

Synergistic supply offer and demand bidding strategies for wind producers and electric vehicle aggregators in day-ahead electricity markets

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Abstract

This work evaluates the opportunities for increased profits owing to the better management of energy deviations under a synergistic supply offer and demand bidding strategy of a wind energy producer and an electric vehicle (EV) aggregator that participate in day-ahead energy and regulation reserve market. The new market player acts as a prosumer and participates in the electricity market with synergistic offers and bids of the two entities he represents. Key factors of uncertainty affecting the bidding strategy are identified and incorporated in a stochastic optimization framework. The case of night residential EV charging is examined and unidirectional interaction between EVs and the grid is considered, i.e. the EVs do not discharge energy back to the grid. The possibility for increased profits through the holistic consideration and better management of the energy deviations under specific market rules is examined in this work. Finally, the impact of wind curtailment opportunity in energy deviation management was also examined.

Index Terms—Aggregator, ancillary services, batteries, electric vehicles, electricity market, prosumer, regulation, stochastic optimization, wind power, wind producer, wind curtailment.

Nomenclature

Indices/Sets:

i (I)	index (set) of electric vehicles
t (T)	index (set) of hourly time intervals
k (K)	index (set) of sub-hourly time intervals,

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

K_t	set of sub-hourly time intervals within hour t
$K_t = \left\{ k : k \in \left\{ \frac{t-1}{\Delta t} + 1, \frac{t-1}{\Delta t} + 2, \dots, \frac{t}{\Delta t} \right\} \right\}$	
ω (Ω)	index (set) of scenarios

Parameters:

Δt	duration of each sub-hourly time interval, in h (i.e 0.25 for 15min 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-hourly real-time prices within hour t), in \$/MWh
$E_{k,\omega}^W$	real-time maximum available wind energy production during sub-hourly interval k , in MWh
$P^{W,rtd}$	rated wind farm capacity, in MWp
$E_i^{bat,max}$	battery maximum energy of the i -th electric vehicle, in kWh
$R_{k,\omega}^{dc+(-)}$	dispatch to contract ratio – up (/down) reserve
η_i^c	charging efficiency of the i -th electric vehicle (EV)
$T_{i,\omega}^{arr/dep}$	arrival / departure time of the i -th EV
$SOE_{i,\omega}^{arr}$	battery state-of-energy of the i -th EV at arrival time $T_{i,\omega}^{arr}$, in pu
SOE_i^{dep}	desired state-of-energy of the i -th EV at departure time $T_{i,\omega}^{dep}$, in pu

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P_i^{chrg}	maximum charger power of the i -th EV, in kW
$u_{i,k,\omega}$	parameter which is equal to 1 during the time interval $[T_{i,\omega}^{arr}, T_{i,\omega}^{dep}]$ that the i -th EV is plugged
M_{dev}^{fx}	price penalty for energy deviations, in \$/MWh
dev	Threshold, expressed as percentage of DA energy offer and bid, above which energy deviations are penalized

Variables:

E_t^{DA}	day-ahead synergistic energy offer/bid, in MWh
$E_t^{DA,+}$	day-ahead synergistic energy offer, in MWh
$E_t^{DA,-}$	day-ahead synergistic energy bid, in MWh
$E_t^{W,DA}$	day-ahead wind producer's energy offer, in MWh
$E_t^{EV,DA}$	day-ahead EV aggregator's energy bid, in MWh
$R_t^{DA+(-)}$	up (/down) day-ahead regulation offer, in MW
$R_{t,\omega}^{RT+(-)}$	up (/down) regulation offer revised one hour prior to operating hour (real-time regulation offer), in MW
$E_{k,\omega}^{EV,RT}$	real-time EV fleet consumption, in MWh
$E_{k,\omega}^{W,RT}$	real-time actual wind energy during sub-hourly interval k , 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
$\Delta E_{t,\omega}$	net energy deviation between real-time synergistic production/consumption and day-ahead synergistic energy offer/bid, in MWh
$\Delta E_{t,\omega}^{EV}$	deviation between real-time EV fleet energy consumption and day-ahead EV aggregator's energy bid, in MWh
$\Delta E_{t,\omega}^U$	net uninstructed energy deviation between real-time synergistic energy production/consumption and day-ahead synergistic energy offer/bid, in MWh
$\Delta E_{t,\omega}^{U,W}$	deviation between real-time wind energy production and day-ahead wind producer's energy offer, in MWh
$\Delta E_{t,\omega}^{I,EV}$	instructed deviation between real-time energy consumption and day-ahead EV aggregator's energy bid, in MWh

$\Delta E_{t,\omega}^{U,EV}$	uninstructed deviation between real-time energy consumption and day-ahead EV aggregator's energy bid, in MWh
$E_{i,k,\omega}^{EV,RT}$	real-time energy consumption of the i -th EV, kWh
$SOE_{i,k,\omega}$	state-of-energy of the i -th EV, in pu
$P_{i,k,\omega}^{RT,max}$	maximum real-time charging power capability of the i -th EV, in kW
$Pnly_{t,\omega}^{U,Up}$	Penalty for uninstructed energy deviation surplus higher than threshold, $dev \cdot E_t^{DA}$, in \$
$Pnly_{t,\omega}^{U,Dn}$	Penalty for uninstructed energy deviation deficit higher than threshold, $dev \cdot E_t^{DA}$, in \$
b_t	binary variable which equals 1 when $E_t^{DA} \geq 0$ and 0 when $E_t^{DA} \leq 0$

Introduction

The integration of wind power is increasing rapidly throughout the world mainly because of environmental concerns and political directions [1]. However, wind power is a challenging supply market product for an energy producer due to its uncertainty and variability which expose the producer to quantity risk and possible penalties for energy deviations between day-ahead cleared energy quantities and real-time actual production [2].

Modern electricity markets provide a variety of market arrangements for wind producers. For example, in the Netherlands and the United Kingdom wind producers participate in the day-ahead market [3], [4], while in Iberia market a wind producer may participate in day-ahead market and in any of the six adjustment markets [4]. In some markets wind producers offer the expected wind production one hour before the operating hour [2]. A comparison of different market designs and support policies can be found in [5]. Deviations from day-ahead cleared quantities are traded at real-time (RT) balancing price and may incur deviation penalties if the energy deviation exceeds a certain threshold. Deviation penalties in most markets are usually calculated on a cumulative basis for periods longer than a specific market session, i.e. on a monthly base [2]). Offering strategies in electricity markets for wind producers and producers are discussed in [6], [7], [8].

On the other hand, the EV battery provides a new flexible tool for active participation in electricity markets. The concept of an EV aggregator that acts as a load serving entity (LSE), bidding in the day-ahead energy and ancillary services markets on behalf of the EV owners is

extensively proposed in recent works. The EV participation in energy and ancillary services markets has been extensively studied, e.g. in [9] and [10]. Although a coordinated "smart" charging at hours of low electricity prices is a first step to reduced charging costs, higher benefits for EV owners are expected through participation in the regulation market. Demonstration project [11] shows the possible ways an EV could respond to Automatic Generation Control (AGC) signal for successful participation in this kind of market.

In addition to charging only (uni-directional interaction with the grid) EVs are also capable of discharging energy back to the grid (bi-directional interaction with the grid), given that the necessary infrastructure is in place. This flexibility makes EVs ideal distributed storage devices that can provide ancillary services to electricity markets with considerable benefits for efficient system operation.

Bidirectional interaction (also known as Vehicle-to-Grid - V2G) is more flexible than unidirectional interaction (charging-only mode); however it causes extra battery degradation cost due to cycling wear and reduces the battery lifetime due to battery utilization for different than transportation purposes. Unidirectional interaction does not suffer the above drawbacks and should possibly be considered as a first step for EV interaction with the smart grid. In charging-only mode EV charging rate can vary around a set point, the "preferred operating point" (POP) [12], [13]. POP is the reference charging rate for an EV at certain time and can vary on command upward between POP and maximum charging rate (offering down regulation) and downward between POP and zero charging (offering up regulation). The POP can be scheduled appropriately, giving EV flexibility to modulate charging according to system balancing needs, thus creating an opportunity for regulation reserve market participation.

The possible benefits of V2G and wind coordination for a more profitable participation of both entities in electricity markets are investigated in the literature (i.e. [14]). In the few works that include synergies for unidirectional EV interaction, regulation market participation of EVs is not taken into consideration [15] and the synergies include conventional generation units [16]. In [17] a hierarchical control algorithm to realize the synergy between PEV charging and wind power for electric vehicle charging is developed. The authors conclude that synergy could lead to a considerable reduction of dispatch cost. However, they concentrate on system cost reduction and not on optimal market participation strategies. Power system benefits from wind and EV synergy are also investigated in [18], where it is concluded that no important system benefits and dispatch correlations from coupling must-take wind and PEVs seem to exist. In [19]

opportunity for wind balancing using EV is investigated comparing a heuristic and model predictive control approach. Although balancing opportunities exist, the paper does not focus on market participation strategies. To the best of our knowledge there is no study undertaken on potential profits of a synergistic market participation strategy between unidirectional EV interaction and wind trading.

In this paper the new market entity that participates in the electricity market on behalf of a wind producer and an EV aggregator can be considered as a prosumer, aiming to make profit by co-optimizing energy supply offers and demand bids for the production assets and loads of his portfolio. The concept of a prosumer is relative new, his role in energy market is only vaguely defined, but it is described as an emerging approach for the way end-consumers or energy communities in conjunction with distributed energy production will participate in future smart electricity markets with benefits for market operation [20]. In particular, the idea under investigation examines the self-balancing opportunity for the prosumer, i.e. a real-time wind energy production in excess of the energy quantity cleared in the day-ahead market could be balanced by a real-time increase of EV consumption rate, offering a decentralized balancing opportunity so that the total deviation perceived by the system operator is zero, and vice versa. However, opportunity for deviation elimination is confined by the time-coupling introduced by the energy-limited nature of the EV battery storage which should be incorporated into the optimization model.

Market Framework

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 [21] are used for the financial settlement of DA and RT energy deliveries. Under the TSS the EV aggregator pays and the wind producer is paid for energy delivery,

$E_t^{DA} \cdot \lambda_t^{DA,E} + (E_{t,\omega}^{RT} - E_t^{DA}) \cdot \lambda_{t,\omega}^{RT,E}$ \$, where the term in parenthesis is the energy deviation between RT actual energy delivery and DA contracted energy, $\Delta E_{t,\omega}$, 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 participant offers and bids, 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 minutes, 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) [22], [23]. 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).

Loads participating in the regulation market 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 [24]. Instructed deviations (following either manual or automatic dispatch instructions) are not penalized, since they are not the EV aggregator's responsibility.

Under the market framework described above, a wind producer participates in the short-term (DA and RT) wholesale electricity markets by submitting energy offers. He is assumed to act as price taker, by submitting non-priced (quantity only) DA energy offers (i.e. offers at zero price). In addition, he could curtail wind in real-time to avoid energy deviation penalties. In this paper wind curtailment is based only on wind producer's decision and not on SO command (e.g. for system reliability reasons) [25]. Thus, any wind energy deviation between DA and RT markets, owing either to available wind generation forecast errors or to wind curtailment by the wind producer is considered as uninstructed energy deviation.

Due to the high wind potential uncertainty, the wind producer's offering strategy is based on wind power forecasts. There is extensive bibliography on wind forecasting methods and tools. A detailed review can be found in [26].

An EV aggregator, managing a fleet of I EVs, also participates in the short-term (DA and RT) wholesale electricity markets described above as a 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). The EV 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 this work, the EV aggregator and the wind producer optimize their offering and bidding strategy assuming that they optimally respond to a deterministic forecast of DA energy and regulation (up/down) prices. Even ignoring DA price forecast uncertainties, the EV aggregator has to factor a number of other uncertainties into his optimal bidding strategy. These uncertainties are first due to the random commuting behavior of the individual EV drivers. Deriving the statistical patterns for one EV is not an easy

task; however for a large EV fleet statistical patterns could be derived, as most of commuting has a daily / weekly repeated pattern [27]. Based on these patterns the EV aggregator can design suitable forecasting approaches for EV fleet behavior [28]. In addition, uncertainty exists in balancing market prices, and in RT deployment of the EV aggregator's contracted regulation capacity by the SO (instructed deviations). The two main sources of uncertainty for the wind producer are the uncertainty in balancing market prices and the RT available wind power.

The prosumer that participates in the market on behalf of the wind producer and the EV aggregator follows the same market rules for energy offers and bids as well as regulation offers. However, these quantities are a result of a co-optimized strategy.

The stochastic parameter used to quantify uncertainty in the energy content of the RT deployment of the contracted regulation capacity is the dispatch-to-contract ratio R_{dc} , defined as the ratio of the RT deployed energy to the contracted regulation capacity of the EV aggregator. R_{dc} can be estimated by statistical analysis of the AGC signal to the EV 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 [29]. The energy content of the AGC signal followed by the EV 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 prosumer does not know which specific scenario will materialize at the time he decides his DA market participation strategy. Therefore, stochastic optimization with recourse [30] is used in order to devise the optimal strategy. The input parameters of the stochastic model are the deterministic forecast of the 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 $\{\lambda_{k,\omega}^{RT,E}, R_{k,\omega}^{dc+(-)}, E_{k,\omega}^{W,RT} \forall k, \omega\}$ and aggregate fleet characteristics $\{T_{i,\omega}^{arr}, T_{i,\omega}^{dep}, SOE_{i,\omega}^{arr}, \forall i, \omega\}$.

Mathematical Model Formulation

The problem of the optimal synergistic market participation strategy of a wind producer and an EV aggregator in the day-ahead energy and regulation markets is formulated as a two-stage stochastic mixed integer linear programming problem (SMILP) as follows:

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

Subject to:

$$E_t^{DA} = E_t^{W,DA} - E_t^{EV,DA} \quad \forall t \quad (2)$$

$$E_t^{W,DA} \leq P^{W,rtld} \cdot 1h \quad \forall t \quad (3)$$

$$E_t^{EV,DA} \leq \sum_i P_i^{chrg} \cdot 1h \quad \forall t \quad (4)$$

$$E_t^{DA} = E_t^{DA,+} - E_t^{DA,-} \quad \forall t \quad (5)$$

$$E_t^{DA,+} \leq b_t \cdot P^{W,rtld} \cdot 1h \quad \forall t \quad (6)$$

$$E_t^{DA,-} \leq (1 - b_t) \cdot \sum_i P_i^{chrg} \cdot 1h \quad \forall t \quad (7)$$

$$\Delta E_{t,\omega} = \Delta E_{t,\omega}^{U,W} - \Delta E_{t,\omega}^{EV} \quad \forall \omega, t \quad (8)$$

$$\Delta E_{t,\omega}^U = \Delta E_{t,\omega}^{U,W} - \Delta E_{t,\omega}^{U,EV} \quad \forall \omega, t \quad (9)$$

$$\Delta E_{t,\omega}^{EV} = \sum_{k \in \mathcal{K}_t} E_{k,\omega}^{EV,RT} - E_t^{EV,DA} \quad \forall \omega, t \quad (10)$$

$$\Delta E_{t,\omega}^{EV} = \Delta E_{t,\omega}^{I,EV} + \Delta E_{t,\omega}^{U,EV} \quad \forall \omega, t \quad (11)$$

$$\Delta E_{t,\omega}^{I,EV} = \sum_{k \in \mathcal{K}_t} (E_{k,\omega}^{RT,R-} - E_{k,\omega}^{RT,R+}) \quad \forall \omega, t \quad (12)$$

$$E_{k,\omega}^{RT,R+} = R_{k,\omega}^{dc+} \cdot R_{t,\omega}^{RT+} \cdot \Delta t \quad \forall \omega, t, k \in \mathcal{K}_t \quad (13)$$

$$E_{k,\omega}^{RT,R-} = R_{k,\omega}^{dc-} \cdot R_{t,\omega}^{RT-} \cdot \Delta t \quad \forall \omega, t, k \in \mathcal{K}_t \quad (14)$$

$$\Delta E_{t,\omega}^{U,W} = \sum_{k \in \mathcal{K}_t} E_{k,\omega}^{W,RT} - E_t^{W,DA} \quad \forall \omega, t \quad (15)$$

$$E_{k,\omega}^{EV,RT} = \sum_i E_{i,k,\omega}^{EV,RT} \quad \forall \omega, k \quad (16)$$

$$P_{i,k,\omega}^{RT \max} = u_{i,k,\omega} \cdot P_i^{chrg} \quad \forall i, \omega, k \quad (17)$$

$$E_{i,k,\omega}^{EV,RT} \leq P_{i,k,\omega}^{RT \max} \cdot \Delta t \quad \forall i, \omega, k \quad (18)$$

$$SOE_{i,k+1,\omega} = SOE_{i,k,\omega} + \frac{\eta_i^c}{E_i^{bat,\max}} E_{i,k,\omega}^{RT} \quad \forall i, \omega, k \quad (19)$$

$$SOE_{i,T_i,\omega}^{dep} = SOE_i^{dep} \quad \forall i, \omega \quad (20)$$

$$R_{t,\omega}^{RT+} \leq \frac{E_t^{EV,DA} + \Delta E_{t,\omega}^{U,EV}}{1h} \quad \forall \omega, t \quad (21)$$

$$R_{t,\omega}^{RT-} \leq \sum_i \left[u_{i,k,\omega} P_{i,k,\omega}^{RT \max} \right] - \frac{(E_t^{EV,DA} + \Delta E_{t,\omega}^{U,EV})}{1h} \quad (22)$$

$$\forall \omega, t, k \in \left\{ \frac{t-1}{\Delta t} + 1, \frac{t}{\Delta t} + 1 \right\}$$

$$R_{t,\omega}^{RT+(-)} \leq R_t^{DA+(-)} \quad \forall \omega, t \quad (23)$$

$$E_{k,\omega}^{W,RT} \leq E_{k,\omega}^W \quad \forall k, \omega \quad (24)$$

$$E_{k,\omega}^{W,RT} = E_{k,\omega}^W \quad \forall k, \omega \quad (25)$$

$$Pnlty_{t,\omega}^{U,Up} \geq 0 \quad \forall \omega, t \quad (26)$$

$$Pnlty_{t,\omega}^{U,Up} \geq M^{fx} (\Delta E_{t,\omega}^U - dev \cdot (E_t^{DA,+} + E_t^{DA,-})) \quad \forall \omega, t \quad (27)$$

$$Pnlty_{t,\omega}^{U,Dn} \geq 0 \quad \forall \omega, t \quad (28)$$

$$Pnlty_{t,\omega}^{U,Dn} \geq M^{fx} (-\Delta E_{t,\omega}^U - dev \cdot (E_t^{DA,+} + E_t^{DA,-})) \quad \forall \omega, t \quad (29)$$

The mathematical model can be easily decomposed to two separate problems, the one of the EV aggregator or the one of the wind producer, by fixing to zero the variables concerning the other market entity.

The objective function (1) is the maximization of the profits from the participation in the DA and RT energy markets (assuming two settlement system), as well as in the regulation market, minus the penalties for energy deviations. 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 [31]. Constraint (2) defines the synergistic (net) day-ahead energy quantity which equals the wind energy offer minus the EV aggregator's energy bid. Constraints (3) and (4) impose upper bounds on the day-ahead energy quantities. The wind producer energy offer cannot exceed the rated

wind farm capacity and the EV aggregator energy bid cannot exceed the EV fleet charging capability. Multiplication by $1h$ is necessary to convert power to energy quantities, assuming hourly dispatch interval. In (5), only one of $E_t^{DA,+}$ and $E_t^{DA,-}$ equals the synergistic day-ahead energy quantity (E_t^{DA}) every hour. Both variables are positive and mutually exclusive so that when $E_t^{DA} \geq 0$, $E_t^{DA} = E_t^{DA,+}$ and $E_t^{DA,-} = 0$. When $E_t^{DA} \leq 0$ (i.e. the EV aggregator bid is higher than the wind producer offer), $E_t^{DA,-} = -E_t^{DA}$ and $E_t^{DA,+} = 0$. Mutual exclusivity is ensured by using the binary variable b_t in (6) and (7) and is necessary for the correct energy deviation penalization modeling in (27) and (29). In (6) and (7) upper bounds are also implied for $E_t^{DA,+}$ and $E_t^{DA,-}$ which are the same as in (3) and (4).

The synergistic, net energy deviation is calculated from the wind energy deviation (always uninstructed as explained in Market Framework Section) minus the EV aggregator energy deviation in (8). The net uninstructed energy deviation is calculated in (9). In (10) the EV aggregator total energy deviation between real-time and day-ahead markets is defined, which is separated in "instructed" and "uninstructed" energy deviations in (11). "Instructed" deviations for the aggregator are calculated in (12) and derive from the instructed deviations due to the energy content of the AGC signal that are given in (13) and (14) in terms of the contracted regulation capacity and the corresponding stochastic (scenario-dependent) dispatch-to-contract ratio. The wind producer energy deviation between the two markets is defined in (15). Since hourly average RT prices are used for settlement, there is no need for sub-hourly differentiation of the respective deviations $\Delta E_{t,\omega}$, $\Delta E_{t,\omega}^W$, $\Delta E_{t,\omega}^{EV}$, $\Delta E_{t,\omega}^I$, $\Delta E_{t,\omega}^U$.

The real-time fleet energy consumption is the sum of all individual EV consumptions (16). Note that only real-time energy quantities are dispatched to individual EVs. Power and energy charging capability for every EV are defined in (17) and (18) respectively. In (17) $u_{i,k,\omega}$ ensures that the EV can charge only when it is plugged-in. In (18) charging energy must be equal to or lower than the maximum charging energy. Equation (19)

calculates the State-of-Energy² $SOE_{i,k,\omega}$ and constraint (20) defines the target SOE at departure time T_i^{dep} . In addition, revised up regulation offers should not exceed the possible load reduction capability (21) and down regulation offers should not exceed the possible load increase capability³ (22). Numerators of the last terms in (21) and (22) denote the aggregator “Preferred Operating Point” (POP), which may be different from the day-ahead energy bid if the aggregator decides to cause an uninstructed deviation. Through uninstructed deviations the EV aggregator can exercise arbitrage between RT and DA markets. Constraint (23) models the market rule requesting that the revised regulation capacity offer quantities should be less than or equal to the DA offer quantities. In case wind curtailment is possible (24) is used. In other case eq. (25) is used. Constraints (26)-(29) 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 (26) and (28) are converted to equality (zero penalty for both up and down deviation). In case of a positive net uninstructed deviation, deviation penalty is determined by equation (27), while in case of a negative net uninstructed deviation penalty is determined by equation (29). It is noted again that due to the binary variable used in (6) and (7), only one of $E_i^{DA,+}$, $E_i^{DA,-}$ is non-zero.

Residential Night Charging - Problem Set-Up

Residential night charging of EV is a suitable business case for EV aggregation approaches. We assume that residential night charging spans the period starting at 16:00 of a trading day and ending at 11:00 of the next trading day. Thus the EV aggregator DA market bidding strategy must cover two consecutive DA market periods. As shown in Fig 1, at 12:00 of Day 1, which is the DA market (DAM) Gate Closure (GC) for Day 2 (first trading day), the EV aggregator submits energy bids and regulation offers for the time period from 16:00 till 24:00

of Day 2. For the same period the wind producer offering strategy is based on wind forecasts 29-36 hours ahead. Energy bids and regulation offers from 24:00 of Day 2 till 11:00 of Day 3 are submitted before the GC of Day 3 (i.e. at 12:00 of Day 2). For this second period the wind producer submits energy offers based on updated forecasts (12-24 hours ahead). It is noted that the wind producer does not face time-coupling constraints in his offering optimization problem, whereas the EV aggregator does, owing to the EV battery storage.

The synergistic strategy that spans the two trading days (Day 2 and Day 3 in Fig. 1) is as follows.

1. The co-optimized model is solved before 12:00 of Day 1 (DAM GC of Day 2) and computes the energy and regulation offers from 16:00 of Day 2 to 11:00 of Day 3 (20-hour horizon). For this scheduling horizon wind forecasts produced the hour before DAM GC for Day 2 are 29-48 hours ahead forecasts. Perfect knowledge of the EV fleet characteristics is assumed. After solving the co-optimized model, the synergistic energy and regulation offers from 16:00 to 24:00 of Day 2 are submitted to the market operator (Day 2 DAM session) and are considered as fixed input parameters in the next step.
2. The co-optimized model is solved again for the same time horizon, from 16:00 of Day 2 to 11:00 of Day 3. However wind forecast is now updated before GC of Day 3 (wind forecast horizon is now 5 - 24 hours ahead). Offer quantities between 16:00 and 24:00 are fixed from the previous problem solution (Step 1), and now the energy and regulation offers from 24:00 of Day 2 to 11:00 of Day 3 are computed and submitted to the market operator (Day 3 DAM session).

Case Study

A case study is examined where a wind producer and an EV aggregator form a coalition for market participation using the approach described above. The co-optimized synergistic offering and bidding strategy is compared with the case where the wind producer and the EV aggregator optimize their strategy individually. One hundred (100) equiprobable scenarios were created for the simulation.

² In this work, we use State-of-Energy instead of State-of-Charge (SOC), because of the easy derivation of power and energy quantities in

the model, $SOE_{i,k} = \frac{E_{i,k}^{bat}(kWh)}{E_i^{bat,max}(kWh)}$

³ 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 (20), ensures that the full power of the $R_t^{RT,-}$ contract 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.

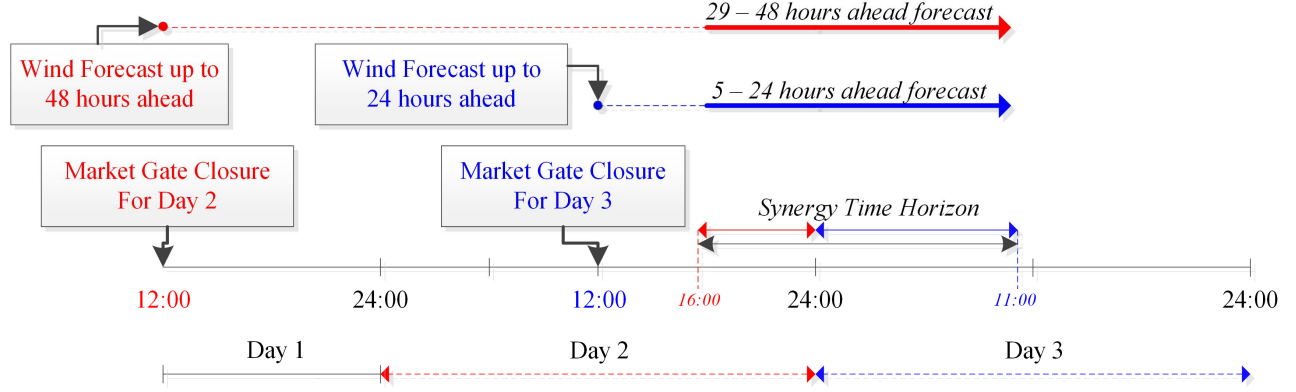


Fig. 1 Market operation and problem set-up for successful participation of an EV aggregator or a prosumer in EV Residential Night Charging aggregating program.

EV fleet Modeling

For the EV fleet modeling truncated Gaussian distributions (TGD) for arrival and departure times were used. For battery SOE at arrival uniform distribution was adopted. Final SOE was set at 97%. Battery Capacity (kWh) was considered to be uniformly distributed between 5 and 30 kWh. Charging efficiency was considered 90%. Maximum charger power was set to 3.3 kW for all EVs. Details for EV fleet distributions are given in Table 1.

Table 1: Probability Distributions for EV Data
UD: uniform distribution, TGD: truncated Gaussian distribution

	Distr.	Mean	St. dev	Min	Max
Battery capacity (kWh)	UD	17.5	7.21	5	30
Arrival Time (h)	TGD	19	2	16	1
Departure Time (h)	TGD	7	2	5	11
Initial Battery SOE (%)	UD	60	20.2	25	95

Wind Scenarios

Wind power scenarios were created based on time series analysis [32]. A Greek wind farm with rated capacity 6.3 MWp was selected and time series modeling was based on 15-min data from 2 years measurements. The best time series model was selected after evaluating ARMA, ARIMA models and transformed time series based on Box-Cox transformations [33]. The ARMA(3,0,6) model was chosen based on BIC criterion [33]. After selecting the model, 100 scenarios of wind production realizations were created based on the methodology explained in [34]. It is noted that this paper does not focus on the most

accurate wind forecasting modeling approach. Other approaches (e.g. using inputs from numerical weather prediction tools [26]) could possibly lead to more accurate wind scenarios; however state-of-the art forecast modeling is out of the scope of this paper.

Price Scenarios

DA and RT weighted-average hourly prices from the PJM RTO [35] were compared for July 2011 and for every hour of the day the standard deviation between the two prices (RT-DA) were calculated. Price differences larger than twice the standard deviation were excluded from the statistical analysis. Assuming perfect DA price-forecast for 17 July 2011, 100 RT price scenarios were created based on 24-hour DA price time series and the RT-DA price standard deviation. For regulation price, the hourly prices found at PJM for the same day were used. In Fig. 2 DA energy and regulation price together with some RT energy price scenarios are presented.

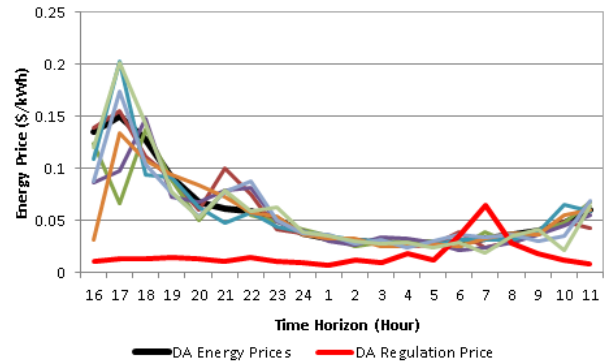


Fig. 2 DA energy and regulation price and RT energy price scenarios

AGC Signal

A statistical processing of the PJM RTO [35] AGC signal for one week (17-24 December 2011) was carried out. The signal sampling frequency was 4 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.

Four approaches to energy deviation penalty scheme were simulated.

- A) No penalty to uninstructed energy deviations is imposed.
- B) Uninstructed energy deviations higher than 20% of the DA offer or bid are penalized at PJM RTO Balancing Operating Reserve (BOR) deviation charge rate equals to 5.280173 \$/MWh, as specified for 17-Jul-2011 [36].
- C) All uninstructed energy deviations are penalized at BOR deviation charge rate.
- D) Uninstructed energy deviations higher than 20% are penalized at 150\$/MWh. This price is the price cap of the Greek electricity market [37] and it is used for penalizing LSE's energy deviations bigger than a non-penalized deviation band. The non-penalized band changes according to bids' magnitude. In our case study it is considered 20% for both offers and bids.

In addition, we examine two different cases.

- I) The entire wind production is fed into the grid, maximizing the RES share on electricity production.
- II) The wind producer may curtail wind generation to avoid energy deviation penalties.

From Table 2 and Table 3 it is concluded that with or without wind curtailment there is no profit increase owing to the synergistic market participation strategy in the case that no penalty is imposed to the energy deviations (case A). However, in the case of BOR deviation charge, the synergistic approach could increase profits, but only marginally (case B and C). For the case of 150\$/MWh deviation penalty however significant economic gains can be achieved.

Comparing Table 2 and Table 3 again, wind curtailment plays no role in the case that no penalty or BOR deviation charge is imposed (cases A, B, C) but it plays an

important role in case D. This result was expected: if the energy deviation penalty is low compared to the energy prices, the wind producer makes always profit by selling all wind energy at the market price, even if he is charged with a small penalty for all (case C) or a portion (case B) of his energy deviation. However, a penalty of 150\$/MWh is higher than the average energy price, therefore the wind producer may decide to curtail wind power to avoid high penalties.

Of course, the EV aggregator's profit is the same in the two Tables (independent of whether there is wind curtailment or not). Although he is a load serving entity and he purchases energy for his clients (EV owners) from the DAM, he ends up earning a profit from his participation in the DAM. This profit is a result of his participation in the regulation market. For the specific case study, his revenue from the regulation market is higher than his cost of energy purchases in the energy market, thus he earns a net profit.

Table 2: Profits from individual and synergistic strategy, no wind curtailment

Profit (\$)				
	Individual Strategies			Synergy
Case	EV Aggregator	Wind Producer	Total Profit	Synergy
A	181	2996.2	3177.2	3177.2
B	132	2797.7	2929.6	2935.3
C	124.1	2743.3	2867.4	2877.6
D	96	58.8	154.9	694.4

Table 3: Profits from individual and synergistic strategy, with wind curtailment

Profit (\$)				
	Individual Strategies			Synergy
Case	EV Aggregator	Wind Producer	Total Profit	Synergy
A	181.0	2996.2	3177.2	3177.2
B	132	2797.7	2929.6	2935.3
C	124.1	2743.3	2867.4	2877.6
D	96.0	1094.4	1190.5	1381.4

In Fig. 3 the optimized DA energy offering strategy of the wind producer for case B is presented together with the wind energy production of all 100 scenarios.

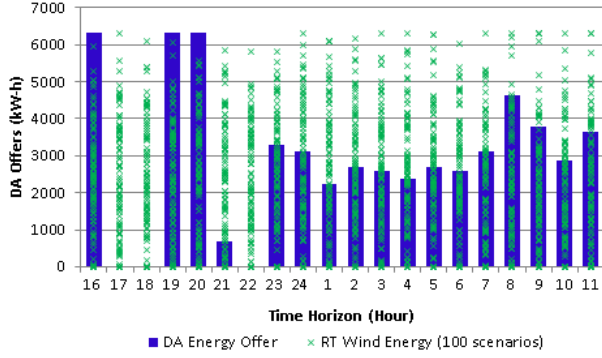


Fig. 3 Energy offers of wind producer's offering strategy (individual) and scenario-dependent real-time energy production – case B.

In Fig. 4 the optimized DA energy bidding and regulation offering strategy of the EV aggregator is presented for the same case. The maximum hourly charging power of the EV fleet is also presented.

In Fig. 5 the net DA energy offers/bids for individual and synergistic strategy are presented for case B. Energy quantities for the two strategies are close enough except from hour 4, when a bigger difference is noticed.

In Fig. 6 a substantial change in DA up regulation offering strategy appears. As explained before (23) DA regulation offers are actually equal to the larger expected (scenario-dependent) revised regulation capacity offer, therefore through the synergy opportunity for increased up regulation offer is created. For DA down regulation offering strategy, differences between the two approaches are negligible. The EV aggregator favors down regulation offering because a capacity compensation (at regulation market clearing price) accompanies the EV charging. Therefore, the DA down regulation offer is already increased even in case the EV aggregator participates individually in the market.

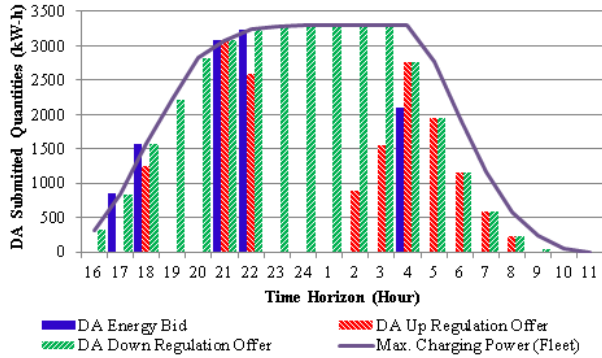


Fig. 4 DA energy bids and regulation offers from EV aggregator's bidding strategy(individual) – case B.

In Fig. 7 changes in the EV Aggregator's DA energy bidding and the wind producer's DA energy offering strategy before and after the synergy are presented for case D (with opportunity for wind curtailment), together

with the upper bounds for maximum allowed market submitted quantities. Through (2) these quantities determine the prosumer's net offers/bids which are presented in Fig. 8. Before synergy there was a net bid at hour 4 which turns to a net offer under the synergistic approach.

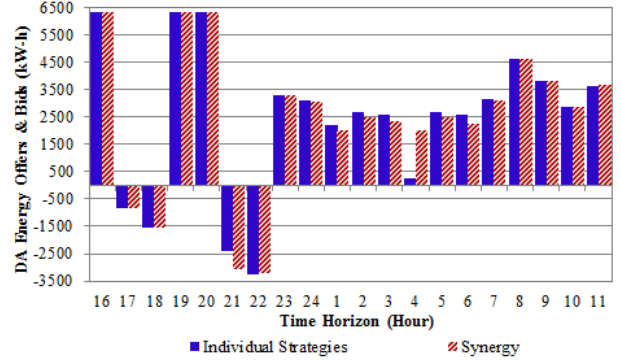


Fig. 5 Energy offers and bids from synergistic and individual strategies for the wind producer and the EV aggregator – case B.

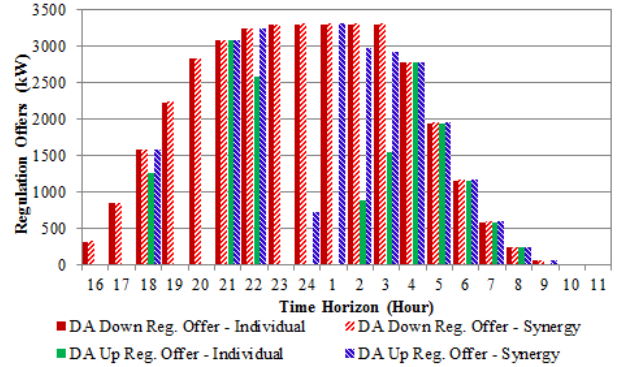


Fig. 6 DA regulation offers from synergistic and individual strategies for the wind producer and the EV aggregator – case B.

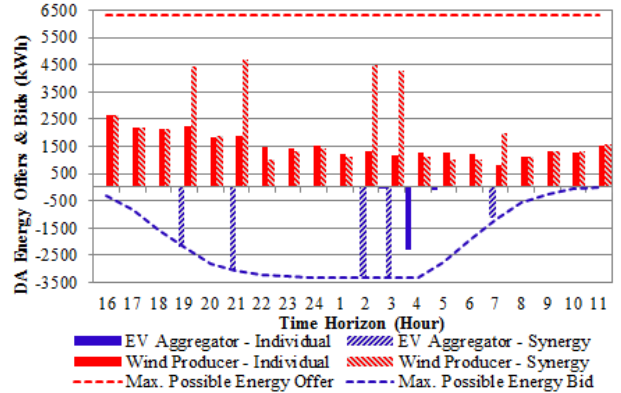


Fig. 7 Wind producer offering and EV Aggregator bidding strategy under individual and synergistic approach – case D (with opportunity for wind curtailment). Bids are presented as negative quantities.

In Fig. 9, DA up regulation offers expand to all hours in case of synergistic strategy. Again, changes in DA down regulation offer are negligible. In Fig. 10, synergistic

offers are presented for case D without wind curtailment opportunity. Compared to Fig. 8, higher deviations between the individual and synergistic strategy are noticed. In addition, offer quantities are larger. In Fig. 11 DA regulation offers are presented. As before, a substantial increase in DA up regulation offer is noticed.

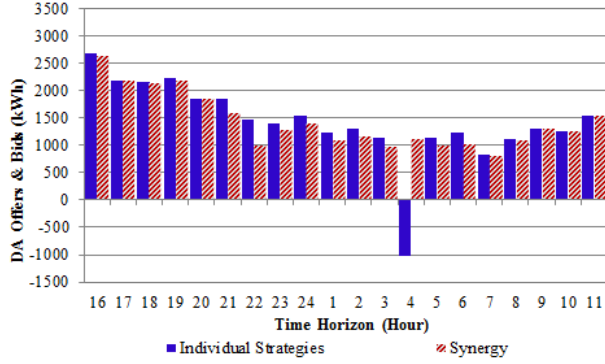


Fig. 8 Energy offers and bids from synergistic and individual strategies for the wind producer and the EV aggregator – Case D (with opportunity for wind curtailment).

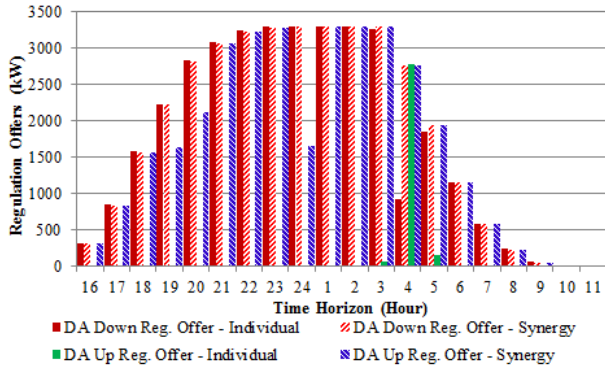


Fig. 9 DA regulation offers from synergistic and individual strategies for the wind producer and the EV aggregator – Case D (with opportunity for wind curtailment).

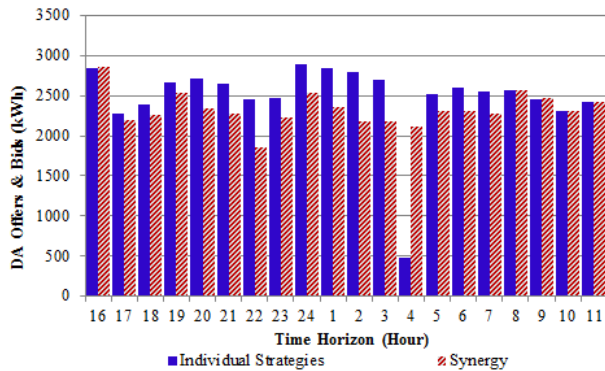


Fig. 10 Energy offers and bids from synergistic and individual strategies for the wind producer and the EV aggregator – Case D (without wind curtailment opportunity).

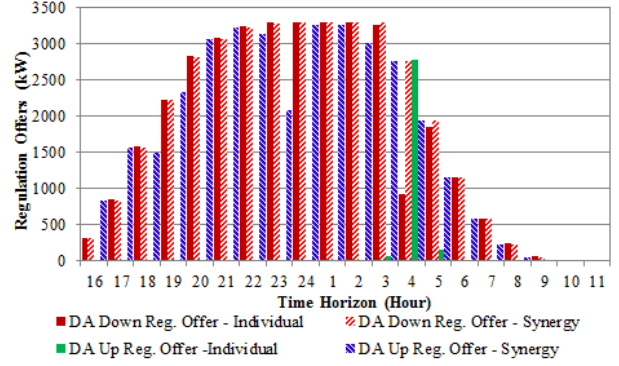


Fig. 11 DA regulation offers from synergistic and individual strategies for the wind producer and the EV aggregator – Case D (without wind curtailment opportunity).

In Fig. 12 uninstructed energy deviations for the individual and synergistic strategy are presented for one scenario. Results are for one scenario of case D without wind curtailment opportunity. It is obvious that through synergistic market participation energy deviations can be reduced to some extent. The same result is observed in Fig. 13 for the same scenario but with wind curtailment opportunity. The net uninstructed energy deviation is smaller than the case in Fig. 12, however reduction in energy is smaller because through wind curtailment energy deviations have already been reduced to some extent before exploiting the synergy's possible benefits.

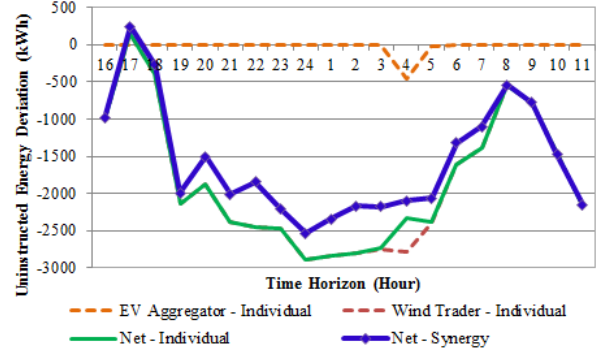


Fig. 12 Uninstructed energy deviations for individual and synergistic strategy – Case D (without wind curtailment opportunity).

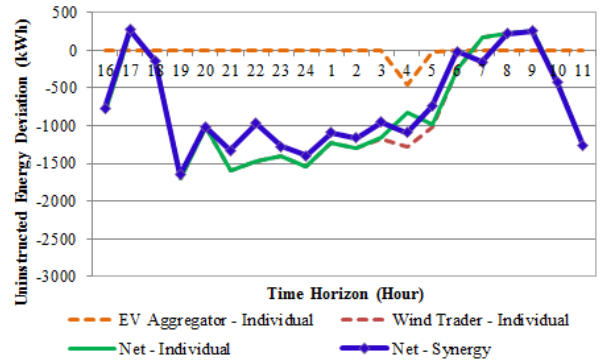


Fig. 13 Uninstructed energy deviations for individual and synergistic strategy – Case D (with wind curtailment opportunity).

In Table 4 and 5, the mean absolute hourly net uninstructed energy deviation for the 100 scenarios is presented for the two approaches. In case A of Table 4 (when no penalty is imposed), the synergy does not create any benefit as stated before and the energy deviations are identical. In cases B and C of the same Table, the synergy leads to smaller mean absolute energy deviations and in case D (with a much higher penalty imposed) the mean absolute energy deviations are further reduced. Wind curtailment plays no role in cases A, B and C (Table 5) where reductions are exactly the same with those of Table 4, but in case D a reduced mean absolute energy deviation compared to individual strategy is noticed again.

Table 4: Mean hourly absolute net uninstructed energy deviation, individual and synergistic strategy, no wind curtailment

Case	Synergy (kWh)	Individual (kWh)
A	4426.6	4426.6
B	2423.3	2472.9
C	2165.3	2269.7
D	1088.1	1351.6

Table 5: Mean hourly absolute net uninstructed energy deviation, individual and synergistic strategy, with wind curtailment

Case	Synergy (kWh)	Individual (kWh)
A	4426.6	4426.6
B	2423.6	2472.9
C	2165.3	2269.7
D	520	567.1

Conclusion

The benefits from the synergistic market participation of a wind producer and an EV aggregator in day-ahead electricity markets are strongly dependent on the specific market rules of the energy deviation penalty scheme. If no penalty is imposed to energy deviations between day-ahead and real-time market, the synergistic market participation cannot create any extra profit. However, when energy deviation penalties are imposed, the higher the penalty, the higher the profit from the synergistic market participation. Wind curtailment creates an opportunity for extra profit only in case of a high deviation penalty. Finally, a significant change in DA up regulation offer quantity is recorded in cases a deviation penalty is imposed, indicating the synergy's impact on DA regulation offering strategy.

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