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Real-Time Trading Strategies of Proactive DISCO with Heterogeneous DG Owners

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Abstract—This paper presents a methodology to obtain the optimal trading strategies between the proactive distribution company (PDISCO), heterogeneous distributed generation owners (DGs) and wholesale market in a real-time trading framework. In this framework, the PDISCO’s decisions cover the power procurements from DGs and the transactions within the real-time market. A one-leader multi-follower-type bilevel model is proposed to embody the PDISCO-DGO gaming structure. The numerical results of the case studies show the effectiveness and scalability of the proposed model.

Index Terms—Distributed generation (DG), proactive distribution company (PDISCO), distributed generation owner (DGO), Bayesian game, bilevel model, multi-period AC power flow, mathematical program with equilibrium constraints (MPEC).

 NOMENCLATURE

Sets and Indices

\[ i, j, B \] Index and set of distribution buses.
\[ ij, A \] Index and set of distribution feeders.
\[ d, D \] Index and set of demands.
\[ g, G \] Index and set of stochastic DGs.
\[ s, S \] Index and set of storage devices (SDs).
\[ m, M \] Index and set of DGs or SDs with stochastic DGs.
\[ n, N \] Index and set of DGs with only SDs.
\[ k, K \] Index and set of DGs with both stochastic DGs and SDs.
\[ t, T \] Index and set of time periods (e.g., hours per day).
\[ \omega, \Omega \] Index and set of scenarios.

Mapping of the set of demands onto the set of buses.
Mapping of the set of DGs or SDs onto the set of buses respectively.
Mapping of the set of DGs and SDs onto the set of DGs.

\[ \lambda \] Bidding price and generation quantity of respective Type1,2,3 DGs at time \( t \).
Active and reactive power generated by respective Type1,2,3 DGs at time \( t \) for scenario \( \omega \).
Active and reactive power bought from the PDISCO for DG \( g \) by Type1 DGs at time \( t \) for scenario \( \omega \).
Active and reactive power discharged by SD at time \( t \) for scenario \( \omega \).
Active and reactive power charged by SD at time \( t \) for scenario \( \omega \).
Residual energy of SD at time interval \( t \) for scenario \( \omega \).
Active and reactive power exchanging in real-time market at time \( t \) for scenario \( \omega \).
Active and reactive power of load-shedding at demand \( d \) at time \( t \) for scenario \( \omega \).
Reactive power supplied by the shunt compensator at bus \( i \) at time \( t \) for scenario \( \omega \).
Active and reactive power flows through feeder \( i j \) at time \( t \) for scenario \( \omega \).
Voltage magnitude and phase angle at bus \( i \) at time \( t \) for scenario \( \omega \).

Parameters

\[ P_{DG}^{ij}, Q_{DG}^{ij} \] Active and reactive power generation realization of DG \( g \) at time \( t \) for scenario \( \omega \).
Generating cost of DG \( g \).
Discharging and charging cost of SD \( s \).
Maximum active and reactive power generation bounds of stochastic DG \( g \).
Maximum active and reactive power discharging bounds of SD \( s \).
Maximum active and reactive power charging bounds of SD \( s \).


\[ E_s, \bar{E}_s \] Lower and upper bounds of residual energy of SD \( s \).
\[ \eta_d^s, \eta_c^s \] Discharging and charging energy efficiencies of SD \( s \).
\[ P_{t}^{DA}, Q_{t}^{DA} \] Active and reactive power purchased from the day-ahead market at time \( t \).
\[ P_{d}^{D}, Q_{d}^{D} \] Active and reactive power of demand \( d \) at time \( t \).
\[ \lambda_{t}^{DA} \] Day-ahead market price at time \( t \).
\[ \lambda_{t}^{RT} \] Real-time price at reference bus from the real-time market at time \( t \).
\[ \lambda_{t}^{ED} \] Electricity sales price to the demands from PDISCO at time \( t \).
\[ \lambda_{t}^{shed} \] Load-shedding penalty price for PDISCO operation at time \( t \).
\[ \lambda_{t}^{pen} \] Penalty price for stochastic DGs to purchase power deviation at time \( t \).
\[ \lambda_{t}^{sc} \] Contract prices for SDs to buy charging power from PDISCO at time \( t \).
\[ S, \bar{S}_{ij} \] Capacity limits of the main substation and each feeder \( ij \).
\[ Q_{i}^{C}, \bar{Q}_{i}^{C} \] Reactive power limits of the shunt compensator at bus \( i \).
\[ \xi_{i}, \tau_{i} \] Limits of voltage magnitude at bus \( i \).
\[ G_{ij}, B_{ij}, b_{ij} \] Conductance, susceptance and charging susceptance of feeder \( ij \).
\[ \Upsilon_{t}^{TP(1,2,3)} \] Profit guarantee factor of the DGO of Type1,2,3 respectively at time \( t \).

I. INTRODUCTION

HIGH integration of DGs in the distribution network inspires a possible deregulated environment for the distribution company (DISCO) directly procuring the DGs’ productions in the local area. In the U.S., one of the latest initiatives is to make regulatory changes to establish a distribution-level market for cost-effective utilization of DGs, as addressed in the New York Reforming Energy Vision (NY REV) [1]. Such an advisable insight can motivate the distributed generation owner (DGO) to play an essential role as an emerging business entity to trade with the DISCO. To this end, the DISCO has to make optimal decisions about the wholesale market transactions and the local power procurements.

Traditionally, the DISCO purchases electricity from the wholesale market and supplies the demands in a single-direction. Currently, besides supplying the local demands, the advanced smart grid technology enables the DISCO to perform in a bi-direction power exchanging fashion, i.e. selling or purchasing electricity with the transmission-level markets. This provides an ambitious scheme for the DISCO to sell the excess power (procured from DGOs) to the transmission-level markets profitably, acting as an active electricity producer. With the characteristics above, the proactive DISCO (PDISCO) is so-defined in this paper.

As reviewed in [2], since the distribution-level DGs are small-scale, diverse, and dispersed, the differing ownerships of DGs can render heterogeneous DGOs. As profit-driven entities, the DGOs with stochastic DGs have to consider their production uncertainties, while the DGOs with SDs have to consider their price-based discharging/charging. In addition, with the superiority of DGs’ quick response and low cost, the DGOs are more conducive to participate in the real-time trading process. Thus, we propose a real-time trading framework to capture a PDISCO’s trading strategies interacting with various types of DGOs.

In order to obtain the real-time trading strategies, the PDISCO trading with heterogeneous DGs can be formulated as a one-leader multi-follower-type Bayesian game model [3], following a bilevel structure. At each time \( t \): Categorized in a certain follower type, a lower-level (LL) problem per DGO is to maximize its own profit (minimizing minus-profit) by behaving rationally on bidding prices and generation quantities, in which the scenario-based uncertainty handling method [4] can be adopted to characterize the DGs’ stochastic productions. The upper-level (UL) problem represents the minus-profit minimization of the PDISCO with the optimal decisions on offering prices and power procurements.

Note that the UL problem is non-linear and non-convex, while the LL problems are linear and thus convex. The proposed bilevel model is complex, but solvable by reformulating it to an MPEC with an alternative approach, such as a primal-dual approach [5].

In the literature, to achieve a competitive circumstance, a static day-head DISCO acquisition market model is proposed in [6], including a Pool setup and bilateral contracts. The energy providers are seen as the wholesale market, independent/self-owned DGs, and load curtailment options. However, the DGs are assumed to be dispatchable, which is not realistic since the DGs’ outputs are intermittent and uncontrollable. In [7], to address the competition between the participants, a DISCO-ISO bilevel model is presented to deal with the DGs and interruptible loads in a day-ahead market. The UL problem seeks revenue maximization of the DISCO, and the LL simulates the ISO’s market clearing problem. The DGs are only considered as DISCO self-owned units, which limits the liberty of the DGs’ ownership. Additionally, the DGs’ output and load-shedding price are fixed, while the network constraints are not accounted for. Taking the DGO’s interests into account, the DGO-DISCO contract pricing is also issued by a bilevel model in [8]. The UL problem is to maximize one DGO’s profit equipped with the network constraints listed in the LL problem, but the formulation is simplified by only concerning the active power and voltage value. At the distribution level, a market framework is presented in [9], interacting with the transmission-level markets, the PDISCO’s procurement strategies between the distribution-level aggregator-based demand responses (DRs) and wholesale market transactions are derived through a proposed one-leader multi-follower bilevel model [10]. As fully discussed in [11]–[14], the bilevel modeling has been widely used to identify the wholesale market outcomes with multiple game players during the decision-making process.

To achieve the cost-effective use of distributed energy resources (DERs), a cake cutting game is investigated in [15] to price energy in a smart community. In [16], a hybrid
stochastic/robust optimization model is proposed to render a bidding strategy for a microgrid (MG) to participate in the day-ahead market. At the real-time stage, a multiagent-based game-theoretic reverse auction model is presented in [17] for MG market operations. Considering the uncertainties of market prices, the loss payment is minimized in [18] by scheduling DR and energy storage system (ESS). To maximize the profit of a commercial virtual power plant (CVPP), a three-stage stochastic bilevel model is used to make offering strategies on the basis of various DERs and storages [19]. From the management perspective, a dual-horizon rolling scheduling framework is presented in [20] to optimally operate a set of DERs. An hourly electricity pricing scheme is reported in [21] to build network tariffs for mobilizing price-responsive customers. To exploit DG’s benefits, a multi-agent system-based modeling of an active distribution network is studied in [22] to enhance control strategies for decreasing energy cost.

Originated from the differing DGs’ ownerships, the heterogeneous DGOs can be categorized into three types respectively indexed by $m, k$ and $n$, i.e. DGO $m$ with stochastic DGs, DGO $k$ with both stochastic DGs and SDs, and DGO $n$ with only SDs. The uncertainties of DGs can be represented by the scenario-based method [4]. At each time $t$ per scenario $\omega$: Individual DGs have the thorough knowledge of the cost $(C_g, C_{sd}, C_{sc})$ and the production $(P_{DG}^{d}, P_{sd}^{d}, P_{sc}^{d})$ pertaining to the related DGs. For profit maximization, each DGO should behave rationally to submit the appropriate bids to meet the PDISCO’s request, implying the heterogeneous competition and peer pricing among the DGOs. For DGO $m$, if the actual power production can not meet the committed power generation, the power deviation $P_{dev}$ occurs. In this case, DGO $m$ has to purchase $P_{dev}^{d}$ from the PDISCO with a high penalty price $\lambda_{perm}^{m}$. For DGO $k$, the self-owned SDs can assist in dealing with this kind of contingency. For both DGO $k$ and DGO $n$, the PDISCO supplies the charging power $P_{C}^{d}$ for each affiliated SD with a contract price $\lambda_{C}^{m}$.

III. PROBLEM FORMULATION

The PDISCO-DGO real-time trading problem can be formulated as a bilevel one-leader multi-follower-type game-theoretic model [3]. To embody the heterogeneous competition and peer pricing between three types of DGOs, an LL problem per DGO of a certain type indicates its rational bids to minimize its own minus-profit, see these categorized in (1)-(3), respectively. While the UL problem (4) represents the PDISCO’s minus-profit minimization.

A. Assumptions

The proposed bilevel model involves the following assumptions:

1) The PDISCO is assumed to only own and operate the network, and only one main substation is recognized as the exclusive interconnection point to the transmission network.

2) The real-time trading strategies of a single PDISCO are considered in this paper, including the power procurements from heterogeneous DGOs and power exchanging with the real-time market.

3) Only the active power is eligible to be traded between the PDISCO, DGOs and the real-time market, since the uniform reactive power market is not acknowledged.

4) Linking with $\lambda_{b}^{d(1,2,3)}$, a DGO of a certain type can explicitly predict the impact of its bids (bidding prices and generation quantities), versus the PDISCO’s offers (offering prices and power procurements).

5) We assume the Pay-as-bid (PAB) pricing [2] is the PDISCO-DGO trading mechanism, while the DGOs are further imposed to only be involved in the real-time trading with the PDISCO. One bid per DGO is allowed at each time $t$. 

Fig. 1. Real-time trading framework of PDISCO with heterogeneous DGOs.
B. DGO LL Problems

Note that the bidding prices and generation quantities, put forward by the differing DGOs from the LL problems, vary the PDISCO’s procurement strategies in the UL problem. Therefore, the individual formulations for the three types of DGOs are enumerated below.

1) Type1: DGOs with stochastic DGs.

\[
\begin{align*}
\text{Min}_{\Xi_{DGO1}} & = \sum_t \lambda_{B1}^k p_{1m}^B + E \left[ \sum_{t,g} \left( C_g p_{Dg}^G + \lambda_{p}^{en} p_{tgw}^D \right) \right] \\
\text{s.t.} & \\
p_{t_mw}^T & = \sum_g \left( p_{Dg}^G + p_{d/g}^D \right), \forall t, m, \omega \quad (1a) \\
q_{t_mw}^T & = \sum_g \left( q_{Dg}^G + q_{d/g}^D \right), \forall t, m, \omega \quad (1b) \\
p_{t_mw}^T & \leq p_{1m}^B \leq \sum_g p_{Dg}^G, \forall t, m \quad (1c) \\
0 & \leq p_{t_mw}^D \leq \sum_g p_{Dg}^G, \forall t, m, \omega \quad (1d) \\
0 & \leq q_{t_mw}^D \leq \sum_g q_{Dg}^G, \forall t, m, \omega \quad (1e) \\
0 & \leq p_{t_mw}^D \leq \sum_g p_{Dg}^G, \forall t, g, \omega \quad (1f) \\
0 & \leq q_{t_mw}^D \leq \sum_g q_{Dg}^G, \forall t, g, \omega \quad (1g) \\
0 & \leq \sum_g \left( p_{Dg}^G - p_{tgw}^D \right), \forall t, m \quad (1h)
\end{align*}
\]

where \( \Xi_{DGO1} = \left\{ \left( p_{1m}^B, q_{t_mw}^T, p_{t_mw}^T, p_{t_mw}^D, q_{t_mw}^D \right) \right\}_{(g,m) \in M_o} \) is the variable set of the LL problem for DGO \( m \) pertaining to Type1.

The objective function (1a) is to minimize the minus-profit of DGO \( m \), which consists of the minus-revenue of selling the committed generation quantities with the bidding prices, and the expected cost of the stochastic DGs’ productions plus power deviation penalties. At each time \( t \) per scenario \( \omega \): Constraints (1b) and (1c) impose the total active/reactive power generated by DGO \( m \), which are further limited through constraints (1e) and (1f). Constraints (1d) enforce the rational bidding quantity to cover each plausible realization of the DGs’ generation. Constraints (1g) and (1h) express the limits of the power deviation caused by the generation uncertainty per DG.

2) Type2: DGOs with both stochastic DGs and SDs.

\[
\begin{align*}
\text{Min}_{\Xi_{DGO2}} & = \sum_t \lambda_{B2}^k p_{1m}^B + E \left[ \sum_{t,s} \left( C_s^D p_{s}^D + \lambda_{p}^{en} p_{tsw}^D \right) \right] \\
\text{s.t.} & \\
p_{t_mw}^T & = \sum_g \left( p_{Dg}^G + p_{d/g}^D \right), \forall t, m, \omega \quad (2a) \\
p_{t_kw}^T & = \sum_g \left( p_{Dg}^G - p_{d/g}^D \right), \forall t, k, \omega \quad (2b) \\
q_{t_kw}^T & = \sum_g \left( q_{Dg}^G - q_{d/g}^D \right), \forall t, k, \omega \quad (2c) \\
p_{t_kw}^2 & \geq p_{t_kw}^2, \forall t, k, \omega \quad (2d)
\end{align*}
\]

where \( \Xi_{DGO2} = \left\{ \left( p_{1m}^B, p_{t_mw}^T, q_{t_mw}^T, p_{t_kw}^T, q_{t_kw}^T, p_{t_kw}^D, q_{t_kw}^D \right) \right\}_{(g,m,k) \in M_o} \) is the variable set of the LL problem for DGO \( k \) regarding Type2.

The objective (2a) indicates the minus-profit minimization of DGO \( k \), i.e., the minus-revenue of selling the committed supplies to the PDISCO plus the excepted cost of the DGs’ and SDs’ productions. At each time \( t \) per scenario \( \omega \): Constraints (2b), (2c), (2d) and (2e) identify the active/reactive power availability of DGO \( k \). To cover each plausible realization of the DGs’ generation, constraints (2f) impose the bidding quantity \( P_{t_kw}^B \) towards a rational bid. Considering only positive bids have the possibility to be accepted by the PDISCO, the bidding quantity bounds are further restricted by (2e). The residual energy of each SD \( s \) is enforced by constraints (2h) and bounded by constraints (2i), while the capabilities of the discharged/charged active/reactive power are constrained via (2j),(2k), (2l) and (2m). Furthermore, the dual variables for each group of constraints are indicated correspondingly, separated by a colon.

3) Type3: DGOs with only SDs.

\[
\begin{align*}
\text{Min}_{\Xi_{DGO3}} & = \sum_t \lambda_{B3}^k p_{1m}^B + E \left[ \sum_{t,s} \left( C_s^D p_{s}^D + \lambda_{p}^{en} p_{tsw}^D \right) \right] \\
\text{s.t.} & \\
p_{t_mw}^T & = \sum_g \left( p_{Dg}^G - p_{d/g}^D \right), \forall t, m, \omega \quad (3a) \\
p_{t_kw}^T & = \sum_g \left( p_{Dg}^G - p_{d/g}^D \right), \forall t, k, \omega \quad (3b) \\
q_{t_kw}^T & = \sum_g \left( q_{Dg}^G - q_{d/g}^D \right), \forall t, k, \omega \quad (3c) \\
p_{t_kw}^B & \geq p_{t_kw}^B, \forall t, k, \omega \quad (3d) \\
0 & \leq p_{t_kw}^B \leq \sum_s p_{s}^D, \forall t, k, \omega \quad (3e) \\
0 & \leq q_{t_kw}^B \leq \sum_s q_{s}^D, \forall t, k, \omega \quad (3f) \\
0 & \leq q_{t_kw}^E \leq \sum_s q_{s}^E, \forall t, k, \omega \quad (3g) \\
E_{t+1,s,\omega} & = E_{t,s,\omega} + \Delta t_{ts}^B - \Delta t_{ts}^E \quad (3h)
\end{align*}
\]
\[ \min_{\forall t, s, \omega} \sum_{i \in \mathcal{M}} \lambda^D_i P^D + \sum_{i \in \mathcal{M}} \sum_{s} \lambda_s^B P^B_s + \sum_{t, k} \lambda^B_{tk} P^B_{tk} + \sum_{t, s} \lambda_s^R P^R_{ts} + \sum_{t, s} \lambda_s^c P^c_{ts} \]
\[ = \text{DGO1, DGO2, DGO3, SDs' power charging, and the minus-revenue of electricity time operation model. Constraints (4e) and (4f) represent the shed, \sum_{i \in \mathcal{M}} P^D - P^{shed} \]
\[ \text{s.t.,} \]
\[ \forall t, s, \omega \]
\[ \sum_{(g) \in \mathcal{G}} C_g \leq \lambda^B_{tm} \leq \lambda^R_{tm}, \forall t, m \]
\[ \sum_{(k) \in \mathcal{K}} C_g + \sum_{(s,k) \in \mathcal{M}_O} (C^s + C^sc + \lambda^c_s) \leq \lambda^B_{tk} \leq \lambda^R_{tk}, \forall t, k \]
\[ \sum_{(s,k) \in \mathcal{M}_O} (C^s + C^sc + \lambda^c_s) \leq \lambda^B_{tk} \leq \lambda^R_{tk}, \forall t, k \]
\[ \lambda^B_{tn} \leq \lambda^R_{tn}, \forall t, n \]

For the main substation (reference bus 1):
\[ \sum_{(g,1) \in \mathcal{M}_G} (P^{DG} - P^{dev}) + \sum_{(s,1) \in \mathcal{M}_S} (P^{sd} - P^{sc}) \]
\[ = \sum_{i \in \mathcal{M}} P^D_i + P^R_i + P^{shed} - P^D = \sum_{i \in \mathcal{M}} P^f_i, \forall t, \omega \]
\[ \sum_{(g) \in \mathcal{M}_G} (Q^{DG} - Q^{dev}) + \sum_{(s) \in \mathcal{M}_S} (Q^{sd} - Q^{sc}) \]
\[ = \sum_{i \in \mathcal{M}} Q^f_i, \forall t, \omega \]
limit of the main substation is identified by constraints (4i). Constraints (4j) and (4k) enforce the AC power balance at the other buses, in which the voltage angle and voltage value are bounded by constraints (4n) and (4o). Constraints (4l) and (4m) identify the AC power flow through feeder i-j. Constraints (4p) specify the capacity limits of individual feeders. Constraints (4q) and (4r) indicate the load-shedding limits. Constraints (4s) depict the capacity bounds of each compensator. Constraints (4t) maintain a constant demand limits. Constraints (4u) depict the capacity bounds of each transformer. Constraints (4v), (4w) and (4x) indicate the heterogeneous DGOs within Types1-3 intend to maximize their own profits, individually.

D. MPEC

Note that the UL PDISCO problem is nonlinear and non-convex, while the LL DGOs’ problems are linear and thus convex. To transform the proposed bilevel model into a single-level optimization problem, the varied DGOs’ problems can be replaced by their first-order optimality conditions, which renders an MPEC. Here, two alternative approaches are available for the reformulation of this problem, i.e., Karush-Kuhn-Tucker (KKT) conditions and primal-dual approach.

In general, the primal-dual approach renders a mathematical program with primal and dual constraints (MPPDC), which is more tractable and efficient for off-the-shelf branch-and-cut software than its associated KKT conditions [5] [23]. Thus, the primal-dual approach is employed in this paper. For brevity, the DGO k within Type2 of the LL problems is taken as an illustrative example to carry out the MPPDC transformation, as shown in (5). Constraints (5a)-(5h) are the dual constraints of the primal constraints (2b)-(2m). Constraint (5i) is the associated strong duality equality, which ensures the equality of the primal and dual objective values, one per DGO k. Subsequently, the similar MPPDC transformations can be applied to the DGOs characterized in Type1 and Type3, respectively.

\[
\begin{align*}
-\lambda_{tk}^L - \gamma_{tkw} + \mu_{tk}^+ - \mu_{tk}^- &= 0, \forall t, k \\
\alpha_{tkw}^+ + \gamma_{tkw} + \psi_{tkw}^+ - \psi_{tkw}^- &= 0, \forall t, k, \omega \\
\beta_{tkw}^+ + \rho_{tkw} - \rho_{tkw}^- &= 0, \forall t, k, \omega \\
C_{s}^{sd} - \alpha_{tkw} + \Delta \xi_{tskw}/\mu_{tskw} + \theta_{tskw} + \theta_{tskw}^- &= 0, \forall t, s, (s, k) \in \mathcal{M}_O, \omega \\
-\beta_{tkw}^+ + \sigma_{tskw}^+ - \sigma_{tskw}^- &= 0, \forall t, s, s, (s, k) \in \mathcal{M}_O, \omega \\
C_{s}^{sc} + \lambda_{ts}^+ + \alpha_{tkw} - \Delta \xi_{tskw}/\mu_{tskw} + \phi_{tskw}^+ - \phi_{tskw}^- &= 0, \forall t, s, (s, k) \in \mathcal{M}_O, \omega \\
\beta_{tkw}^+ + \nu_{tskw}^+ - \nu_{tskw}^- &= 0, \forall t, s, (s, k) \in \mathcal{M}_O, \omega \\
\xi_{tskw} - \xi_{tskw}^- + \xi_{tskw}^- &= 0, \forall t, s, (s, k) \in \mathcal{M}_O, \omega \\
\sum_t \lambda_{tk}^B P_{tk}^B + \sum_t \mu_{tk} \left( \sum_g P_{tg}^{DG} + \sum_s P_{ts}^{sd} \right) +
\end{align*}
\]

Replacing the heterogeneous LL DGOs’ problems with the corresponding MPPDC, the proposed bilevel problem finally results in a single-level model structured with the PDISCO’s objective, subject to the PDISCO’s constraints and individual DGOs’ MPPDC constraints, as shown in (6). The final non-linear model can be solved by the commercial off-the-shelf large-scale non-linear optimization solver CONOPT3 [24].

\[
\begin{align*}
\min_{\xi_{tskw}^-, \xi_{tskw}^+, \xi_{tskw}^+: (g, k, s) \in \mathcal{M}_O} & (4a) \\
\text{s.t.} & \quad \text{PDISCO’s problem constraints: (4b) – (4x)} \\
& \quad \text{Type1 DGOs’ problems MPPDC constraints;} \\
& \quad \text{Type2 DGOs’ problems MPPDC constraints:} \\
& \quad (2b) – (2m) \text{ and } (5a) – (5i) \\
& \quad \text{Type3 DGOs’ problems MPPDC constraints.}
\end{align*}
\]

IV. CASE STUDIES

To validate the effectiveness of the methodology presented in Section III, a modified 33-bus distribution network [25] is used to identify the PDISCO-DGO trading decisions and individual participants’ profits. A 119-bus distribution network [26], [27] is used to verify the scalability of this approach. Applying the uncertainty handling method [4], 1000 scenarios are generated and reduced to 15 scenarios in these cases.

A. 33-bus Distribution Network

The 33-bus network is assumed to be owned and operated by the PDISCO. The capacity of the main substation \( S \) and each feeder \( S_{ij} \) are respectively set to 20 MVA and 10 MVA. The voltage is 1 p.u. at the reference bus, while it ranges from 0.9 to 1.1 p.u. at the other buses. The tap ratio \( \tau_i \) of each transformer is imposed to 1. 0-200 kVar is the capacity per compensator. The wind turbines (WTs) and PVs are selected to represent the stochastic DGs. Two DGOs per type per hour are considered to be engaged in the real-time trading with the PDISCO, i.e. 24 times per
day. The related mappings and parameters of the assorted DGOs with DGs are described in Table I. For simplicity, the SDs’ discharging/charging limits and costs are identical with a unified efficiency 0.9, while the contracted charging price $\lambda^{c}_{i}$ can be assumed as half the price of the day-ahead prices. The profit guarantee factors $\Upsilon_{m,k,n}$ follow the rate of change of the real-time prices with the individual base-values 14, 6 and 7. The power factors are recognized as 0.90/WT, 0.95/PV, and 0.99/SD. For the PDISCO, the real-time demand $P_{D}$ and day-head purchases $P_{DA}$ are shown in Table II, in which the prices $\lambda^{DA}_{i}$, $\lambda^{RT}_{i}$ and $\lambda^{D}_{i}$ are estimated by the NordPool [28] prices. The penalty price $\lambda^{pen}_{i}$ is also claimed for the potential power deviation caused by the DGOs’ output mismatching the committed capacity. In addition, the load-shedding price $\lambda^{shed}_{i}$ is considered as 200 times as $\lambda^{RT}_{i}$. The other parameters can be found in [25].

### Table I

<table>
<thead>
<tr>
<th>Type</th>
<th>DGO (m, k, n)</th>
<th>$M_{G}$, $M_{O}$ (g : i, s : i)</th>
<th>$P_{DA}$ [kW]</th>
<th>$P_{RT}$ [kW]</th>
<th>$E_{B}$ [kWh]</th>
<th>$C_{o}$ [10^6€/kW]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type1</td>
<td>m=1</td>
<td>WT1:21</td>
<td>500</td>
<td>500</td>
<td>1188.80</td>
<td>0.30</td>
</tr>
<tr>
<td></td>
<td>m=2</td>
<td>WT2:7</td>
<td>500</td>
<td>-</td>
<td>1114.50</td>
<td>0.28</td>
</tr>
<tr>
<td></td>
<td>m=2</td>
<td>PV17</td>
<td>500</td>
<td>-</td>
<td>1270.13</td>
<td>0.20</td>
</tr>
<tr>
<td>Type2</td>
<td>k=1</td>
<td>WT4:25</td>
<td>500</td>
<td>500</td>
<td>2414.75</td>
<td>0.28</td>
</tr>
<tr>
<td></td>
<td>k=2</td>
<td>SD4:29</td>
<td>500</td>
<td>500</td>
<td>2972.00</td>
<td>0.30</td>
</tr>
<tr>
<td>Type3</td>
<td>n=1</td>
<td>SD3:24</td>
<td>500</td>
<td>500</td>
<td>2972.00</td>
<td>0.28</td>
</tr>
<tr>
<td></td>
<td>n=2</td>
<td>SD6:14</td>
<td>500</td>
<td>500</td>
<td>2283.58</td>
<td>0.30</td>
</tr>
</tbody>
</table>

### Table II

<table>
<thead>
<tr>
<th>$t$ [Hour]</th>
<th>$\lambda^{DA}_{i}$ [€/kW]</th>
<th>$P_{DA}$ [kW]</th>
<th>$\lambda^{RT}_{i}$ [€/kW]</th>
<th>$\lambda^{D}_{i}$ [€/kW]</th>
<th>$P_{D}$ [kW]</th>
<th>$\lambda^{pen}_{i}$ [€/kW]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.10</td>
<td>1057.63</td>
<td>0.16</td>
<td>0.20</td>
<td>1114.50</td>
<td>2.08</td>
</tr>
<tr>
<td>11</td>
<td>0.33</td>
<td>3646.99</td>
<td>0.39</td>
<td>0.73</td>
<td>4086.50</td>
<td>1.03</td>
</tr>
<tr>
<td>17</td>
<td>0.37</td>
<td>3606.12</td>
<td>0.39</td>
<td>0.73</td>
<td>4086.50</td>
<td>1.03</td>
</tr>
<tr>
<td>19</td>
<td>0.38</td>
<td>3455.36</td>
<td>0.39</td>
<td>0.73</td>
<td>3967.75</td>
<td>0.98</td>
</tr>
</tbody>
</table>

The results of power exchanging in the real-time market are shown in Fig. 2. As expected, the PDISCO behaves as an active producer to provide productions at certain periods, e.g., scenario-based ($\omega=1$) power exchanging in hours 8-9, 14-15, and 17-19. Hours (8-9, 14-15) reflect that the PDISCO has the ability to sell the excess power reversely to the transmission level in medium-price areas. Observe that two peaks appear at hours 11-13 and 19-21, while the results of the power transactions are distinct. During hours 11-13, the PDISCO acquires only a little power, implying the PDISCO executes the proper strategy to avoid the volatile real-time prices and insufficient day-ahead purchases with the DGOs’ bids. Hour 19 overlaps with the system’s peak and the PDISCO’s active performance, indicating the PDISCO’s arbitrage capability to facilitate the sales strategy in a profitable high-price time slot with abundant generation from DGOs and sufficient day-ahead dealings. Running through the low-price intervals, e.g., hours 1-7 and 23-24, the PDISCO strategically launches large-volume procurements to increase the revenue by selling charging power to the SD-equipped DGOs.

Interacting with the PDISCO, as profit-driven entities, the individual DGOs perform rationally to submit bids ($\lambda^{B}_{m,k,n}$, $P_{B}$) resulting in the PDISCO’s offering prices and power procurements, as shown in Fig. 3 in detail. As observed, in Fig. 3 (a), the DGOs with only stochastic DGs continuously obtain offers with lower prices, versus large amounts. Since the DGs’ power deviation against committed generation is inevitable, the DGOs’ repurchases negatively accompany the offers per hour, e.g., scenario-based ($\omega=1$) power deviations. The minor difference between the WT-PV and the WT-WT DGOs is that the later bids are at lower prices with higher quantities. In contrast, the WT-SV and PV-SV DGOs generally bid at higher prices, as shown in Fig. 3 (b). However, the generation quantities are not comparable, reduced critically for WT-SV DGO, and even declined in some periods for PV-SV DGO, although the SDs are functional to cover the hourly power deviation. Fig. 3 (c) reveals that the two SD-SV DGOs take similar actions to respond the DISCO’s request with the highest bidding prices only at the peaks. Note that the generation quantities are quite limited, the DGO with higher capacity leads to a higher competitiveness.

In other words, the characteristics of heterogeneous competition and peer pricing among DGOs have been achieved in the proposed methodology. Accordingly, the profits of each participant per hour are obtained and shown in Fig. 4, and the daily profits are summarized in Profit1 of Table III.

Considering each Type1 DGO’s profit mainly depends on the owned DGs’ total capacity, while the stochastic outputs are
The profit results are enumerated as Profit6 in Table III.

<table>
<thead>
<tr>
<th>Participant</th>
<th>Profit1 [€]</th>
<th>Profit2 [€]</th>
<th>Profit3 [€]</th>
<th>Profit4 [€]</th>
<th>Profit5 [€]</th>
<th>Profit6 [€]</th>
</tr>
</thead>
<tbody>
<tr>
<td>PDISCO</td>
<td>7125.45</td>
<td>3253.33</td>
<td>11726.64</td>
<td>7484.31</td>
<td>6136.00</td>
<td>27562.29</td>
</tr>
<tr>
<td>WT-WT</td>
<td>2589.67</td>
<td>475.77</td>
<td>5718.36</td>
<td>2588.96</td>
<td>2547.32</td>
<td>2576.13</td>
</tr>
<tr>
<td>WT-PV</td>
<td>2493.79</td>
<td>460.87</td>
<td>5432.55</td>
<td>2438.55</td>
<td>2461.55</td>
<td>2421.55</td>
</tr>
<tr>
<td>WT-SD</td>
<td>1848.77</td>
<td>399.80</td>
<td>3272.46</td>
<td>2030.27</td>
<td>1773.29</td>
<td>1822.10</td>
</tr>
<tr>
<td>PV-SD</td>
<td>1108.16</td>
<td>283.51</td>
<td>2597.36</td>
<td>1315.85</td>
<td>1054.24</td>
<td>1110.28</td>
</tr>
<tr>
<td>SD-SD1</td>
<td>348.49</td>
<td>341.24</td>
<td>351.49</td>
<td>1040.07</td>
<td>186.95</td>
<td>475.77</td>
</tr>
<tr>
<td>SD-SD2</td>
<td>203.76</td>
<td>198.19</td>
<td>209.16</td>
<td>612.87</td>
<td>109.04</td>
<td>276.88</td>
</tr>
</tbody>
</table>

TABLE III

DAILY PROFIT OF THE PDISCO AND INDIVIDUAL DGOs

B. 119-bus Distribution Network

The 119-bus network [26], [27] is modified to further test the scalability of the proposed approach. The parameters are set as Case 6. Particularly, individual demands are proportionately adjusted to follow the variation of the corresponding data in Section IV-A Case 1. The mappings of DGs and buses are WT1:7, WT2:19, WT3:66, WT4:110, PV1:33, PV2:89, SD1:40, SD2:78, SD3:10, SD4:116, SD5:29, and SD6:103. The other system-wide parameters remain the same as in Section IV-A.

The profit results are enumerated as Profit6 in Table III. Each DGO’s profit is nearly consistent as in Case 1, whereas the minor differences can be caused by the differing layout of the physical network. The PDISCO’s daily profit is increased by 427%, primarily from sales revenue, since the demand is considerably high.
C. Computational Issue

All cases are carried out on a 3.6 GHz Intel Core i7 processor with 16 GB of RAM and 64-bit Windows 7 system, and solved by CONOPT3 with GAMS 24.4.1 [24].

Table IV summarizes the computational time for solving the problem corresponding to each case. Note that the computational burden increases significantly with the scale and complexity of the distribution network. However, it is also worth noting that the computational performance is acceptable for a hourly-based trading.

<table>
<thead>
<tr>
<th>Case</th>
<th>CPU time (s)</th>
<th>Case</th>
<th>CPU time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>498.63</td>
<td>4</td>
<td>499.70</td>
</tr>
<tr>
<td>2</td>
<td>499.35</td>
<td>5</td>
<td>500.38</td>
</tr>
<tr>
<td>3</td>
<td>503.22</td>
<td>6</td>
<td>2761.03</td>
</tr>
</tbody>
</table>

V. Conclusion

This paper proposes a bilevel game-theoretic model to investigate the PDISCO’s real-time trading strategies between the type-oriented DGOs and the transmission-level market. Three types of DGOs and a real-time trading framework are well defined to enhance competitiveness, as in the distribution-level market environment. Accompanying the UL PDISCO’s optimal decisions, an LL DGO’s problem also achieves its goal for profit maximization with the rational multi-period bids. With the primal-dual approach, the proposed model is reformulated to a solvable MPEC. The numerical results of the case studies successfully illustrate the heterogeneous competition and peer pricing characteristics of the DGOs, also demonstrate the PDISCO’s trading strategies are suitable and effective.

REFERENCES


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ity modeling.

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