A Stochastic Bilevel Model for an Electricity Retailer in a Liberalized Distributed Renewable Energy Market

Josue Campos Do Prado, *Student Member, IEEE*, and Wei Qiao, *Fellow, IEEE*

***Abstract*—This article presents a short-term decision-making model for an electricity retailer using bilevel stochastic programing. In the proposed model, a liberalized distributed renewable energy (DRE) market in which the retailer competes with other load serving entities (LSEs) for procuring DRE is proposed. The retailer, in the upper level, decides its level of involvement in the day-ahead and real-time markets, as well as the price bids offered to DRE producers for every time period, with the goal of minimizing its expected procurement cost at a predefined risk level. On the other hand, DRE producers, in the lower level, react to the price bids offered by the retailer under study and other LSEs, to maximize their total revenues. The stochastic nature of day-ahead and real-time market prices, DRE production, electricity demand, and price bids of the retailer's rival market agents (RMAs) is taken into the formulation of the proposed model. By using the Karush-Kuhn-Tucker (KKT) optimality conditions and duality theory, the bilevel problem is transformed into its equivalent single-level mixed-integer linear programming (MILP) problem. Case studies are performed to show the effectiveness of the proposed model.**

***Index Terms*—Bilevel stochastic programming, distributed renewable energy (DRE), electricity retailer, retail electricity market.**

NOMENCLATURE

Indices and Sets

t, N_t Index and set of time periods, respectively.

ω, N_ω Index and set of scenarios of day-ahead and real-time market prices, electricity demand, and DRE, respectively.

r, N_ω Index and set of all LSEs participating in the liberalized DRE market, respectively. Hereinafter, the index $r = 0$ denotes the retailer under study.

ξ, N_Ξ Index and set of price bid scenarios of the RMAs, respectively.

Input Parameters and Constants

π_ω Probability of scenario ω.

π_ξ Probability of scenario ξ.

α Conditional Value at Risk (CVaR) per-unit confidence level.

β Risk-aversion parameter of the retailer.

M_1, M_2 Large auxiliary constants.

$\varphi_{t,\omega}$ Minimum DRE purchases set by the retailer for period t and scenario ω.

$\hat{P}_t^{DT}$ Expected DRE exported to the local grid during period t (MWh).

$\hat{\lambda}_t^{DA}$ Expected day-ahead market price during period t (\$/MWh).

$\hat{\lambda}_t^{RT}$ Expected real-time market price during period t (\$/MWh).

$\hat{\lambda}_t^{RMA}$ Expected value of DRE price bids of the RMAs during period t (\$/MWh).

σ_t^{DA} Standard deviation of day-ahead market price scenarios during period t (\$/MWh).

σ_t^{RT} Standard deviation of real-time market price scenarios during period t (\$/MWh).

σ_t^{RMA} Standard deviation of the RMAs' price bid scenarios during period t (\$/MWh).

Random Variables

$\lambda_{t,\omega}^{DA}$ Day-ahead market price during period t and scenario ω (\$/MWh).

$\lambda_{t,\omega}^{RT}$ Real-time market price during period t and scenario ω (\$/MWh).

$P_{t,\omega}^{N}$ Net power demand of the retailer's clients during period t and scenario ω (MWh). It is the difference between the total hourly demand and the power purchased from occasional forward contracts.

$P_{t,\omega}^{DT}$ Total DRE exported to the local grid during period t and scenario ω (MWh).

$\lambda_{t,r,\xi}^{DRE}$ DRE price bid of RMA r during period t and scenario ξ (\$/MWh).

Decision Variables

P_t^{DA} Power purchased from the day-ahead market by the retailer during period t (MWh).

Manuscript received September 29, 2019; revised January 20, 2020; accepted February 24, 2020. Date of publication February 28, 2020; date of current version September 18, 2020. This work was supported in part by the U.S. National Science Foundation under CAREER Award ECCS-0954938, in part by the Nebraska Public Power District through the Nebraska Center for Energy Sciences Research, and in part by the Brazilian National Council for Scientific and Technological Development (CNPq). Paper no. TSTE-01070-2019. *(Corresponding author: Wei Qiao)*

The authors are with the Power and Energy Systems Laboratory, Department of Electrical and Computer Engineering, University of Nebraska-Lincoln, Lincoln, NE 68588-0511 USA (e-mail: josue@huskers.unl.edu; wqiao3@unl.edu).

Color versions of one or more of the figures in this article are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TSTE.2020.2976968

1949-3029 © 2020 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission. See https://www.ieee.org/publications/rights/index.html for more information.

Authorized licensed use limited to: University of Nebraska - Lincoln. Downloaded on July 19,2021 at 18:56:18 UTC from IEEE Xplore. Restrictions apply.

$P_{t,\omega}^{RT}$ Power purchased from the real-time market by the retailer during period t and scenario ω (MWh).

$P_{t,\omega}^{DRE}$ Power purchased from DRE producers by the retailer during period t and scenario ω (MWh).

$C_{t,\omega}^{DRE}$ Retailer's cost from purchasing DRE during period t and scenario ω ($).

$\lambda_{t,0}^{DRE}$ DRE price offered by the retailer during period t ($/MWh).

$x_{t,r,\xi}$ Fraction of the total DRE that is sold to LSE r during period t and scenario ξ.

$u_{t,r,\xi}^{x}$ Binary variable used in the linearization of the complementary slackness condition of LSE r for period t and scenario ξ.

$\mu_{t,\xi}$ Lagrange multiplier associated with the power balance of the retailer's clients during period t and scenario ξ.

η_{ω} Auxiliary variable used to compute the CVaR in scenario ω.

ζ Auxiliary variable used to compute the CVaR.

I. Introduction

The deregulation of the retail electricity market has promoted liberalization, competition, and increased innovation in many states and countries around the world. In deregulated jurisdictions, end-user retail customers have the power to choose their electricity suppliers along with tariff schemes and services that better satisfy their needs and preferences [1]. Today, more than 25 countries in the European Union and 13 in the Asia-Pacific region have fully deregulated markets [2]. In the United States, more than 16 million customers in 17 states participated in retail choice programs in 2017 [3]. Electricity retailers are important load serving entities (LSEs) in deregulated electricity markets. They are intermediary agents between electricity producers and consumers which provide energy products to retail customers and operate independently of generation and distribution companies [4]. Retailers usually obtain electricity from forward contacts, self-production, and the pool-based electricity market to supply it to their customers through retail contracts. The pool-based electricity market is usually the main source of uncertainties in a retailer's decision-making model due to the high price variability [5]. Such uncertainties impose risks that should be carefully considered and properly managed. Green energy programs (GEPs) are an example of innovative programs offered by retailers to retail customers in deregulated retail markets. Through GEPs, retail customers can choose to purchase electricity from different clean and renewable sources. In the U.S., over one million retail customers procured more than 17 million MWh of renewable energy from GEPs in 2017 [6].

The generation from DRE technologies [7] (i.e., distributed generation technologies based on renewable resources) has been increasing exponentially around the world in the last years. Photovoltaic (PV) systems represent one of the fastest growing DRE systems in the residential, commercial, and industrial sectors due to installation cost reductions and the development of new technologies that can be adapted to customers' needs and preferences [1]. In the U.S., generation from small-scale PV systems with less than 1 MW of generating capacity more than doubled from 2014 to 2018, totaling about 40% of the total annual PV generation in 2018 [8]. However, the integration of DRE into the electricity market is still very limited. The existing net metering and feed-in tariff programs for DRE offer very limited customer participation and competitiveness in the present retail electricity market. Such programs have been in the center of increasing controversy and there is no consensus among LSEs and policy makers on how retail customers should be compensated for the DRE they export to the grid. In addition, DRE has also played a limited role in wholesale electricity markets. According to the U.S. Federal Energy Regulatory Commission (FERC), DRE generators on a stand-alone basis do not meet the minimum size requirements and do not satisfy the operation performance required to participate in wholesale electricity markets. For instance, commercial PV systems in the U.S. have 200 kW of capacity on average [9]. Most of these systems cannot participate in many U.S. wholesale markets which require at least 1 MW of generation capacity [10]. DRE aggregation in the wholesale market can potentially solve this issue. However, the existing DRE aggregation programs are very limited and do not promote competition or effective customer integration. Therefore, the current retail electricity market is not fully liberalized since DRE is not considered a competitive resource and DRE producers are still considered passive market agents. In addition, the lack of business models and trading mechanisms for DRE along with limited distributed system awareness makes DRE "invisible" to many LSEs. However, the next-generation retail electricity markets will need trading mechanisms aimed to promote more visibility of DRE to LSEs along with increased competition, flexibility, and customer integration [1].

During the last years, increasing attention has been devoted to the development of decision-making strategies for electricity retailers and other LSEs considering the integration of distributed energy resources. Most of the works in the literature, however, consider only the participation of proactive retail customers in demand response (DR) programs [4]-[5], [11], [12]. In [13]–[16], distributed generation (DG) is integrated into the decision-making models of LSEs. However, all DG units were considered to be owned and operated by the LSEs under study. In [17], [18], the optimal acquisition of DG from independent producers in distribution networks was studied. However, such works were restricted to dispatchable and non-renewable DG technologies. Bilevel programming, which models Stackelberg leader-follower games, has been used to model the hierarchical decisions of LSEs and DRE producers. In [19]–[22], bilevel programming models were proposed in which DRE producers compete with each other by reacting to the prices offered by LSEs. Other game-theory-based approaches were proposed to model the relationship between LSEs and DRE producers via Energy Internet models [23], [24] and distribution system market clearing approaches [25], [26]. However, the existing work that modeled the interactions between DRE producers and LSEs considered only the competitiveness among DRE producers. Thus, in such approaches, DRE producers are limited to trading DRE with only one LSE. However, a liberalized DRE market may help several market agents avoid high price fluctuations in the wholesale market and fulfill the GEP requirements, as well

Authorized licensed use limited to: University of Nebraska - Lincoln. Downloaded on July 19,2021 at 18:56:18 UTC from IEEE Xplore. Restrictions apply.

Fig. 1. Competitive DRE market framework.

as encourage more production of DRE and make DRE producers active agents in the retail electricity market [1].

This paper presents a short-term decision-making model for an electricity retailer through a bilevel stochastic programming approach. In the proposed model, a liberalized market for short-term DRE is proposed. Through such a market, LSEs such as retailers and aggregators compete with each other to purchase DRE by submitting price bids to DRE producers to minimize their energy procurement cost and/or diversify their portfolios of renewable energy. On the other hand, DRE producers determine the amount of DRE to be sold to each market agent based on all received offers. The retailer, in the upper level, minimizes its total expected procurement cost for the following day. DRE producers, in the lower level, react to the price offered by the retailer under study and its RMAs, and maximize their total revenues. The stochastic nature of day-ahead and real-time prices, DRE production, electricity demand, and the RMAs' price bids is considered in the proposed model. To the best of the authors' knowledge, no previous work considered a liberalized DRE market in the retail level or its impact on a retailer's short-term decision-making model.

The remainder of this paper is organized as follows. Section III describes the proposed DRE market and the decision-making framework of a retailer and DRE producers. Section IV presents the mathematical formulation of the proposed decision-making model. Case studies are performed and discussed in Section V. Finally, concluding remarks and discussions are provided in Section VI.

II. Competitive DRE Market and Bilevel Framework

The competitive DRE market framework considered in this paper is illustrated in Fig. 1. In such a framework, DRE producers can sell their energy surplus directly to LSEs which include the retailer under study and its RMAs, such as other retailers and aggregators. LSEs send DRE price bids to DRE producers for every time period t of the following operating day. On the other hand, DRE producers react to all prices received and determine the percentage of DRE to be supplied to each LSE. In the proposed framework, it is assumed that all market agents are provided with smart grid technologies and trading platforms that enable safe and efficient interactions among all agents.

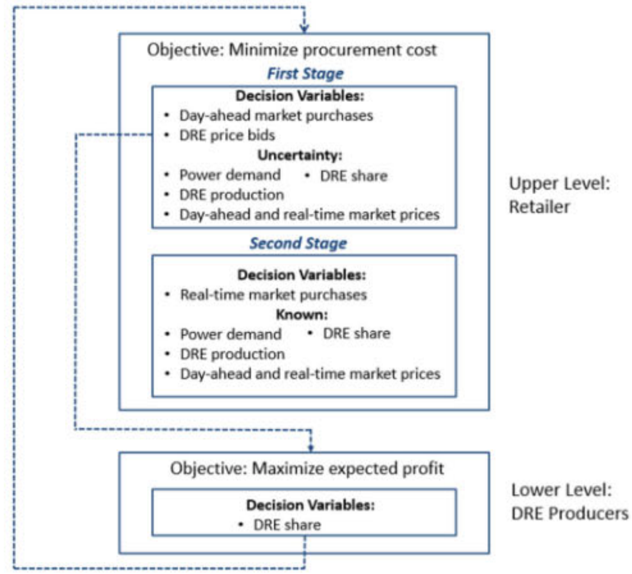

Fig. 2. Bilevel modeling framework.

The bilevel decision-making framework of the retailer and the DRE producers is illustrated in Fig. 2. The retailer, in the upper level, minimizes its expected procurement cost in two stages. In the first stage, the retailer defines the optimal offering curves for the day-ahead market as well as the DRE price bid for every period of the following operating day without the information on day-ahead and real-time market prices, DRE production, electricity demand, and DRE share. The decisions in the first stage are also called here-and-now decisions since they are made before the random variables are known [27]. On the following operating day, after the day-ahead market is cleared as well as the DRE production, electricity demand, and DRE share are known, the retailer determines its involvement in the real-time market for every time period in the second stage. The decisions in the second stage are also called wait-and-see decisions since they are made after the random variables are known. Note that the real-time market, also known as balancing market, is the platform whereby the retailer can amend its energy deviations from the first stage in order to ensure the balance of energy supply and demand. In the lower level, DRE producers react to the prices offered by the retailer under study and its RMAs by determining the percentage of DRE (i.e., the DRE share) to be supplied to each market agent with the objective of maximizing their total revenues.

In this paper, a seasonal autoregressive integrated moving average (SARIMA) model is used to generate a large number of scenarios for day-ahead and real-time market prices, DRE production, and electricity demand based on historical data. According to [27] and [28], a stochastic process Y can be mathematically expressed as the following SARIMA model:

$$\left(1-\sum_{g=1}^{p}\phi_g B^g\right)\left(1-\sum_{i=1}^{P}\Phi_i B^{iS}\right)(1-B)^d(1-B^s)^D y_t$$
$$=\left(1-\sum_{h=1}^{q}\theta_h B^h\right)(1-\sum_{j=1}^{Q}\Theta_j B^{jS})\varepsilon_t \quad (1)$$

Authorized licensed use limited to: University of Nebraska - Lincoln. Downloaded on July 19,2021 at 18:56:18 UTC from IEEE Xplore. Restrictions apply.

where $\phi_1, \phi_2, \ldots, \phi_p$ are p autoregressive parameters; $\theta_1, \theta_2, \ldots, \theta_q$ are q moving-average (MA) parameters; $\Phi_1, \Phi_2, \ldots, \Phi_P$ are P seasonal autoregressive parameters; $\Theta_1, \Theta_2, \ldots, \Theta_Q$ are Q seasonal MA parameters; ε_t is an error term, which is represented by an independent normal stochastic process; and B is the backward shift operator whose function is expressed as follows:

$$B^d y_t = y_{t-d} \tag{2}$$

Then, a fast-forward scenario reduction algorithm [29] is used to reduce the original scenarios of each random variable to a sufficiently small number, to alleviate the computational burden of the model. Each resulted scenario ω represents a scenario combination of the random variables in the upper level and has a probability of occurrence π_ω such that $\sum_{\omega}^{N_\Omega} \pi_\omega = 1$. Similarly, the uncertainty associated with DRE price bids of the RMAs for every time period are modeled as random variables $\lambda_{t,r,\xi}^{DRE}$ using a finite number of scenarios. Each scenario ξ has as probability of occurrence τ_ξ such that $\sum_{\xi}^{N_\Xi} \tau_\xi = 1$.

III. Mathematical Formulation

A. Bilevel Modeling

The decision-making model of the electricity retailer is formulated as the following bilevel programming problem:

$$\begin{aligned}\text{Minimize} \quad & \sum_{\omega}^{N_\Omega} \sum_{t}^{N_T} \pi_\omega \left[P_t^{DA} \lambda_{t,\omega}^{DA} + P_{t,\omega}^{RT} \lambda_{t,\omega}^{RT} \right. \\ & \left. + P_{t,\omega}^{DRE} \lambda_{t,0}^{DRE}\right] \\ & + \beta \left(\zeta + \frac{1}{1-\alpha} \sum_{\omega}^{N_\Omega} \pi_\omega \eta_\omega \right)\end{aligned} \tag{3}$$

Subject to:

$$P_t^{DA} + P_{t,\omega}^{RT} + P_{t,\omega}^{DRE} = P_{t,\omega}^{N}; \qquad \forall t, \forall \omega \tag{4}$$

$$P_{t,\omega}^{DRE} \geq \varphi_{t,\omega} P_{t,\omega}^{DT}; \qquad \forall t, \forall \omega \tag{5}$$

$$P_{t,\omega}^{DRE} = P_{t,\omega}^{DT} \sum_{\xi}^{N_\Xi} \pi_\xi x_{t,0,\xi}; \qquad \forall t, \forall \omega \tag{6}$$

$$P_{t,\omega}^{DA} = P_{t,\omega'}^{DA}, \text{ if } \lambda_{t,\omega}^{DA} = \lambda_{t,\omega'}^{DA}; \qquad \forall t, \forall \omega, \forall \omega' \tag{7}$$

$$\left(\lambda_{t,\omega}^{DA} - \lambda_{t,\omega'}^{DA}\right)\left(P_{t,\omega}^{DA} - P_{t,\omega'}^{DA}\right) \leq 0; \quad \forall t, \forall \omega, \forall \omega' \tag{8}$$

$$\sum_{t}^{N_T} \left[P_t^{DA} \lambda_{t,\omega}^{DA} + P_{t,\omega}^{RT} \lambda_{t,\omega}^{RT} + P_{t,\omega}^{DRE} \lambda_{t,0}^{DRE}\right] - \zeta \leq \eta_\omega; \forall \omega \tag{9}$$

$$\eta_\omega \geq 0; \qquad \forall \omega \tag{10}$$

$$P_t^{DA}, P_{t,\omega}^{RT} \geq 0; \qquad \forall t, \forall \omega \tag{11}$$

where $x_{t,0,\xi} \in$

$$\arg \left\{ \text{Maximize } \hat{P}_t^{DT} \left[\lambda_{t,0}^{DRE} x_{t,0,\xi} + \sum_{\substack{r \in R \\ r \neq 0}}^{N_R} \lambda_{t,r,\xi}^{DRE} x_{t,r,\xi} \right] \right. \tag{12}$$

Subject to:

$$\sum_{r}^{N_R} x_{t,r,\xi} = 1; \tag{13}$$

$$\left. x_{t,r,\xi} \geq 0; \right\} \tag{14}$$

The proposed model (3)–(14) comprises an upper-level problem (3)–(11) and a set of lower-level problems (12)–(14) for each time period t and each scenarios ξ of the RMAs' price.

The upper-level objective function (3) comprises two terms: 1) the expected procurement cost of the retailer from acquiring energy in the day-ahead, real-time, and DRE markets; and 2) the CVaR multiplied by a weighting factor β, which controls the risk-aversion of the retailer. For a given confidence level α, the CVaR is defined as the expected profit associated with the $(1-\alpha) \times 100\%$ worst scenarios. The weighting parameter β in (3) is predetermined by the retailer to control its risk-aversion level. The larger the value of β, the greater the risk aversion of the retailer, which results in a lower CVaR and a higher expected procurement cost. The decision variables associated with the retailer's expected procurement cost in (3) are the amount of power purchased from the day-ahead market P_t^{DA}, the real-time market $P_{t,\omega}^{RT}$, and the proposed liberalized DRE market $P_{t,\omega}^{DRE}$. In addition, the auxiliary decision variables η_ω and ζ are used to compute the CVaR.

Constraint (4) determines the energy balance of the retailer for each time period and each scenario. Constraint (5) sets the minimum amount of DRE that the retailer is willing to acquire in every time period and scenario. This amount is represented as a percentage $\varphi_{t,\omega}$ of the total available DRE in the local grid in time t and scenario ω. Note that (5) can be adjusted to enforce that a certain amount of DRE is purchased by the retailer. However, since the actual DRE is uncertain (i.e., modeled by a set of scenarios), it may lead the problem to become easily infeasible since the amount of DRE purchases set by the retailer may be higher than the actual DRE production. The amount of DRE acquired by the retailer in time t and scenario ω is given by (6) and is equal to the total available DRE in the local grid multiplied by the retailer's share of DRE $x_{t,0,\xi}$, which is defined by the DRE producers in the lower level. Constraint (7) constitutes the nonanticipativity conditions related to the decisions made in the day-ahead market. Constraint (8) enforces a decreasing offer curve in the day-ahead market. Constraints (9) and (10) are used to compute the CVaR for every scenario ω. Constraint (11) constitutes non-negative variable declarations.

Although the distribution network constraints are generally not considered in the decision-making models of retailers, the DRE price bids submitted by the retailer and its RMAs are assumed to be restricted in order not to violate distribution network limits, such as bus voltage limits and the capacity limits

Authorized licensed use limited to: University of Nebraska - Lincoln. Downloaded on July 19,2021 at 18:56:18 UTC from IEEE Xplore. Restrictions apply.

of distribution and substation transformers, and network security requirements. Such limits are assumed to be imposed by the distribution network operator in real-time.

The lower-level objective function (12) comprises two terms associated with the revenues of the DRE producers. The first term represents the revenue obtained from selling DRE to the retailer under study. The second term represents the revenue obtained from selling DRE to the RMAs.

Constraint (13) sets the total DRE production to be sold to the LSEs in the set N_R. Constraint (14) enforces the percentage of DRE sold to each LSE to be positive. In the proposed model, the day-ahead and real-time prices are considered to be independent of the DRE productions and the actions of DRE producers.

B. Equivalent Single-Level Model

The bilevel problem (3)–(14) is nonlinear due to the existence of the bilinear product $P_{t,\omega}^{DRE}\lambda_{t,0}^{DRE}$ in (3) and (9). The nonlinear bilevel programming problem is then converted to its equivalent single-level mixed-integer linear programming (MILP) problem through the following steps in order to be efficiently solved by existing commercial solvers:

1) The bilevel problem is transformed into an equivalent single-level problem by replacing each lower-level problem (12)–(14) by its corresponding KKT optimality conditions [30].
2) The nonlinear complementary slackness conditions of Step 1 are replaced by a set of equivalent linear expressions [31].
3) The bilinear product $P_{t,\omega}^{DRE}\lambda_{t,0}^{DRE}$ is equivalently replaced by a linear expression using the duality theory, as described in the Appendix.

The converted equivalent single-level MILP problem is expressed as follows:

$$\text{Minimize} \quad \sum_{\omega}^{N_\Omega}\sum_{t}^{N_T}\pi_\omega\left[P_t^{DA}\lambda_{t,\omega}^{DA} + P_{t,\omega}^{RT}\lambda_{t,\omega}^{RT} + C_{t,\omega}^{DRE}\right] + \beta\left(\zeta + \frac{1}{1-\alpha}\sum_{\omega}^{N_\Omega}\pi_\omega\eta_\omega\right) \tag{15}$$

Subject to:

$$P_t^{DA} + P_{t,\omega}^{RT} + P_{t,\omega}^{DRE} = P_{t,\omega}^{N}; \qquad \forall t, \forall\omega \tag{16}$$

$$P_{t,\omega}^{DRE} \geq \varphi_{t,\omega}P_{t,\omega}^{DT}; \qquad \forall t,\ \forall\omega \tag{17}$$

$$P_{t,\omega}^{DRE} = P_{t,\omega}^{DT}\sum_{\xi}^{N_\Xi}\pi_\xi x_{t,0,\xi}; \qquad \forall t, \forall\omega \tag{18}$$

$$P_{t,\omega}^{DA} = P_{t,\omega'}^{DA}, \text{ if } \lambda_{t,\omega}^{DA} = \lambda_{t,\omega'}^{DA}; \qquad \forall t, \forall\omega, \forall\omega' \tag{19}$$

$$\left(\lambda_{t,\omega}^{DA} - \lambda_{t,\omega'}^{DA}\right)\left(P_{t,\omega}^{DA} - P_{t,\omega'}^{DA}\right) \leq 0; \quad \forall t, \forall\omega, \forall\omega' \tag{20}$$

$$\sum_{t}^{N_T}\left[P_t^{DA}\lambda_{t,\omega}^{DA} + P_{t,\omega}^{RT}\lambda_{t,\omega}^{RT} + P_{t,\omega}^{DRE}\lambda_{t,0}^{DRE}\right] - \zeta \leq \eta_\omega; \quad \forall\omega \tag{21}$$

$$\sum_{r}^{N_R} x_{t,r,\xi} = 1; \qquad \forall t, \forall\xi \tag{22}$$

$$-\hat{P}_t^{DT}\lambda_{t,0}^{DRE} - \mu_{t,\xi} \geq 0; \qquad \forall t, \forall\xi \tag{23}$$

$$-\hat{P}_t^{DT}\lambda_{t,r,\xi}^{DRE} - \mu_{t,\xi} \geq 0, \quad r = 1\ldots N_r; \quad \forall t, \forall\xi \tag{24}$$

$$-\hat{P}_t^{DT}\lambda_{t,0}^{DRE} - \mu_{t,\xi} \leq M_1 u_{t,0,\xi}^{x}; \qquad \forall t, \forall\xi \tag{25}$$

$$-\hat{P}_t^{DT}\lambda_{t,r,\xi}^{DRE} - \mu_{t,\xi} \leq M_1 u_{t,r,\xi}^{x}, \quad r = 1\ldots N_r; \quad \forall t, \forall\xi \tag{26}$$

$$x_{t,r,\xi} \leq M_2\left(1 - u_{t,r,\xi}^{x}\right); \qquad \forall t, \forall r, \forall\xi \tag{27}$$

$$u_{t,r,\xi}^{x} \in \{0,1\}; \qquad \forall t, \forall r, \forall\xi \tag{28}$$

$$C_{t,\omega}^{DRE} = \frac{-P_{t,\omega}^{DT}}{\hat{P}_t^{DT}}\left\{\sum_{\xi}^{N_\Xi}\tau_\xi\left[\sum_{\substack{r\in R\\ r\neq 0}}^{N_R}\left(\hat{P}_t^{DT}\lambda_{t,r,\xi}^{DRE}x_{t,r,\xi}\right) + \mu_{t,\omega}\right]\right\}; \qquad \forall t,\ \forall\omega \tag{29}$$

$$x_{t,r,\xi}, P_t^{DA}, P_{t,\omega}^{RT}, \eta_\omega \geq 0; \qquad \forall t, \forall r, \forall\xi, \forall\omega \tag{30}$$

Through Steps 1–3, a new set of constraints is integrated in the resulting model. Constraints (22)–(28) represent the linearized KKT optimality conditions obtained in Steps 1 and 2. In particular, (25)–(27) represent the complementary slackness conditions, which were linearized through the Big-M method [32], [33]. Note that the values of M_1 and M_2 should be sufficiently large (e.g., larger than the bound of the Lagrange multiplier $\mu_{t,\xi}$), but are expected to be as small as possible to avoid the problems of substantially increasing the solution time and introducing rounding errors, as described in [34]. In (29), $C_{t,\omega}^{DRE}$ represents the retailer's cost of buying DRE in the time period *t* and scenario ω, i.e., $C_{t,\omega}^{DRE} = P_{t,\omega}^{DRE}\lambda_{t,0}^{DRE}$. This bilinear product is converted into a linear expression in Step 3, as described in the Appendix. Finally, Constraint (30) constitutes the overall non-negative variable declarations of the single-level MILP model.

IV. Case Studies

A. Data

The effectiveness of the proposed model is illustrated through two case studies. In the first case, the RMAs' price bids have the expected value nearly the same as and the standard deviation lower than those of the real-time market prices, respectively, in every time period. In the second case, the RMAs' price bids have an expected value higher than and a standard deviation lower than those of the real-time market prices, respectively, in every time period. In both cases, the standard deviations considered are calculated for the RMAs' price bid scenarios

Authorized licensed use limited to: University of Nebraska - Lincoln. Downloaded on July 19,2021 at 18:56:18 UTC from IEEE Xplore. Restrictions apply.

and real-time market price scenarios, respectively. A retailer participating in the PJM market is considered. In addition, a group of commercial-scale PV producers, with a total capacity of 200 MW is assumed to participate in the proposed liberalized DRE market. For the sake of completeness, an operating day with 24 hours is considered. However, the liberalized DRE market is assumed to be comprised of ten hours, from 09:00 AM to 06:00 PM (hours 9–18), which corresponds to the period with significant PV production in a spring day. Thus, the retailer may only participate in the DRE market during these hours. Each period t corresponds to one hour. The uncertainties associated with the PV production are generated based on historical data from the National Renewable Energy Laboratory (NREL) website [35]. The uncertainties associated with the demand of the retailer's clients and the wholesale electricity market prices are generated based on PJM historical data [36].

An SARIMA model was obtained from the MATLAB econometrics toolbox [37] to generate 500 scenarios for electricity demand, day-ahead and real-time market prices, and PV power exported to the local grid for every hour, respectively. To attain tractability while preserving sufficient stochastic information in the scenario set, the numbers of scenarios of electricity demand, day-ahead price, real-time price, and PV power are then reduced to 3, 4, 4, and 4, respectively, thus resulting in 192 scenarios in the upper level problem. For illustrative purposes, 6 RMAs are considered, and their respective DRE price bids are modeled by 4 randomly generated scenarios with equal probabilities [31]. The resulting model expressed by (15)–(30) is a MILP problem, which is modeled using Yalmip [38] and solved with Gurobi 8.1 in MATLAB R2018b [39].

B. Case 1

In this case, the RMAs' price bids have the expected value nearly the same as and the standard deviation lower than those of the real-time market prices in every hour. No minimum amount of DRE purchases is set by the retailer, i.e., $\varphi_{t,\omega} = 0$. Table I shows the RMAs' price scenarios for hours 9–18. Table II shows the expected values and standard deviations of the day-ahead, real-time, and RMAs' price scenarios. Initially, the retailer is considered to be a risk-neutral agent, i.e., $\beta = 0$. The expected procurement costs of the retailer from participating in the wholesale (i.e., day-ahead and real-time) markets only versus the costs from participating in the wholesale and liberalized DRE markets are compared in Fig. 3 for every hour of the operating day. The hourly cost reduction of the retailer from participating in the liberalized DRE market in the periods with significant PV productions is shown in Fig. 4. The results show that the retailer can always reduce costs in these periods by participating in the competitive DRE market using the proposed model in Case 1.

To analyze the impact of the risk aversion on the retailer's decisions and expected costs, the confidence level α is set to 0.95, and the risk-aversion parameter β is varied from 0 to 10. The efficient frontier in terms of the total expected cost and the CVaR of the retailer is depicted in Fig. 5. A risk-neutral retailer (i.e., $\beta = 0$) expects a lower procurement cost with a higher CVaR. On the other hand, a risk-averse retailer (e.g., $\beta = 10$) expects a higher procurement cost with a lower CVaR. The tradeoff between the expected profit and CVaR should be carefully considered by the retailer. Fig. 6 shows the impact of risk management on the retailer's DRE price bid for the 16th hour, which corresponds to the period from 3 PM to 4 PM,

TABLE I
RMAS' PRICE SCENARIOS IN CASE 1 ($/MWH)

Hour	Scenario	RMA					
		1	2	3	4	5	6
9	1	17.01	17.03	17.04	17.01	17.02	17.00
9	2	22.06	22.51	22.40	22.48	22.12	22.44
9	3	24.02	23.87	24.56	24.56	24.50	24.53
9	4	25.50	25.40	25.60	25.25	25.33	25.31
10	1	19.56	19.84	20.06	20.05	20.04	20.02
10	2	23.76	24.25	24.21	24.21	23.83	24.18
10	3	25.85	25.71	26.45	26.45	26.38	26.41
10	4	27.47	27.36	27.64	27.18	27.61	27.25
11	1	20.95	20.75	19.90	20.45	21.01	20.15
11	2	21.55	21.15	21.05	21.45	21.40	21.51
11	3	26.15	24.95	24.75	24.65	25.95	25.25
11	4	29.6	27.95	28.80	28.45	30.10	28.77
12	1	22.95	23.50	23.75	23.85	23.20	23.90
12	2	25.95	26.90	26.80	27.10	26.95	27.05
12	3	28.9	28.85	29.00	29.32	28.65	29.44
12	4	33.45	32.60	32.45	33.65	31.95	34.12
13	1	25.25	23.95	22.85	22.30	24.71	23.75
13	2	26.90	24.95	26.85	27.15	27.05	26.75
13	3	28.55	28.10	28.95	28.85	29.80	28.90
13	4	32.55	33.00	33.50	32.95	34.51	34.20
14	1	26.85	25.90	26.80	26.75	26.95	26.95
14	2	29.45	29.55	29.35	29.35	29.15	29.47
14	3	33.80	33.60	34.90	34.90	33.91	34.35
14	4	35.95	36.45	36.55	36.45	35.85	36.45
15	1	28.15	27.79	28.09	27.97	28.02	27.99
15	2	30.99	31.07	31.00	30.88	31.02	31.00
15	3	36.27	36.12	36.05	35.95	36.04	35.88
15	4	38.15	38.05	38.09	37.97	38.43	38.07
16	1	30.50	30.30	29.99	30.25	30.45	30.41
16	2	32.10	32.07	32.05	32.07	31.99	32.09
16	3	37.45	37.12	36.99	37.28	37.33	37.29
16	4	40.10	39.05	39.08	39.00	38.95	39.07
17	1	32.78	32.57	32.24	32.51	32.73	32.68
17	2	34.15	34.12	34.05	34.14	33.93	34.09
17	3	40.25	39.90	39.76	40.07	40.12	40.08
17	4	43.10	41.88	41.01	41.92	41.87	42.00
18	1	29.50	28.70	28.20	29.12	28.27	29.54
18	2	30.05	30.00	29.56	30.00	29.56	30.04
18	3	36.22	35.97	35.90	35.87	36.07	34.56
18	4	38.99	37.70	38.00	36.72	38.26	37.79

TABLE II
EXPECTED VALUES AND STANDARD DEVIATIONS OF DAY-AHEAD, REAL-TIME, AND RMAS' PRICES IN CASE 1 ($/MWH)

Hour	$\hat{\lambda}_t^{DA}$	σ_t^{DA}	$\hat{\lambda}_t^{RT}$	σ_t^{RT}	$\hat{\lambda}_t^{RMA}$	σ_t^{RMA}
9	22.94	7.44	22.78	7.87	22.30	3.30
10	25.45	6.16	24.55	8.47	24.41	2.91
11	27.64	8.48	24.16	5.66	24.03	3.47
12	29.65	9.68	28.00	13.46	28.09	3.57
13	31.67	11.14	28.10	14.63	28.18	3.69
14	34.46	13.96	31.98	19.29	31.66	3.90
15	36.78	16.60	34.85	24.07	33.29	4.10
16	39.42	20.42	36.30	26.28	34.71	3.72
17	41.46	22.91	39.00	27.99	37.17	4.03
18	38.08	17.01	34.58	25.75	33.11	3.95

Authorized licensed use limited to: University of Nebraska - Lincoln. Downloaded on July 19,2021 at 18:56:18 UTC from IEEE Xplore. Restrictions apply.

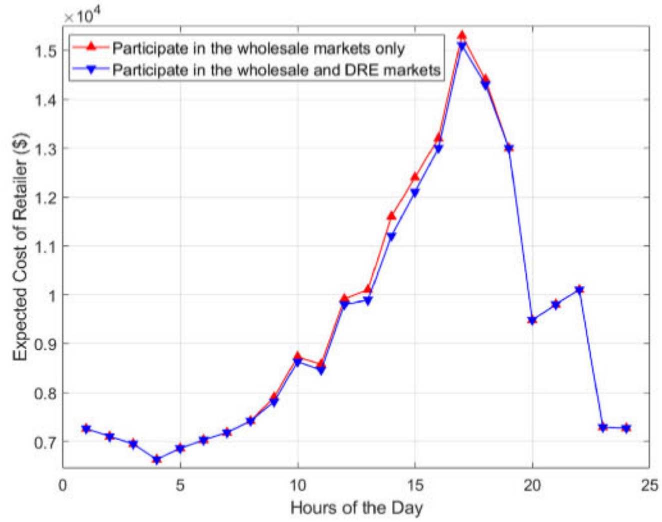

Fig. 3. Expected costs of the retailer in Case 1.

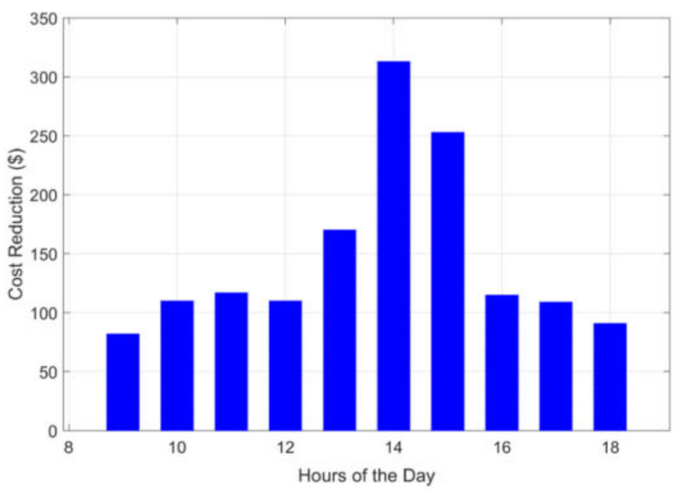

Fig. 4. Hourly cost reduction of the retailer from participating in the liberalized DRE market in Case 1.

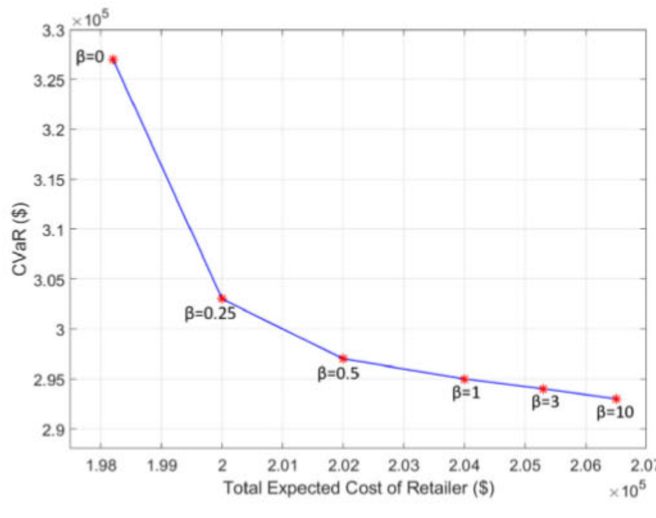

Fig. 5. Total expected cost and CVaR of the retailer for different values of β in Case 1.

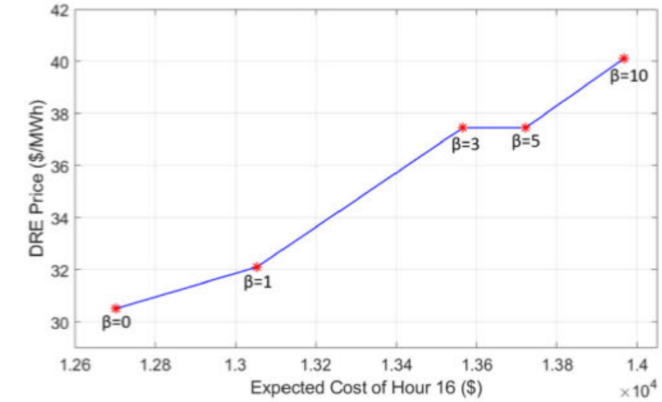

Fig. 6. DRE price bids of the retailer versus the expected cost in the 16th hour for different values of β in Case 1.

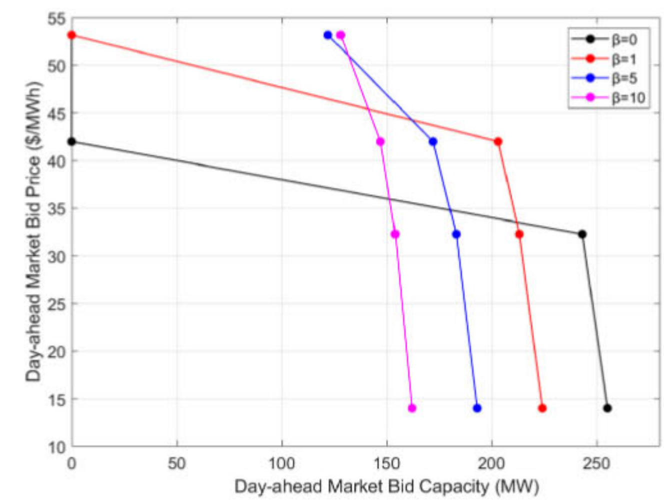

Fig. 7. Day-ahead market curves generated by the retailer in the 16th hour for different values of β in Case 1.

and presents a high variability of the day-ahead and real-time market prices. As the retailer becomes more risk averse, it offers a higher DRE price bid in order to purchase more energy in the competitive DRE market, and less in the volatile electricity pool. Fig. 7 shows the impact of the risk management on the retailer's offering curve in the day-ahead market in the 16th hour. A risk-neutral retailer is willing to buy power only at lower day-ahead market prices. On the other hand, a risk-averse retailer is willing to buy less power at lower day-ahead prices and more power from DRE, due to the lower variability of DRE prices; and some power at higher day-ahead market prices, since day-ahead market prices have lower variability than real-time market prices in that hour.

C. Case 2

In this case, the RMAs' price bids have the expected value higher than and a standard deviation lower than those of the real-time market prices in every hour. Here, a minimum amount

Authorized licensed use limited to: University of Nebraska - Lincoln. Downloaded on July 19,2021 at 18:56:18 UTC from IEEE Xplore. Restrictions apply.

TABLE III
RMAs' PRICE SCENARIOS IN CASE 2 ($/MWh)

Hour	Scenario	RMA					
		1	2	3	4	5	6
9	1	32.49	32.77	32.09	32.67	32.49	32.73
9	2	35.17	35.79	34.08	35.81	35.73	35.81
9	3	38.48	38.58	38.76	39.17	39.09	39.17
9	4	41.15	41.04	41.05	41.10	41.09	41.57
10	1	35.01	35.32	34.58	35.21	35.02	35.28
10	2	37.91	38.58	36.74	38.59	38.50	38.60
10	3	41.67	41.58	41.77	42.21	42.13	42.21
10	4	44.35	44.26	44.24	44.29	44.29	44.81
11	1	34.35	35.00	35.15	35.05	34.75	35.05
11	2	37.55	38.35	35.25	38.25	38.25	38.30
11	3	40.85	41.15	41.70	41.85	41.55	41.80
11	4	44.15	44.55	44.80	44.90	44.15	45.00
12	1	40.05	40.00	38.15	39.70	39.60	39.85
12	2	42.95	43.55	42.95	43.70	43.50	43.65
12	3	47.25	47.15	46.95	47.80	47.95	47.85
12	4	50.00	49.25	49.00	49.00	49.85	50.05
13	1	38.15	39.85	39.00	39.20	39.60	39.05
13	2	41.95	43.00	42.95	41.95	42.95	42.50
13	3	46.35	46.95	47.55	46.7	47.40	47.50
13	4	48.90	49.00	49.00	48.25	49.25	49.95
14	1	44.20	45.30	45.00	45.00	45.00	45.25
14	2	48.50	48.20	49.15	49.00	48.70	49.00
14	3	52.50	52.00	52.10	52.70	51.35	51.95
14	4	55.10	54.70	55.00	54.90	54.00	54.35
15	1	48.25	50.05	49.30	50.00	49.15	48.35
15	2	51.95	51.95	53.90	53.80	53.25	52.85
15	3	56.15	57.00	56.15	57.80	57.95	57.45
15	4	58.35	58.35	58.95	56.95	59.50	60.00
16	1	52.28	52.74	51.65	52.59	52.29	52.68
16	2	56.61	57.61	54.86	57.63	57.50	57.64
16	3	61.93	62.09	62.38	63.05	62.92	63.04
16	4	66.23	66.07	66.07	66.15	66.14	66.91
17	1	54.28	54.75	53.62	54.59	54.29	54.69
17	2	58.77	59.81	56.96	59.83	59.69	59.84
17	3	64.29	64.46	64.76	65.45	65.32	65.45
17	4	68.76	68.57	68.59	68.67	68.66	69.46
18	1	55.67	56.16	54.99	55.99	55.68	56.09
18	2	60.27	61.34	58.42	61.36	61.22	61.37
18	3	65.94	66.11	66.42	67.13	66.99	67.12
18	4	70.52	70.32	70.35	70.43	70.42	71.24

TABLE IV
EXPECTED VALUES AND STANDARD DEVIATIONS OF DAY-AHEAD, REAL-TIME, AND RMAs' PRICES IN CASE 2 ($/MWh)

Hour	$\hat{\lambda}_t^{DA}$	σ_t^{DA}	$\hat{\lambda}_t^{RT}$	σ_t^{RT}	$\hat{\lambda}_t^{RMA}$	σ_t^{RMA}
9	22.94	7.44	22.78	7.87	37.00	3.39
10	25.45	6.16	24.55	8.47	39.88	3.66
11	27.64	8.48	24.16	5.66	39.65	3.82
12	29.65	9.68	28.00	13.46	44.99	3.94
13	31.67	11.14	28.10	14.63	44.45	4.00
14	34.46	13.96	31.98	19.29	50.12	3.74
15	36.78	16.60	34.85	24.07	54.47	3.87
16	39.42	20.42	36.30	26.28	59.54	5.45
17	41.46	22.91	39.00	27.99	61.81	5.65
18	38.08	17.01	34.78	25.75	63.40	5.80

of DRE purchases is set, so that the retailer aims to purchase a fraction $\varphi_{t,\omega}$ of the total DRE exported to the local grid at time t and scenario ω. Table III shows the RMAs' price scenarios for hours 9–18. Table IV shows the expected values

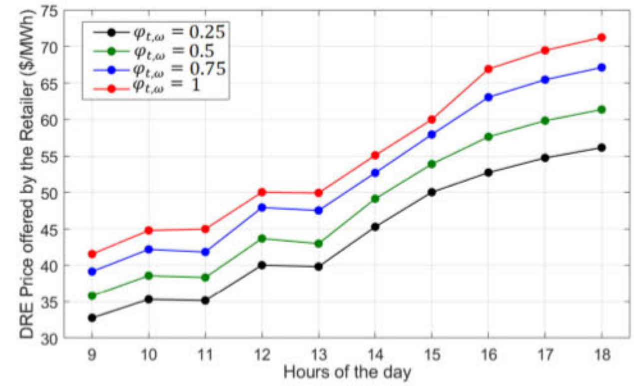

Fig. 8. DRE price bids of the retailer in hours 9–18 for different values of $\varphi_{t,\omega}$ in Case 2.

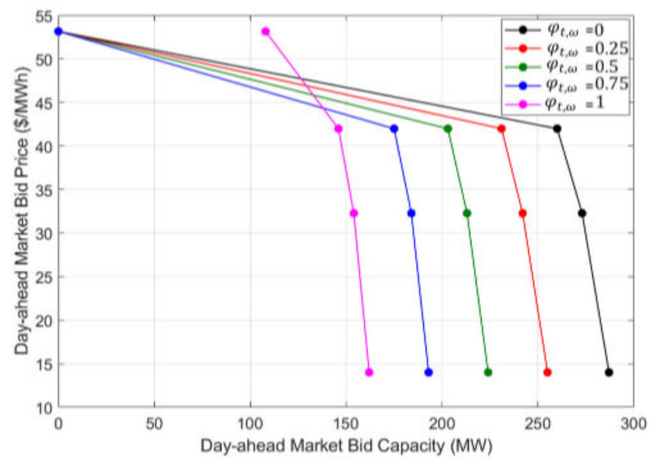

Fig. 9. Retailer's offering curves in the day-ahead market in the 16th hour for different values of $\varphi_{16,\omega}$ in Case 2.

and standard deviations of the day-ahead, real-time, and RMAs' price scenarios. Initially, the risk parameters α and β are set to 0.95 and 0.5, respectively. The parameter $\varphi_{t,\omega}$ is varied from 0 to 1. Fig. 8 shows the DRE price offered by the retailer in hours 9–18 for different values of $\varphi_{t,\omega}$. The higher the value of $\varphi_{t,\omega}$, the higher the DRE price bid offered by the retailer. Fig. 9 shows the retailer's offering curves in the day-ahead market in the 16th hour for different values of $\varphi_{16,\omega}$. As the retailer is willing to buy more DRE, it bids less power in the day-ahead market.

To analyze the impact of the risk aversion in Case 2, the value of β is varied from 0 to 10 while keeping $\alpha = 0.95$. The efficient frontier in terms of the total expected cost and CVaR of the retailer for different values of β and $\varphi_{t,\omega}$ in hours 9–18 is depicted in Fig. 10. The higher the values of β and $\varphi_{t,\omega}$, the higher the expected cost and the lower the CVaR of the retailer. The expected cost of the retailer increases since the expected DRE prices are higher than the expected day-ahead and real-time market prices. On the other hand, the CVaR of the retailer decreases since DRE prices have lower variability than day-ahead and real-time market prices.

Authorized licensed use limited to: University of Nebraska - Lincoln. Downloaded on July 19,2021 at 18:56:18 UTC from IEEE Xplore. Restrictions apply.

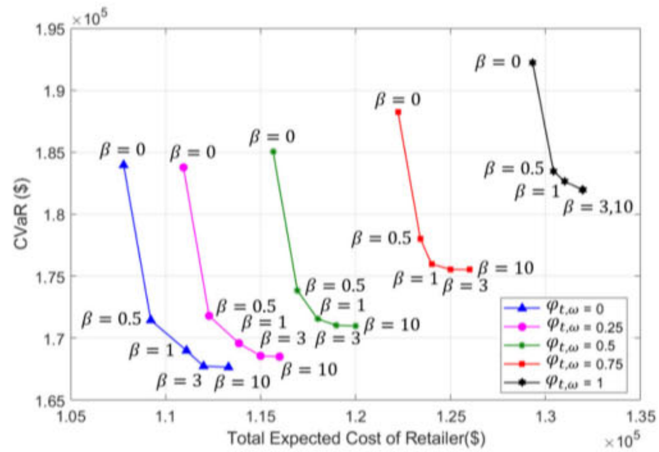

Fig. 10. Total expected cost and CVaR of the retailer for different values of β in hours 9–18 in Case 2.

V. Conclusion

The next-generation retail electricity markets will have new business models and market mechanisms designed to better integrate distributed energy resources into the grid, thus promoting liberalization, competitiveness, sustainability, and increased customer participation at the grid edge. This paper has presented a short-term decision-making model for an electricity retailer participating in a liberalized DRE market. The uncertainties faced by the retailer include day-ahead and real-time market prices, client demands, DRE capacity exported to the local grid, and DRE price bids from the RMAs. Bilevel stochastic programming has been used to model the reaction of DRE producers to the price bids received in the proposed liberalized DRE market. The bilevel nonlinear stochastic program is then converted into an equivalent single-level linear one by using the KKT optimality conditions and duality theory. Two cases of the RMAs' price scenarios have been studied to show the effectiveness of the proposed model. The results have shown that the retailer could reduce its expected cost by participating in the competitive DRE market when the RMAs' price bids have nearly the same expected value as and lower variability than the real-time market prices. In addition, the retailer's day-ahead and real-time market bids as well as the DRE price bids are significantly affected when the RMAs' price bids have a higher expected value than the real-time market prices and a minimum amount of DRE purchases is set by the retailer. In both cases, the proposed model provides the optimal decisions for the retailer under different risk-aversion levels, which have been modeled by CVaR. Further research can be conducted to study the decision-making strategies of a single RMA or a group of RMAs under the proposed liberalized DRE market.

Appendix
Bilinear Product Linearization Using Duality Theory

The bilinear product $P_{t,\omega}^{DRE}\lambda_{t,0}^{DRE}$ in (3) and (9) can be replaced by an equivalent linear expression by using the duality theory. The dual objective function of each lower-level problem is:

$$\text{Maximize } \mu_{t,\xi} \tag{A1}$$

where $\mu_{t,\xi}$ is the dual variable associated with the equality constraint (13) of each lower-level problem. This dual variable is also equivalent to the corresponding Lagrange multiplier associated with the constraint (13). Based on the strong duality theorem [40], the optimal solution is obtained by equating the primal and the dual objective functions as follows:

$$-\hat{P}_t^{DT}\left[x_{t,0,\xi}\lambda_{t,0}^{DRE} + \sum_{\substack{r\in R\\ r\neq 0}}^{N_R}\left(\lambda_{t,r,\xi}^{DRE}x_{t,r,\xi}\right)\right] = \mu_{t,\xi};\quad \forall t, \forall \xi \tag{A2}$$

By rearranging the terms in (A2), the bilinear product $x_{t,0,\xi}\lambda_{t,0}^{DRE}$ can be expressed as follows:

$$x_{t,0,\xi}\lambda_{t,0}^{DRE} = \frac{-1}{\hat{P}_t^{DT}}\left[\sum_{\substack{r\in R\\ r\neq 0}}^{N_R}\left(\hat{P}_t^{DT}\lambda_{t,r,\xi}^{DRE}x_{t,r,\xi}\right) + \mu_{t,\xi}\right];\ \forall t, \forall \xi \tag{A3}$$

By multiplying both sides of (6) by $\lambda_{t,0}^{DRE}$ and combining the resulting expression with (A3), the product $P_{t,\omega}^{DRE}\lambda_{t,0}^{DRE}$ can be equivalently replaced by the following linear expression:

$$P_{t,\omega}^{DRE}\lambda_{t,0}^{DRE} = \frac{-P_{t,\omega}^{DT}}{\hat{P}_t^{DT}}\left\{\sum_{\xi}^{N_\Xi}\pi_\xi\left[\sum_{\substack{r\in R\\ r\neq 0}}^{N_R}\left(\hat{P}_t^{DT}\lambda_{t,r,\xi}^{DRE}x_{t,r,\xi}\right) + \mu_{t,\xi}\right]\right\};\quad \forall t, \forall\omega,\ \forall\xi \tag{A4}$$

References

[1] J. C. Do Prado, W. Qiao, L. Qu, and J. R. Agüero, "The next generation retail electricity market in the context of distributed energy resources: Vision and integrating framework," *Energies*, vol. 12, no. 3, pp. 1–24, Feb. 2019.

[2] Electric Choice. [Online]. Available: https://www.electricchoice.com/blog/energy-deregulation-world/

[3] U.S. Energy Information Administration (EIA), "Annual electric power industry report," Jan. 2019. [Online]. Available: https://www.eia.gov/electricity/data/eia861/

[4] J. Yang, J. Zhao, F. Luo, F. Wen, and Z. Y. Dong, "Decision-making for electricity retailers: A brief survey," *IEEE Trans. Smart Grid*, vol. 9, no. 5, pp. 4140–4153, Sep. 2018.

[5] J. C. Do Prado and W. Qiao, "A stochastic decision-making model for an electricity retailer with intermittent renewable energy and short-term demand response," *IEEE Trans. Smart Grid*, vol. 10, no. 3, pp. 2581–2592, May 2019.

[6] E. O'Shaughnessy, J. Heeter, and J. Sauer, "Status and trends in the U.S. voluntary green power market (2017 data)," , National Renewable Energy Laboratory (NREL), Golden, CO, USA, Rep. NREL/TP-6A20-72204, Oct. 2018.

[7] H. Tazvinga, M. Thopil, P. B. Numbi, and T. Adefarati, "Distributed renewable energy technologies," in *Handbook of Distributed Generation*. Cham, Switzerland: Spring, 2017.

Authorized licensed use limited to: University of Nebraska - Lincoln. Downloaded on July 19,2021 at 18:56:18 UTC from IEEE Xplore. Restrictions apply.

[8] U.S. Energy Information Administration (EIA), "Electric powermonthly," Dec. 2019. [Online]. Available: https://www.eia.gov/electricity/monthly
[9] R. Fu, D. Feldman, and R. Margolis, "U.S. solar photovoltaic system cost benchmark: Q1 2018," National Renewable Energy Laboratory (NREL), Golden, CO, USA, Rep. NREL/TP-6A20-72399, Nov. 2018.
[10] Federal Energy Regulatory Commission (FERC), "Electric storage participation in markets operated by regional transmission organizations and independent system operators," *Federal Register*, vol. 81, no. 230, pp. 1–29, Nov. 2016.
[11] F. Hu, X. Feng, and H. Cao, "A short-term decision model for electricity retailers: Electricity procurement and time-of-use pricing," *Energies*, vol. 11, no. 12, pp. 1–18, Nov. 2018.
[12] C. Zhao, S. Zhang, X. Wang, X. Li, and L. Wu, "Game analysis of electricity retail market considering customers' switching behaviors and retailers' contract trading," *IEEE Access*, vol. 6, pp. 75099–75109, 2018.
[13] H. Li, Y. Li, and Z. Li, "A multiperiod energy acquisition model for a distribution company with distributed generation and interruptible load," *IEEE Trans. Power Syst.*, vol. 22, no. 2, pp. 588–596, May 2007.
[14] A. Safdarian, M. Fotuhi-Firuzbad, and M. Lehtonen, "A stochastic framework for short-term operation of a distribution company," *IEEE Trans. Power Syst.*, vol. 28, no. 4, pp. 4712–4721, Nov. 2013.
[15] A. Safdarian, M. Fotuhi-Firuzbad, and M. Lehtonen, "Integration of price-based demand response in DisCos's short-term decision model," *IEEE Trans. Smart Grid*, vol. 5 no. 5, pp. 2235–2245, Sep. 2014.
[16] A. Safdarian, M. Fotuhi-Firuzbad, and M. Lehtonen, "A medium-term decision model for DisCos: Forward contracting and TOU pricing," *IEEE Trans. Power Syst.*, vol. 30, no. 3, pp. 1143–1154, May 2015.
[17] R. Palma-Behnke, J. L. Cerda A., L. S. Vargas, and A. Jofré, "A distribution company energy acquisition market model with integration of distributed generation and load curtailment options," *IEEE Trans. Power Syst.*, vol. 20, no. 4, pp. 1718–1727, Nov. 2005.
[18] J. M. L.-Lezama, A. P.-Feltrin, J. Contreras, and J. I. Muñoz, "Optimal contract pricing of distributed generation in distribution networks," *IEEE Trans. Power Syst.*, vol. 26, no. 1, pp. 128–136, Feb. 2011.
[19] B. Zeng *et al.*, "A bilevel planning method of active distribution system for renewable energy harvesting in a deregulated environment," in *Proc. IEEE Power and Energy Soc. General Meeting*, Jul. 2015, pp. 1–5.
[20] C. Zhang, Q. Wang, J. Wang, P. Pinson, and J. Østergaard, "Real-time trading strategies of proactive DISCO with heterogeneous DG owners," *IEEE Trans. Smart Grid*, vol. 9, no. 3, pp. 1688–1697, May 2018.
[21] S. Bahramara, P. Sheikhahmadi, M. Y. Damavandi, M. S.-Khah, G. J. Osório, and J. P. S. Catalão, "Strategic behavior of a distribution company in the wholesale energy market: A risk-based stochastic bi-level model," in *Proc. IEEE Int. Conf. Environment Elect. Eng.*, Jun. 2018, pp. 1–6.
[22] S. Bahramara, M. Parsa Moghaddam, and M. R. Haghifam, "Modelling hierarchical decision making framework for operation of active distribution grids," *IET Gener., Transmiss. Distrib.*, vol. 9, no. 16, pp. 2555–2564, Nov. 2015.
[23] W. Su and A. Q. Huang, "A game theoretic framework for a next-generation retail electricity market with high penetration of distributed residential electricity suppliers," *Appl. Energy*, vol. 119, no. 1, pp. 341–350, Apr. 2014.
[24] N. Zhang, Y. Yan, and W. Su, "A game-theoretic economic operation of residential distribution system with high participation of distributed electricity prosumers," *Appl. Energy*, vol. 154, no. 1, pp. 471–479, Sep. 2015.
[25] Z. Liang and W. Su, "Game theory based bidding strategy for prosumers in a distribution system with a retail electricity market," *IET Smart Grid*, vol. 1, no. 3, pp. 104–111, Oct. 2018.
[26] T. Chen, H. Pourbabak, and W. Su, "A game theoretic approach to analyze the dynamic interactions of multiple residential prosumers considering power flow constraints," in *Proc. IEEE Power Energy Soc. General Meeting*, Jul. 2016, pp. 17–21.
[27] A. J. Conejo, M. Carrion, and J. M. Morales, *Decision Making Under Uncertainty in Electricity Markets*, 1st ed. New York, NY, USA: Springer, 2010, vol. 17.
[28] D. Xiao, W. Qiao, and L. Qu, "Risk-constrained stochastic virtual bidding in two-settlement electricity markets," in *Proc. IEEE Power Energy Soc. General Meeting*, Aug. 2018, pp. 1–5.
[29] H. Heitsch and W. Römisch, "Scenario reduction algorithms in stochastic programming," *Comput. Optim. Appl.*, vol. 24, no. 2/3, pp. 187–206, Mar. 2003.
[30] S. Boyd and L. Vandenberghe, *Convex Optimization*. New York, USA: Cambridge Univ. Press, 2004.
[31] M. Carrión, J. M. Arroyo, and A. J. Conejo, "A bilevel stochastic programming approach for retailer futures market trading," *IEEE Trans. Power Syst.*, vol. 24, pp. 1446–1456, Aug. 2009.
[32] S. A. MirHassani and F. Hooshmand, *Methods and Models in Mathematical Programming*, 1st ed. Cham, Switzerland: Springer, 2019, vol. 1.
[33] B. Zeng and Y. An, "Solving bilevel mixed integer program by reformulations and decomposition," Jun. 2014, [Online]. Available: http://www.optimization-online.org/DB_FILE/2014/07/4455.pdf
[34] P. Rubin, "Choosing big M values," Sep. 2018, [Online]. Available: https://spartanideas.msu.edu/2018/09/17/choosing-big-m-values/
[35] National Renewable Energy Laboratory (NREL) website [Online]. Available: https://www.nrel.gov/, Accessed on: Jan. 2020.
[36] PJM Data Miner 2. [Online]. Available: https://dataminer2.pjm.com/, Accessed on: Jan. 2020.
[37] MATLAB Econometrics Toolbox [Online]. Available: https://www.mathworks.com/products/econometrics.html, Accessed on: Jan. 2020.
[38] J. Lofberg, "YALMIP: A toolbox for modeling and optimization in MATLAB," in *Proc. IEEE Int. Conf. Robot. Autom.*, Sep. 2004, pp. 284–289.
[39] W. Yin, "Gurobi Mex: A MATLAB interface for gurobi," Nov. 2011, [Online]. Available: http://www.convexoptimization.com/wikimi-ztion/index.php/Gurobi_Mex:_A_MATLAB_interface_for_Gurobi
[40] H. Cui, F. Li, X. Fang, H. Chen, and H. Wang, "Bilevel arbitrage potential evaluation for grid-scale energy storage considering wind power and LMP smoothing effect," *IEEE Trans. Sustain. Energy*, vol. 9, no. 2, pp. 707–718, Apr. 2018.

Josue Campos do Prado (Student Member, IEEE) received the B. Eng. degree in electrical engineering from Santa Catarina State University, Joinville, Brazil, in 2012. He is currently working toward the Ph.D. degree in electrical engineering with the University of Nebraska-Lincoln, Lincoln, NE, USA. From October 2018 to August 2019, he worked as a Graduate Intern at the Joint Institute for Strategic Energy Analysis of the National Renewable Energy Laboratory (NREL). Since August 2019, he has been conducting collaborative research with NREL. His research interests include distributed energy resources, electricity market planning and operation, and optimization under uncertainty applied to power systems.

Wei Qiao (Fellow, IEEE) received the B.Eng. and M.Eng. degrees in electrical engineering from Zhejiang University, Hangzhou, China, in 1997 and 2002, respectively, the M.S. degree in high-performance computation for engineered systems from Singapore-MIT Alliance, Singapore, in 2003, and the Ph.D. degree in electrical engineering from the Georgia Institute of Technology, Atlanta, GA, USA, in 2008. Since August 2008, he has been with the University of Nebraska–Lincoln, Lincoln, NE, USA, where he is currently a Professor with the Department of Electrical and Computer Engineering. His research interests include renewable energy systems, smart grids, condition monitoring, power electronics, electric motor drives, energy storage systems, and emerging electrical energy conversion devices. He is the author or coauthor of more than 250 papers in refereed journals and conference proceedings and holds eight U.S. patents issued. He is an Editor for the IEEE TRANSACTIONS ON ENERGY CONVERSION and an Associate Editor for the IEEE TRANSACTIONS ON POWER ELECTRONICS and the IEEE JOURNAL OF EMERGING AND SELECTED TOPICS IN POWER ELECTRONICS. He was the recipient of a 2010 U.S. National Science Foundation CAREER Award and the 2010 IEEE Industry Applications Society Andrew W. Smith Outstanding Young Member Award.

Authorized licensed use limited to: University of Nebraska - Lincoln. Downloaded on July 19,2021 at 18:56:18 UTC from IEEE Xplore. Restrictions apply.