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Risk-Constrained Offering Strategy for a Hybrid Power Plant Consisting of Wind Power Producer and Electric Vehicle Aggregator

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ABSTRACT

Renewable energy producers such as wind power producers (WPP) and electric vehicle (EV) aggregators are playing an increasingly important role in the electricity market as their large capacity could strategically influence the electricity price. This paper proposes a bi-level stochastic optimization model of offering strategy for an aggregated WPP-EV hybrid power plant (HPP) as a price maker in the day-ahead (DA) market while considering the uncertainties of the energy production and spot price in the real-time (RT) market. While the HPP's profits is maximized in the upper level of the proposed model with the use of conditional-value-at-risk (*CVaR*) to manage the risk of expected revenues, the social welfare from the perspective of the grid is maximized in the lower level. The formulated bi-level model is first transformed into a single-level mathematical program with equilibrium constraints (MPEC) and then further transformed into a mixed integer linear programming (MILP) problem for solution. Simulation results have demonstrated the effectiveness of the proposed HPP model with strategically bidding price to increase profits and reduce volatility of profits by considering the risk-metric.

HIGHLIGHTS

- EV aggregators with both V2G and G2V services and WPPs are integrated as a HPP.
- A bi-level model of offering strategy for a HPP in the DA market is proposed.
- Renewable energy production and real market prices are considered as uncertainties.
- EVs and elastic loads as DR sources are price makers and price takers respectively.

KEYWORDS

Electric vehicle, hybrid power plant, offering strategy, renewable energy

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NOMENCLATURE

Indices:

l	Loads
g	Traditional generation units
k	EV aggregator units
ω	WPP units
h	HPP units
n	Nodes
α	Real-time market scenarios

Sets:

Ω	Loads at node *n*
	Traditional generation units at node *n*
	EV aggregator units at node *n*
	WPP units at node *n*
	HPP units at node *n*
	All nodes connected to the node *n*
	The number of time periods
	The number of scenarios for RT market prices
	The number of scenarios for WPPs'/ EV aggregators' energy productions

Parameters:

	The weight of RT market prices
	The weight of WPPs'/ EV aggregators' energy productions
	The RT market price based on scenario
	The EV capacity for the *k*th EV aggregator at time *t* based on scenario β, in MW
	The wind capacity for the ωth WPP based on scenario β, in MW
	The maximum energy bought or sold for the *k*th EV aggregator in the RT market, in MW
	The maximum energy bought or sold for the ωth WPP in the RT market, in MW
	The minimize state of charge for EVs, in %

SOC^{max}	The maximum state of charge for EVs, in %
E_{ev}^{max}	The maximum total charging energy of the aggregator *k* at time *t*, in MWh
γ_{charge}	The charging efficiency, in %
$\gamma_{discharge}$	The discharging efficiency, in %
γ^{max}	The maximum charging/discharging rate at time *t*, in %
λ_g^{DA}	The offer price for the *g*th traditional generation unit located at node *n* in the DA market
λ_l^{DA}	The bid price for the *l*th load unit located at node *n* in the DA market
$\lambda_{ch/disch}$	The charging/discharging price between EV aggregators and EV owners at time *t*
B_{ab}	The susceptance of the transmission line between nodes *a* and *b*
f_{ab}^{max}	The maximum capacity of the transmission line between nodes *a* and *b*
P_g^{max}	The maximum energy production for the *g*th traditional generation unit
P_l^{max}	The maximum consuming for the *l*th load unit
D_{factor}	The demand factor
$T_{battery}$	The battery lifetime
$C_{battery}$	The capital cost for battery
ξ	The parameter to weigh the expected revenue and *CVaR*
α_{CVaR}	The confidence level

Variables:

$\varphi_{n,t}$	The clearing LMP price at node *n* and time *t*
$P_{k,t}^{EV,DA}$	The *k*th EV aggregator' energy production for the DA market at time *t*, in MW
$P_{\omega,t}^{Wind,DA}$	The ωth WPP' energy production for the DA market at time *t*, in MW
$P_{h,t}^{HPP,DA}$	The *h*th HPP' energy production for the DA market at time *t*, in MW
$P_{k,t,\beta}^{EV,BAL}$	The *k*th EV aggregator' energy bought or sold for the RT market in scenario β at time *t*, in MW
$P_{\omega,t,\beta}^{Wind,BAL}$	The ωth WPP' bought or sold for the RT market in scenario β at time *t*, in MW
$P_{h,t,\beta}^{HPP,BAL}$	The *h*th HPP' energy bought or sold for the RT market in scenario β at time *t*, in MW
$P_{k,t,\beta}^{PEV}$	The *k*th EV aggregator' energy production in scenario β at time *t*, in MW
$P_{\omega,t,\beta}^{Wind}$	The ωth WPP' energy production in scenario β at time *t*, in MW
$P_{h,t,\beta}^{HPP}$	The *h*th HPP' energy production in scenario β at time *t*, in MW

$SOC_{k,t}$	The state of charge for EVs connected to the aggregator *k* at time *t*, in %
$P_{k,t}^{V2G,DA}$	The *k*th EV aggregator' energy from EVs to the grid for the DA market at time *t*, in MW
$P_{k,t}^{G2V,DA}$	The *k*th EV aggregator' energy from the grid to EVs for the DA market at time *t*, in MW
$\lambda_{h,t}^{HPP,offer}$	The offer price for the *h*th HPP in the DA market at time *t*
$P_{g,t}^{G,DA}$	The energy scheduled to be produced in the DA market for traditional generation units located at node *g* and time *t*, in MW
$P_{l,t}^{L,DA}$	The energy scheduled to be consumed in the DA market for fixed and reduced loads located at node *l* and time *t*, in MW
$\theta_{n,t}^{DA}$	The voltage angle at node *n* and time *t* in the DA market
$P_{k,t}^{HPP,offer}$	The energy scheduled to be offered in the DA market for the kth HPP at time *t*, in MW
σ^{DA}	The value-at-risk in the DA market
$\rho_{\alpha,\beta}^{DA}$	The auxiliary variable to calculate the *CVaR* in the DA market
χ	The expected revenue of the HPP unit

I. INTRODUCTION

Towards low carbon emission and conservation of fossil fuels, the integration of various renewable energy resources to the grid has been actively researched in the past few decades for sustainable electricity [1]. Renewable energy generation has been predicted to account for 80% of the total electricity production by 2030 and 100% by 2050, of which 37% will be provided by wind energy [2]. With significant growth in installed capacity of wind turbines and greatly improved wind generation technologies, WPPs have played a major role in some electricity markets such as in Denmark, in which it could bid strategically to influence the electricity price according to its own interest [3]. Traditional demand side management considers industrial, commercial and residential consumers as price-takers to make demand response (DR) for peak shaving [4]. EVs are new DR resources which not only could buy the electricity as consumers in G2V (Grid-to-Vehicle) mode but also sell the electricity back to the grid in V2G (Vehicle-to-Grid) mode. With the number of EVs dramatically increased, such price taker consumers are expected to supply energy as a virtual price maker on a large scale [5]. As EVs cannot directly engage in the market, an intermediary EV aggregator existed in the electricity market dispatches aggregated EVs and exchanges information between the ISO (independent system operator) and individual EV owners [6]. The flexible charging and discharging characteristic of EVs motivates EV aggregators to cooperate with WPPs to form a HPP. The aggregated HPP is promising for taking part in the electricity market and strategically bidding to fix electricity prices and increase their overall profits.

Previously, WPPs and EVs could not affect electricity prices as their proportions in the market were small and negligible [7]. As installed wind capacity and the number of EVs increased, WPPs and EVs become large-scale market participants and make bidding strategies as price takers [8, 9]. Offering strategies for energy suppliers as price makers are initially researched for traditional thermal generators [10-12]. Then traditional energy producers are extended to the hydro-generator combined with the pumped storage plant as a price-maker in [13]. However, models of these traditional energy producers have not yet considered the uncertainty of the renewable energy production. Offering strategies for renewable energy suppliers such as WPPs acting as price makers in the electricity market have been proposed and researched in recent years [14-16]. WPPs combined with hydro units to make an offering strategy was proposed in [17]. Utilizing storage devices to manage wind fluctuations was proposed in [18]. Optimal strategies for WPPs considering gas turbines and compressed air storage devices to compensate fluctuations of WPPs are proposed in [19]. As the development of DR resources in recent years, aggregated DR resources were suggested to balance the volatility of the wind energy production. The effect of DR resources on the wind generation is studied in [20] and [21]. Trading DR loads in a separate intra-day market increases revenues of WPPs was presented in [22]. A few researchers studied profits of DR sides from the perspective of WPPs [23]. An offering strategy only considered the DR aggregator as a price maker is developed in [24]. For combining aggregated EVs with WPPs, [25] increased profits by considering unidirectional G2V services (night residential EV charging) to manage energy deviations and [26] investigated the coordination of unidirectional V2G units and traditional generating units and wind generating units for effecting market prices and outcomes. However, little researches have been done for the EV aggregator with both G2V and V2G services cooperating with WPPs as a price maker in the electricity market to increase their overall profits. In the future smart grid, EVs will be increasingly important to affect the electricity price, and flexible EV sources used in DR programs would bring more profits to the society [27, 28]. However, renewable energy resources involve a lot of uncertainties, which would cause fluctuations and lead to economic losses for renewable energy producers [29]. Therefore, a risk-constrained offering strategy for the aggregated HPP with consideration of WPP and EV aggregator in oligopoly electricity market to be price-makers is proposed here.

The main contributions of this paper include: (1) The effective integration of WPPs and EV aggregators is performed as a HPP to improve their conjunct interests, in which EV aggregators cooperating with WPPs for satisfying high energy offered in V2G mode and using wind energy to meet EVs' charging requirement in G2V mode at moments of low energy offered; (2) A bi-level stochastic model of the offering strategy in the pool-based market is proposed to maximize the aggregated HPP's revenues and manage expected revenues' risks with uncertainties of renewable energy productions and real market prices; (3) The aggregated EVs and elastic loads, as the price maker and the price taker in the market respectively, are implemented as flexible DR sources in the proposed model. Case studies are implemented to illustrate the validity of the proposed approach.

II. PROBLEM DESCRIPTION

The electricity market consists of the offering stage and clearing stage in both DA and RT markets. Most of the energy trading is completed in the DA market, while the energy deviations are compensated in the RT market. In a pool-based electricity market shown as Fig.1, all participants provide optimal offer prices and energy to the ISO in the offering stage. Then ISO uses the collected data for market clearing to obtain locational marginal prices (LMP) paid to energy providers in the clearing stage [30]. This paper focuses on developing a stochastic offering strategy for the proposed HPP considering uncertainties of renewable energy in the offering stage of the DA market.

In a pool-based DA market, all participants have to submit their sales or purchases offer to the ISO for each hour of the next day and several hours in advance. Participants could be categorized into two different groups, which are energy sellers such as traditional generators and multiple renewable energy providers, and energy buyers such as various consumers. In a fully competitive market environment, all participants could participate in setting prices. However, the actual market is closer to an oligopoly market. It means energy providers with large-scale capacities are easier to alter electricity prices according to their interests, while other small-scale participants are just price takers. The increasing installed capacities of WPPs and growing numbers of EVs connected to the grid results in these two distributed renewable resources to be aggregated to strategically affect the market prices [31]. It could be beneficial to cost and price reduction for EV aggregators and WPPs bidding separately in the electrical market. These EV aggregators may not be able to compete with WPPs for bidding prices as the battery capacity of aggregated EVs is much less than WPPs. As a result, the aggregated EVs are expected to cooperate with WPP to offer in the DA market. Meanwhile, interests of the gird should not be ignored with price-maker participants strategically offering to bring their economic benefits. Consequently, this paper focuses on the coordination of WPPs and EV resources as a HPP to develop the optimal offering strategy for improving their own interests. This would be solved by peak shaving as flexible charging or discharging characteristics of EVs. To be specific, EV owners may provide energy by V2G in due time to compensate with the WPP for satisfying the high energy offered, then use the wind energy to meet charging demand for EV owners when the energy offered is relatively low. In this way, EV owners could help the WPP to sell more electricity and earn more money at the high energy offered time while the wind energy would not be wasted during periods of the low energy offered, which is beneficial to both the HPP and the grid.

Therefore, EV aggregators and WPPs are collaborated as a price-maker HPP in this paper. This central planner makes decisions based on collecting necessary information from WPPs and EV aggregators, and then uniformly schedules their individual energy. Other participants including traditional generators and DR loads are set as price-takers. They would offer productions at their marginal costs, and offer prices are known for strategic energy providers [2]. In this study, the transmission network is represented by a DC model without losses, and uncertainties of actual energy productions and real-time market prices are modeled by corresponding scenarios based on the stochastic approach [32]. Scenarios of actual energy productions for the WPP and EV aggregator are represented by the maximum output energy derived from historical wind speeds and historical data for the number of EVs connected to the aggregator, respectively with τ_β and τ_α represented their probabilities, respectively. The expected profit is finally characterized by corresponding probability distribution for these uncertainties. As uncertainties will take high volatility for energy providers' revenues, a well-established risk management measure *CVaR* is added in problem formulation to evaluate the expected profits according to offering decisions [33].

III. MATHEMATICAL FORMULATION

Aiming at the market described above, a stochastic optimization model of risk-constrained offering strategy for the aggregated HPP including the WPP and EV aggregator in the DA market is proposed. It is further developed as a bi-level model as shown in equations (1)-(2-h), in which the upper level is used to maximize profits of the strategical HPP while the lower level aims to maximize the social welfare from the perspective of ISO in the grid.

A. HPP Model

In this model, the HPP in the upper level first provides energy offered $P_{h,t}^{HPP,offer}$ and offer price $\lambda_{h,t}^{HPP,offer}$ to the ISO in the lower level. Then ISO clears market combining this information with offers and bids from non-strategical traditional generators and DR loads separately by using the optimal power flow (OPF). After that, scheduled energy production in the DA market $P_{h,t}^{HPP,DA}$ and LMP $\varphi_{n,t}$ are provided to the HPP in the upper level to maximize profits. Lastly, optimized offer results $P_{\omega,t}^{Wind,offer}$ and $\lambda_{h,t}^{HPP,offer}$ for the WPP, $P_{k,t}^{EV,offer}$ and $\lambda_{h,t}^{HPP,offer}$ for the EV aggregator could be obtained and provided to the DA market. These optimized price-energy production curves are the offering strategies in this research.

1) Upper level

By combining the WPP and EV aggregator to be a HPP, the offering strategy model corresponding to the expected profit function can be expressed as follows:

$$\chi = HPP_{revenue} - HPP_{\cos t} \tag{1}$$

Maximum

$$\begin{aligned}
&\sum_{n\in\Omega_n^N}\sum_{h\in\Omega_n^h}(\sum_{t\in T}\varphi_{n,t}\cdot P_{h,t}^{HPP,DA} - \sum_{t\in T}\sum_{\beta\in N_\beta}\tau_\beta\cdot\lambda_{ch/disch}\cdot P_{k,t,\beta}^{EV} \\
&-\sum_{t\in T}\sum_{\beta\in N_\beta}\sum_{\alpha\in N_\alpha}\tau_\beta\cdot\tau_\alpha\cdot(\varphi_\alpha^{BAL}\cdot P_{k,t,\beta}^{EV,BAL}) \\
&-\sum_{t\in T}(C_{battery}/T_{battery})\cdot P_{k,t}^{V2G,DA} \\
&-\sum_{t\in T}\sum_{\beta\in N_\beta}\sum_{\alpha\in N_\alpha}\tau_\beta\cdot\tau_\alpha\cdot(\varphi_\alpha^{BAL}\cdot P_{\omega,t,\beta}^{Wind,BAL}) \\
&+\xi\cdot(\sigma^{DA} - \frac{1}{1-\alpha_{CVaR}}\cdot\sum_{\alpha\in N_\alpha}\sum_{\beta\in N_\beta}\tau_\beta\cdot\tau_\alpha\cdot\rho_{\alpha,\beta}^{DA})
\end{aligned} \tag{1-a}$$

Subject to

$$P_{h,t}^{HPP,DA} = P_{\omega,t}^{Wind,DA} + P_{k,t}^{EV,DA}, \quad \forall t \tag{1-b}$$

$$P_{h,t,\beta}^{HPP} = P_{\omega,t,\beta}^{Wind} + P_{k,t,\beta}^{EV}, \quad \forall t \tag{1-c}$$

$$P_{h,t,\beta}^{HPP} \le P_{\omega,t,\beta}^{Wind,\max} + P_{k,t,\beta}^{EV,\max}, \quad \forall t \tag{1-d}$$

$$P_{h,t,\beta}^{HPP,BAL} = P_{\omega,t,\beta}^{Wind,BAL} + P_{k,t,\beta}^{EV,BAL}, \quad \forall t \tag{1-e}$$

$$\begin{aligned}
&-P_\omega^{Wind,BAL,\max} - P_k^{EV,BAL,\max} \\
&\le P_{h,t,\beta}^{HPP,BAL} \le P_\omega^{Wind,BAL,\max} + P_k^{EV,BAL,\max}, \quad \forall t
\end{aligned} \tag{1-f}$$

$$P_{k,t}^{EV,DA} - P_{k,t,\beta}^{EV,BAL} = P_{k,t,\beta}^{EV}, \forall k,\beta,t \tag{1-g}$$

$$P_{\omega,t}^{Wind,DA} - P_{\omega,t,\beta}^{Wind,BAL} = P_{\omega,t,\beta}^{Wind}, \forall \omega,\beta,t \tag{1-h}$$

$$SOC^{\min} \le SOC_{k,t} \le SOC^{\max}, \forall k,t \tag{1-i}$$

$$SOC_{k,t} = SOC_{k,t-1} - \frac{\frac{P_{k,t-1}^{G2V,DA}}{E_{ev}^{\max}}}{\gamma_{discharge}} + (\frac{P_{k,t-1}^{V2G,DA}}{E_{ev}^{\max}})\cdot\gamma_{charge}, \forall k,t \tag{1-j}$$

$$\begin{aligned}
&(SOC_{k,t} - SOC_{k,t-1}) / \gamma_{charge} \\
&+(SOC_{k,t-1} - SOC_{k,t})\cdot\gamma_{discharge} \le \gamma^{\max}, \forall k,t
\end{aligned} \tag{1-k}$$

$$P_{k,t}^{EV,DA}=P_{k,t}^{V2G,DA}\cdot\gamma_{charge}-\frac{P_{k,t}^{G2V,DA}}{\gamma_{discharge}},\forall k,t \tag{1-l}$$

$$U_{k,t}\cdot P_{k}^{EV,\min}\le P_{k,t}^{V2G,DA}\le U_{k,t}\cdot P_{k}^{EV,\max},\forall k,t \tag{1-m}$$

$$V_{k,t}\cdot P_{k}^{EV,\min}\le P_{k,t}^{G2V,DA}\le V_{k,t}\cdot P_{k}^{EV,\max},\forall k,t \tag{1-n}$$

$$U_{k,t}+V_{k,t}\le 1,\forall k,t \tag{1-o}$$

$$\begin{aligned}\sigma^{DA}-(&\sum_{h\in\Omega_n^h}\sum_{t\in T}\varphi_{n,t}\cdot P_{h,t}^{HPP,DA}-\sum_{k\in\Omega_n^k}\sum_{t\in T}\lambda_{ch/disch}\cdot P_{k,t,\beta}^{EV}\\&-\sum_{k\in\Omega_n^k}\sum_{t\in T}\varphi_{\alpha}^{BAL}\cdot P_{k,t,\beta}^{EV,BAL}-\sum_{k\in\Omega_n^k}\sum_{t\in T}(C_{battery}/T_{battery})\cdot P_{k,t}^{V2G,DA}\\&-\sum_{\omega\in\Omega_n^{\omega}}\sum_{t\in T}\varphi_{\alpha}^{BAL}\cdot P_{\omega,t,\beta}^{Wind,BAL})\le\rho_{\alpha,\beta}^{DA},\forall\alpha,\beta\end{aligned} \tag{1-p}$$

$$\rho_{\alpha,\beta}^{DA}\ge 0,\forall\alpha,\beta \tag{1-q}$$

The objective function in the upper level is to maximize the HPP's profit. It should be noticed that an EV aggregator is unable to produce energy by itself. It takes part in the electricity market as an agent for buying electricity from individual EV owners and selling electricity to the grid. The payoff function *(1-a)* consists of six terms. The first term is the revenues of selling electricity in the DA market $\varphi_{n,t}\cdot P_{h,t}^{HPP,DA}$. The second term is EV aggregator' cost of energy production in DA and RT market $\tau_{\beta}\cdot\lambda_{ch/disch}\cdot P_{k,t,\beta}^{EV}$, which is followed by EV aggregator's incomes or expenses from selling or buying electricity in the RT market $\tau_{\beta}\cdot\tau_{\alpha}\cdot(\varphi_{\alpha}^{BAL}\cdot P_{k,t,\beta}^{EV,BAL})$. The next two terms are compensation cost for battery degradation $\sum_{t\in T}\frac{C_{battery}}{T_{battery}}\cdot P_{k,t}^{V2G,DA}$and wind's incomes or expenses from selling or buying electricity in the RT market $\tau_{\beta}\cdot\tau_{\alpha}\cdot(\varphi_{\alpha}^{BAL}\cdot P_{\omega,t,\beta}^{Wind,BAL})$. $\varphi_{n,t}$ is the LMP calculated from the lower level as a dual variable in constraint *(2-a)* for energy balance, which is used to pay for the EV aggregator and the WPP. There are two kinds of uncertainties considered in the model, which are spot price in the RT market φ_{α}^{BAL} and actual energy production capacities $P_{\omega,\beta}^{Wind,max}+P_{k,t,\beta}^{EV,max}$. As actual energy productions $P_{h,t,\beta}^{HPP}$ may be more or less than energy scheduled in the DA market $P_{h,t}^{HPP,DA}$, HPP needs to buy deficit or sell surplus energy $P_{h,t,\beta}^{HPP,BAL}$ in the RT market to compensate the energy deviation in the DA market, and hence, $P_{h,t,\beta}^{HPP,BAL}$could be positive or negative. The last term is *CVaR*. Here, the weight parameter ξ is used to weigh expected profit and *CVaR*, and to show different offering strategy. If ξ is zero, the proposed model will be a risk-neutral model, which considers the maximum profits for EV aggregator and neglects the risk. As ξ becomes larger, the EV aggregator considers not only its profit but also its risk. When ξ is large enough, a risk-averse offering model is considered, which means profits for the EV aggregator is neglected while a minimum revenue should be maintained for a confidence level α_{CVaR} [34].

(1-b)-*(1-q)* constrain the upper level objective function *(1-a).* Constraint *(1-b)* states the relationship between scheduled energy productions in the DA market by the WPP, the EV aggregator, and the HPP. Constraint *(1-c)* imposes the relationship between actual energy generated by the WPP, the EV aggregator, and the HPP. Constraint *(1-d)* imposes the limit of available energy for the HPP according to each scenario. Then *(1-e)* gives the relationship between scheduled energy productions in the RT market by the WPP, the EV aggregator, and the HPP. *(1-f)* limits energy bought or sold for the HPP in the RT market. *(1-g)* and *(1-h)* state the relationship between scheduled energy productions in the DA market, RT market, and total energy productions for the EV aggregator and WPP separately. Constraint *(1-i)* is used to maintain EVs to avoid overcharging and over-discharging. Equation *(1-j)* gives state changes of charging/discharging for EVs connected to the EV aggregator. The charging / discharging rate in each hour is limited in *(1-k)*. Equation *(1-l)* shows the *k*th EV aggregator' scheduled energy in the DA market, which is equal to the energy provided in V2G minus the energy consumed in G2V. Besides, $U_{k,t}$ and $V_{k,t}$ are binary variables as *(1-o)*. So inequalities *(1-m)* and *(1-n)* are used to constrain $P_{k,t}^{V2G,DA}$ and $P_{k,t}^{G2V,DA}$ not to exist at the same time. Additionally, the lower limit for $P_{k,t}^{V2G,DA}$ and $P_{k,t}^{G2V,DA}$ is a nonzero value $P_{k,t}^{EV,min}$. It means that the EV aggregator may provide energy by V2G in due time with WPP to satisfy the high energy offered, and use wind energy to meet charging demand for EV owners when offered energy is relatively low. Finally, *(1-p)* and *(1-q)* are used to compute the *CVaR* [34].

2) Lower Level

In the pool-based electricity market, ISO collects all producers' offer prices and consumers' bid prices and finishes market clearing. Finally, ISO provides price signals and the scheduled energy to all participants in the upper level. This process is finished in the lower level model. As demands are considered as elastic, the objective function *(2)* in the lower level is to maximize social welfare from the perspective of the grid. Besides, traditional OPF is used to clear the market transaction.

Maximize

$$\begin{aligned}\sum_{t\in T}\Big(\sum_{l\in\Omega_n^L}\lambda_l^{DA}\cdot P_{l,t}^{L,DA}-\sum_{g\in\Omega_n^G}\lambda_g^{DA}\cdot P_{g,t}^{G,DA}\\-\sum_{h\in\Omega_n^h}\lambda_{h,t}^{HPP,offer}\cdot P_{h,t}^{HPP,DA}\Big)\end{aligned} \tag{2}$$

Subject to

$$\lambda_{h,t}^{HPP,offer}\geq 0,\forall h,t \tag{2-a}$$

$$\sum_{g\in\Omega_n^G} P_{g,t}^{G,DA} + \sum_{h\in\Omega_n^h} P_{h,t}^{HPP,DA} - \sum_{a\in\Omega_n^N} B_{na}\cdot(\theta_{n,t}^{DA}-\theta_{a,t}^{DA}) = \sum_{l\in\Omega_n^L} P_{l,t}^{L,DA} : \varphi_{n,t}, \forall n,t \quad (2\text{-}b)$$

$$-f_{na}^{\max} \le B_{na}\cdot(\theta_{n,t}^{DA}-\theta_{a,t}^{DA}) \le f_{na}^{\max} : \mu_{na,t}^{L,DA}, \mu_{na,t}^{U,DA}, \forall a,n\in\Omega_n^N, \forall t \quad (2\text{-}c)$$

$$P_g^{\min} \le P_{g,t}^{G,DA} \le P_g^{\max} : \mu_{g,t}^{L,DA}, \mu_{g,t}^{U,DA}, \forall g,t \quad (2\text{-}d)$$

$$P_l^{\min}\cdot D_{factor} \le P_{l,t}^{L,DA} \le P_l^{\max}\cdot D_{factor} : \mu_{l,t}^{L,DA}, \mu_{l,t}^{U,DA}, \forall l,t \quad (2\text{-}e)$$

$$0 \le P_{h,t}^{HPP,DA} \le P_{h,t}^{HPP,offer} : \mu_{h,t}^{L,DA}, \mu_{h,t}^{U,DA}, \forall h,t \quad (2\text{-}f)$$

$$\theta_{n,t}^{DA} = 0 : \mu_{\theta,t}^{DA}, n : ref, \forall t \quad (2\text{-}g)$$

$$-\pi \le \theta_{n,t}^{DA} \le \pi : \mu_{\theta,t}^{L,DA},\ \mu_{\theta,t}^{U,DA}, \forall n\setminus n : ref, \forall t \quad (2\text{-}h)$$

The first constraint *(2-a)* defines the offer price of HPP in the DA market which should be nonnegative. *(2-b)* enforces the energy balance between supply and demand, which is associated with a dual variable $\varphi_{n,t}$ to donate the LMP used in the upper-level. Inequality *(2-c)* limits the energy flow in each transmission line. Maximum and minimum productions of scheduled energy for traditional generation units, load consumptions and the HPP in the DA market are shown in *(2-d)*, *(2-e)* and *(2-f)* individually. It shall be noted that load consumptions, including fixed load requirement represented by minimum load values and curtailed load as DR, are considered as variables in the model. Equation *(2-g)* sets the voltage angle at the reference node as zero and inequality *(2-h)* constrains voltage angles at nodes except the reference node. Additionally, $\mu_{na,t}^{L,DA}, \mu_{na,t}^{U,DA}, \mu_{g,t}^{L,DA}, \mu_{g,t}^{U,DA}, \mu_{l,t}^{L,DA}, \mu_{l,t}^{U,DA}, \mu_{h,t}^{L,DA}$, $\mu_{h,t}^{U,DA}, \mu_{\theta,t}^{DA}, \mu_{\theta,t}^{L,DA}, \mu_{\theta,t}^{U,DA}$ are the corresponding dual variables for constraints from *(2-b)* to *(2-h)*.

B. Solution methodology

To obtain the optimal value, the proposed bi-level model is first transformed into a single-level model by translating the lower level model using KKT (Karush-Kuhn-Tucker) constraints [3]. Then, transformed constraints are added to constraints in the upper level to limit the upper objective function. In this way, the original bi-level model could become a single-level MPEC problem. The MPEC model contains two terms of nonlinearities. Replacing these two non-linear terms using strong duality theorem (SDT) and the Fortuny-Amat transformation respectively, this MPEC model could be further transformed into a MILP model [35].

After the transformation above, the transformed MILP model is solved by MOSEK through YALMIP interface. Computing times are affected by the number of buses in the system and the number of scenarios used to represent uncertainties. In addition, large numbers of binary variables are required to linearize complementary constraints in MEPC model, which may greatly increase the complexity of calculation.

IV. CASE STUDIES

The proposed model is tested in the IEEE six-bus and thirty-bus systems for a day divided into 24 hours. While the traditional generation unit capacities are assumed constant throughout the day, the capacities of loads would change over time with the demand factor shown in Fig.2 [3]. The uncertainties of the RT market price φ_{α}^{BAL} are represented by the same 10 scenarios in 24 hours with corresponding probabilities selected from [3]. Fig.3 and Fig.4 show respectively the uncertainties of maximized productions for the WPP and the number of EVs that can be aggregated by the EV aggregator over time [36, 37]. For the sake of simplicity, probabilities of all scenarios for energy productions are considered as (0.1). Additionally, the charging / discharging cost for the EV aggregator and the rated power for every EV are set to 20$/MWh and 10kW, respectively. Other parameters for the EV aggregator are listed in Table 1.

A. Six-Bus System

The IEEE six-bus system consists of 3 generators, 3 demands, and 11 transmission lines. A WPP and an EV aggregator are located at node 4 and node 5, respectively. Table 2 lists capacities, offer prices and bid prices for traditional generation units and load units [3].

1) Offering curve of the HPP model

With system settings described above, Fig.5 presents optimized offering results of the aggregated HPP. The blue curve and the green curve refer to energy offered and offer prices, respectively, in 24 hours for the DA market. As uncertainties of actual energy productions and RT market prices, the energy offered would vary throughout the day. Besides, the curve of offer prices would change with the curve of the energy offered. The energy offered in Fig.5 is relatively high in the first few hours, 9:00-15:00, and last three hours, while corresponding prices are comparatively low. This is because it will take an economic risk for the HPP with offer prices being relatively high at these moments. Specifically, if the actual energy production is lower than the energy offered, the HPP will have to buy the energy at a high price in the RT market for meeting the energy offered in the DA market. As a result, the HPP offers relatively low prices at moments of comparatively high energy offered, in which it could sell the surplus to the RT market with the actual production exceeding the energy offered. Similarly, the HPP offers a relatively high price when the energy offered is comparatively low. In this way, the HPP may only need to buy a small amount of deficiency at a high price in the RT market once the actual production is lower than the energy offered. Conversely, the HPP could sell the surplus at a high price when the actual production exceeds the energy offered, which makes sense for the HPP's profits. In general, the HPP adjusts the offer price and set the electricity price according to the energy offered. After the clearing process in the DA market, the LMP is equal to the offer price at the same node. Then energy providers at each node will be paid at the corresponding LMP in the RT market. Besides, all clearing LMPs are equal at all nodes in a six-bus system with no congestion occur. To sum up, the influence of energy quantities offered on cleared market prices shows how large-scale renewable resources strategically affect electricity prices in the electricity market.

2) Optimal offering energy quantity of the HPP model

Optimal quantities of energy offered for the HPP model in the six-bus system is shown in Fig.6. Offering quantities of the aggregated HPP increase at times of 9:00 to 15:00 and 20:00 to 24:00. At these moments, the cooperated EV aggregator calls for EV owners to discharge and provides energy to the WPP for the energy offered in Fig.6. Besides, the EV aggregator may use redundant wind energy to satisfy the charging demand for EV owners when the energy offered is relatively low.

3) Comparison and Discussion

In this paper, the proposed HPP model is compared to three other models. The first one has only a WPP strategically offering price to be price-makers and the clearing process consists of the WPP, traditional units and loads. The second model is similar to the first one but has only an EV aggregator strategically offering price instead. The third is the sum model in which a HPP and an EV aggregator offer price together but without cooperating. In the proposed model, EVs are required to compensate with the WPP to provide energy to satisfy the high energy offered and the WPP is used to meet charging demand for EV owners when the offered energy is relatively low.

Fig.7 shows the comparison of revenues from these three models with the proposed one. According to revenue graphs in 24 hours, the HPP model takes more profits. This is due to the EV aggregator mitigates uncertainties of the WPP and the change of demand sides by controlling V2G and G2V flexibility, which further improves the profits by selling energy during high energy offered time and increasing EV owners' consumption for storing more energy at moments of low energy offered.

4) Impact of Incorporating Risk on the HPP model

Table 3 compares the expected revenues and the *CVaR* for different weighting parameter ξ in the sum model and the HPP model. The confidential level α_{CVaR} is set to 0.95. As the weighting parameter ξ increases from 0.01

to 1, the expected profit decreases while the *CVaR* increases. Specifically, the revenue decreases by 1.1% and 0.64% for the sum model and the combined HPP model respectively, while the *CVaR* increases by 2.7% and 1.7% respectively. Therefore, just a small decrease in revenues could diminish the risk. Besides, $-\frac{\Delta(CVaR)}{\Delta(\square)}$ means the changing rate of *CVaR* relating to the change of revenue. The higher $-\frac{\Delta(CVaR)}{\Delta(\square)}$ implies less decrease in revenue and more increase in *CVaR*, which also means the profit volatility is better controlled. Table 3 shows this ratio is higher for the HPP model. Meanwhile, offering curves would change with different risk weighing parameters. The HPP reduces its profit's volatility caused by uncertainties with introducing the *CVaR* to offer strategically.

B. Thirty-Bus System

The IEEE thirty-bus system consists of 6 generators, 20 demands, and 41 transmission lines. A strategic WPP and an EV aggregator are located at node 17 and node 26, respectively.

Offer results for the HPP model are plotted in Fig.8. As uncertainties of actual energy productions and RT market prices, the energy scheduled to offer would vary throughout the day. Besides, the curve of offer prices would change as the curve of the energy offered. In Fig.8, the energy scheduled to offer are relatively high in the first few hours, 13:00-19:00 and last two hours. During these periods, corresponding prices are comparatively low. The analysis for this case is similar to the IEEE six-bus system.

Optimal energy quantities of the HPP model offered in this case system is shown in Fig.9, in which offering quantities increase at 13:00, 14:00 and from 23:00 to 24:00. At these moments, the cooperated EV aggregator calls for EV owners to discharge for the energy offered in Fig. 8. Then the EV aggregator could use the wind energy to satisfy the charging demands from EV owners during periods of low energy offered such as 11:00-12:00 and 21:00-22:00. Fig.10 shows the comparison of combined HPP revenues with the sum model, in which the EV aggregator and the WPP participates in the electricity market offer separately. According to revenue curves in 24 hours, the HPP model takes more profits.

V. CONCLUSION

This paper proposes a stochastic optimization model to derive the offering strategy for the aggregated HPP to be a price maker in the DA pool-based market. The model consists of two levels, with offering decisions to make to maximize the HPP's profits in the upper level and market clearing to complete to maximize revenues of the grid in the lower level. This bi-level problem was then transformed into a MPEC problem by KKT conditions and further solved as a MILP problem with Strong Duality theory and the Fortuny-Amat transformation. By combining WPPs and EVs, several promising results have demonstrated the validity of the proposed HPP model: 1) Large-scale renewable resources could be aggregated for strategical bidding and setting electricity prices according to their and the grid's interests. 2) The proposed model shows cooperative energy provided by the WPP and the EV aggregator during different time slots. In this way, the total cost of energy consumptions and the waste of wind resources are reduced, which is cost-effective and more environmentally friendly. 3) The proposed HPP model has been demonstrated that it could take more profits by comparing with three other models. 4) With the consideration of risk in the HPP model, the profit volatility caused by uncertainties could be coped with more effective.

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Table 1 DATA FOR THE EV AGGREGATOR

EV Aggregator	SOC^{max} (pu)	SOC^{min} (pu)	γ_{charge}	$\gamma_{discharge}$	γ^{max}	E_{ev}^{max} (MWh)
Value	0.9	0.3	0.9	0.85	0.2	600

Table 2 OFFER AND BID DATA FOR GENERATORS AND LOADS

	Traditional Generators			Loads		
Bus	1	2	3	4	5	6
Offer price($/MWh)	49	50	44	0	0	0
Bid price ($/MWh)	0	0	0	59	50	40

Table 3 COMPARISON OF REVENUES AND CVAR FOR DIFFERENT WEIGHTING PARAMETER ξ

ξ	Sum		HPP	
	Revenue ($)	CVaR ($)	Revenue($)	CVaR ($)
0.01	137955.70	72.29	179632.29	76.30
0.1	137933.30	681.22	179622.87	749.25
0.2	137730.75	1115.71	179585.16	1451.05
0.5	137165.48	1906.29	179294.70	3160.38
0.8	136497.45	2278.35	178877.82	3673.69
1	136430.83	2771.84	178487.78	4514.93
$-\frac{\Delta(CVaR)}{\Delta(\xi)}$	1.77		3.88	

FIGURES

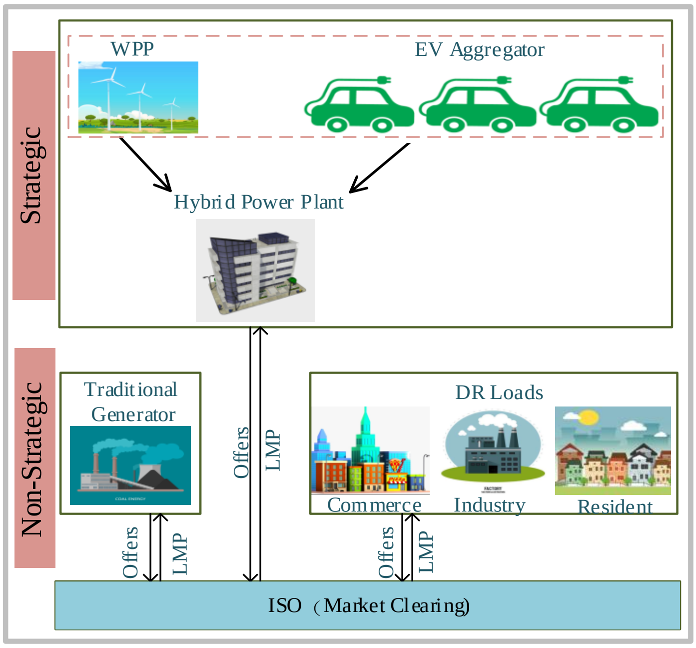

Figure 1 Schematic representation of proposed HPP model

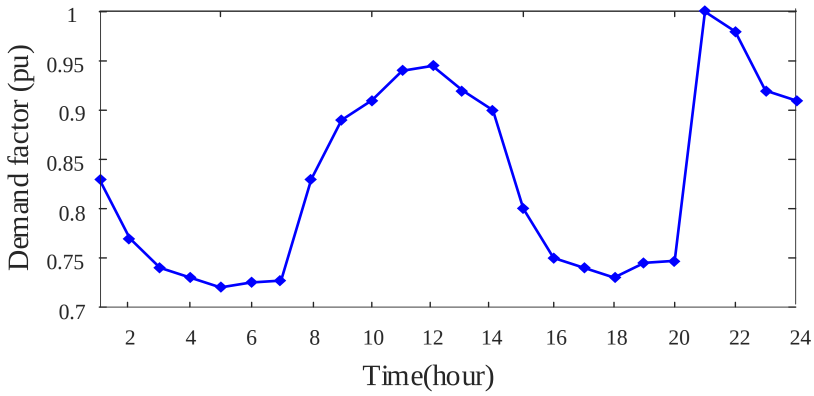

Figure 2 Demand factors over time

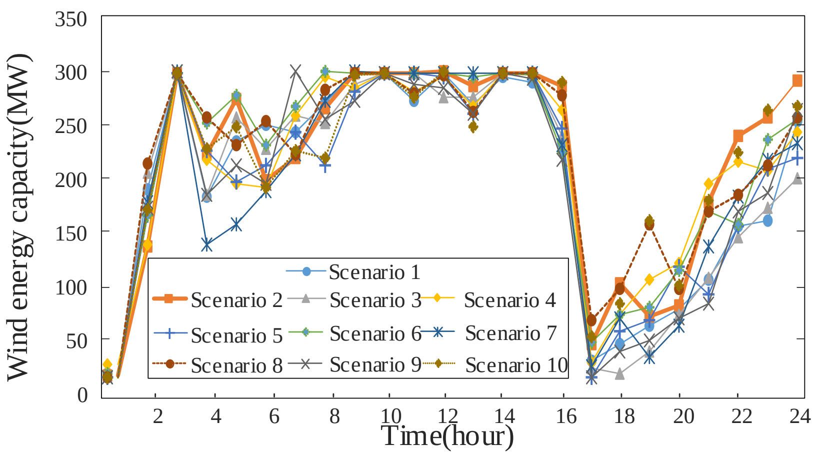

Figure 3 Scenarios data for actual maximize output of the wind energy

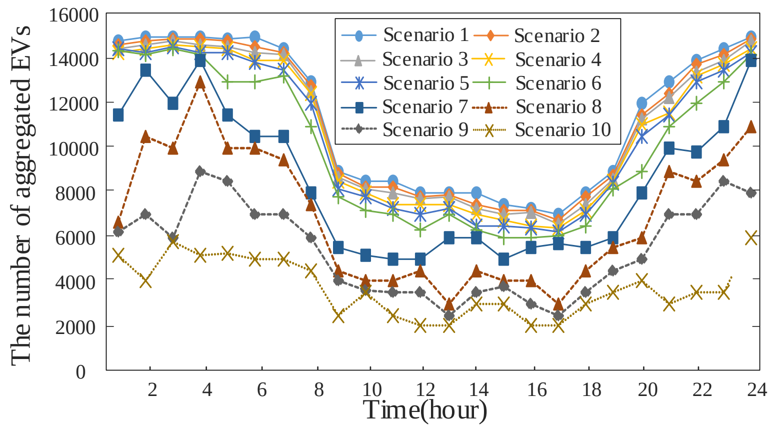

Figure 4 Scenarios data for the number of aggregated EVs

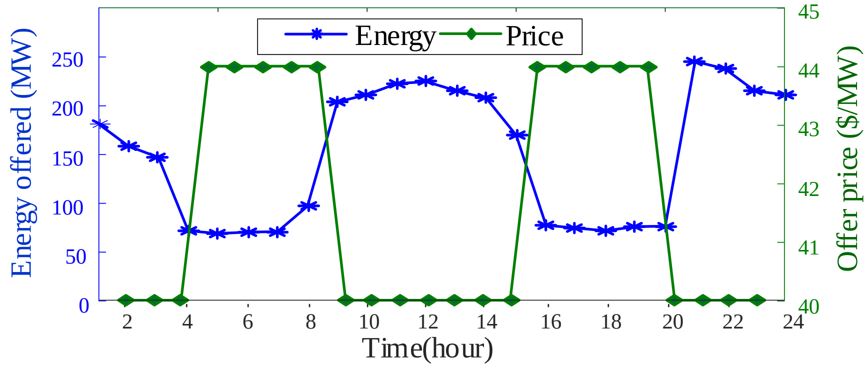

Figure 5 Offer results for aggregated HPP in six-bus system

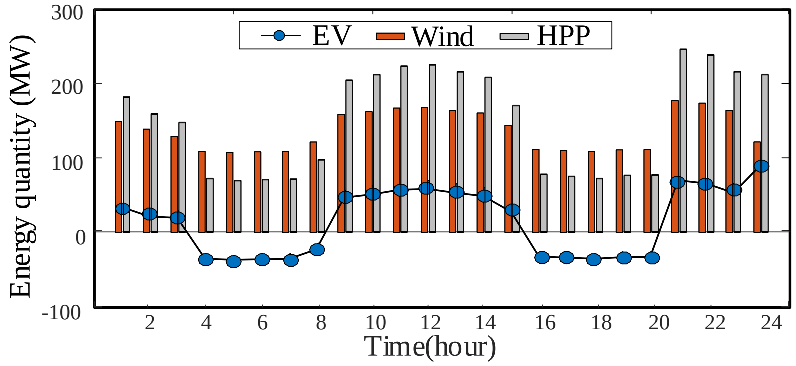

Figure 6 Energy quantity of HPP for the DA market in six-bus system

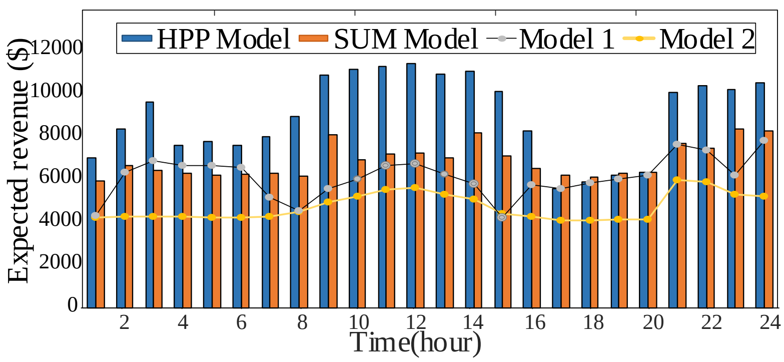

Figure 7 Comparison of revenues with other three models

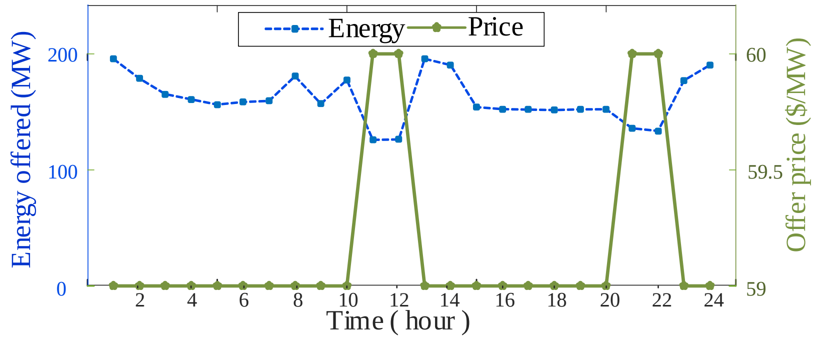

Figure 8 Offer results for aggregated HPP in thirty-bus system

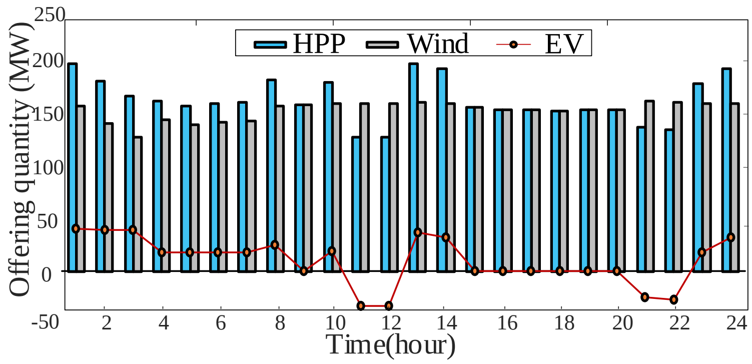

Figure 9 Energy quantity of HPP for the DA market in thirty-bus system

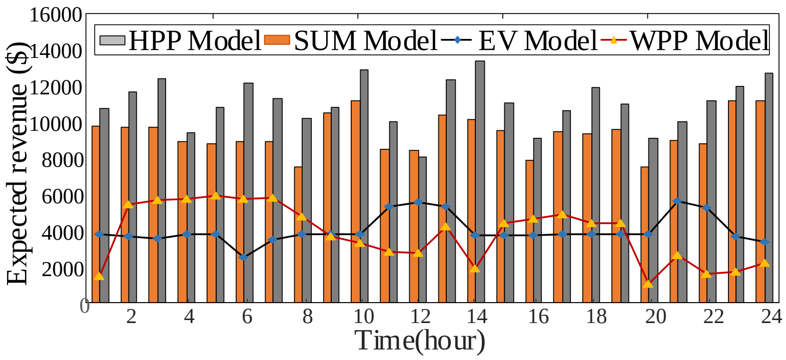

Figure 10 Comparison of revenues from other models