A Two-stage Stochastic Programming DSO Framework for Comprehensive Market Participation of DER Aggregators under Uncertainty

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Abstract—In this paper, a distribution system operator (DSO) framework is proposed for comprehensive retail and wholesale markets participation of distributed energy resource (DER) aggregators under uncertainty based on two-stage stochastic programming. Different kinds of DER aggregators including energy storage aggregators (ESAGs), demand response aggregators (DRAGs), electric vehicle (EV) aggregating charging stations (EVCSs), dispatchable distributed generation (DDG) aggregators (DDGAGs), and renewable energy aggregators (REAGs) are modeled. Distribution network operation constraints are considered using a linearized power flow. The problem is modeled using mixed-integer linear programming (MILP) which can be solved by using commercial solvers. Case studies are conducted to investigate the performance of the proposed DSO framework.

I. INTRODUCTION

The installed capacity of DERs is increasing, thanks to their low operational costs and growing demand. Being capable of providing fast ramping services, DER aggregators can effectively participate in the wholesale energy and regulation markets. However, uncontrolled participation of DER aggregators may cause security issues to distribution system operations. Hence, there is a need for an entity to enable DER aggregators to participate in the wholesale market and monitor the distribution system for secure and reliable operation.

Many topics have been examined in the context of market participation of DERs. In [1], [2], the concepts of DER aggregator and virtual power plant are introduced to enable DERs for wholesale market participation. A decentralized approach using Dantzig-Wolfe decomposition is presented for DER coordination in [3]. The proposed approach allows households to participate in the electricity market to minimize the total cost. In [4], [5], a microgrid is presented for wholesale market participation. The mentioned works ignore distribution grid operations. Hence, they neglect distribution grid security/reliability constraints which are necessary for DER’s market participation. In [6], a bidding strategy for market participation of a virtual power plant is proposed considering a demand response market which is considered as a stage between day-ahead and real-time markets. In [7], a bidding strategy is proposed for day-ahead and real-time markets participation of EV aggregators. In [6], [7], in order to consider power balance equations, DC load flow is proposed, which is inappropriate due to high impedances in distribution grids.

Inspired by the smart grid technologies and growing DER installed capacity, the system operators call for a distribution level electricity market in which DERs can easily participate while assuring distribution grid security/reliability. The concept of distribution system operator (DSO) is presented recently in order to integrate DERs while operating the distribution network based on a retail market framework [8]–[10]. In [8], a DSO is introduced for operating a day-ahead retail market. The distribution locational marginal price (D-LMP) is presented as a method for paying the market participants. However, the distribution network operation and corresponding security constraints are not included in the proposed model. In [9], the authors proposed a two-stage stochastic programming approach for a DSO to operate day-ahead energy and reserve markets. In [10], a distribution market operator (DMO) is proposed which collects offers from microgrids in order to participate in the wholesale market. To represent the relationship between D-LMP and transmission-level LMP, a penalty factor is defined. Both [9] and [10] adopt DC load flow, which is inappropriate for distribution grid modeling.

To the best of our knowledge, the DSO framework for comprehensive market participation of DER aggregators under uncertainty in the retail market as well as wholesale energy and regulation markets has not been studied yet. In this paper, a two-stage stochastic programming DSO framework is proposed for comprehensive market participation of DER aggregators under uncertainty. Various DER aggregators, including Energy storage aggregators (ESAGs), demand response aggregators (DRAGs), electric vehicle (EV) aggregating charging stations (EVCSs), dispatchable distributed generation (DDG) aggregators (DDGAGs), and renewable energy aggregators (REAGs), are considered. The proposed DSO optimally coordinates these DER aggregators for their participations in the retail market and wholesale energy/regulation markets, while maintaining distribution grid security. Case studies verify the effectiveness of the proposed DSO framework.

II. TWO-STAGE STOCHASTIC DSO MARKET FORMULATION

In this paper, the DSO is defined as an entity which interacts with DER aggregators and end-user customers on one side and trades with the wholesale market on the other side. The
DSO collects offers from various types of DER aggregators and runs the retail market as well as coordinates the offers for constructing an aggregated offer for participating in the wholesale energy and regulation markets which is operated by the independent system operator (ISO) whose pay-for-performance regulation market is considered [11], [12].

The wholesale electricity market involves two stages: the day-ahead stage and balancing stage. For instance, California ISO (CAISO), which is adopted here, is a two-settlement market consisting of day-ahead and real-time markets, which is used for adjusting balance between supply and demand [12]. Market participants can participate in the day-ahead market and wait-and-see variables are decisions related to the real-time market in the case that their production or consumption has changed. In practice, usually, there is a difference between the offer and its production or consumption, especially for renewable energy producers. Hence, participation in the real-time market is necessary for them.

One important characteristic of a DSO is being capable of handling uncertainties in the system operation. An appropriate method for a market operator to cover uncertainties is using two-stage stochastic programming [13]. In this method, the objective function, expected operational costs, including costs related to the day-ahead operation and costs related to the compensating actions in the real-time, is minimized. In this model, here-and-now variables are decisions related to the day-ahead market and wait-and-see variables are decisions related to the real-time market. Day-ahead market prices usually can be predicted with high accuracy [14]. Hence, sources of uncertainties are inelastic loads, renewable energy aggregator production, and real-time prices. The two-stage stochastic programming introduced in [15] is adopted here.

A. Objective Function

The DSO minimizes the distribution grid’s total operational cost, considering 1) costs of buying/selling energy and selling regulation services to the wholesale energy and regulation markets; 2) costs of paying DER aggregators for their retail market participations. The objective function of the proposed two-stage stochastic programming is given by (1).

\[
\min \sum_{t \in T} [P_{t,1} \pi_{t,1}^e - r_{t,1} \pi_{t,1}^e \pi_{t,1}^c + r_{t,1} \pi_{t,1}^d] + \sum_{k \in \{2, K\}} P_{t,k} \pi_{t,k} \sum_{k \in \{2, K\}} P_{t,k} \pi_{t,k} \pi_{t,k}^{up} + \sum_{t \in T} \Omega_t \left( P_{t,w}^e \pi_{t,w}^e - P_{t,w}^e \pi_{t,w}^e \right)
\]

where \( t \) and \( T \) are the index and set for the entire operating timespan; \( k \) and \( K = \{K_1, K_2, K_3, K_4\} \) are the index and set for all DER aggregators; \( k_1 \) (\( K_1 \)), \( k_2 \) (\( K_2 \)), \( k_3 \) (\( K_3 \)), and \( a \) (\( A \)) are the indices (sets) for all DRAGs, ESAGs, EVCSs, DDAGs, and demand blocks, respectively; \( P_{t,1}^e, P_{t,1}^c, \) and \( P_{t,1}^d \) are the DSO’s aggregated quantity offers to the wholesale energy, regulation capacity-up and capacity-down markets, respectively; \( \pi_{t,1}^e, \pi_{t,1}^c, \) and \( \pi_{t,1}^d \) are the wholesale energy, regulation capacity-up (capacity-down), and regulation mileage-up (mileage-down) prices, respectively; \( r_{t,1}^e \) and \( r_{t,1}^d \) are historical scores for providing regulation mileage-up and mileage-down services; \( \pi_{t,w}^e \) and \( \pi_{t,w}^d \) are the regulation mileage-up and mileage-down ratios (the expected mileage for 1MW provided regulation capacity); \( \pi_{a,t,k}^e \) and \( \pi_{a,t,k}^d \) are the power consumption and the corresponding energy price at each demand block; \( \Omega_t \) is the probability of scenario \( w; P_{t,w}^{b,r,l} \) is amount of power purchased from the wholesale real-time market with corresponding price \( \pi_{t,w}^{b,r,l} \); \( P_{t,w}^{b,r,l} \) is amount of power sold to the wholesale real-time market with price \( \pi_{t,w}^{b,r,l} \).

In (1), the wholesale energy market is modeled as a producer in the DSO, while the wholesale regulation market is modeled as a consumer in the DSO. Therefore, cost terms related to the energy and regulation markets are associated with the positive and negative signs, respectively. The DSO is modeled as a price taker in the wholesale energy and regulation markets.

B. Constraints for Demand Response Aggregators (DRAGs)

The operating constraints for DRAGs are as follows:

\[
\sum_{a \in A} P_{a,t,k_1} - r_{t,k_1}^{cap,dn} \geq 0; \quad \forall t \in T, \forall k_1 \in K
\]

\[
\sum_{a \in A} P_{a,t,k_1} + r_{t,k_1}^{cap,up} \leq \sum_{a \in A} P_{a,t,k_1}^{max}; \quad \forall t \in T, \forall k_1 \in K
\]

\[
0 \leq P_{a,t,k_1} \leq P_{a,t,k_1}^{max}; \quad \forall a \in A, \forall t \in T, \forall k_1 \in K
\]

\[
0 \leq r_{t,k_1}^{cap,up} \leq r_{t,k_1}^{cap,up,max}; \quad \forall t \in T, \forall k_1 \in K
\]

\[
0 \leq r_{t,k_1}^{cap,down} \leq r_{t,k_1}^{cap,down,max}; \quad \forall t \in T, \forall k_1 \in K
\]

where \( P_{a,t,k_1}^{max} \) is the maximum power consumption at each demand block; \( r_{t,k_1}^{cap,up,max} \) and \( r_{t,k_1}^{cap,down,max} \) are the maximum allowed regulation capacity-up and capacity-down quantity offers, respectively.

Equations (2)-(3) ensure the total power consumed by the DRAG for buying/selling energy and offering regulation service is less than the maximum power consumption across all demand blocks within the DRAG. Equation (4) limits the amount of power offered by each demand block to its maximum value. Equations (5)-(6) limit the regulation capacity-up and capacity-down quantity offers to their maximum values.

C. Constraints for Energy Storage Aggregators (ESAGs)

The operating constraints for ESAGs are as follows:

\[
P_{t,k_2} = E_{t-1,k_2} - E_{t,k_2} + (1/\eta_{k_2}^{dc}) r_{t,k_2}^{cap,up} \mu_{t,k_2}^{up} - (\eta_{k_2}^{dc}) r_{t,k_2}^{cap,down} \mu_{t,k_2}^{dn}; \quad \forall t \in T, \forall k_2 \in K_2
\]
\[ P_{t,k_2} = (1/\eta_{k_2}) P^{\text{di}}_{t,k_2} - (\eta_{k_2}) P^{\text{ch}}_{t,k_2}; \quad \forall t \in T, \forall k_2 \in K_2 \]  
\[ r^{\text{cap,up}}_{t,k_2} = r^{\text{cap,up,di}}_{t,k_2} + r^{\text{cap,up,ch}}_{t,k_2}; \quad \forall t \in T, \forall k_2 \in K_2 \]  
\[ r^{\text{cap,dn}}_{t,k_2} = r^{\text{cap,dn,di}}_{t,k_2} + r^{\text{cap,dn,ch}}_{t,k_2}; \quad \forall t \in T, \forall k_2 \in K_2 \]  
\[ E^{\text{min}}_{k_2} \leq E_{t,k_2} \leq E^{\text{max}}_{k_2}; \quad \forall t \in T, \forall k_2 \in K_2 \]  
\[ 0 \leq r^{\text{cap,up,di}}_{t,k_2} \leq b_{k_2} DR^{\text{max}}_{k_2}; \quad \forall t \in T, \forall k_2 \in K_2 \]  
\[ 0 \leq r^{\text{cap,up,ch}}_{t,k_2} \leq b_{k_2} DR^{\text{max}}_{k_2}; \quad \forall t \in T, \forall k_2 \in K_2 \]  
\[ 0 \leq r^{\text{cap,dn,di}}_{t,k_2} \leq b_{k_2} DR^{\text{max}}_{k_2}; \quad \forall t \in T, \forall k_2 \in K_2 \]  
\[ 0 \leq r^{\text{cap,dn,ch}}_{t,k_2} \leq b_{k_2} DR^{\text{max}}_{k_2}; \quad \forall t \in T, \forall k_2 \in K_2 \]  
\[ 0 \leq r^{\text{cap,up,di}}_{t,k_2} \leq (1 - b_{k_2}) CR^{\text{max}}_{k_2}; \quad \forall t \in T, \forall k_2 \in K_2 \]  
\[ 0 \leq r^{\text{cap,up,ch}}_{t,k_2} \leq (1 - b_{k_2}) CR^{\text{max}}_{k_2}; \quad \forall t \in T, \forall k_2 \in K_2 \]  
\[ 0 \leq r^{\text{cap,dn,di}}_{t,k_2} \leq (1 - b_{k_2}) CR^{\text{max}}_{k_2}; \quad \forall t \in T, \forall k_2 \in K_2 \]  
\[ 0 \leq r^{\text{cap,dn,ch}}_{t,k_2} \leq (1 - b_{k_2}) CR^{\text{max}}_{k_2}; \quad \forall t \in T, \forall k_2 \in K_2 \]  
where \( E_{t,k_2} \) is the charging level; \( P^{\text{di}}_{t,k_2} \) and \( \eta_{k_2} \) \((\eta_{k_2})\) are the charging (discharging) power and charging (discharging) efficiencies, respectively; \( r^{\text{cap,up,di}}_{t,k_2} \) and \( r^{\text{cap,up,ch}}_{t,k_2} \) are the regulation capacity-up (capacity-down) offers in charging and discharging modes, respectively; \( CR^{\text{max}}_{k_2} \) and \( DR^{\text{max}}_{k_2} \) are the maximum charging and discharging rates, respectively; \( b_{k_2} \) is a binary variable indicating the charging \((b_{k_2} = 0)\) and discharging \((b_{k_2} = 1)\) modes. ESAG’s power injection is given by (7). ESAG’s quantity offers for energy and regulation capacity-up/down markets are decomposed into charging and discharging terms by (8)-(10). The charge level of ESAGs is limited by (11). Equations (12)-(17) assure that ESAG’s offers to the energy and regulation capacity-up/down markets are lower than their maximum values. In (18)-(19), the total power offered by ESAG to the energy and regulation capacity-up/down markets lies within the maximum charging rate. Equation (20) assures the charge level of EVs is full.

E. Constraints for Dispatchable DG Aggregators (DDGAGs)

The operating constraints for DDGAGs are as follows:

\[ P_{t,k_4} + r^{\text{cap,up}}_{t,k_4} \leq P^{\text{max}}_{k_4}; \quad \forall t \in T, \forall k_4 \in K_4 \]  
\[ P_{t,k_4} - r^{\text{cap,dn}}_{t,k_4} \geq P^{\text{min}}_{k_4}; \quad \forall t \in T, \forall k_4 \in K_4 \]  
\[ 0 \leq r^{\text{cap,up}}_{t,k_4} \leq RU_{k_4}; \quad \forall t \in T, \forall k_4 \in K_4 \]  
\[ 0 \leq r^{\text{cap,dn}}_{t,k_4} \leq RD_{k_4}; \quad \forall t \in T, \forall k_4 \in K_4 \]  
where \( P^{\text{max}}_{k_4} \) and \( P^{\text{min}}_{k_4} \) are the maximum and minimum power generations, respectively; \( RU_{k_4} \) and \( RD_{k_4} \) are the maximum ramp-up and ramp-down rates, respectively.

In (26)-(27), the total power offered by DDGAG to the energy and regulation capacity-up/down markets lies within the DDGAG’s maximum and minimum power generations. In (28)-(29), the DDGAG’s regulation capacity-up/down offers are limited by its maximum ramp-up/down rates.

F. Distribution Power Flow Equations

The linearized power flow equations are adopted from [16]:

\[ \sum_{k_1 \in K_1} H_{n,k_1} P_{n,t,k_1} + \sum_{k_1 \in K_1} H_{n,k_1} P_{t,k_1} + P^D_{t,n} \]  
\[ - \sum_{k_2 \in K_2} H_{n,k_2} P_{t,k_2} - \sum_{k_1 \in K_1} H_{n,k_1} P_{t,k_4} \]  
\[ - \sum_{k_5 \in K_5} H_{n,k_5} P_{t,k_5} + H^{\text{sub}}_{t,n} \sum_{j \in J} P_{j,t} A_{j,n} = 0; \quad \forall t \in T, \forall n \in N \]  
\[ \sum_{k_1 \in K_1} H_{n,k_1} P_{t,k_1} \tan \phi_{k_1} + Q^D_{t,n} \]  
\[ + H^{\text{sub}}_{t,n} Q^D_{t,n} + \sum_{j \in J} Q_{j,t} A_{j,n} = 0; \quad \forall t \in T, \forall n \in N \]  
\[ V_{m,t} = V_{n,t} - (t_j P_{j,t} + x_j Q_{j,t}); \quad \forall t \in T, \forall m \in N, \forall n \in N, C(m,n) = 1, A(j,n) = 1 \]  
\[ V^{\text{min}} \leq V_{n,t} \leq V^{\text{max}}; \quad \forall t \in T, \forall n \in N \]  
\[ - P^{\text{max}} \leq P_{j,t} \leq P^{\text{max}}; \quad \forall t \in T, \forall j \in J \]  
\[ - Q^{\text{max}} \leq Q_{j,t} \leq Q^{\text{max}}; \quad \forall t \in T, \forall j \in J \]  
\[ r^{\text{cap,up}}_{t,k_2} = \sum_{k_2 \in K_2} r^{\text{cap,up}}_{t,k_2} + \sum_{k_3 \in K_3} r^{\text{cap,up}}_{t,k_3} \]  
\[ + \sum_{k_1 \in K_1} r^{\text{cap,up}}_{t,k_1} \]  
\[ + \sum_{k_3 \in K_3} r^{\text{cap,dn}}_{t,k_3} \]  
\[ - \sum_{k_2 \in K_2} r^{\text{cap,dn}}_{t,k_2} \leq \sum_{t \in T'} C_{i}^{\text{max}} b_{k_3}; \quad \forall k_3 \in K_3 \]  
\[ 0.9 C_{i}^{\text{max}} b_{k_3} \leq \sum_{t \in T'} [P_{t,k_3} + r^{\text{cap,up}}_{t,k_3} \mu^D_{t}\mu^D_{t}] - r^{\text{cap,dn}}_{t,k_3} \mu^D_{t}\mu^D_{t} \leq C_{i}^{\text{max}} b_{k_3}; \quad \forall k_3 \in K_3 \]  
where \( T' \subseteq T \) is the set of hours when EVs are available at the charging station; \( ER^{\text{max}}_k \) is the maximum charging rate; \( CL^{\text{max}}_k \) is the maximum allowed regulation capacity offers; \( CL^{\text{max}}_k \) is the maximum charge level; \( C^{\text{init}}_k \) is the initial charge level; \( \eta^D \) is the charging efficiency; \( b_{k_3} \) is a binary variable which enables the DSO not to allocate the minimum power to EVCSs when their offering price is low. In (20)-(22), EVCS’s offers to the energy and regulation capacity-up/down markets are limited by their corresponding maximum values. In (23)-(24), the total power offered by EVCS to the energy and regulation capacity-up/down markets lies within the maximum charging rate. Equation (25) assures the charge level of EVs is full.
In this section, two-stage stochastic programming introduced in Section II is used to obtain simulation results. Case studies are performed on the small distribution network in Fig.1. The system contains 5 nodes, where \( N = \{1, 2, 3, 4, 5\} \); 4 lines, where \( J = \{1, 2, 3, 4\} \); a DRAG, where \( k_1 = \{1\} \); an ESAG, where \( k_2 = \{2\} \); an EVCS, where \( k_3 = \{3\} \); a DDGAG, where \( k_4 = \{4\} \); a REAG, where \( k_5 = \{5\} \), and an inelastic load. The studies are performed over 24 hours, \( T = \{1, 2, ..., 24\} \). EVs are available during Hours 16-24, \( T = \{16, 17, ..., 24\} \). Initial charge level of ESAG is 8MW. The following parameters are assumed: \( \eta = 2 \text{MW}, \ P_{\text{max}} = 10 \text{MW}, \ DR = 5 \text{MW}, \ E_{\text{int}} = 2 \text{MW}, \ ER_{\text{cap}} = 5 \text{MW}, \ ER_{\text{up}} = 0.5 \text{MW} \). Power production of REAG is considered to be \( 3 \text{MW} \) at all times and is located at Node 5. Also, the maximum power production of REAG is considered to be \( 3 \text{MW} \). Hourly energy prices, capacity up/down prices, and hourly regulation signals are generated by using hourly factors introduced in [17] and are given in [18]. Case studies below focus on uncertainty. Market outcomes in deterministic cases can be found in [18].

1) Single Source of Uncertainty: In this case, for simplicity, only one source of uncertainty is considered, which is the REAG production given in Table I. Wholesale real-time market prices are considered to be 2 \$/MWh higher than the corresponding day-ahead market prices. It is assumed the DSO can only buy energy from the real-time market. In two-stage stochastic programming, the first-stage LMP corresponds to the day-ahead market price, which is the dual variable of the power balance equation (30). The second-stage LMP corresponds to the real-time price, which is equal to the dual variable of power balance adjustment equation (38) divided by probability of occurrence of each scenario. Fig. 2 shows the first-stage (day-ahead) and second-stage (real-time) LMPs. Market participants are first settled by day-ahead LMPs. After
that, market participants which need real-time compensation due to their uncertainties are settled by real-time LMPs.

Fig. 3(a) shows the REAG’s second-stage (real-time) revenue in each scenario. In Scenario 3, REAG’s scheduled power in the day-ahead stage is the same as that in the real-time stage. Hence, there is no need for real-time correction. In other scenarios, REAG’s scheduled power in the day-ahead stage is higher than that in the real-time stage. This power deficiency should be compensated by purchasing from the wholesale real-time market. As a result, the REAG’s second-stage (real-time) revenue is negative, which means it purchases power from the wholesale real-time market. Fig. 3(b) shows the REAG’s first-stage (day-ahead) revenue, expected second-stage (real-time) revenue, and expected total revenue.

2) Multiple Sources of Uncertainties: As mentioned above, there are three sources of uncertainties including REAG production, inelastic load, and real-time prices. Random scenarios can be generated using scenario generation methods based on the probability distribution function. Scenario reduction methods can be applied to reduce computation burden. In this case, for simplicity, normal distribution in Fig. 4 with mean value $\mu$ and standard deviation $\sigma$ is considered as the probability distribution of random variables. Seven scenarios from $-3\sigma$ to $3\sigma$ are considered. The mean value of each random variable is assumed to be the same as its value in the deterministic case. The standard deviation $\sigma$ is considered to be 5%, 15%, and 8% for real-time prices, inelastic load, and REAG production, respectively. The REAG production scenarios are considered to change in the opposite direction of the real-time prices and inelastic load. In the second-stage (real-time), the price of selling energy to the wholesale market is considered to be 0.8 of the price of buying energy from it.

Fig. 5 shows the first-stage (day-ahead) LMPs and second-stage (real-time) LMPs in different scenarios. LMPs in Scenarios 1–3 equal the real-time prices of selling energy to the wholesale market, since in these scenarios, the demand is lower than the production in the retail market operated by the DSO. However, in Scenarios 5–7 the LMPs equal the real-time prices of buying energy from the wholesale market, since in these scenarios the demand is greater than the production.

3) Sensitivity Analysis: Sensitivity analysis is carried out on the REAG’s revenue with respect to changing the real-time prices in both previous case studies.

Fig. 6(a) shows the changes in REAG’s first-stage (day-ahead) revenue, expected second-stage (real-time) revenue, and total revenue with respect to changes in the real-time prices under one source of uncertainty. 25 sensitivity cases are simulated. In each case, the base-case wholesale real-time market prices are multiplied by $i$, where $i$ varies from 1 to 25. When $i = 1$, the REAG’s second-stage (real-time) compensation cost is very low. Hence, its first-stage (day-ahead) revenue is high. Also, the REAG’s second-stage (real-time) revenue is negative, which indicates the REAG buys power from the real-time market to compensate its power deficiency. Two factors affect the second stage revenues: 1) real-time prices; 2) amount of power deficiency that should be compensated in the real-time market. These two factors are negatively correlated with each other, which means when one factor increases the other factor decreases. The total effect of the two factors depends on the studied sensitivity case. For instance, when $i = 3$, effect of real-time price on second-stage revenue is higher than that of power deficiency.
After stage (real-time) revenue to increase when REAG production. This causes the REAG's expected second-cost becomes expensive. As a result, the DSO schedules the sale market. When inelastic load and REAG production by trading with the whole-production at its mean value and covers the variations of compensation cost is low. Hence, the DSO schedules the REAG varies from 1 to 25, which decreases the second-stage revenue. However, when \( i \) increases, the effect of power deficiency grows. Hence, the second-stage revenue becomes zero after \( i = 10 \). However, the REAG’s first-stage revenue and total revenue always decrease when the real-time prices increase.

Fig. 6(b) shows the changes in REAG’s first-stage (day-ahead) revenue, expected second-stage (real-time) revenue, and total revenue with respect to changes in the real-time prices under multiple sources of uncertainties. To increase REAG’s real-time compensation cost, REAG’s real-time selling/purchasing prices are multiplied/divided by \( i \), where \( i \) varies from 1 to 25. When \( i \) is small, the real-time compensation cost is low. Hence, the DSO schedules the REAG production at its mean value and covers the variations of inelastic load and REAG production by trading with the wholesale market. When \( i \) increases, the real-time compensation cost becomes expensive. As a result, the DSO schedules the REAG production at a lower level to avoid trading with the wholesale market and compensate inelastic load variation by REAG production. This causes the REAG’s expected second-stage (real-time) revenue to increase when \( i \) becomes greater. After \( i = 14 \), the DSO schedules the minimum production for REAG, which causes the curves to become constant.

IV. CONCLUSION

This paper proposes a two-stage stochastic programming DSO framework for coordination of DER aggregators to participate in the retail market as well as wholesale energy and regulation markets. Various kinds of DER aggregators are modeled in the proposed DSO framework. Case studies carried out on a small distribution network show key factors between the first-stage (day-ahead) and second-stage (real-time) LMPs. The REAG participates in day-ahead and real-time markets with uncertainties. Sensitivity analysis shows as the real-time price increases, the DSO schedules less power production to REAG as an uncertain market participant.

REFERENCES

[1] M. Di Somma, G. Graditi, and P. Siano, “Optimal bidding strategy for a der aggregator in the day-ahead market in the presence of demand flexibility,” IEEE Trans. Ind. Electron., vol. 66, no. 2, pp. 1509–1519, Feb 2019.
[2] A. Baringo, L. Baringo, and J. M. Arroyo, “Day-ahead self-scheduling of a virtual power plant in energy and reserve electricity markets under uncertainty,” IEEE Trans. Power Syst., vol. 34, no. 3, pp. 1881–1894, May 2019.
[3] M. F. Anjos, A. Lodi, and M. Tannene, “A decentralized framework for the optimal coordination of distributed energy resources,” IEEE Trans. Power Syst., vol. 34, no. 1, pp. 349–359, Jan 2019.
[4] G. Liu, Y. Xu, and K. Tomsovic, “Bidding strategy for microgrid in day-ahead market based on hybrid stochastic/robust optimization,” IEEE Trans. on Smart Grid, vol. 7, no. 1, pp. 227–237, Jan 2016.
[5] F. Lezama, J. Soares, P. Hernandez-Leal, M. Kaisers, T. Pinto, and Z. Vale, “Local energy markets: Paving the path toward fully transactive energy systems,” IEEE Trans. Power Syst., vol. 34, no. 5, pp. 4081–4088, Sep. 2019.
[6] H. T. Nguyen, L. B. Le, and Z. Wang, “A bidding strategy for virtual power plants with the intraday demand response exchange market using the stochastic programming,” IEEE Trans. Ind. Appl., vol. 54, no. 4, pp. 3044–3055, July 2018.
[7] H. Yang, S. Zhang, J. Qiu, D. Qiu, M. Lai, and Z. Dong, “Cvar-constrained optimal bidding of electric vehicle aggregators in day-ahead and real-time markets,” IEEE Trans. Ind. Informat., vol. 13, no. 5, pp. 2555–2565, Oct 2017.
[8] M. N. Faqiry, A. K. Zarabie, F. Nassery, H. Wu, and S. Das, “A day-ahead market energy auction for distribution system operation,” in 2017 IEEE International Conference on Electro Information Technology (EIT), May 2017, pp. 182–187.
[9] J. C. do Prado, H. Vakilzadian, W. Qiao, and D. P. F. Miller, “Stochastic distribution system market clearing and settlement via sample average approximation,” in 2018 North American Power Symposium (NAPS), Sep. 2018, pp. 1–6.
[10] S. Parhizi and A. Khodaei, “Interdependency of transmission and distribution pricing,” in 2016 IEEE Power Energy Society Innovative Smart Grid Technologies Conference (ISGT), Sep. 2016, pp. 1–5.
[11] R. Khalilisobehari and M. Wu, “Optimal participation of price-maker battery energy storage systems in energy, reserve and pay as performance regulation markets,” in 2019 North American Power Symposium (NAPS), 2019, pp. 1–6.
[12] California iso. [Online]. Available: https://goo.gl/bBGvVG
[13] J. Zhao, T. Zheng, E. Livinov, F. Zhao, and I. N. England, “Pricing schemes for two-stage market clearing models,” in Technical Conference: Increasing Real-Time and Day-Ahead Market Efficiency through Improved Software, FERC, 2015.
[14] A. Sadeghi-Mobarakeh, A. Shahsavari, H. Haghighat, and H. Mohsenian-Rad, “Optimal market participation of distributed load resources under distribution network operational limits and renewable generation uncertainties,” IEEE Trans. on Smart Grid, vol. 10, no. 4, pp. 3549–3561, July 2019.
[15] J. M. Morales, A. J. Conejo, H. Madsen, P. Pinson, and M. Zugno, Integrating renewables in electricity markets: operational problems. Springer Science & Business Media, 2013, vol. 205.
[16] M. E. Baran and F. F. Wu, “Network reconfiguration in distribution systems for loss reduction and load balancing,” IEEE Trans. Power Del., vol. 4, no. 2, pp. 1401–1407, April 1989.
[17] M. Mousavi, M. Rayati, and A. M. Ranjbar, “Optimal operation of a virtual power plant in frequency constrained electricity market,” IET Gener. Transm. Distrib., vol. 13, no. 11, pp. 2123–2133, 2019.
[18] M. Mousavi and M. Wu, “A dos framework for comprehensive market participation of der aggregators,” arXiv preprint arXiv:2006.06673, 2020.