Pool Strategy of a Producer Coordinated with Vehicle-to-Grid Services to Maximize Profitability

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Abstract— This paper investigates the impact of coordinating vehicle-to-grid (V2G) services with a producer on the price amounts and the market outcomes. A stochastic intra-hour bilevel model is developed for an electricity pool including the day-ahead and real-time markets. The conditional value at risk (CVaR) function takes into account to control high trading risks which are arisen from uncertainties due to high wind penetration and EVs. The problem is formulated from a mathematical program with equilibrium constraints (MPEC) to a mixed-integer linear program (MILP). The simulation results demonstrate the benefits of coordinating V2G services with a strategic producer for the increasing profitability, social welfare and optimizing EV charging profiles.

Index Terms- Electricity market equilibrium, electric vehicles, wind power, CVaR, mathematical program with equilibrium constraints (MPEC), and mixed-integer linear program (MILP).

NOMENCLATURE

Indices:

d	Demands.
ev	Electric vehicle units.
g	Conventional generating units.
i	Intrahour (sub-hour) time intervals.
s	Scenarios.
t	Hourly time intervals.
w	Wind energy units.

Parameters:

$D_{ev,t,i}^{s}$	Energy consumption by EV while driving.
$E_{ev,t}^{max}, E_{ev,t}^{min}$	Max/Min available energy in EV aggregator.
$N_{ev,t,i}^{s}$	Plugged-in EV number scenarios.
N_I	Number of intrahour intervals.
N_s	Number of scenarios.
N_T	Number of hour intervals.
C_g	Marginal cost of conventional units ($/MWh).
$C_{d,t}^{L}$	Load curtailment cost ($/MWh).
L_d^{max}	Max load demand (MW).
$P_{(.)}^{max}$	Max power generation of units (MW).
$P_{w,t,i}^{RT^s}$	Real-time forecasted wind power (MW).
P^{CGenCO}	Total conventional units power capacity.
$SOC_{EV}^{max,min}$	Max/Min state of the charge.
$R_{(.)}^{up^{max}}, R_{(.)}^{d^{max}}$	Max regulation up/down (MW).

ρ^{T}	Fixed EV charging tariff ($/MWh).
π_s	Probability of scenarios.
$B_{d,t}^{DA}$	Day-ahead bid price of demand ($/MW).
λ	Risk-aversion parameter.

Variables:

φ_s, γ	Auxiliary variables for computing CVaR
ρ_t^{DA}	Day-ahead clearing price ($/MWh).
$\rho_{t,i,s}^{RT}$	Real-time clearing price ($/MWh).
$\alpha_{(.),t}^{DA}\ \alpha_{(.),t,i}^{RT^s}$	Day-ahead / Real-time offer price ($/MW).
$\beta_{(.),t}^{DA}$	Day-ahead bid price ($/MW)
$\mu_{(.),t}^{DA^{min}}\ \mu_{(.),t}^{DA^{max}}$	Max/Min day-ahead dual variables.
$\mu_{(.),t,s}^{RT^{min}}\ \mu_{(.),t,s}^{RT^{max}}$	Max/Min real-time dual variables.
$E_{ev,t,i}^{s}$	Real-time energy of EV aggregator.
$L_{d,t}^{DA}$	Day-ahead demand (MW).
$L_{d,t,i}^{C^s}$	Demand load curtailment (MW).
$P_{(.),t}^{DA}$	Day-ahead (MW) power generations (MW).
$P_{(.),s,t,i}^{RT}$	Real-time power generations (MW).
$P_{w,t,i}^{C^s}$	Wind power curtailment (MW).
$PoP_{ev,t}$	Preferred operating point (day-ahead power-drawn) of the EVs (MW).
$R_{(.),t,i}^{down^s}$	Regulation down power (MW).
$R_{(.),t,i}^{up^s}$	Regulation up power (MW).

I. INTRODUCTION

The future of humanity is dependent on saving the environment of global warming caused by CO_2 emission from electricity generation and transportation systems [1-2]. The remedies are the increasing in the penetration of renewable energy in electricity generation and electric vehicles (EVs) in transportation [1].

The Electric Vehicles Initiative (EVI) members include 8 of the 10 largest vehicle markets in the world, account for about 63% of the world's total vehicle demand, and are projected to account for 83% of EV sales by 2020 [3]. The report shows that wind power could supply up to 17-19% and 25-30% by 2030, and 2050 of global electricity supply, respectively [4].

The main operational problem associated with a high wind penetration and EVs comes from intermittency and unpredictability [2]. Also, EVs might impose excessive load on the grid [5]. Therefore, price amounts and the market outcomes are influenced by participating of the wind power

and EV loads in high penetration [6-7]. It is vital for producers and market operator to review equilibrium analysis to investigate the sensitivity analysis of diverse parameters on the expected profit, social welfare, and active players in vehicle-to-grid (V2G) markets [6-8].

A mechanism is necessary to integrate the electrified transportation within the power system and encourage EV's owners as active players in the electricity market [9-10]. Unidirectional vehicle-to-grid (V2G) technology is a mechanism that the EV load aggregators in a sizeable number can participate in energy ancillary services due to much faster ramping capability than gas turbines [11-12].

However, the highest benefits for EV aggregators are expected through participation in ancillary services [13]. The EV aggregator is not able to consider both less tariff to be active player and high probability to be competitive on its own. In addition, power systems are likely to face increasing uncertainties in both generation and load and there is no coordination between them [2]. Therefore, coordinating EV aggregator with the generating companies (GenCOs) in electricity market can be useful in power systems, which is demonstrated in several studies in literature. In [14], a stochastic unit commitment model is used to simulate wind-thermal power system scheduling with different charging patterns for EVs to reduce operating costs of a power system. The authors of [15] have examined the effect of EV integration in a wind-thermal power system on emissions produced. Study [9] proposed coordinating unidirectional vehicle-to-grid (V2G) services with energy trading. In [2], power exchange between WGenCO and EV loads in the energy and ancillary service prices are modeled. However, these studies have assumed participants as price-taker, since they are non-dominant entities [2].

There is a lack of a focus on impact of high wind penetration and EVs on the energy and balancing markets equilibria for both coordinated and uncoordinated strategies in the literature. However, only a limited study has been carried out in [6] on the impact of wind power uncertainty on market equilibria. In [16], an offering strategy for a wind power producer with market power that participates in the day-ahead market as a price-maker and in the balancing market as a deviator is proposed in [16]. Unlike [16], in [17], the producer is a price-taker in the day-ahead market, but a price-maker in the balancing market, and aims at optimizing its expected revenues from these market floors [17]. In [6], the equilibrium problem in a pool-based two-settlement electricity market where wind power is included in the generation portfolio of strategic producer in addition to its dispatchable units [6]. Also, in [7], the bidding strategy of the EV aggregator is formulated as a bilevel problem to take into account the EV aggregator to potentially influence market prices, in contrast to what is commonly found in the literatures [7].

This paper proposes a firm with the optimal offering strategies of power producers and bidding/offering strategies of coordinated EV aggregators in a pool-based electricity market. This study investigates impact of coordinating unidirectional V2G services with energy trading including the conventional generating companies (CGenCOs) and the wind generating companies (WGenCO) on price amounts and the market outcomes.

The main contributions of the paper are as follows:
- The development of an intra-hour equilibrium problem in a two-settlement electricity pool where coordinated V2G services is included within the portfolio of a firm.
- The development of an optimal bidding/offering strategy for EV load demands with participating in the energy market and ancillary service to optimizing EV charging profiles.
- The uncertainties associated with wind forecast, and EV owners' behavior based on driving patterns.

The rest of this paper is organized as follows. Section II discusses the market framework. Section III provides a mathematical model formulation. A case study is described in Section IV. Section V concludes the paper.

II. MARKET FRAMWORK

The day-ahead market and a real-time balancing market are the two settlement systems considered in this paper. A strategic firm including CGenCOs, WGenCOs, and EV aggregators submits supply-offers/demand-bids to the market operator (MO) to participate in the day-ahead and real-time market. The MO run the day-ahead market clearing process to determine day-ahead price, power production schedules of CGenCOs, WGenCOs, LSEs and EVs. Also, the real-time market is cleared for each scenario based on achieved from day-ahead data to determine real-time prices, regulation capacity, and wind power and load curtailments.

The model assumptions are as follow:
1) *EV aggregator* participates as dispatchable loads in the energy and ancillary service markets by submitting strategic bid and offer prices to the day-ahead and the real-time markets, respectively. The EV charging energy and up and down regulation directly influences the strategic producers' expected profit. The amount of regulation contracted is the total amount by which power can deviate from a baseline level. The baseline is often called the preferred operating point (POP) [18]. The term POP itself comes from ancillary services markets. It represents the average level of operation for a market participant providing regulation services [10]. It is assumed that the EV aggregator can deviate from the day-ahead power-drawn (or POP) to balance energy by reducing or increasing their charging rate with consideration of EV aggregator energy constraints.
2) *WGenCO* submits strategic offer prices to the day-ahead and the real-time markets. Moreover, the wind power production excess/shortage, and curtailment power influence the strategic producers' expected profit.
3) *Uncertainties* include wind forecast, and EV owners' behavior based on driving patterns. Scenario generation and reduction methods can be found in [2, 19-22].
4) *CGenCO* participates as dispatchable units in the energy and ancillary service markets by submitting strategic offer prices to the day-ahead and the real-time markets, respectively. The energy production cost functions are assumed to be linear [23].

5) *CVaR* is included to control high trading risks which are arisen from uncertainties due to high wind penetration and EVs [9, 24].
6) *The Load-side entities (LSEs)* submit bid prices for energy and curtailment (to be elastic) to the day-ahead and real market but not strategically [6, 25-26].
7) *A transmission network* is neglected to be simple computation.
8) *The price scheme* is based on paper [23]. Each generating unit is paid for its scheduled power production and EV loads are charged for its power consumption in day-ahead market at the price ρ_t^{DA}. Additionally, each generating unit and EV aggregator is paid/charged for its regulation up/down at the prices $\rho_{t,i}^{RT,s}$ as repurchased prices [23].

III. Mathematical Model Formulation

A. Bilevel Model

A stochastic bilevel model is taken into account where an upper-level problem corresponds to strategic producer's profit maximization with risk aversion using a CVaR function, while the lower-level problems correspond to markets clearing for maximization of social welfare. The mathematical formulation of electricity markets is based on offering/bidding strategy presented in papers [6, 23, and 26].

The primal variables Ω_{prim} of the upper-level problem are including positives offering/bidding variables $\alpha_{g,t}^{DA}$, $\alpha_{w,t}^{DA}$, $\beta_{ev,t}^{DA}$, $\alpha_{g,t,i}^{RT^s}$, $\alpha_{w,t,i}^{RT^s}$, $\alpha_{ev,t,i}^{RT^s}$ and variable sets $\Omega_{prim}^{DA} = \{\rho_t^{DA}, P_{g,t}^{DA}, P_{w,t}^{DA}, POP_{ev,t}\}$, and $\Omega_{prim}^{RT} = \begin{Bmatrix} \rho_{t,i,s}^{RT}, R_{ev,t,i}^{up^s}, R_{ev,t,i}^{down^s} \\ R_{g,t,i}^{up^s}, R_{g,t,i}^{down^s}, P_{w,t,i}^{C^s} \end{Bmatrix}$.

The risk-constrained profit-maximization of a strategic firm is summarized as follows:

$$\underset{\Omega_{prim}, \Omega_{dual}}{Max} \quad Profit^s + \lambda.CVaR_\theta \tag{1}$$

where

$$CVaR = \gamma - \frac{1}{1-\alpha}\sum_s^{Ns} \pi_s.\varphi_s \tag{2}$$

$$Profit^s + \varphi_s \geq \gamma \qquad\qquad \forall s \tag{3}$$

The Objective function of maximizing the expected profits of a strategic firm which owns both CGenCOs and WGenCOs and constitutes V2G services is as follows:

$$\underset{\Omega_{prim}, \Omega_{dual}}{Max} \quad Profit^s$$
$$= \sum_s \pi_s.[PF_s^{CGenCO} + PF_s^{WGenCO} + PF_s^{V2G}] \tag{4}$$

The expected profit of CGenCOs is revenue minus cost of generations in the day-ahead market, and revenue minus cost of regulation up/down in the real-time markets, given by (5).

$$PF_s^{CGenCO} = +\sum_t \sum_g P_{g,t}^{DA}.(\rho_t^{DA} - C_g)$$
$$+ \frac{1}{N_I}\sum_i \sum_t \sum_g \left(R_{g,t,i}^{up^s} - R_{g,t,i}^{down^s}\right)\left(\rho_{t,i,s}^{RT} - C_g\right) \tag{5}$$

The expected profit of WGenCOs is revenue of generations in the day-ahead market, and revenue minus cost of

excess/shortage generation in the real-time markets, given by (6).

$$PF_s^{WGenCO} = +\sum_t \sum_w P_{w,t}^{DA}.\rho_t^{DA}$$
$$- \frac{1}{N_I}\sum_i \sum_t \sum_w \left(P_{w,t}^{DA} + P_{w,t,i}^{C^s} - P_{w,t,i}^{RT^s}\right).\rho_{t,i,s}^{RT} \tag{6}$$

Finally, the EV aggregator's revenue is obtained by selling ancillary services, as well as selling energy to its clients at a fixed price (ρ^T). In this paper, the tariff charged to EV clients is assumed to be constant (fixed). The aggregator encourages EV owners to join in by offering an attractive price for charging in comparison with petrol and energy prices. The EV aggregator's cost is associated with buying energy for EV charging. Hence, the EV aggregator's payoff is represented as,

$$PF_s^{V2G} = -\sum_t \sum_{ev} POP_{ev,t}(\rho_t^{DA} - \rho^T)$$
$$+ \frac{1}{N_I}\sum_i \sum_t \sum_{ev} \left(R_{ev,t,i}^{up^s} - R_{ev,t,i}^{down^s}\right)\left(\rho_{t,i,s}^{RT} - \rho^T\right) \tag{7}$$

The energy balance equation for the EV aggregator is given below:

$$E_{ev,t,i}^s = E_{ev,t,i-1}^s + \left(1 - N_{ev,t,i}^s\right).D_{ev,t,i}^s$$
$$+ \frac{1}{N_I}\left(POP_{ev,t} - R_{ev,t,i}^{up^s} + R_{ev,t,i}^{down^s}\right) \quad \forall ev,s,t,i \tag{8}$$

The EV energy constraint is presented in (9).

$$E_{ev,t}^{Min}.N_{ev,t,i}^s.SOC_{EV}^{min}$$
$$\leq E_{ev,t,i}^s$$
$$\leq E_{ev,t}^{Max}.N_{ev,t,i}^s.SOC_{EV}^{max} \quad \forall ev,s,t,i \tag{9}$$

The lower-level problem (10)-(15) represents the day-ahead market clearing with the aim of maximization of social welfare given by

$$\underset{\{\Omega_{prim}^{DA}, \Omega_{dual}^{DA}\}}{Min} \left[\begin{array}{l} \sum_{g,t} \alpha_{g,t}^{DA} P_{g,t}^{DA} + \sum_{w,t} \alpha_{w,t}^{DA} P_{w,t}^{DA} - \\ \sum_{d,t} B_{d,t}^{DA} L_{d,t}^{DA} - \sum_{ev,t} \beta_{ev,t}^{DA} POP_{ev,t} \end{array} \right] \tag{10}$$

The primal variables of the lower-level problem (10) are those in set Ω_{prim}^{DA}, and its dual variables are represented by the set Ω_{dual}^{DA} which are indicated at the corresponding constraints following a colon.

The energy balance in the day-ahead market is as below:

$$\sum_g P_{g,t}^{DA} + \sum_w P_{w,t}^{DA} - \sum_d L_{d,t}^{DA} - \sum_{ev} POP_{ev,t} = 0 : \rho_t^{DA} \tag{11}$$

where dual variable ρ_t^{DA} provides the day-ahead equilibrium price.

A constraint for the EV's POP is given in (12).

$$0 \leq POP_{ev,t} \leq P_{ev}^{max} \qquad : \mu_{ev,t}^{DA\,max}, \mu_{ev,t}^{DA\,min} \quad \forall ev,t \tag{12}$$

Constraints (13) and (14) limit the scheduled power production of conventional and wind units, respectively.

$$0 \leq P_{g,t}^{DA} \leq P_g^{max} \qquad : \mu_{g,t}^{DA\,max}, \mu_{g,t}^{DA\,min} \quad \forall g,t \tag{13}$$

$$0 \le P_{w,t}^{DA} \le P_w^{max} \qquad : \mu_{w,t}^{DA^{max}}, \mu_{w,t}^{DA^{min}} \qquad \forall w,t \qquad (14)$$

The day-ahead scheduled demand is limited in (15).

$$0 \le L_{d,t}^{DA} \le L_d^{max} \qquad : \mu_{d,t}^{DA^{max}}, \mu_{d,t}^{DA^{min}} \qquad \forall d,t \qquad (15)$$

The lower-level problem (16)-(27) represents the real-time market clearing with aim of maximization of social welfare for scenario s given by

$$Min_{\{\Omega_{prim}^{RT}, \Omega_{dual}^{RT}\}} \begin{bmatrix} \sum_{g,t,i}\left(R_{g,t,i}^{up^s} - R_{g,t,i}^{down^s}\right).\alpha_{g,t,i}^{RT^s} + \\ \sum_{ev,t,i}\left(R_{ev,t,i}^{up^s} - R_{ev,t,i}^{down^s}\right).\alpha_{g,t,i}^{RT^s} + \\ \sum_{w,t,i}(P_{w,t,i}^{C^s}.\alpha_{w,t,i}^{RT^s}) + \sum_{d,t,i} C_d^L L_{d,t,i}^{C^s} \end{bmatrix} \qquad (16)$$

The primal variables of the lower-level problem (16) are those in set Ω_{prim}^{RT}, and its dual variables are represented by the set Ω_{dual}^{RT} which are indicated at the corresponding constraints following a colon.

The energy balance in the real-time market is given in (17).

$$\sum_w\left(P_{w,t}^{DA} + P_{w,t,i}^{C^s} - P_{w,t,i}^{RT^s}\right) - \sum_g\left(R_{g,t,i}^{up^s} - R_{g,t,i}^{down^s}\right) - \\ \sum_d L_{d,t,i}^{C^s} - \sum_{ev}\left(R_{ev,t,i}^{up^s} - R_{ev,t,i}^{down^s}\right) = 0 \qquad :\rho_{t,i,s}^{RT}, \forall s,t,i \qquad (17)$$

where dual variable $\rho_{t,i,s}^{RT}$ provides the real-time equilibrium prices.

The capacity limits for regulation down $(R_{ev,t,i}^{down^s})$ to increase the EV charging rate, and regulation up $(R_{ev,t,i}^{up^s})$ to decrease the EV charging rate are given in (18)-(21).

$$0 \le R_{ev,t,i}^{up^s} \le R_{ev}^{up^{max}} \qquad : \mu_{ev,t,i}^{up^{max}}, \mu_{ev,t,i,s}^{up^{min}} \quad \forall ev,s,t,i \qquad (18)$$

$$R_{ev,t,i}^{up^s} \le POP_{ev,t} \qquad : \mu_{ev,t,i,s}^{up} \qquad \forall ev,s,t,i \qquad (19)$$

$$0 \le R_{ev,t,i}^{down^s} \le R_{ev}^{d^{max}} \qquad : \mu_{ev,t,i,s}^{d^{max}}, \mu_{ev,t,i,s}^{d^{min}} \quad \forall ev,s,t,i \qquad (20)$$

$$POP_{ev,t} + R_{ev,t,i}^{down^s} \le P_{ev}^{max} \qquad : \mu_{ev,t,i,s}^{down} \qquad \forall ev,s,t,i \qquad (21)$$

Constraints (22) and (23) refer to the lower and upper bounds on the up and down regulations deployed from each dispatchable unit.

$$0 \le R_{g,t,i}^{up^s} \le R_g^{up^{max}} \qquad : \mu_{g,t,i,s}^{up^{max}}, \mu_{g,t,i,s}^{up^{min}} \quad \forall g,s,t,i \qquad (22)$$

$$P_{g,t}^{DA} + R_{g,t,i}^{up^s} \le R_g^{up^{max}} \qquad : \mu_{ev,t,i,s}^{up} \qquad \forall g,s,t,i \qquad (23)$$

Constraints (24) and (25) guarantee that the power productions of conventional units are less than its capacities.

$$0 \le R_{g,t,i}^{down^s} \le R_g^{d^{max}} \qquad : \mu_{g,t,i,s}^{d^{max}}, \mu_{g,t,i,s}^{d^{min}} \quad \forall g,s,t,i \qquad (24)$$

$$R_{g,t,i}^{down^s} \le P_{g,t}^{DA} \qquad : \mu_{g,t,i,s}^{down} \qquad \forall g,s,t,i \qquad (25)$$

The constraints (26) and (27) limit the minimum and maximum for the wind power and load demand curtailment.

$$0 \le P_{w,t,i}^{C^s} \le P_{w,t,i}^{RT^s} \qquad : \mu_{w,t,i,s}^{c^{max}}, \mu_{w,t,i,s}^{c^{min}} \quad \forall w,s,t,i \qquad (26)$$

$$0 \le L_{d,t,i}^{C^s} \le L_d^{max} \qquad : \mu_{d,t,i,s}^{c^{max}}, \mu_{d,t,i,s}^{c^{min}} \quad \forall d,s,t,i \qquad (27)$$

B. MPEC

The bilevel model (10) – (27) can be formulated as a single-level stochastic mathematical program with equilibrium constraints (MPEC). The lower problems are linear and it can be replaced by its Karush-Kuhn-Tucker conditions [27].

C. MILP

The MPEC are converted to a MILP by linearizing of two nonlinearities as follow:

1) Nonlinear terms in $Profit^s$ can be linearized by the strong duality conditions and some KKT equalities [26].

$$Profit^s = \sum_t \sum_{ev} POP_{ev,t}.\rho^T - \sum_t \sum_g P_{g,t}^{DA}.C_g - \\ \sum_t \sum_d L_d^{max}.\mu_{d,t}^{DA^{max}} + \sum_{dt} \sum_d B_{d,t}^{DA}.P_{d,t}^{DA} + \\ \frac{1}{N_I}\sum_i \sum_t \sum_{ev} \sum_s \left(R_{ev,t,i}^{up^s} - R_{ev,t,i}^{down^s}\right).\rho^T - \\ \frac{1}{N_I}\sum_i \sum_t \sum_g \sum_s \left(R_{g,t,i}^{up^s} - R_{g,t,i}^{down^s}\right).C_g + \\ \frac{1}{N_I}\sum_i \sum_t \sum_d \sum_s (C_{d,t}^L.L_{d,t,i}^{C^s} - L_d^{max}.\mu_{d,t,i,s}^{c^{max}}) \qquad (65)$$

2) The complementarity conditions in the form of $0 \le P \perp \mu \ge 0$ can be linearized by,

$$P \ge 0, \mu \ge 0, \mu \le b.M_1, \ P \le (1-b).M_2 \qquad (66)$$

where b is an auxiliary binary variable, and M_1 and M_2 are large enough constants. Note that the values of M_1 and M_2 are selected by trial-and error approach [25]. To test validity of these values, the amounts of equations (4) and (65) must be identical.

IV. CASES STUDIES

To test the proposed model, the total demand is considered as 4.5GWh with five demand blocks of 2.25, 0.675, 0.675, 0.45, and 0.45 GWh. Fig. 2 provides demand bids prices for each period of time in five demand blocks. The system has a WGenCO with a single wind farm and four CGenCOs including nuclear, coal, oil, and gas units which are assumed dispatchable. Generators' data are listed in Table I. The total wind and dispatchable units' power capacity are the percentage of a total installed CGenCO power capacity (P^{CGenCO}) of 5GW (see Table I).

In this paper, intra-hour wind power and EV number scenarios are generated and reduced using the method presented in [2] based on [19-21]. The number of intra-hour intervals is 6 (10 min each).

The maximum EV charging power is assumed to be 7.3kW, and the energy capacity of each EV is 27.4 kWh. Average annual driving distance of an EV is assumed to be 20,000 km with an average daily distance of 52.91 km. The required energy for an EV is 9 kWh/day with an average of 5.87 km/kWh [28]. We assume that the required energy for driving in one direction is the same as that of returning to the starting point. For the EV aggregator, we consider different EV numbers from zero to one million. The EV fleet has its own commute time based on the region, city, traffic patterns, etc. In this paper, the number of EV fleets is assumed to be one with commute intervals between 7a.m. and 9a.m., and between 5p.m. and 8p.m.

TABLE I
SUMMARY OF DATA

Unit Type	Nuclear	Coal	Oil	Gas
P_g^{Max} (% of P^{CGenCO})	20%	40%	10%	30%
Cg ($/MWh)	12	20	25	30
$R_{g,Max}^{UP}$, $R_{g,Min}^{DOWN}$ (% of P_g^{Max})	0	25%	30%	50%
Total Demand (GW)	4.5			
P^{CGenCO} (GW)	5			
Total Wind (GW)	20% of P^{CGenCO}			
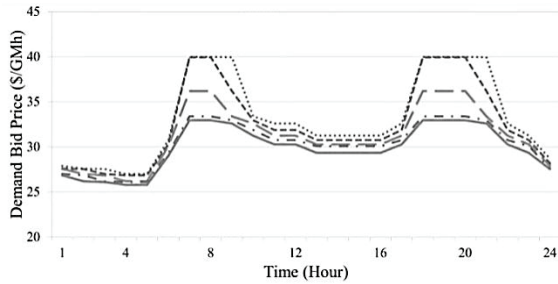
Fig. 2 Demand bids prices in five demand blocks

The results of energy trading with uncoordinated EV charging are considered as a benchmark to compare it with coordinated EV strategy. In this case, EV loads consider as an elastic load and submit the bid price as a tariff price.

Table II reports results of coordinated and uncoordinated strategy for average wind capacity (20%), risk aversion (0.4), EV tariff (20$), and EV numbers (100,000). The firm's expected profit increase by 5% despite the firm is imposed 100,000 EVs (730MW load) in its portfolio. For uncoordinated EVs, it is clear that a decrease in the day-ahead equilibrium price to $20 occurs at 2 a.m and 11 a.m because of EV bidding in tariff price ($20), as shown in Fig. 3. Also, the peak loads occur in these hours (4419 MW and 4267 MW) as shown in Fig. 4. However, for coordinated EVs strategy, the peak load is 3690 MW and EVs are charged during the lower load demand as shown in Fig. 5. CVaR reported in Table II shows the fact that coordination with V2G services helps the producer to trade energy at lower risk levels.

Overall, the coordinated strategy increases social welfare associated with the firm's expected profit at lower risk levels. Moreover, EV-energy trading coordination concludes optimal generation and EV demand dispatch.

V. CONCLUSION

This paper studies the impact of wind energy and EVs penetration on the price amounts, and the energy and balancing market outcomes for both coordinated and uncoordinated strategies. A stochastic bilevel model is taken into account where an upper-level problem corresponds to strategic producer's profit maximization with risk aversion using a CVaR function, while the lower-level problems correspond to markets clearing for maximization of social welfare in day-ahead and real-time markets. The uncertainties associated with wind forecast, and EV owners' behaviors based on driving patterns are considered. The simulation results show the effectiveness of the coordinated EV strategy with GenCOs in increasing the producer's expected profit at

lower risk levels and optimizing generation and EV demand dispatch. Moreover, this strategy leads to the increasing in the social welfare.

TABLE II
NUMERICAL RESULTS FOR COORDINATED AND UNOORDINATED STRATEGIES

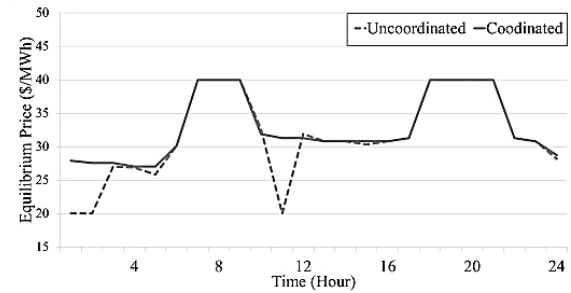|	Uncoordinated	Coordinated
Expected Profit ($)	1338688	1410402
Social Welfare	1466693	1485978
CVaR	-375429	-291153
EV Profit ($)	-4685	-49364
Wind Profit ($)	662845	325368
CGenCO Profit ($)	675843	1134399
Nuclear Profit ($)	469958	498185
Coal Profit ($)	166966	283683
Oil Profit ($)	78837	59981
Gas Profit ($)	-39919	292547

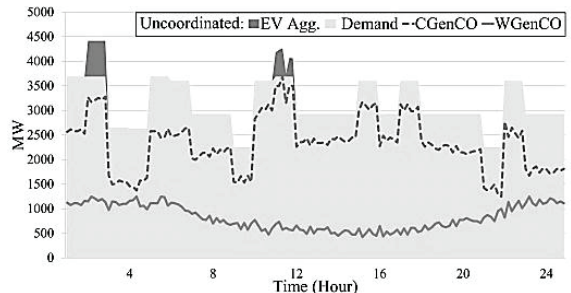Fig. 3 The day-ahead equilibrium price in coordinated and uncoordinated strategies

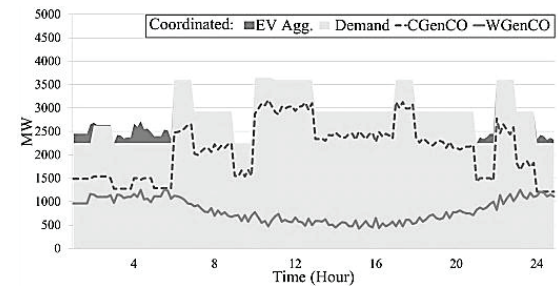Fig. 4 Generation and demand dispatch in uncoordinated strategy

Fig. 5 Generation and demand dispatch in coordinated strategy

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