}, \mathrm{T}_{i,\omega}^{dep}, SOE_{i,\omega}^{arr}, \forall i, \omega\}$ for the fleet are available.

This paper focuses on the day-ahead market bidding strategy of the Aggregator and does not provide test results on the RT bidding strategy.

IV. Case Study

The models described in Section III. were tested for an EV aggregator representing one thousand EVs. Although charging during the day (i.e., in future parking lots of commercial buildings) is also of interest, in this work night residential charging is studied for the following reasons: EV drivers seem more willing to participate in night charging programs [10], driving patterns are more easily predictable [10] and the probability of unplanned departure is the lowest. Night charging does not coincide with peak load period and the night load valley filling could bring important benefits by reducing wind spillage in markets with high wind energy penetration. Finally, in several markets (e.g., PJM) low energy prices and high down regulation prices (Fig. 2) coincide at night, thus night charging gives opportunities for higher profits.

[3]The RT energy bid quantity (submitted one hour prior to the dispatch hour) is equal to $E_t^{DA} - \Delta E_{\tau}^{U}$. The DA cleared quantity is known parameter for the RT bidding problem.

TABLE I
EV Data Probability Distributions

	Distr.	Mean	St. dev	Min	Max
Battery capacity (kWh)	UD	18	6.93	6	30
Arrival Time (h)	TGD	19	2	16	1
Departure Time (h)	TGD	7	2	5	12
Initial Battery SOE (%)	TGD	75	25	25	95

* UD: uniform distribution, TGD: truncated Gaussian distribution

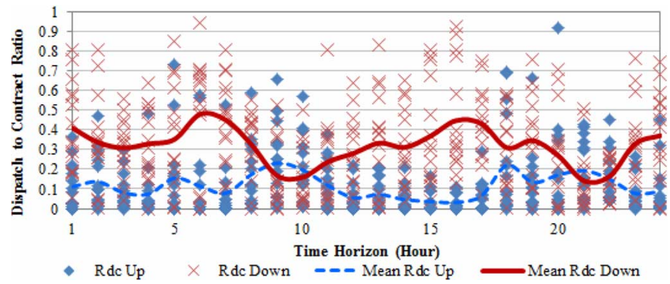

Fig. 1. $R_k^{dc+(/-)}$ of hourly mean regulation signal for 15 days.

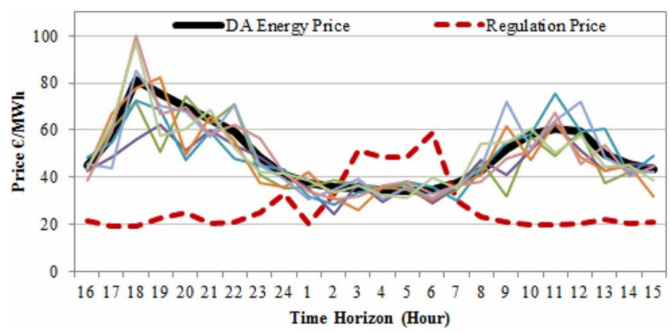

Fig. 2. Day-ahead energy price mean value, regulation price mean value and real-time energy price scenarios.

For the EV fleet modeling truncated Gaussian distributions (TGD) for arrival time, departure time and battery SOE at arrival were used, with parameters as in [15] and [22]. Final SOE was set at 97% [18]. Battery capacity (kWh) was considered to be uniformly distributed (UD) between 6 and 30 kWh. EV data probability distribution parameters are presented in Table I.

The SOE level for the transition from CC to CV charging generally depends on the charging power level and the specific battery charging management system. For example, in [18] this level was taken 90% and in [36], 80% for fast charging. We assume that $SOE_i^{cc,cv}$ is 85% for all EVs. Charging efficiency was considered 90%.

A statistical processing of the PJM RTO [24] AGC signal for 15 days (December 17–31, 2008) was carried out. The signal sampling frequency was 2 sec. In the case study, the sub-hourly time interval (dispatch period) is 15 min. The 15-min average values of R_k^{dc+} and R_k^{dc-} were calculated and then used to create 100 scenarios for $R_{k,\omega}^{dc+(/-)}$. Maximum and minimum value for every quarter-hour during the 15 days was considered, thus the truncated Gaussian distribution was adopted. In Fig. 1 hourly mean values are presented for simplicity.

For the same period the mean and standard deviation of the difference between PJM RTO weighted-average RT and DA hourly prices was calculated. Values are presented in Table II.

TABLE II
MEAN AND STANDARD DEVIATION VALUES OF THE DIFFERENCE BETWEEN REAL TIME AND DAY AHEAD WEIGHTED AVERAGE ENERGY PRICES OF PJM FOR THE PERIOD DECEMBER 17–31, 2008

Hour	1	2	3	4	5	6
Mean Value ($)	-3.07	-2.41	-1.81	-0.34	-1.24	-1.33
St. Dev ($)	3.93	5.04	3.69	4.83	2.64	4.19
Hour	7	8	9	10	11	12
Mean Value ($)	-2.46	0.06	-0.5	-2.82	-3.43	-2.47
St. Dev ($)	5.02	8.03	8.81	6.75	7.94	7.64
Hour	13	14	15	16	17	18
Mean Value ($)	-1.91	-2.58	-1.92	-2.58	-1.83	-2.78
St. Dev ($)	6.44	3.4	3.58	4.88	9.08	11.34
Hour	19	20	21	22	23	24
Mean Value ($)	-2.05	-6.36	-2.27	-2.04	0.95	-1.63
St. Dev ($)	17.29	10.31	5.34	7.71	6.63	4.79

Price differences larger than twice the standard deviation were excluded from the statistical analysis.

The correlation between $R_k^{dc+(/-)}$ values and RT and DA prices was studied and found weak (correlation coefficient =0.09), thus the $R_k^{dc+(/-)}$ and RT-DA price scenarios were created independently. Sample random RT price scenarios are shown in Fig. 2. One hundred (100) equiprobable scenarios were created for the simulation. Perfect forecasts of DA energy and regulation prices were considered. Regulation prices were based on mean hourly values of a 15-day period (Fig. 2).

It is clarified that in our study fleet characteristics, although randomly created, are considered deterministically known to the Aggregator. Stochastic scenarios here refer only to $R_{k,\omega}^{dc+(/-)}$ and $\lambda_{k,\omega}^{RT,E}$.

Four cases of smart charging and four cases of simultaneous participation in energy and regulation markets are examined: (a) all uninstructed deviations are penalized at 150 $/MWh, (b) uninstructed deviations higher than 20% are penalized at 150 $/MWh, (c) uninstructed deviations higher than 20% are penalized at PJM balancing operating reserve (BOR) deviation charge of 2.9832 $/MWh [30] and (d) deviations are not penalized. Case (c) is an extension of the deviation charging scheme of economic load response found in PJM market [30] for regulation market participation. The other three cases are used for comparison. The deviation penalty price of 150 $/MWh in cases (a) and (b) is used in the Greek electricity market [14]. Direct charging has also been examined as the reference case for comparative reasons. EVs start charging as soon as they are plugged-in. The aggregator purchases energy for the inflexible, in this case, load. Summary economic results of all cases are presented in Table IV.

In Figs. 3–5, DA energy bidding and RT energy consumption for the case of smart charging are presented. For comparison, the RT energy consumption for direct charging case is also presented. Maximum charger power, RT energy consumption and maximum RT charging power capability are aggregated values for the whole fleet. In addition, RT energy consumption and maximum RT charging power capability are presented for all 100 scenarios to show the diversity of different scenario realizations. It is obvious that with smart charging, charging is

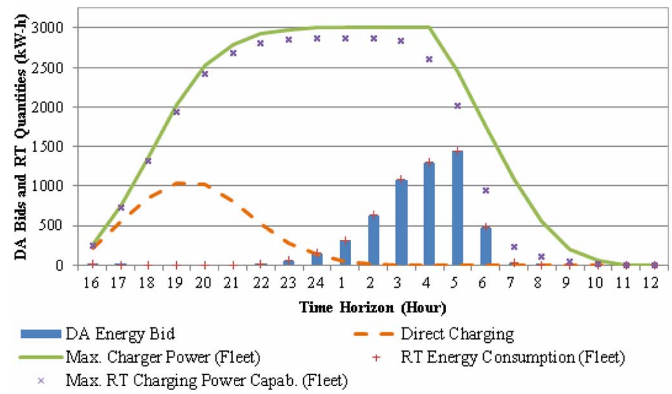

Fig. 3. Smart Charging—Case (a): All uninstructed deviations are penalized at a price of 150 $/MWh.

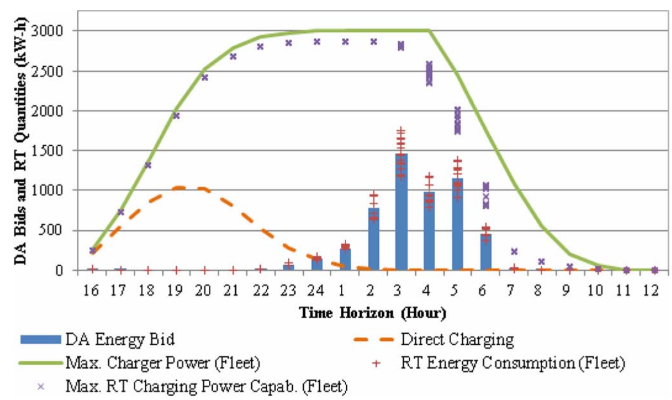

Fig. 4. Smart Charging—Case (b): Uninstructed deviations higher than 20% are penalized at 150 $/MWh.

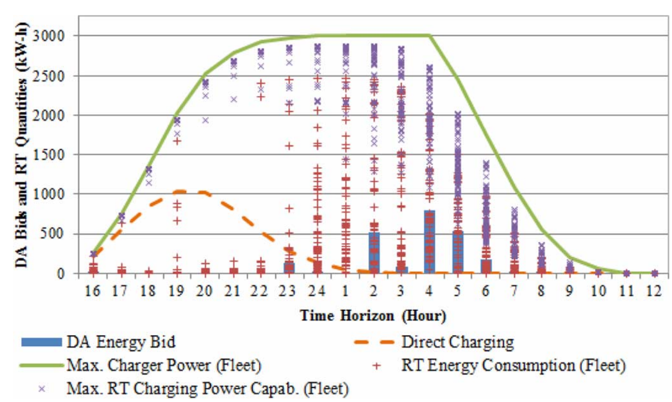

Fig. 5. Smart Charging—Case (c): Uninstructed deviations higher than 20% are penalized at BOR deviation charge, 2.9856 $/MWh.

shifted to hours with lower energy prices. DA prices and fleet characteristics are considered perfectly forecasted, as already mentioned.

When all uninstructed deviations are penalized at 150 $/MWh (Fig. 3), the aggregator bids in the DA market the exact amount of his real time energy needs and avoids high uninstructed deviation penalties (Table III). In case (b) when only deviations higher than 20% are penalized at 150 $/MWh (Fig. 4), the aggregator fully exploits the non-penalized tolerance for arbitraging between the DA and RT markets. However, in all scenarios the uninstructed deviation is lower than the 20% tolerance and no

TABLE III
ENERGY BID IN DA MARKET, MEAN AVERAGE ABSOLUTE UNINSTRUCTED ENERGY DEVIATION AND MEAN DEVIATION PENALTY PER SCENARIO

Case	a	b	c
Penalty ($/MWh)	150	150	2.98
Deviation Tolerance (%)	-	20	20
Smart Charging			
DA Energy Bid (kWh)	5495.6	5356.6	2285.6
Mean Uninstructed Energy Deviation per Scenario (kWh)	0	964.9	4071.1
Mean Deviation Penalty per Scenario ($)	0	0	10.8
Co-participation in Energy and Regulation Markets			
DA Energy Bid (kWh)	801.9	812.7	604.55
Mean Uninstructed Energy Deviation per Scenario (kWh)	0.14	148.3	361.7
Mean Deviation Penalty per Scenario ($)	0.02	0	0.73

TABLE IV
CHARGING COSTS FOR DIRECT CHARGING, SMART CHARGING AND SMART CHARGING WITH CO-PARTICIPATION IN REGULATION MARKET

Case	a	b	c	d
Penalty ($/MWh)	150	150	2.98	No
Deviation Tolerance (%)	-	20	20	-
Direct Charging ($)	364.8	360.4	352.7	335.1
Smart Charging ($)	194.8	190.4	172.1	154.7
Cost Reduction (%)	46.6	47.1	51.2	53.8
Regulation Market Participation ($)	-468.3	-470.4	-472.7	-477.74
Cost Reduction (%)	-228.4	-230.5	-234.0	-242.5

penalty is imposed. The EV charging cost reduces from 194.80 $ to 190.40 $ (by 2.26%). The cost reduction is higher in case (c) when deviations higher than 20% are penalized at a much lower price of 2.9832 $/MWh (PJM case). The aggregator's DA energy bid is more aggressive and for every RT scenario realization completely different charging trajectories are preferred (Fig. 5). Owing to the fact that RT energy prices are on average lower than DA prices (Table II, Fig. 2) the aggregator submits underestimated energy bids in the DA market and purchases most of his energy needs in the RT market. Despite the high uninstructed deviations, his total cost is reduced to 172.06 $ (11.67%). In case (d) where no deviations penalty is considered, the energy bid is more aggressive and the charging cost is reduced to 154.74 $ (20.56%).

Figs. 6–8, present the results of simultaneous participation in energy and regulation markets. The maximum RT charging power capability (for the whole fleet) is presented for the first quarter of each hour. The aggregator shows a notable preference for offering down regulation to up regulation. The energy purchased DA is lower than the daily charging needs (5495.6 kWh) because of (a) the anticipation that down reserve provision may lead to EV charging owing to reserve deployment in RT and (b) the arbitrage between DA and RT market. The daily sum of the DA Energy bids and the mean absolute daily uninstructed energy deviation per scenario for the three cases

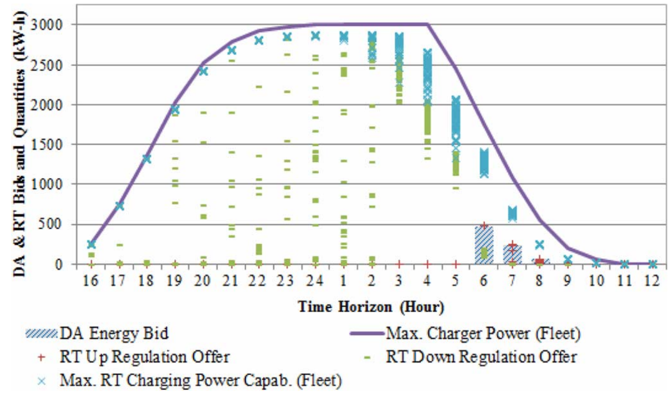

Fig. 6. Co-participation in energy and regulation markets. All deviations are penalized at a price of 150 $/MWh.

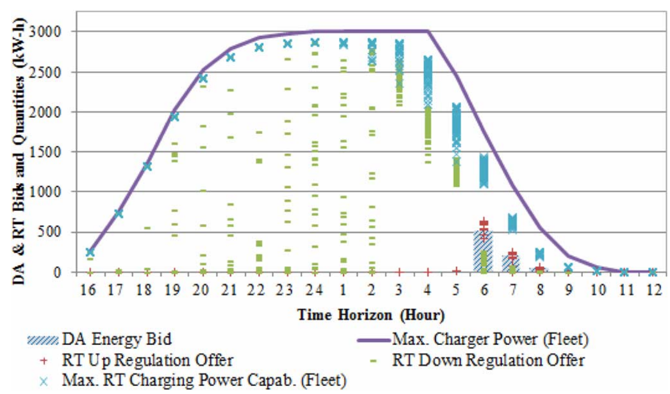

Fig. 7. Co-participation in energy and regulation markets. 20% deviations between DA and RT are not penalized. Higher deviations are penalized at 150 $/MWh.

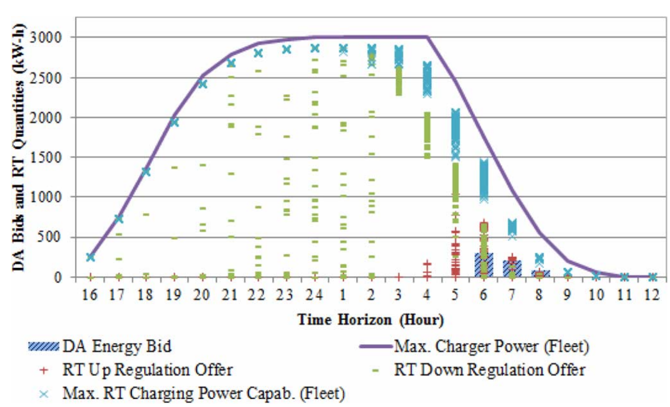

Fig. 8. Co-participation in energy and regulation markets. 20% deviations between DA and RT are not penalized. Higher deviations are penalized at BOR deviation charge, 2.9856 $/MWh.

(a)–(c) are presented in Table III. It is observed that the deviation penalty scheme affects the level of the uninstructed energy deviations. Since regulation capacity offers can be revised hour-ahead, uninstructed deviations (and thus deviation penalties) are almost eliminated in case (a). In case (b) the non-penalized band allows for higher uninstructed deviations which, however, are restricted within the band. In case (c) the low deviation penalty permits higher uninstructed deviations and higher

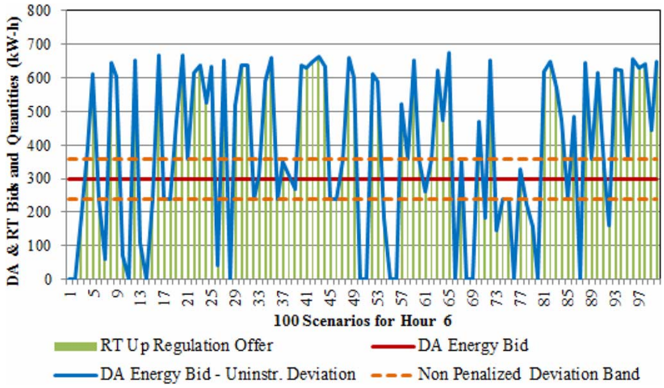

Fig. 9. Arbitrage opportunity between DA and RT market. Uninstructed deviations higher than 20% are penalized at 2.9856 \$/MWh.

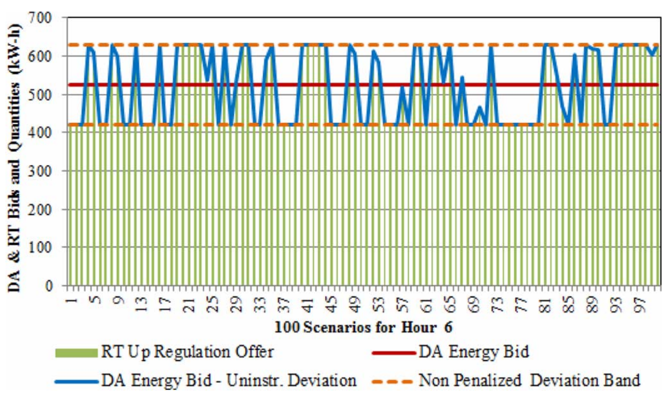

Fig. 10. Arbitrage opportunity between DA and RT market. Uninstructed deviations higher than 20% are penalized at 150 \$/MWh.

profits. Finally, the participation in the regulation market reduces the uninstructed deviations (cases (b) and (c)) compared to the smart charging only case.

In Figs. 9 and 10, results for hour 6:00, for all the 100 scenarios are presented. In Fig. 9 (corresponding to Fig. 8) the preferred operating point $(E_t^{DA} - \Delta \mathrm{E}_{t,\omega}^{U})$ differs from the DA energy bid (E_t^{DA}) noticeably: uninstructed energy deviations frequently exceed the width of the non-penalized deviation band since the penalty imposed is very low. On the contrary, if uninstructed deviations are highly penalized, as in Fig. 10 (corresponding to Fig. 7), all uninstructed deviations remain within the non-penalized deviation band. In both cases, the revised up regulation offers do not exceed the possible load reduction capability.

Table IV demonstrates that EV charging costs turn into net profits when the Aggregator participates in the regulation market. The Aggregator net profits from his participation in the energy and regulation markets decrease when the non-instructed energy deviations are highly penalized.

Fig. 11, presents results of case (c) for simultaneous participation in energy and regulation markets with a simplified battery charging characteristic model assuming constant charging power equal to the rated power, regardless of the battery charging level, i.e., omitting (11) from the model. In this case the cost is computed -565 \$ (19.5% reduced relative to the full model) and all charging energy is bought real-time,

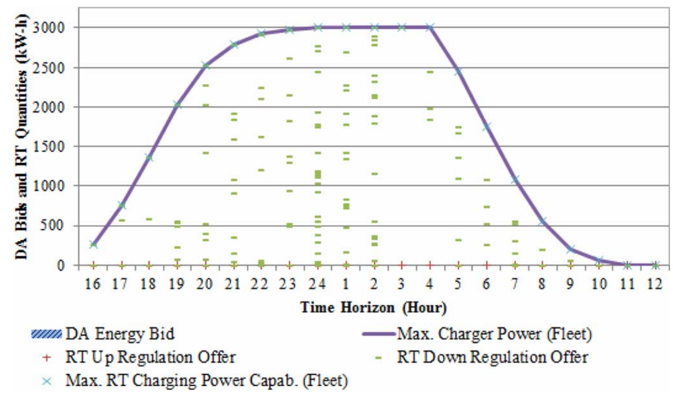

Fig. 11. Simplified battery charging characteristic model—Co-participation in energy and regulation markets. 20% deviations between DA and RT are not penalized. Higher deviations are penalized at BOR deviation charge, 2.9856 \$/MWh.

TABLE V
MODEL STATISTICS, ENERGY AND REGULATION MARKET PARTICIPATION CASE

EV Number	Variables (millions)	Equations (millions)	Matrix Sparsity	Sol. Time (min)
500	12.144	16.949	1.94e-7	9.59
1000	24.251	33.856	0.97e-7	17.43
1500	36.351	50.763	0.64e-7	26.28

exploiting the flexibility provided by the increased maximum charging power provided by the simplified model. However, the results of the simplified model are optimistic, since the battery saturation close to full charging is ignored.

All tests were performed on a PC with Intel Core™ i7 CPU @3.20 GHz and 64 GB RAM. The models are solved using IBM ILOG CPLEX® 12.4 and GAMS® IDE. The CPLEX barrier LP algorithm was employed. Model size and execution times for case (b) with varying number of EVs are presented in Table V. It is observed that the execution time increases almost linearly with the number of EVs. With the simplified battery charging characteristic model (i.e., omitting (11) from the model) the 1000 EV problem for the same case is solved in 42 s.

V. CONCLUSION

A stochastic optimization model for the optimal participation of an EV Aggregator in the short-term electric energy and regulation markets has been developed. Test results demonstrate that the careful consideration of the instructed and uninstructed energy deviations play a key role in the design of the Aggregator's bidding strategy. Market rules, concerning the uninstructed deviations, influence the profits and the bidding strategy of the Aggregator. Finally, the accurate modeling of the battery charging characteristic is important because it reveals the true capability of EV participation in regulation markets.

APPENDIX
EV BATTERY CHARGING CHARACTERISTIC MODELING

Li-ion battery type seems to be the next decade's automotive choice because of several advantages including energy and power density [37]. The most suitable charging method for

Li-ion batteries is considered the CC, CV method [38]. Initially, the battery is charging with a constant current (CC) and the battery cell voltage is rising. For the CC method we assume a constant maximum charging power P_i^{chrg} as in [36]. When the voltage reaches its maximum value $V^{\max}$ at a specific SOC ($SOC_i^{cc,cv}$), the charging method changes to avoid battery degradation. Now the voltage is kept constant (CV) at $V^{\max}$ and current is reduced exponentially $I_{i,t} = I_i^{chrg} \cdot e^{-\lambda t}, \lambda > 0$ following the ampere-hour law [38]. Therefore, maximum charging power decreases exponentially during CV charging, $P_{i,t}^{RT\max} = V^{\max} \cdot I_i^{chrg} \cdot e^{-\lambda t} = P_i^{chrg} \cdot e^{-\lambda t}$ During CV charging the state-of-energy is

$$\begin{aligned} SOE_{i,t} &= SOE^{cc,cv} + \frac{\eta_i^c}{E_i^{bat,\max}} \cdot \int_0^t P_{i,t}^{RT\max} d\tau \\ &= SOE^{cc,cv} + \frac{\eta_i^c}{E_i^{bat,\max}} \cdot P_i^{chrg} \int_0^t e^{-\lambda\tau} d\tau \end{aligned} \tag{24}$$

which is written after evaluating the integral as

$$SOE_{i,t} = SOE^{cc,cv} + \frac{\eta_i^c}{\lambda \cdot E_i^{bat,\max}} \cdot \left(P_i^{chrg} - P_{i,t}^{RT\max} \right). \tag{25}$$

From the above equation we calculate

$$P_{i,t}^{RT\max} = P_i^{chrg} - \frac{\lambda \cdot E_i^{bat,\max}}{\eta_i^c} (SOE_{i,t} - SOE^{cc,cv}). \tag{26}$$

The energy required to fully charge the battery ($SOE = 1$) after CC-CV switching ($SOE = SOE^{cc,cv}$) is $(1 - SOE^{cc,cv}) \cdot E_i^{bat,\max}$. However, this amount of energy is also equal to $\int_0^\infty \eta_i^c \cdot P_i^{chrg} \cdot e^{-\lambda t} = \eta_i^c \cdot P_i^{chrg} \cdot (1/\lambda)$, therefore, $\eta_i^c \cdot P_i^{chrg} \cdot (1/\lambda) = (1 - SOE^{cc,cv}) \cdot E_i^{bat,\max}$ and

$$\lambda = \frac{\eta_i^c \cdot P_i^{chrg}}{E_i^{bat,\max}} \cdot \frac{1}{(1 - SOE^{cc,cv})}. \tag{27}$$

Substituting (27) to (26) the charging power during CV mode is

$$P_{i,t}^{RT\max} = P_i^{chrg} \cdot \left[1 - \frac{SOE_{i,t} - SOE^{cc,cv}}{1 - SOE^{cc,cv}} \right]. \tag{28}$$

Thus, battery model can be mathematically expressed as shown in (29) at the bottom of the page, whose equivalent linear expression is incorporated in our SLP model through (10) and (11).

$$P_{i,t}^{RT\max} = \left\{ \begin{array}{cc} P_i^{chrg} & 0 < SOE_{i,t} < SOE^{cc,cv} \\ P_i^{chrg} \cdot \frac{1 - SOE_{i,t}}{1 - SOE_i^{cc,cv}} & SOE^{cc,cv} < SOE_{i,t} < 1 \end{array} \right\} \tag{29}$$

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