Optimal coordinated bidding of a profit-maximizing EV aggregator under uncertainty

1 author:

Y. Vardanyan
Technical University of Denmark

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Yelena Vardanyan
DTU Compute
Danish Technical University
Email: yeva@dtu.dk

Frederik Banis
DTU Compute
Danish Technical University
Email: freba@dtu.dk

S. Ali Pourmousavi
Global Change Institute
The University of Queensland
Email: a.pour@uq.edu.au

Henrik Madsen
DTU Compute
Danish Technical University
Email: hmad@dtu.dk

***Abstract*—An aggregator acts as a middleman between the small customers and the system operator (SO) offering a mutually beneficial agreement to trade electric power, where each market player (system operator, aggregator and electric vehicle (EV owner) has its own economic incentives. The EV aggregator aims to maximize its profit while trading energy and providing balancing power in wholesale markets. This paper develops a stochastic and dynamic mixed integer linear program (SD-MILP) for optimal coordinated bidding of an EV aggregator to maximize its profit from participating in competitive day-ahead and real-time markets. Under uncertain day-ahead and real-time market prices as well as fleet mobility, the proposed SD-MILP model finds optimal EV charging/discharging plans for every EV. The degradation costs of EV batteries are modeled. To reflect the continuous clearing nature of the real-time market, rolling planning is applied which allows re-forecasting and re-dispatching. The proposed SD-MILP is used to derive a bidding curve of an aggregator managing 1000 EVs.**

Index terms: Coordinated bidding, two-settlement market, EV aggregator, stochastic programming.

I. Nomenclature

A. Indices

k	index for storages, $k = 1, \dots, K$;
t	planning periods, $t = 1, \dots, T$;
s	scenarios, $s = 1, \dots, S$;
i	index for possible bid prices $i = 1, \dots, I$;

B. Parameters

ω_s	Probabilities associated with the scenarios;
$\overline{P}_k$	Max. storage rate of discharge, charge [kW];
$\underline{P}_k$	Min. storage rate of discharge, charge [kW];
$\overline{E}_k$	Max. capacity of a storage [kWh];
$\overline{\gamma}_k$	Scalar to calculate max SoC (State of Charge);
$\underline{\gamma}_k$	Scalar to calculate min SoC;
$\eta_k^{ch/dch}$	Charge, discharge efficiency of a storage;
$SoC^{B}_{k,t=0}$	Starting storage level [kWh];
$SoC^{Bend}_{k,}$	Storage level at the end of the day [kWh];
$\lambda_{s,t}$	Day-ah. market price scenarios [€/MWh];
$\lambda_{s,t}^{up/dn}$	Real-time market price scenarios [€/MWh];
ρ_i	Fixed bid price for day-ah. market [€/MWh];
$\rho_i^{up/dn}$	Fixed bid price for real-time market [€/MWh];
c_t	Aggregator's offer to storage owner [€];
c_k^{cap}	Capital cost of a storage [€];
μ_k	The slope of the linear approximation of the battery life as a function of the cycles;
$A_{s,k,t}$	Availability matrix indicating whether EV is available or not;
$D_{s,k,t}$	Average hourly driving distance of an EV [km];
η_k^{dr}	driving efficiency of an EV;
Γ_1, Γ_2	Sufficiently large Constant;

C. Variables

$p_{s,k,t}^{DAch}$	Day-ah. charge dispatch level for k^{th} storage [kWh];
$p_{s,k,t}^{DAdch}$	Day-ah. discharge dispatch level for k^{th} storage [kWh];
$p_{s,k,t}^{Bch}$	Real-time charge dispatch level for k^{th} storage [kWh];
$p_{s,k,t}^{Bdch}$	Real-time discharge dispatch level for k^{th} storage [kWh];
$\mathbb{P}_{s,t}^{DAch}$	Energy as day-ah. buying position [MWh];
$\mathbb{P}_{s,t}^{DAdch}$	Energy as day-ah. selling position [MWh];
$\mathbb{P}_{s,t}^{Bch}$	Real-time down-regulating volume [MWh];
$\mathbb{P}_{s,t}^{Bdch}$	Real-time up-regulating volume [MWh];
$C\mathbb{P}_{s,t}^{DAch}$	Total day-ah. charge cost [€];
$C\mathbb{P}_{s,t}^{DAdch}$	Total day-ah. discharge cost [€];
$C\mathbb{P}_{s,t}^{Bch}$	Total real-time charge cost [€];
$C\mathbb{P}_{s,t}^{Bdch}$	Total real-time discharge cost [€];
$x_{i,t}^{DAch}$	Day-ah. charge bid volume [kWh];
$x_{i,t}^{DAdch}$	Day-ah. discharge bid volume [kWh];
$x_{i,t}^{Bch}$	Real-time charge bid volume [kWh];
$x_{i,t}^{Bdch}$	Real-time discharge bid volume [kWh];
$SoC_{s,k,t}^{B}$	Storage level at the end of time step t [kWh];
$\hat{\alpha}_{s,t,i}$	binary variable;
$\hat{\alpha}_{s,t,i}^{up/dn}$	binary variable;

II. Introduction

According to [1], worldwide EV penetration is assumed to increase up to 20 million units by 2020. Therefore, there is a huge potential using EV batteries to assist the electric power grid [2]. However, single EV can not enter to electricity market to trade their energy for the following two reasons: 1) the available trading power of individual EV is below the required threshold to participate in electricity markets [3], and 2) the participation of individual EVs will increase the number of market actors which will increase the difficulty of managing electricity markets. Therefore, a new market entity, an aggregator, will be required in order to enable smooth cooperation between EV owners and SO.

The main target of the aggregator, as a market entity, is to buy the electric power at the lowest possible cost to satisfy driving needs of its fleet of EVs [2] and [4]. Meanwhile, the economic incentive of the aggregator is to increase its revenue by performing energy arbitrage [5], [6], [7] and [8]. With the vehicle-to-grid (V2G) capability of EVs, the idea of using EVs as an electric power source to provide balancing power is the focus of many researchers in the field. Having a flexible power source, EV aggregator can provide reserve power and increase its profit. The possibilities of using EVs as a resource for real-time balancing and system reserves by providing ancillary services are studied in [9], [10], [11], [12] and [13].

The EV interaction with the grid can be categorized as unidirectional and bidirectional. While the problem of bidding regulation and spinning reserves for unidirectional EV interaction is explored in [10], the bidirectional mode offers higher flexibility and profits. Bidirectional EV interaction with the grid is modeled in [11] and [13]. However, using the batteries as storage devices for grid purposes reduces their lifetime [13] and [14]. Thus, EV owners must be compensated for the lost utility of their batteries due to degradation when providing services.

Taking into consideration the uncertain nature of market conditions and fleet characteristics, stochastic approaches fit better to the aggregators optimal bidding problem. In [9] and [12], the authors develop an optimal bidding strategy of an EV aggregator participating in day-ahead energy and regulation markets using stochastic optimization.

This paper develops an optimal bidding strategy model for an EV aggregator who participates in the day-ahead and real-time markets considering the uncertain nature of market conditions and fleet characteristics. Unlike previous formulations [9], [12] and [13], this formulation accounts dynamically for clearing nature of the real-time market while deriving optimal bids for day-ahead and real-time markets. In order to benefit from the released information over time, rolling planing framework is employed to update the scenario tree of real-time prices within the planning day. In addition, the developed model enables the aggregator to manage both stationary storages and EVs. The main contributions of the paper are:

- The development of a stochastic and dynamic mixed-integer linear program (SD-MILP) for an aggregator who manages a large number of stationary storages and EVs to obtain the optimal coordinated bidding in two-settlement markets.
- The derivation of optimal coordinated charge (discharge) bids for day-ahead and real-time markets with moderate computation time when applying scenario-reduction techniques.
- The inclusion of uncertainty in both market prices as well as EV mobility parameters.

The paper is structured as follows. Section III describes the mathematical model formulation of an aggregator. Section IV provides case-study results and in Section V the conclusion is drawn.

III. Mathematical problem formulation

The mathematical formulation of an EV aggregator interacting with day-ahead and real-time markets is stated below.

A. Stochastic optimal strategy of an EV Aggregator

The stochastic optimization problem stated in (1) aims at maximizing scenario-weighted expected profits from day-ahead energy trading $\Pi^{DA}_{s,t}$ and real-time power exchange $\Pi^{B}_{s,t}$.

$$\text{Maximize}_{\Phi}\ \mathbb{E}[\Pi^{Tot}] = \sum_{s} \omega_s \Big(\sum_{t=1}^{T} (\Pi^{DA}_{s,t} + \Pi^{B}_{s,t})\Big) \tag{1}$$

where $\Pi^{DA}_{s,t}$ and $\Pi^{B}_{s,t}$ are expressed as in (2) and (3) correspondingly.

$$\Pi^{DA}_{s,t} = \lambda_{s,t}\mathbb{P}^{DAdch}_{s,t} - C\mathbb{P}^{DAdch}_{s,t} - \lambda_{s,t}\mathbb{P}^{DAch}_{s,t} + C\mathbb{P}^{DAch}_{s,t} \tag{2}$$

$$\Pi^{B}_{s,t} = \lambda^{up}_{s,t}\mathbb{P}^{Bdch}_{s,t} - C\mathbb{P}^{Bdch}_{s,t} - \lambda^{dn}_{s,t}\mathbb{P}^{Bch}_{s,t} + C\mathbb{P}^{Bch}_{s,t} \tag{3}$$

The different components in (2) and (3) are expressed as follows:

$$\mathbb{P}^{DAdch/ch}_{s,t} = \sum_{k} p^{DAdch/ch}_{s,k,t}, \quad \mathbb{P}^{Bdch/ch}_{s,t} = \sum_{k} p^{Bdch/ch}_{s,k,t} \tag{4}$$

$$C\mathbb{P}^{DAdch}_{s,t} = \sum_{k}\Big(c_t \frac{p^{DAdch}_{s,k,t}}{\eta^{dch}_k} + \Big|\frac{\mu_k}{100}\Big| \frac{c^{cap}_k}{\overline{E}_k} p^{DAdch}_{s,k,t}\Big) \tag{5}$$

$$C\mathbb{P}^{DAch}_{s,t} = \sum_{k}\Big(c_t p^{DAch}_{s,k,t}\eta^{ch}_k - \Big|\frac{\mu_k}{100}\Big| \frac{c^{cap}_k}{\overline{E}_k} p^{DAch}_{s,k,t}\Big) \tag{6}$$

$$C\mathbb{P}^{Bdch}_{s,t} = \sum_{k}\Big(c_t \frac{p^{Bdch}_{s,k,t}}{\eta^{dch}_k} + \Big|\frac{\mu_k}{100}\Big| \frac{c^{cap}_k}{\overline{E}_k} p^{Bdch}_{s,k,t}\Big) \tag{7}$$

$$C\mathbb{P}^{Bch}_{s,t} = \sum_{k}\Big(c_t p^{Bch}_{s,k,t}\eta^{ch}_k - \Big|\frac{\mu_k}{100}\Big| \frac{c^{cap}_k}{\overline{E}_k} p^{Bch}_{s,k,t}\Big) \tag{8}$$

It is obvious that the equations (2) and (3) express the aggregator's revenue minus cost while providing optimal discharge/charge bids in day-ahead and real-time markets, respectively. Note that the positive terms represent revenue and the negative terms express cost for the aggregator. The equation (4) provides the aggregated charge/discharge bids in both markets. The aggregator's cost in both markets while providing charging/discharging optimal bids is set out in equations (5)-(8), where the first term is the aggregator's payment to the EV owner and the second term is the battery degradation cost.

To derive the step-function bidding curve for hour t of the day-ahead market, we first fix the parameters ρ_1, ρ_2, ..., ρ_I at

I arbitrary prices. The unknown variables x_1, x_2, ..., x_I of the step function are solved as follows:

$$\mathbb{P}_{s,t}^{DAch/DAdch} = \sum_{l=0}^{i} x_{i-l,t}^{DAch/DAdch} \quad if \quad \rho_i \leq \lambda_{s,t} \leq \rho_{i+1} \tag{9}$$

Using binary variable $\hat{\alpha}_{s,t,i}^{ch/dch}$ and a large enough constant Γ_1, (9) can be reformulated as constraints (10)-(12):

$$\rho_i - \Gamma_1(1 - \hat{\alpha}_{s,t,i}^{ch/dch}) \leq \lambda_{s,t} \leq \rho_{i+1} + \Gamma_1(1 - \hat{\alpha}_{s,t,i}^{ch/dch}) \tag{10}$$

$$\sum_{l=0}^{i} x_{i-l,t}^{DAch/DAdch} - \Gamma_1(1 - \hat{\alpha}_{s,t,i}^{ch/dch}) \leq \mathbb{P}_{s,t}^{DAch/DAdch}$$

$$\leq \sum_{l=0}^{i} x_{i-l,t}^{DAch/DAdch} + \Gamma_1(1 - \hat{\alpha}_{s,t,i}^{ch/dch}) \tag{11}$$

$$\sum_{i=1}^{I} \hat{\alpha}_{s,t,i}^{ch/dch} = 1 \tag{12}$$

The up- and down-regulating bids for real-time market are expressed in (13).

$$\mathbb{P}_{s,t}^{Bch/Bdch} = \sum_{l=0}^{i} x_{i-l,t}^{Bch/Bdch}$$

$$if \quad \rho_i^{up/down} \leq \lambda_{s,t}^{up/dn} \leq \rho_{i+1}^{up/down} \tag{13}$$

In the similar way, using binary variables $\hat{\alpha}_{s,t,i}^{dn/up}$ and a large enough constant Γ_2, (13) can be reformulated as:

$$\rho_i^{dn/up} - \Gamma_2(1 - \hat{\alpha}_{s,t,i}^{dn/up}) \leq \lambda_{s,t}^{dn/up} \leq \rho_{i+1}^{dn/up}$$

$$+ \Gamma_2(1 - \hat{\alpha}_{s,t,i}^{dn/up}) \tag{14}$$

$$\sum_{l=0}^{i} x_{i-l,t}^{Bch/Bdch} - \Gamma_2(1 - \hat{\alpha}_{s,t,i}^{dn/up}) \leq \mathbb{P}_{s,t}^{Bch/Bdch}$$

$$\leq \sum_{l=0}^{i} x_{i-l,t}^{Bch/Bdch} + \Gamma_2(1 - \hat{\alpha}_{s,t,i}^{dn/up}) \tag{15}$$

$$\sum_{i=1}^{I} \hat{\alpha}_{s,t,i}^{dn/up} = 1 \tag{16}$$

The constants Γ_1 and Γ_2 must be tuned carefully to avoid introducing extra bounds or ill-conditioning in the optimization problem. The state of charge balance constraint can be modeled as:

$$SoC_{s,k,t}^{B} = SoC_{s,k,t-1}^{B} + [p_{s,k,t}^{DAch}\eta_k^{ch} - \frac{p_{s,k,t}^{DAdch}}{\eta_k^{dch}} + p_{s,k,t}^{Bch}\eta_k^{ch}$$

$$- \frac{p_{s,k,t}^{Bdch}}{\eta_k^{dch}}]A_{s,k,t} - D_{s,k,t}\eta_k^{dr}(1 - A_{s,k,t}) \tag{17}$$

Equation (17) states that for each hour the new content of the storage is equal to its old content plus energy inflow minus energy outflow. Please note that, (17) allows to model both stationary and mobile (EV) storages. For stationary storages, the availability matrix $A_{s,k,t}$ is always 1; hence the last term which is energy spend on driving purposes vanishes. For EVs the availability matrix is either 0 or 1 depending on weather the EV is available or on a trip. The storage level is bounded by its minimum and maximum levels (18).

$$\underline{\gamma}_k \overline{E}_k \leq SoC_{s,k,t}^{B} \leq \overline{\gamma}_k \overline{E}_k \tag{18}$$

The constraints (19) prevents discharging/charging in the periods of unavailability.

$$A_{s,k,t}\underline{P}_k \leq p_{s,k,t}^{DAdch} - p_{s,k,t}^{DAch} + p_{s,k,t}^{Bdch} - p_{s,k,t}^{Bch} \leq A_{s,k,t}\overline{P}_k \tag{19}$$

Finally the constraint (20) states the end SoC condition.

$$SoC_{s,k,T}^{B} \geq SoC_k^{Bend} \tag{20}$$

The day-ahead market is cleared at noon the day before delivery day while the real-time market is continuous, hourly market. This means the EV aggregator has new price information realized after the day-ahead market clearing and before the real-time market closure. In order to benefit from the released information over time, the scenario tree of real-time prices can be updated within the planning day using rolling planning. Let $\Omega_{[t,T]}$ be the scenario tree predicted for hours t to T using the historical prices up to hour t. In the rolling planning, $\Omega_{[t,T]}$ is dynamically updated by real-time prices revealed until hour t. The ideal case would be to update $\Omega_{[t,T]}$ on hourly base. However, the solution time to solve the stochastic model dynamically increases exponentially. Thus, in order to keep the model computationally tractable, $\Omega_{[t,T]}$ is updated every few hours which is called 'iteration'. For each iteration, new scenario tree is used which contains the updated forecasts for real-time market prices.

The stochastic and dynamic optimal bidding strategy for deriving the coordinated bidding curves in day-ahead and real-time markets follows as:

$$\text{Maximize}_{\Phi} \quad \sum_{s=1}^{|\Omega_{[t,T]}|} \omega_s (\sum_{t=1}^{T} (\Pi_{s,t}^{DA} + \Pi_{s,t}^{B})) \tag{21}$$

subject to :

$$(2), (3), (4), (5) - (8), (10) - (12), (14) - (16), (17) - (20) \tag{22}$$

IV. Case study

In order to study the applicability of the developed SD-MILP optimal bidding strategy, both charging and discharging modes are studied. The developed approach is applied to derive a bidding discharge/charge curve of an aggregator managing a fleet of 1000 EVs.

A. input data

1) Market data acquisition: The historical price data, for both day-ahead and real-time markets, are taken from the Nordic electricity market website, from March 10, 2012 to March 10, 2013 [15].

2) Market price scenario generation and reduction: The modeling and forecasting of electricity prices are very challenging due to its complex structure. Its stochastic behavior is typically mean-reverting and spiky with high volatility [16]. The existing dynamics between day-ahead and real-time markets make the price forecasting even more complicated. Substantial amount of work has been done on modeling and forecasting of day-ahead market prices [17]. However, the existing references on real-time price modeling and forecasting is very limited [18], [19] and [20]. This section develops the Markov-based Holt Winter (HW) model for modeling and predicting the day-ahead and real-time prices. The proposed model has the following steps.

a) Step 1: Estimate the parameters of the HW model: Reference [21] presents the HW model for a time series with unique seasonal pattern. The HW model is applied to forecast the electricity demand and imbalance cost in [22] and [23]. The standard HW model for a time series of prices $\{\lambda_t\}_{t=1}^{T}$ is as follows [24], [25]:

$$\hat{\gamma}_t = \alpha(\lambda_t/I_{t-\Xi}) + (1-\alpha)(\hat{\gamma}_{t-1} + T_{t-1}) \tag{23}$$

$$T_t = \beta(\hat{\gamma}_t - \hat{\gamma}_{t-1}) + (1-\beta)T_{t-1} \tag{24}$$

$$I_t = \sigma(\lambda_t/\hat{\gamma}_t) + (1-\sigma)I_{t-\Xi} \tag{25}$$

$$\tilde{p}_t(h) = (\hat{\gamma}_t + hT_t)I_{t-\Xi+h} \tag{26}$$

where γ_t is the exponential component, T_t is the trend and I_t is the seasonal component with period Ξ. α, β, and σ are smoothing parameters which belong to the interval (0,1]. $\tilde{p}_t(h)$ is the h-hour ahead forecast.

b) Step 2: Estimate the transition probability matrix of Markov model for different states of real-time market prices: The magnitude of day-ahead and real-time electricity prices can be estimated using the HW technique. However, the real-time market prices have discrete mode meaning that in addition to price magnitudes, the price states need to be forecasted. In each bidding interval *t*, the real-time market price may have one of the following four states: (1) No up- or down-regulating price exists, (2) Only down-regulating price exists, (3) Only up-regulating price exists, and (4) Both up- and down-regulating prices exist. The state of real-time market prices can be modeled using a four-state Markov process.

The probabilities of the transition matrix for real-time Markov model are estimated using historical real-time market prices. Based on the real-time prices, for each bidding period *t*, the binary pair (b_t^{up}, b_t^{dn}) is defined as follows.

$$b_t^{up(dn)} = \begin{cases} 1 & \text{if an up-(down-regulating) price exists} \\ 0 & \text{Otherwise} \end{cases} \tag{27}$$

We define o_t as the parameter which shows the state of the real-time price at time t.

$$o_t^{Real-time} = \begin{cases} 1 & \text{if} \quad (b_t^{up}, b_t^{dn}) = (0,0) \\ 2 & \text{if} \quad (b_t^{up}, b_t^{dn}) = (0,1) \\ 3 & \text{if} \quad (b_t^{up}, b_t^{dn}) = (1,0) \\ 4 & \text{if} \quad (b_t^{up}, b_t^{dn}) = (1,1) \end{cases} \quad t = 1,2...T \tag{28}$$

Let $O_{ij} = \{o_t^{Real-time} : o_t^{Real-time} = j, o_{t-1}^{Real-time} = i, t = 1, ..., T\}$, then element (i,j) of transition probability matrix pr_{ij} for $i, j = 1, ..., 4$ can be calculated as:

$$pr_{ij} = \frac{Card(O_{ij})}{\sum_{n=1}^{4} Card(O_{i,n})} \; i, j = 1, ...4 \tag{29}$$

c) Step 3: The day-ahead and real-time price scenarios: The prediction technique explained in Step 1 is applied to forecast the day-ahead market price magnitude. Then, using the expected values and the variances of day-ahead market prices and assuming normal distribution, the day-ahead market price scenarios are generated. However, both price magnitude and direction have to be forecasted for real-time market. To predict real-time market price magnitude, the real-time market historical prices are collected and processed. Then the forecasting procedure in Step 1 is applied. The Markov model provided in Step 2 is employed to capture the price direction for the real-time market. Again, the real-time market price scenarios are generated using the predicted price magnitude, direction and assuming normal distribution. For day-ahead and real-time markets, various price scenarios are generated for each planning hour. The backward reduction algorithm is used to reduce the number of price scenarios. This is done in a way that the statistical information in prices is maintained in the best possible way [26]. Using the forecasted prices, 1000 price scenarios with equal probabilities are generated and they are reduced to 10 price scenarios. These preserved price scenarios will be used for calculating the optimal bidding curve of the EV aggregator.

3) Availability simulation: A Monte Carlo simulation tool is used to produce mobility scenarios for imitating the uncertain driving behavior. Then, discrete cumulative distribution functions (cdf) is employed, which is derived considering i) the probability of travel on a specific day, ii) the probability that a trip starts in a specific hour, and iii) the probability that a trip covers a certain distance. Like in [12], independent sampling is executed. Finally, 10 equally probable mobility scenarios are produced and integrated with the 10 price scenarios prepared in Step 3.

4) General parameters: The EV driving patterns are according to the reference [27]. The maximum battery capacity is taken 50 kWh [27], while the battery level is bounded by its minimum of 20 % and maximum of 100 % of the maximum capacity [28]. Both the charging and discharging power rate is taken 6 kW. Finally, the charging and discharging efficiency is set to 90 % and 93 %, respectively [29]. For every scenario, the target state of charge level is equal to the initial state of charge level and assumed to be 60 % of the maximum capacity.

The capital cost for EV battery is set to 200 €$/MWh$ and the slope μ_k=-[0.0013] according to [13].

B. Simulations results

A three-level step function with ρ_1=15€$/MWh$, ρ_2=50€$/MWh$, and ρ_3 =75€$/MWh$ is considered for bidding curves. The proposed Markov-based HW model, scenario backward reduction algorithm and the Monte Carlo simulation tool to produce mobility patterns are coded in MATLAB. The HW parameters are estimated as = = = 0.1. The SD-MILP is coded in GAMS platform and solved using CPLEX solver. All optimization problems are solved with optimality gap of 0%. The whole simulation is run on a computer with 2.66 GHz processor and 4 GB RAM. The objective function values together with the total cost, degredation cost and the computation time for a fleet of 1000 EVs and all iterations are stated in Table I. According to Table I, the computation time is highest for the first iteration. Moreover, the computation time for the second iteration is lowest, then it is slightly increasing in the third and the fourth iterations. Possible answer to this is the application of rolling planning in the SD-MILP optimization model. After the first iteration, all variables for the day-ahead market is fixed to their optimal values. In addition, for the real-time market and for every iteration the information related to previous hours is kept and the information related to remaining hours is updated. The resulting optimization problem becomes tighter.

TABLE I: Model solution report for a fleet of 1000 EVs, It: Itertaion

	It. 1	It. 2	It. 3	It. 4
$\mathbb{E}[\Pi^{Tot}]$(€)	200.35	168.8	167.35	130.24
Total cost (€)	2243	1957	1992	1909
Degredation cost (€)	175	156	159	152
Comp. time (second)	28.64	15.2	18.3	19

The optimal coordinated bids of the storage aggregator in two markets is given in Table II. The bid volumes to day-ahead market remain the same for all iterations (the first and the second columns in Table II). In contrast, Table II shows that real-time bid volumes (up/down regulation) are changing when time evolves and new price information reveals over time. According to Table II, the EV aggregator is actively participating in day-ahead market offering discharging bids and in real-time market providing down-regulation bids.

The day-ahead and real-time bidding curves for hours 2 and 3 are shown in Fig. 1 and Fig. 2. According to the Fig. 1 the model offers to enter directly to real-time market providing up- and down-regulating bids. However, Fig. 2 shows that, for the hour 3 the model yields an incentive to offer discharging bid to day-ahead market and charging bid to real-time market.

V. Conclusion

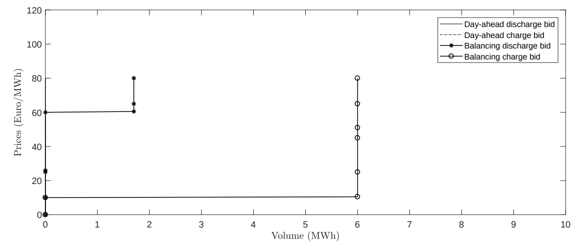

Fig. 1: The bidding curves for hour 2.

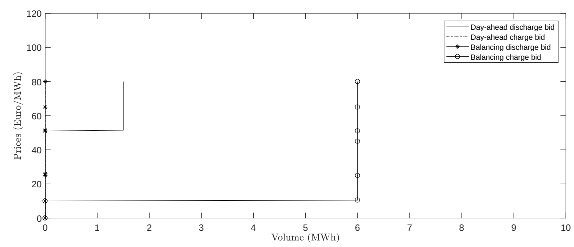

Fig. 2: The bidding curves for hour 3.

The aggregators are required business entities, who enable smooth cooperation of large fleets of EVs and the SO while maximizing their own profit. This paper proposes a SD-MILP for deriving optimal coordinated bidding in day-ahead and real-time markets for a profit-maximizing EV aggregator. The prices in these market places are modeled and predicted using a proposed Markov-based HW model. The HW model predicts the magnitude of day-ahead and real-time market prices. The direction of real-time market prices are predicted using Markov model. The scenario tree is also updated with arrival of new information for real-time market prices. This has been done by implementing the rolling planning in the SD-MILP. The developed procedure is tested using a fleet of 1000 EVs. Results show that EVs can provide a new collection of services to the power system. However, the degradation of the batteries should be accounted precisely in order to motivate the EVs' participation in day-ahead and real-time markets. The current paper can be extended by modeling also the intra-day market.

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TABLE II: The optimal coordinated bidding in day-ahead and real-time markets for four iterations of rolling planning

	Day-ahead market		Up-regulation (discharge)				Down-regulation (charge)			
	discharge	charge	real-time market				real-time market			
Hours	All It.	All It.	It. 1	It. 2	It. 3	It. 4	It. 1	It. 2	It.3	It. 4
1	0	0	0	0	0	0	6	6	6	6
2	0	0	1.7	1.7	1.7	1.7	6	6	6	6
3	1.5	0	0	0	0	0	6	6	6	6
4	6	0	0	0	0	0	6	6	6	6
5	0	0	0	0	0	0	6	6	6	6
6	0	0	0	0	0	0	6	6	6	6
7	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0
10	1.5	0	0	0	0	0	6	6	6	6
11	0	0	0	0	0	0	6	6	6	6
12	0	0	6	0	0	0	6	6	6	6
13	0	0	0	0	0	0	6	6	2.7	2.7
14	6	0	6	0	0	0	6	6	6	6
15	6	0	0	0	0	0	6	6	6	6
16	0	0	0	0	0	0	6	6	6	6
17	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	6	6	6	6
20	0.5	0	0	0	0	0	6	6	6	6
21	0	0	0	0	0	0	6	6	6	6
22	0	0	6	6	6	0.25	6	6	6	6
23	6	0	0	0	0	0	6	6	6	6
24	6	0	0	0	0	0	6	6	6	6

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