A Bidding Strategy for Virtual Power Plants With Intraday Demand Response Exchange Market Using Stochastic Programming

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***Abstract*—This paper presents a mathematical model for the energy bidding problem of a virtual power plant (VPP) that participates in the regular electricity market and the intraday demand response exchange (DRX) market. Different system uncertainties due to the intermittent renewable energy sources, retail customers' demand and electricity prices are considered in the model. The DRX market enables a VPP to purchase demand response (DR) services, which can be treated as "virtual energy resources", from several demand response providers (DRP) to reduce the penalty cost on the deviation between the day-head bidding and the real-time dispatch. This could increase the expected profit and the renewable energy utilization of the VPP. The overall energy bidding problem is modeled as a three-stage stochastic program, which can be solved efficiently by the scenario-based optimization approach. Extensive numerical results show that the DRX market participation can improve the VPP's energy management.**

***Index Terms*—Energy bidding, stochastic programming, virtual power plant, demand response exchange, short term electricity market.**

NOMENCLATURE

Set-Indices

$E, \mathsf{S1}(2,3)$	Expectation and Stages
t, s	Indices of time intervals, $t = 1, 2, \dots, NT$, and indices of scenarios, $s = 1, 2, \dots, NS$
i, j, m	Indices of buses
b, d, e, g, w	Indices of battery energy storages (BES), outside demand response providers (DRP), retail customers, thermal generators, wind generators, respectively
n	Indices of block in price quota curve of retail customer e and price quantity offer of DRP d
B, Ω	Set of all buses and set of all transmission lines linking bus pairs
$\gamma_i^{\mathsf{B(E,G,W)}}$	Set of BESs (retail customers, thermal generators, wind generators) at bus i
$(.)_{.,t,s}$	at time t, in scenario s

Parameters

τ	Length of one time slot, $1h$
NS, NT	Number of scenarios/ Number of time slots (24)
$\lambda_{t,s}^{\mathsf{D}}$	Day-ahead electricity price ($\$/MWh$)
$\lambda_{t,s}^{\mathsf{P(N)}}$	Real-time positive (negative) balancing price, ($\$/MWh$)
λ_i^{deg}	Degradation price for battery at bus i, ($15\$/MWh$)

VPP's parameters:

$P_{i,t,s}^{\mathsf{w}}$	Power of wind plant w at bus i, (MW)
SU_t^g, SD_t^g	Start up and shut down cost of thermal units g, at bus i, (\$)

Outside DRPs' parameters:

NB_d	Number of blocks in price quantity offer curve of outside DRP d
$\lambda_{d,t}^{\mathsf{Bi}}$	Bilateral contract price offer of DRP d, ($\$/MWh$)
$\lambda_{d,t,s}^{\mathsf{n}}$	Pool contract price offer of DRP d in scenario s, pertaining to the n interval price quantity offer curve, ($\$/MWh$)
$p_{d,t,s}^{n,\mathsf{max}}$	DR maximum quantity of DRP d, pertaining to the n interval price quantity offer curve, (MW)
$\mathsf{DR}_d^{\mathsf{cap}}$	DR capacity of DRP d, (MWh)

Retail customers' parameters:

NB_i^e	Number of blocks in price quota curve of customer e at bus i, (MWh)
D_i^e, t, s	Energy demand of customer e at bus i, (MWh)
$l_{i,t,s}^{e,n,\mathsf{max}}$	Demand supplied to customer e, pertaining to the n interval of the price-quota curve, (MW)

First-stage Variables

λ_i^e	Retail price that VPP offer to customer e, at bus i, ($\$/MWh$)
P_t^D	Day-ahead power bidding, (MW)

Second and Third-stage Variables

$P_{t,s}^{\mathsf{del}}$	Power delivered to main grid, (MW)

VPP's operation:

$P_{t,s}^{\mathsf{N(P)}}$	Negative (Positive) power exchange with main grid in RT balancing market, (MW)
$P_{i,t,s}^g$	Generated power of thermal plant g at bus i, (MW)
$P_{i,t,s}^{\mathsf{w,c}}$	Curtailed power of wind plant w at bus i, (MW)
$P_{i,t,s}^{\mathsf{b,c(b,d)}}$	Charging (discharging) power of BES b at bus i, (MW)
$C_{i,t,s}^g$	Generation cost of unit g at bus i, (\$)

DR exchange with outside DRPs:

$p_{d,t,s}^n$	Pool DR quantity purchased from DRP d, at block n, (MW)
$DR_{d,t,s}$	Pool DR quantity purchased from outside DRP d, (MW)
$CDRP_{d,t,s}$	Pool DR purchased cost from outside DRP d, (\$)
$P_{d,t,s}^{\mathsf{Bi}}$	Bilateral DR quantity purchased from outside DRP d, (MW)
$Bi_{d,t,s}$	Bilateral DR purchased cost from outside DRP d, (\$)

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Selling electricity to retail customers:

$P^{e}_{i,t,s}$	Power sold to customer e, at bus i, (MW)
$R^{e}_{i,t,s}$	Revenue of selling electricity to reatil customer e at bus i, ($)
$u^{e,n}_{i,t,s}$	Auxiliary binary variables to calculate λ^{e}_{i}

I. Introduction

Virtual Power Plant (VPP) enables the integration of different generation technologies such as renewable energy, conventional thermal energy, and battery energy system into a unified and flexible unit that can support the upcoming high penetration of distributed renewable energy generations [1]. Studies have shown that a VPP has a better market performance than a single generation entity by compromising the strength and the weakness of different facilities in a cooperative manner [2]. In general, the objective of VPP when participating in the short-term electricity market is to maximize its expected profit from trading energy in the day-ahead (DA) market and selling energy to the retail customers while minimizing the imbalance cost incurred in the real-time (RT) balancing market [3].

Unfortunately, a VPP with high penetration of renewable energy might require a large-scale storage facility to counter the intermittent renewable energy output [1, 2, 4, 5], which results in high investment costs. The VPP also must consider the uncertain demands of its retail customers when setting prices [6]. It is difficult for a VPP to make decisions under these uncertainties because of a significant delay between the closure of the day-ahead market when the bidding quantities are decided, e.g., 12 pm in the prior day, and the beginning of the energy delivery period in the real-time operation. To address these issues, the VPP can either employ demand response services (DR) [7]–[9, 45] or take corrective actions in the intraday market model [3, 9]. A unified solution to this problem, namely, the intraday demand response exchange (DRX) market, has been proposed in the literature [45].

DR can be exploited as a cost effective method to enable large-scale deployment of distributed renewable energy [7, 8, 10]–[12, 45]. Despite the rich literature on DR research, there are quite few efforts in developing a comprehensive and fair scheme for DR designs that consider potential benefits offered by different entities and that can be integrated easily into the current market structure. The suboptimal DR designs can result in unfair benefit sharing among players and distort the energy market, which has been observed in several studies [9, 45]. The concept of DRX market can be viewed as a global solution approach for DR design. The DRX market acts as a virtual commodity between DR providers/sellers such as distribution system operator, load serving entities, and DR customers/buyers such as GENCOS, microgrids, and VPPs, to improve their business effectiveness [9, 45]. The DRX market allows exchanges of DR services among multiple buyers and sellers via two mechanisms, namely pool contracting and bilateral contracting, which are coordinated by the DRX Operators. In short, a DRX market guarantees the fairness in DR allocation, balances benefits of all players, and ensure optimum market efficiency [45]. The intraday DRX is also compatible to the current market structure [9].

There is rich literature on VPP's bidding designs in the energy market. The work in [1] studies the VPP's optimal bidding strategy in the joint day ahead energy market and reserve market. The problem is formulated as a mixed integer nonlinear programming (MINLP), which is solved by the genetic algorithm. References [2, 4] propose optimal bidding strategies for VPP which includes different generation entities using stochastic programming approach. The work in [8] proposes a scoring rule based DR program for a VPP, which requires the design of the local market. Most of these papers, however, do not consider the VPP's bidding design while exploiting the DRX concept in their optimization frameworks.

This paper extends our original work [13] where we presented a mathematical model for energy bidding of the VPP in three energy trading floors including the day-ahead (spot)electricity market, the balancing market, and the novel intraday DRX market. Our model considers uncertainties of renewable energy, market, and customer loads as well as detailed modeling of DR trading. In our design, the VPP acts as a price taker in the day-ahead market to submit energy bidding quantities and acts as a deviator to purchase balancing energy to correct energy mismatch with respect to day-ahead decisions [2]. The VPP also needs to determine price offers when selling energy to several local retail customers [6]. The VPP can purchase DR services from several DR providers in the intraday DRX market to reduce energy imbalance cost from the balancing market and provide more competitive price offers for its customers [9, 45]. Our extension also considers the potential DR services provided by VPP's energy customers via the DRX market. The overall bidding problem is modeled as a three-stage program, which is computationally efficient by using scenario-based approach [2].

The remaining of this paper is organized as follows. Section II provides the system model with detailed assumptions and descriptions. Section III presents the problem formulation of VPP's optimal bidding strategy. Extensive numeral results are provided in Section IV. Section V concludes the paper.

II. System Model

A. Modeling Descriptions and Assumptions

This paper considers a commercial VPP, which consists of renewable energy sources (wind farms), nonrenewable energy sources (thermal generators- DGs), conventional storage facilities (e.g., battery energy systems-BESs). VPP acts as a commercial aggregator that maximizes its revenue by selling energy in the whole sale electricity market and to local retail customers. The VPP can participate in both energy markets and DRX market as shown in Figure 1 [9].

The data of renewable energy generation is taken from the NREL dataset [35]. Since this dataset was studied in [33], its stochastic stochastic model of wind power generations is adopted in this paper as follows:

$$P^{\mathsf{wd}}_{t} = \bar{P}^{\mathsf{wd}}_{t} + \epsilon^{\mathsf{wd}}_{t}$$

where the forecast wind power $\bar{P}^{\mathsf{wd}}_{t}$ at time slot t can be estimated from the historical data [14] by using the ARIMA model. The forecast error $\epsilon^{\mathsf{wd}}_{t}$ is assumed to be an independent and identically distributed (i.i.d.) random noise following a truncated zero mean normal distribution [7, 33]. The estimation toolbox [15] is employed to generate wind power scenarios that capture the stochastic nature of this renewable resource.

The energy consumptions that local retail customers purchase from the VPP depend on the VPP's price offers. We

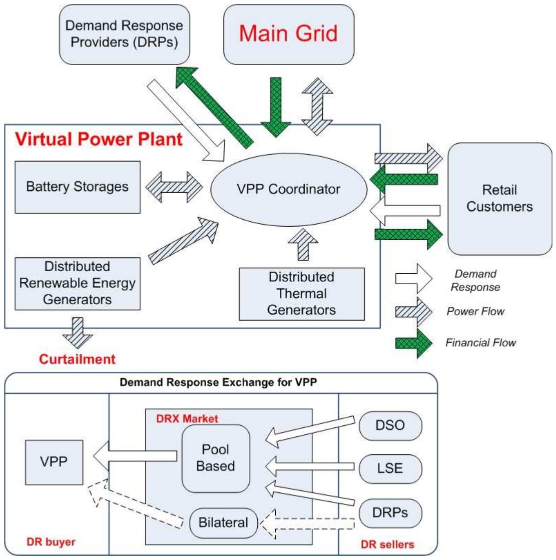

Fig. 1. Virtual Power Plant with Demand Response Exchange Market

assume that the relation between VPP's price offer and the energy purchased by retail customers can be characterized by a stepwise price quota model [6]. In particular, local retail customers such as residential, commercial, and industrial customers [6], exhibit elastic behavior in response to the retail price, i.e., customers are less willing to buy energy as the price is higher. It is worth mentioning that beside the stepwise price quota model [6] considered in this paper, there are other models that describe the relation between price and energy consumptions such as the DR load model in [16] and the multi-block utility function in [17]. These models, which were considered in our previous works [18, 19], can also be incorporated in the framework proposed in this paper. Similar to the wind power, the customer loads are based on historical data and the forecasting error follows a zero mean truncated normal distribution [7, 20][1].

B. Market Framework

The short-term market model in this paper is based on the Nordic market [9, 16]. For simplicity, we ignore the intraday Elbas market (adjustment market) since it is not often activated as discussed in [16]. The VPP's energy imbalance can be resolved by utilizing DR via the DRX market at the intraday timescale, which allows the VPP to utilize the information obtained after the day-ahead market closure, e.g., the realization of DA prices and the update of load forecasts and forecasted RT balancing prices [3, 9]. The balancing price is represented by a pair of positive and negative balancing prices, i.e. ($\lambda^{\mathsf{P}}_{t,s} \leq \lambda^{\mathsf{D}}_{t,s} \leq \lambda^{\mathsf{N}}_{t,s}$) where their relationships with the DA market prices are explained in [3, 16]. In particular, the pair ($\lambda^{\mathsf{P}}_{t,s} \leq \lambda^{\mathsf{D}}_{t,s} \leq \lambda^{\mathsf{N}}_{t,s}$) represents the up and down regulations due to the negative or positive imbalance respectively [3, 16, 34]. If the imbalance is positive then the market has excess energy generation and the regulation down is activated [3, 16, 34]. In contrast, if the imbalance is negative, there is a lack of energy generation in the market and the regulation up is activated [3, 16, 34]. Various methods for generating scenarios and modeling the uncertainties of market prices in the Nordic market are proposed in the literature [3, 16, 32, 34, 40]. In this paper, we use the ARIMA models proposed in [32], which is a extended model of [3], to generate the price scenarios of the day-ahead (i.e., Elspot market). In addition, we use the stochastic model of the Nordic imbalance price proposed in [34] since its validity is already confirmed in [16, 34, 40]. This "dual pricing policy" for balancing markets is widely used in European pool markets [3]. In US markets, the "single pricing policy" is more popular.

C. DRX market Modeling

This paper considers the DRX market model proposed in [9] where the VPP can make extra payments to several Demand Response Providers (DRPs) to realize load reductions to compensate for the energy deficit from DRP [9]. This is equivalent to the purchase of certain "*virtual energy*" from the DRX market, which is more cost-efficient compared to the energy purchase from the balancing market. In particular, the DR can be purchased from DRPs, whose pool based characteristic can be modeled by a price quantity offer [9], as shown in Figure 2, and the bilateral prices are settled in long term.

This paper considers load reduction based DR [9] since load reduction is suitable with current market practices and research [47, 48, 51]. As stated in [51], DR services integrated in the wholesale electricity market are indeed load reductions. In particular, DR can be aggregated by DRPs from *"energy consumers to elicit their load reduction"* using different load reduction strategies such as *load shifting, load curtailment, battery, and on-site generator* [51]. Integrating DR in form of load reduction in the reconstructed wholesale market operations such as market clearing [47] or security constrained unit commitment [48] has been studied in the literature. Demonstration projects such as PowerMatcher and PowerMatching city in Europe; and GridWise in the US also consider DR in form of load reductions [49]. Specifically, energy consumers was paid or rewarded to reduce their energy consumptions in a particular DR event [49]. Load reduction based DR is also used in developing conceptual model of DRX market in [45, 46] and its sole model in [9, 41, 50]. The opposite form of load reduction is load increment or load absorption where the customers were paid to increase their energy consumptions [43, 44]. The load increments can be modeled by allowing negative price in the price quantity offer. Note that there is no technical challenge in considering load absorption, e.g., allowing negative price in the price quantity-curves, in the VPP's bidding model. However, the conceptual models of load increments are not matured yet. There are lacks of field studies and theoretical research for load increments. Hence, load increments are not considered in this paper.

In this paper, we consider the case that DR is traded in the intraday DRX market [9] without the need of modifying traditional wholesale market trading floors [47, 48]. In particular, DRPs participate in the intraday DRX by providing its price quantity offer that describes the relation between the amount of load reduction offered and the service prices set [9]. In general, there is a significant delay between the closure of the day ahead market (12 pm in the previous day) when

[1]The assumption that forecasting errors follow normal distributions can be found in many previous works as discussed in [7].

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VPP submits the bid and the beginning of the energy delivery period in the current day [3]. The integration of the DRX in the intraday time frame allows VPP to take corrective actions by purchasing DR services. These actions can reduce or eliminate the differences between the expected power delivery and the schedule cleared in the day-ahead market. Moreover, formation of liquid markets close to delivery such as the intraday markets guarantees that DR services will be accessible for the VPP with high penetration of renewable energy [9]. The intraday DRX can be considered as a new trading floor. Consequently, the objective of the VPP is to maximize its expected profit considering the entire sequences of operation including three trading floors: day-ahead, intraday, and real time balancing market.

In this paper, the VPP acts as a DR buyer in the DRX market because of the following reasons. Firstly, there are different VPP models proposed in the literature. This paper considers the well known model of VPP, i.e., an aggregator of multiple energy producers that mostly are renewable energy. This VPP model has been widely recognized in the literature [3, 5, 9, 52, 55]. Hence, considering the VPP as a DR buyer in the DRX market fits well with the literature of DRX market [9, 41, 45, 46]. Secondly, as shown in Figure 1, the local retail customers such as industrial, commercial, and residential energy consumers are considered as independent agents, which means their energy consumptions cannot be controlled directly by the VPP [6]. This assumption is adopted in [6, 53, 54] and fits well with the deregulated market context and the concept of DR aggregation [51].

It is worth mentioning that under different models, the VPP can be assumed as a DRP to sell DR services. This assumption fits well with the case the VPP can directly control the energy consumptions [1, 2, 7, 56] of energy customers and/or acts as the aggregation of energy consumers [8, 18, 56]. This model of VPP is different to the case we address in this paper. Note that the case the VPP acts as both microgrid aggregator and DR aggregator has been addressed in our previous work [7] where the impact of DR contracts on microgrid's bidding strategy is investigated. In other work [18], the cooperation of multiple demand side resource aggregator under the VPP concepts is also studied. In particular, we proposed an efficient cost allocation method to fairly distribute the cooperation benefit resulted from the aggregated flexibilities of the cooperation.

D. Decision Making Framework and Scenario Generation/Reduction

In summary, a VPP must make several decisions in three trading floors, which can be formulated as a following multi-stage stochastic optimization problem:

1) **First Stage (S1):** the VPP submits its offering curve in the day-ahead market and determines price offers for its local customers. For example, the Nordic market operator requires all offering curves to be submitted before the gate closure, i.e., 12 p.m of the day before.
2) **Second Stage (S2):** After the gate closure, day-ahead prices are revealed, then the VPP decides the amount of DR services purchased before the intra DRX prices are revealed.
3) **Third Stage (S3):** the VPP adjusts the operation of its facilities when the renewable energy output and the intraday DRX prices are revealed, but before knowing the balancing market prices.
4) **Fourth Stage (S4):** The balancing market prices are revealed. However, this *four-stage* stochastic optimization problem turns into a *three-stage* stochastic program [2, 9] since no decision is made in the fourth stage.

In this paper, uncertainties care captured by scenarios and the scenario tree is constructed as follows. First, we generate $N1 = 100$ day-ahead prices. For each generated day-ahead price scenario, we generate $N2 = 100$ scenarios of pool DRX prices. For each scenario of DRX price, we generate $N3 = 100$ scenarios of renewable energy and load demands. Finally, for each scenario of renewable energy and load demands, we generate $N4 = 100$ balancing prices. Hence the total number of generated scenarios is $\mathsf{NS} = \mathsf{N1} \times \mathsf{N2} \times \mathsf{N3} \times \mathsf{N4} = 10^8$. Details about scenario tree construction for market with multiple trading floors can be found in [3, 21]. Since it is difficult to solve the approximated optimization problem with a large number of generated scenarios, scenario reduction techniques are employed to reduce the computation burden [2, 3, 6, 7, 9, 18]. Scenario reduction is an important research area by itself, whose results can be used to tackle stochastic programming problems [21]. The scenario reduction is usually designed to eliminate scenarios that do not likely affect the final solution such as scenarios with very low probabilities and/or to aggregate similar scenarios based on certain probability metrics [22, 23]. The outputs of a scenario reduction algorithm are a smaller set of NS' scenarios s ($\mathsf{NS}' < \mathsf{NS}$) [21]. Mathematically speaking, the process of scenario reduction can be considered as solving an NP hard combinatorial optimization problem to minimize information loss subject to a cardinality set constraint of reduced scenarios [22, 23]. Among available scenario reduction methods, three methods, namely the *backward, forward, and fast forward* [23] methods, are widely used in the power system research. The *fast-forward* method often yields the "best tree" [21]. In the fast forward reduction method, the reduced scenario tree is built by selecting/adding one scenario from the original tree at each iteration [23]. In this paper, we employ the *fast forward* method to construct the scenario tree and reduce the number of scenarios to $\mathsf{NS}' = 100$ by using GAMS/SCENRED [31]. The GAMS/SCENRED package has been widely used in power system research [2, 3, 6, 9, 21, 36]–[39].

III. Problem Formulation

We are interested in maximizing the VPP's expected profit that is described by the following objective function:

$$\max \sum_{t=1}^{\mathsf{NT}} \Bigg\{ E_{\mathsf{S1}} \Bigg[\lambda^{\mathsf{D}}_{t,s} P^{\mathsf{D}}_t \tau + E_{\mathsf{S2|S1}} \Bigg[-\sum_{d=1}^{ND} \Big(\mathsf{Bi}_{t,s} + \mathsf{CDRP}_{d,t,s} \Big) + E_{\mathsf{S3|S2,S1}} \Bigg[\sum_{i\in B} \sum_{e\in\gamma_i^E} R^e_{i,t,s} - \sum_{i\in B} \sum_{g\in\gamma_i^G} \Big(\mathsf{SU}^g_i y^g_{i,t} + \mathsf{SD}^g_i z^g_{i,t} + C^g_{i,t,s} \Big) - \sum_{i\in B} \sum_{b\in\gamma_i^B} \lambda^{\mathsf{deg}}_i \Big(\eta^{b,c}_i P^{b,c}_{i,t,s} + \frac{P^{b,d}_{i,t,s}}{\eta^{b,d}_i} \Big) \tau - \lambda^{\mathsf{N}}_{t,s} P^{\mathsf{N}}_{t,s} \tau + \lambda^{\mathsf{P}}_{t,s} P^{\mathsf{P}}_{t,s} \tau \Bigg] \Bigg] \Bigg] \Bigg\}. \quad (1)$$

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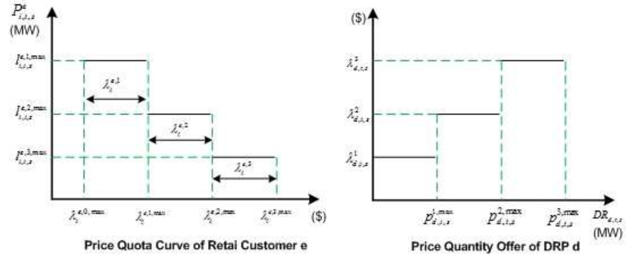

Fig. 2. Retail customer price quota and DR provide price-quantity offer

The function $\mathbf{E}$ is used to calculate the expected values by using the summation of the multiplied values obtained in each scenario and the probability of occurrence of that scenario [9]. The VPP's profit comprises several components: the revenue from Day Ahead $\lambda^{\mathsf{D}}_{t,s}P^{\mathsf{D}}_{t}\tau$, minus the DR cost due to energy purchase from DRPs in the DRX market through pool contracts and bilateral contracts $\sum_{d=1}^{ND}(\mathsf{CDRP}_{d,t,s}+\mathsf{Bi}_{t,s})$, the revenue of retail energy selling to local retail customers $\sum_{i\in B}\sum_{e\in\gamma_i^E} R^e_{i,t,s}$, minus the cost of conventional thermal generators $\sum_{i\in B}\sum_{g\in\gamma_i^G}\left(\mathsf{SU}^g_i y^g_{i,t}+\mathsf{SD}^g_i z^g_{i,t}+C^g_{i,t,s}\right)$ and battery degradation $\sum_{i\in B}\sum_{b\in\gamma_i^B}\lambda^{\mathsf{deg}}_t\left(\eta^{b,c}_i P^{b,c}_{i,t,s}+\frac{P^{b,d}_{i,t,s}}{\eta^{b,d}_i}\right)\tau$, and cost due to energy imbalance (negative and positive) $-\lambda^{\mathsf{N}}_{t,s}P^{\mathsf{N}}_{t,s}\tau+\lambda^{\mathsf{P}}_{t,s}P^{\mathsf{P}}_{t,s}\tau$. This optimization is subject to the following constraints.

A. Power and Market Balance Constraints

Power delivered by VPP to the grid must equal to the power generated from wind farms minus wind power curtailment and power generated from thermal generators, plus energy exchange with BESs and minus the total energy selling to local retail customers. The wind power curtailment is upper-bounded by the wind generations. These constraints are described as follows:

$$P^{\mathsf{del}}_{t,s}=\sum_{i\in\mathsf{B}}\Big\{\sum_{w\in\gamma_i^W}(P^w_{i,t,s}-P^{w,c}_{i,t,s})+\sum_{g\in\gamma_i^G}P^g_{i,t,s} +\sum_{b\in\gamma_i^B}\left(P^{\mathsf{b,d}}_{i,t,s}-P^{\mathsf{b,c}}_{i,t,s}\right)-\sum_{e\in\gamma_i^E}P^e_{i,t,s}\Big\},\ \forall t,s. \tag{2}$$

$$P^{\mathsf{w,c}}_{i,t,s}\le P^{\mathsf{w}}_{i,t,s},\forall t,s. \tag{3}$$

The mismatch between the energy delivered in real time $P^{\mathsf{del}}_{t,s}$ and the bidding energy P^D_t can be positive (the VPP resells surplus energy to the balancing market at a low price $\lambda^P_{t,s}$) or negative (the VPP purchases extra energy from the balancing market at a high price $\lambda^N_{(t,s)}$ or purchases load reduction quantities via DRX market from DRPs $\sum_{d=1}^{\mathsf{ND}}\left(\mathsf{DR}_{d,t,s}+P^{\mathsf{Bi}}_{d,t,s}\right)$. The market balance constraints can be described as follows:

$$P^{\mathsf{del}}_{t,s}-P^D_t=P^{\mathsf{P}}_{t,s}-P^{\mathsf{N}}_{t,s}-\sum_{d=1}^{\mathsf{ND}}\left(\mathsf{DR}_{d,t,s}+P^{\mathsf{Bi}}_{d,t,s}\right). \tag{4}$$

B. Demand Response Exchange

VPP can purchase DR services from DRPs under both pool and bilateral contracts in the DRX market. The DR cost is the product of the DR price offer and DR bidding quantity. In the pool DRX market, each DRP provides a price-quantity offer that presents the relation between the load reduction and the service prices at each time slot as shown in Figure 2. This can be captured by the following constraints [9]:

$$p^n_{d,t,s}\le p^{n,\mathsf{max}}_{d,t,s};\quad \mathsf{DR}_{d,t,s}=\sum_{n=1}^{\mathsf{NB}_d}p^n_{d,t,s}, \tag{5}$$

$$\mathsf{CDRP}_{d,t,s}=\sum_{n=1}^{\mathsf{NB}_d}\lambda^n_{d,t,s}p^n_{d,t,s}\tau. \tag{6}$$

In the bilateral contract, the VPP can purchase DR from DRPs with a predetermined and fixed bilateral price $\lambda^{\mathsf{B}}_{d,t}$. However, the total DR purchased via both contracts cannot exceed the DR capacity of the provider, which is captured by the following constraints:

$$\mathsf{Bi}_{d,t,s}=\lambda^{\mathsf{B}}_{d,t}P^{\mathsf{Bi}}_{d,t,s}\tau, \tag{7}$$

$$\left(\mathsf{DR}_{d,t,s}+P^{\mathsf{Bi}}_{d,t,s}\right)\tau\le\mathsf{DR}^{\mathsf{cap}}_d,\ \forall d,t,s. \tag{8}$$

C. Local Customers' Elastic Demand Curves

The elastic relation between price offer λ^e_i and demand consumed $P^e_{i,t,s}$ of a retail customer e at bus i can be approximated by a step-wise price-quota curve shown in Figure 2. The VPP's revenue by selling energy to retail customer e at bus i is the product of λ^e_i and $P^e_{i,t,s}$, which can be captured by the following constraints [6]:

$$\bar{P}^e_{i,t,s}\le D^e_{i,t,s};\quad \bar{P}^e_{i,t,s}=\sum_{n=1}^{\mathsf{NB}^e_i}l^{e,n,\mathsf{max}}_{i,t,s}u^{e,n}_{i,t,s}, \tag{9}$$

$$\sum_{n}^{NB^e_i}u^{e,n}_{i,t,s}=1;\quad \lambda^e_i=\sum_{n}^{\mathsf{NB^e_i}}\lambda^{e,n}_i, \tag{10}$$

$$\lambda^{e,n-1}_i u^{e,n}_{i,t,s}\le\lambda^{e,n}_i\le\lambda^{e,n}_i u^{e,n}_{i,t,s}, \tag{11}$$

$$\bar{R}^e_{i,t,s}=\sum_{n=1}^{\mathsf{NB}^e_i}\lambda^{e,n}_i l^{e,n,\mathsf{max}}_{i,t,s}\tau, \tag{12}$$

where constraints (9)-(11) represent the demand supplied by the VPP to retail energy customer e at bus i at each time interval t. The power demand $P^e_{i,t,s}$ purchased from the VPP, which is a function of the price offer λ^e_i, equals the level of price quota curve determined by the binary variable $u^{e,n}_{i,t,s}$ as in (9). In particular, $u^{e,n}_{i,t,s}$ is used to identify the price quota-curve interval, which is used to calculate the fixed retail price offer λ^e_i in (10)-(11) [6]. The VPP's revenue of selling energy, which is the product of λ^e_i and $P^e_{i,t,s}$, is transformed to a linear constraint (12) which is based on the step-wise price quota curve approximation [6].

In cases that retail customers do not participate in the DRX market, the VPP's revenue of selling energy to the retail customer e at bus i is:

$$R^e_{i,t,s}=\bar{R}^e_{i,t,s},\ \forall e,i,t,s, \tag{13}$$

and the power consumed by retail customer e at bus i is

$$P^e_{i,t,s}=\bar{P}^e_{i,t,s},\ \forall e,i,t,s. \tag{14}$$

D. Retail Load Reduction Services via DRX Market

We extend the work to consider the participation of retail customers in the DRX market. In fact, energy customers

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such as commercial [10], industrial [11], and residential load [12] can potentially provide DR services to support the VPP operation. In particular, the local retail customer e can also offer load reduction services to VPP via the DRX market as a DRP. Specifically, VPP can buy $\mathsf{DR}^e_{i,t,s}+P^{\mathsf{Bi,e}}_{i,t,s}$ amount of load reduction from customer e via the pool contract and bilateral contract, which can be described similarly to constraints (5)-(8) for outside DRPs.

$$0 \leq p^{e,n}_{i,t,s} \leq p^{e,n,\mathsf{max}}_{i,t,s}; \quad \mathsf{DR}^e_{i,t,s} = \sum_{e\in\gamma_i^B}^{\mathsf{NB}_d} p^{e,n}_{i,t,s}, \qquad (15)$$

$$\mathsf{CDRP}^e_{i,t,s} = \sum_{n=1}^{\mathsf{NB}_d} \lambda^{e,n}_{i,t,s} p^{e,n}_{i,t,s}; \quad \mathsf{Bi}^e_{i,t,s} = \lambda^{\mathsf{B,e}}_{i,t} P^{\mathsf{Bi,e}}_{i,t,s}, \qquad (16)$$

$$\left(\mathsf{DR}^e_{i,t,s} + P^{\mathsf{Bi,e}}_{i,t,s}\right)\tau \leq \mathsf{DR}^{\mathsf{e,cap}}_i, \ \forall e,i,t,s, \qquad (17)$$

where constraints (15)-(16) describe the DR exchange of customer e and VPP via pool based and bilateral contract. However, buying load reduction from customers will reduce the VPP's retail revenue by $L^e_{i,t,s}$:

$$\mathsf{DR}^e_{i,t,s} + P^{\mathsf{Bi,e}}_{i,t,s} = \sum_{n=1}^{\mathsf{NB}^e_i} l^{e,n,\mathsf{max}}_{i,t,s} u^{e,n,dr}_{i,t,s}, \qquad (18)$$

$$L^e_{i,t,s} = \sum_{n=1}^{\mathsf{NB}^e_i} \lambda^{e,n}_i l^{n,\mathsf{max}}_{i,t,s} u^{e,n,dr}_{i,t,s}\tau, \qquad (19)$$

where constraints (18)-(19) describe the revenue loss $L^e_{i,t,s}$ due to the load reduction of the retail customer e. Note that the nonlinear constraint (19) can be converted to a set of mixed integer linear programming (MILP) constraints easily since $u^{e,n,dr}_{i,t,s}$ is binary.

The VPP's revenue of selling energy to the retail customer e at bus i and its actual power consumed are:

$$R^e_{i,t,s} = \bar{R}^e_{i,t,s} - L^e_{i,t,s}, \ \forall e,i,t,s \qquad (20)$$

$$P^e_{i,t,s} = \bar{P}^e_{i,t,s} - \mathsf{DR}^e_{i,t,s} + P^{\mathsf{Bi,e}}_{i,t,s}, \ \forall e,i,t,s. \qquad (21)$$

In general, the VPP needs to provide incentives for their energy customers to modify their demand by using financial rewards. In [7, 8, 16, 19], the financial incentives are realized by real time pricing signals, which require the complex local market designs. In this paper, the VPP's priority is to provide competitive price offers to local energy customers. The VPP can purchase DR services of retail customers in the intraday timescale via the DRX market. Hence, in this case both VPP and retail energy customers can utilize the updated information of generations and demand as well as the revealed DA prices to make corrective actions by exchanging DR services.

E. Other Operation Constraints

Due to space limitation and to avoid overwhelming notations used in the paper, the constraints of thermal generators and battery energy systems such as shut down and start up limits, generation output limits, ramp up and ramp down limits, battery charging/discharging power limits, dynamics and limits of battery's state of charge, charge and discharge operation [2], network power flow constraints [24] are not presented. Detailed formulations of these constraints can be found in our previous works [7, 18, 19].

We acknowledge that linearizing the nonlinear power flow is an important technical issue, especially in the distribution network. Employing directly full model of AC power flow can help us incorporate reactive power in the decision making model, which leads to a mixed integer nonlinear programming (MINLP) based decision making model. Since a large scale MINLP for a day-ahead planning problem cannot be solved by available MINLP solvers, heuristic evolutionary algorithms such as genetic algorithm [1] can be employed. Hence, there are some linear approximation approaches for power flow in the distribution network that keeps the optimization linear. The work [24] proposed to employ lossless DC power flow for modeling a short term decision making problem of a distribution company and employed more complex linearized power flow model in the real-time optimal operation. The work [25] proposes state-of-the-art linearized network power flow equation model that retains the linearity of power flow constraints that is used for the real time energy management of a distribution company. Another linearized model, namely Distflow [26], is also used in the literature [26]–[29]. The main objective of this paper is to illustrate the positive impact of using intraday DRX market in VPP's market optimization problem. For simplicity, we adopt the DC power flow model for distribution network as an approach in [24], which is also used in our previous work [19]. We aware the moderate accuracy of this model in comparison with other models as presented above. However, as stated in [24] and verified in solving the day-ahead planning problem of a large scale distribution company [24], we would like to note that *"the inaccuracy induced by DC network model does not make a great concern since the solution of the Day-ahead problem problem is inherently exposed to various sources of error such as the uncertainty of predicted real-time market prices and loads" [24].* More accuracy models such as the one proposed in [25] or the Distflow model for radial network [26]–[29], however, can be integrated into our decision making framework since it is also linear. Employing this model will be the subject of our future work. The overall problem is a MILP, whose optimal solution can be found by branch and cut algorithm embedded in available commercial solvers such as CPLEX.

IV. Numerical Results

A. Simulation Data

We consider a modified case study of 4 machines based VPP [5] which includes 2 wind farms and 2 conventional thermal units. The local network is modified based on IEEE six-bus system as shown in Figure IV-A, whose line parameters can be found in [30]. Bus 1 is the reference bus connected to the main grid. The VPP serves several local customers, which are classified in three groups: industrial, commercial and residential customers, and exchanges DR with 3 DRPs to minimize its imbalance penalty cost. DRPs are assumed to be outside the VPP and do not interfere the energy demand of VPP's local customers. Wind, electricity price, and load scenario generations are based on [15, 20]. The DR market data are taken from [9] and presented in Tables II and III. The forecast electricity price, wind energy, and retail customers' loads as well as their price quota curves are shown in Figure 4. The electricity price and load forecast errors are assumed to be 15%, negative and positive balancing prices are $1.1\lambda^{\mathsf{D}}_{t,s}$ and

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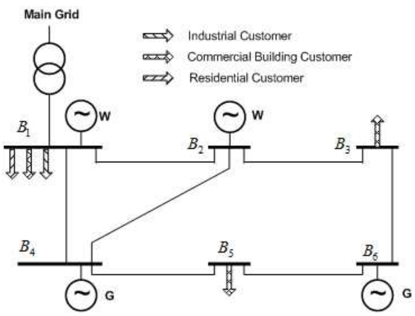


Fig. 3. VPP case study based on 6-bus system

$0.9\lambda^{\mathrm{D}}_{t,s}$ [16] respectively, retail customers with the same type have the same forecast load and the same price quota curves. The distributed thermal generators' data are shown in Table I.

TABLE I
THERMAL GENERATOR DATA FOR 6 BUS SYSTEM CASE STUDY

Bus ID	Lower (MW)	Upper (MW)	Min Down (h)	Min Up (h)	Ramp (MW/h)
B4	5	20	2	4	1
B6	0.8	10	3	3	1
Bus ID	a ($)	b (MBtu MWh)	c ($/ MW^2h)	Start Up ($)	Shut Down ($)
B4	50	6	0.0004	50	20
B6	40	5.5	0.0001	40	20

All numerical experiments are performed in a personal computer using Window 8, Intel Core i5 processor, and 8 GB memory. The MILP problem is solved by CPLEX under GAMS. The relative gap is set to be 10^{-4}.

B. Results and Discussions

Figure 5 presents the day ahead bidding quantities of VPP with different levels of wind uncertainty and DR capacity DR^{cap}. Without DR services, bidding too high energy may result in the high balancing-energy purchase cost since the VPP needs to purchase extra high price energy from the balancing market to compensate for the energy mismatch, which explains how the amount of bidding energy depends on the DR capacity DR^{cap}. It can be observed that when DRPs offer larger capacity $\mathrm{DR^{cap}}$, the bidding quantities are higher since uncertain wind generation outputs can be addressed more easily.

Figure 6(a) shows the total energy bidding in the day-ahead market, i.e., $\sum_t^{\mathrm{NT}} P_t^D$. It can be observed that the total energy bidding in the day-ahead market increases as $\mathrm{DR^{cap}}$ increases. When high DR quantity available ($\mathrm{DR^{cap}} = 30$ MWh), the case with the larger wind forecast error (e.g., 20%) has the larger value of the total energy bidding in the day-ahead market. In fact, when there is higher wind uncertainty and $\mathrm{DR^{cap}}$ is also sufficiently large, the VPP can compensate for the wind energy shortage more easily by exploiting DR market; thus, the VPP tends to bid higher energy to efficiently utilize wind energy surplus.

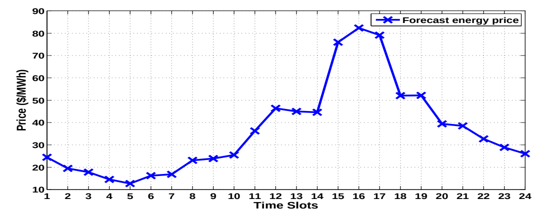
Figure 6(b) reveals that the DRX participation enables the VPP to improve its profit significantly but the VPP's profit improvement becomes flat for a sufficiently high $\mathrm{DR^{cap}}$, which demonstrates the energy level that VPP needs to purchase to counter renewable energy uncertainties. In addition, although all profit curves show the steady increase with $\mathrm{DR^{cap}}$, the curve

TABLE II
PRICE QUANTITY OFFER OF DRPS IN POOL BASED DRX MARKET

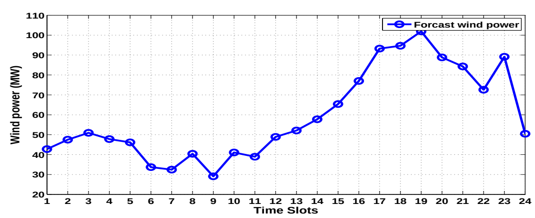
k	1	2	3
$p^{k,\max}_{d,t}$	25%($\mathrm{DR^{cap}}$)	75%($\mathrm{DR^{cap}}$)	100%($\mathrm{DR^{cap}}$)
	Percentage of mean Real time market price		
DRP1 $\lambda^k_{1,t}$	40%	70%	100%
DRP2 $\lambda^k_{2,t}$	50%	80%	110%
DRP3 $\lambda^k_{3,t}$	60%	90%	120%

TABLE III
PRICE OFFER OF DRPS IN BILATERAL CONTRACT

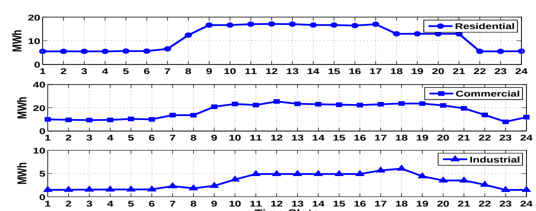
DRP1	DRP2	DRP3
40 ($/MWh)	45 ($/MWh)	50 ($/MWh)



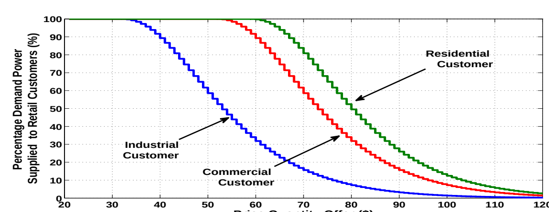
(a) Forecast electricity price



(b) Forecast wind energy



(c) Forecast load



(d) Price quota curves of retail customer

Fig. 4. Simulation Data

associated with smaller wind uncertainties achieves higher profit at low $\mathrm{DR^{cap}}$ and lower profit at sufficiently high $\mathrm{DR^{cap}}$ compared to other curves. When DR resources are abundant (e.g., $\mathrm{DR^{cap}} = 30$ MWh), the VPP can efficiently address wind uncertainties and exploit the wind energy surplus, which slightly increases its expected profit.

Figure 7 shows that the VPP can achieve better profit improvement by participating in both bilateral and pool based

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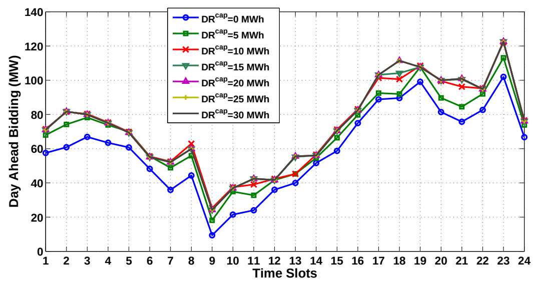
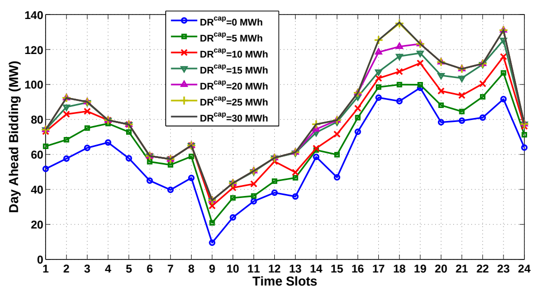
TABLE IV
RETAIL PRICES FOR LOCAL CUSTOMERS

	Bus	Type	DR^{cap} (MWh)	Wind Forecast Error (%)					
				5	10	15	20	25	30
Price ($/MWh)	B_1	Ind	0	61	61	61	61	62	62
			30	60	60	60	61	61	62
		Res	0	70	71	71	71	71	71
			30	70	70	70	70	71	71
		Com	0	57	57	57	57	57	57
			30	56	56	56	57	57	57
	B_3	Com	0	73	73	73	74	74	76
			30	70	71	72	73	74	76
	B_5	Com	0	58	58	58	58	59	59
			30	58	58	58	58	59	59

Abbreviation: Ind=Industrial; Com=Commercial; Res=Residential

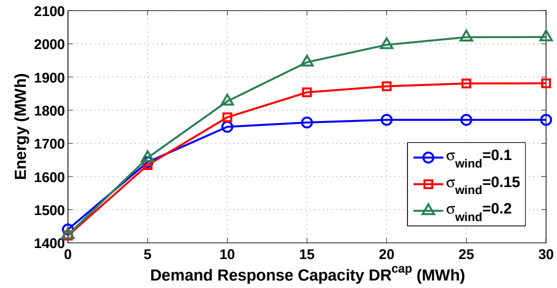


(a) Case with wind forecast error σ_{wind}= 0.1

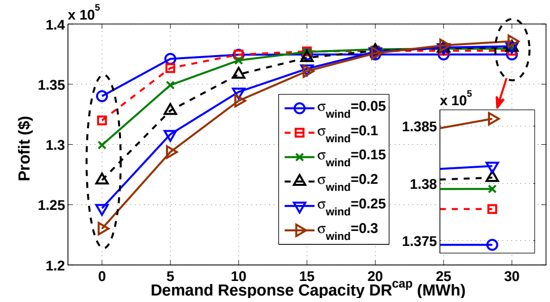


(b) Case with wind forecast error σ_{wind}= 0.2

Fig. 5. Day ahead bidding quantities of VPP



(a) Impact of DR^{cap} on total day ahead bidding



(b) Impact of DR^{cap} on total profit

Fig. 6. Impacts of DR capacity and wind forecast uncertainty when there is no retail customers in DRX market

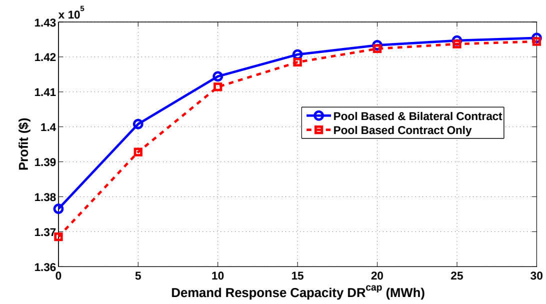


Fig. 7. VPP's profit with/without bilateral based contract participation

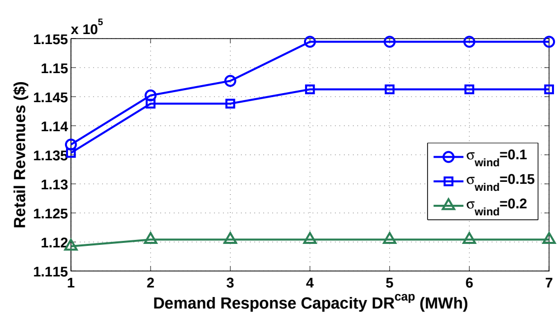


Fig. 8. Impact of DR capacity on VPP's profit with different wind uncertain levels

DRX markets, since it has more flexibility in DR purchase. However, the VPP's profit when participating in both types of contracts is higher than that with pool DRX for small DR^{cap}. The profits in both cases become the same for high DR^{cap}. This can be explained as follows. Due to the nature of the bilateral contract, the price is settled and remains unchanged for a long-term market. The role of the bilateral contract is critical when the transaction in the pool market is small. When DR^{cap} is higher, the absolute values of low-index DR block offers with low price (i.e., 25% of DR^{cap}) also increase, which adversely balances the uncertainties of pool price and reduces the role of the bilateral contract on the VPP's profit improvement. This demonstrates the impact of DR participation on optimal bilateral price determination.

The impact of DRX market on the VPP's expected retail revenues and the VPP's retail price offers to customers are illustrated in Figure 8 and Table IV, respectively. When DR^{cap} increases, the VPP can effectively deal with the energy bidding deficiency in day-ahead whole sale market. Hence, it directly relaxes its retail energy offers for local retail customers to improve the retail revenue, which is explained by the reduction of the retail price offers shown in Table IV. The retail prices also depend on the location of retail customers. For examples, commercial load at bus 5 has the highest price among all commercial customers since it has no direct connection to wind farms at buses 1 and 2 and must rely more on thermal generators at bus 4 and 6 to meet its demand.

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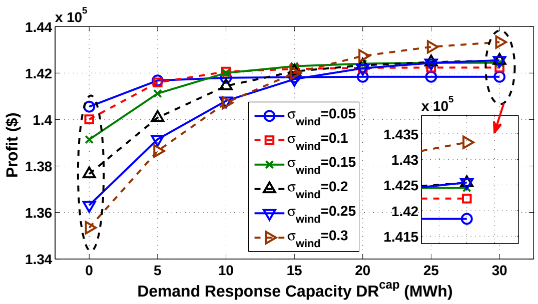


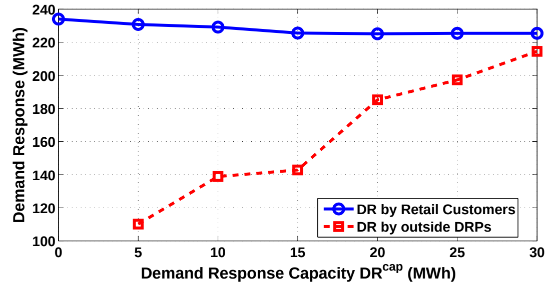
Fig. 9. Impact of DR capacity and wind forecast uncertainty on VPP's profit when retail customers join DRX market

C. Extensions with DR Exchange From Local Retail Customers

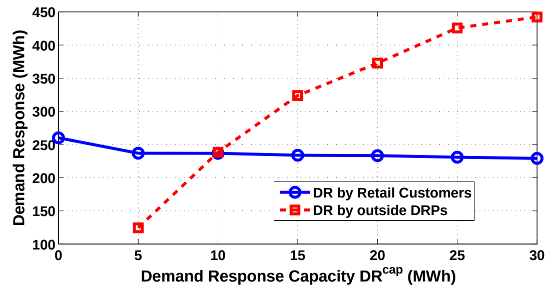
We investigate the case when DR services can be extracted from the VPP's energy customer via the DRX market framework. Figure 9 shows the impact of DR on the VPP's profit when retail customers also join the DRX market. We assume retail customers can also provide DR services to VPP via bilateral and pool contracts in the DRX market. The DRX offer of each retail customer is assumed to be similar to DRP 1 and its $\mathrm{DR}_i^{\mathrm{e,cap}}$ is equal to its purchased energy. The phenomenon is quite similar to that in Figure 6 except the slight increase in the VPP's expected profit. These results demonstrate the positive impact of retail customers since their load reduction services directly help the VPP address retail demands' uncertainties at the local demand side. In general, the availability of retail customers' DR services provide another options for VPP to address the uncertainties in the VPP's market decision making problem.

Figure 10 shows that DR quantities purchased from local customers decrease rapidly when DR resources from outside DRPs increase. This is because buying load reduction services from local customers also results in the reduction of retail revenues. The participation of retail customers in the DRX market only leads to significant impacts when DR resources from outside DRPs are small. When the wind forecast error is small, e.g., 5%, more DR is purchased from local customers than from outside DRPs due to higher uncertainty in the load forecast (10%). When wind uncertainties are higher, the energy imbalance in the wholesale market becomes more critical; therefore, more DR purchased from outside DRPs is needed.

The impact of DRX on reducing VPP's energy imbalances is shown in Figure 11. The negative energy imbalance is nearly zero when DR resources are abundant. DR also allows the VPP to increase its bidding quantities and reduce its energy surplus that must be curtailed or sold with lower price. The positive energy imbalance also reduces when the DR resources are available. It is worth mentioning that the DR services considered in this paper are load reductions [9]. Hence, the lack of VPP's energy generation could be compensated easily by buying load reduction services from DRPs, which *directly* results in a very small amount of negative energy imbalance as shown in Figure 11(b). The employment of DRX market also allows VPPs to be confident in bidding more energy in the DA market to avoid selling surplus energy with cheaper RT positive balancing price, which *indirectly* reduces the VPP's positive energy imbalance as shown in Figure 11(a). Note

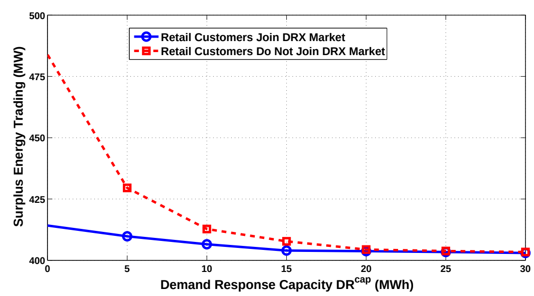


(a) Wind forecast error is 5%

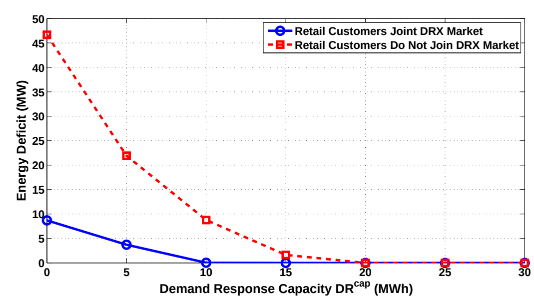


(b) Wind forecast error is 20%

Fig. 10. Demand response purchased from different providers (outside DRPs and local customers)



(a) Impact of DR capacity on positive energy imbalance



(b) Impact of DR capacity on negative energy imbalance

Fig. 11. Impact of DR on expected energy imbalance

that, since the DR services are purchased at the intraday timescale that realizes before the RT balancing market, the DRX market can reduce the energy imbalance. We can see that the participation of retail customers can help reduce the energy imbalance but their impacts are only significant when DR resources from outside DRPs are small.

Figure 12 shows that the participation of local retailers has significant impacts on the battery degradation costs. The re-

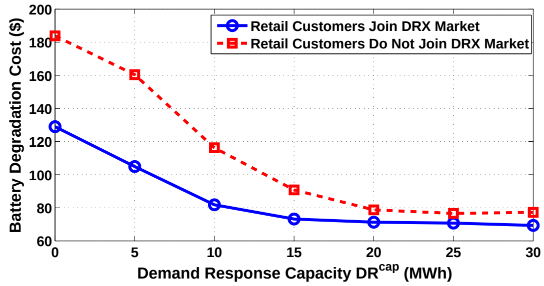


Fig. 12. Impact of DR on expected battery degradation cost

sults imply the positive impact of the DRX on VPP investment and planning since the DRX can reduce the required energy storage capacity of VPP with high penetration of renewable energy. The investment and planning of VPP with the DRX market, however, need to consider the long-term stochastic modeling of the DRX market, which is a challenging research area [45].

V. Conclusion

In this paper, we have proposed to exploit the DRX market for efficient energy management of a VPP model with significant penetration of wind energy. Numerical studies have shown that employing DR market mechanism can improve the VPP's profit. In particular, by exchanging DR with several DR sellers/suppliers via a market framework, the VPP can reduce its energy imbalance cost due to natural uncertainties of renewable energy and customers' loads. The DRX market also increases the confidence level of VPP in bidding energy with higher quantities in the day ahead market, increases the revenue of selling energy to local retail customers.

VI. Acknowledgment

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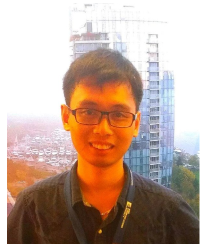

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