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Distributed Bidding Strategy for an Aggregator Valuing Uncertain Prosumers in Energy and Ancillary Service Markets

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***Abstract*— Aggregators have an influential intermediary role to exploit the flexibility of prosumers like smart homes for procuring the required capacity of ancillary services to support power systems. Local generation and consumption uncertainties of prosumers affect their cost reduction objectives which in turn have a significant impact on the flexibility capacity provided by them. So, towards boosting the operational flexibility capacity in the market, the aggregator's bidding and remuneration frameworks should devise a valuing scheme of prosumers considering this impact to induce positive incentives relieving capacity uncertainties. This scheme, simultaneously, should observe data privacy concerns. To this end, this paper proposes a day-ahead distributed bidding strategy framework for an aggregator to participate in regulation and energy markets using a new rewarding scheme derived from a flexibility certainty valuing approach. This framework is developed within the Benders decomposition method, in which the aggregator performs valuing of prosumers in the master problem through their implicit information extracted from home energy management systems modeled in the subproblems. The performance of the framework to appropriately reward prosumers is presented through numerical results for an illustrative case study.**

***Index Terms*— Aggregator, Bidding strategy, Distributed optimization, Regulation market, Remuneration of prosumers.**

I. Introduction

The proliferation of renewable energies in power systems increases the need for ancillary services procured by electricity markets to support system frequency against generation variability [1]-[2]. Satisfying this growing need requires engaging demand-side flexibility resources provided by prosumers like smart homes, electric vehicles, and distributed generations [3]. In the nowadays deregulated power systems, aggregators as the intermediary agents between prosumers and the electricity market play an important role in the procurement of ancillary services [4]. These agents facilitate profitable participation in the markets, establish adequate capacity being allowed by the market regulations, and handle uncertainties caused by the market prices and available flexibility of prosumers. These important tasks are aimed by the bidding strategy of the aggregator in the markets [5]. Regarding different ancillary services, in this work, we focus on the regulation service (i.e, automatic frequency regulation).

The uncertainties of prosumers' resources and market prices highly impact the efficient exploitation of the prosumers' flexibility and the economic profit from participating in the regulation market [6]. Modeling of these uncertainties has been addressed in the bidding strategy of the aggregator in the literature [7]-[11]. Scenario-based stochastic bidding strategies have been introduced based on nonlinear and linear optimization models by the authors in [7]-[8]. They studied the impact of uncertainties of generation and consumption patterns of Photovoltaic (PV) and residential loads on bided power and revenues in the regulation market. To relieve the adverse impact of resource uncertainties on the economic revenues of prosumers in the regulation market, the complementary energy storage capability of devices like Energy Storage Systems (ESSs) and electric vehicles with uncertain prosumers has been employed in [9]-[11]. The decision-making of the developed frameworks, besides optimizing bidding strategy, aims at optimizing the local objective function of prosumers like operation cost in the energy market and comfort level against their resource uncertainties. So, the flexibility capacity of prosumers, and therefore obtained revenues in the regulation market are affected by these local objectives. These objectives are impacted by different uncertainty levels of different prosumers. On the other hand, the aggregator optimization model rewards all prosumers, uniformly, based on the allocated capacity shares at the same market price. This optimization approach discriminates in favor of high-uncertain prosumers who despite inflicting higher uncertainty on the whole optimization problem due to their local objectives, they are unfairly rewarded at the same regulation market price as low-uncertain prosumers. This causes negative incentives for low-uncertain prosumers in keeping to provide better flexibility capacity. Because this capacity is used with the same price for resolving the adverse impact of high-uncertain prosumers, who try to optimize their local objectives, on the total flexibility capacity and bided power. Thus, it lacks positive incentives for high-uncertain prosumers to alleviate the uncertainty of their flexibility capacity in the long term.

Preliminary studies have been performed to remunerate the prosumers taking into account their different levels of flexibility characteristics in the energy market. Two general types of remuneration schemes including price-based and incentive-based methods have been discussed in [12], which allocate power to prosumers in respect of their responsiveness level to demand response programs. The authors in [13] cluster prosumers and apply different tariffs for remuneration of them according to their elasticity and operation flexibility properties. A cluster-based approach, also, was introduced in [14] and integrated into the optimization model of bidding strategy. This study does not propose a remuneration mechanism, and only prosumers with better flexibility characteristics are more likely to be clustered in groups with higher exploitation of flexibility. The remuneration scheme proposed in [15] for storage-equipped prosumers is based on their trustworthiness to provide flexibility but disregards the effect of prosumers' uncertainties in its mathematical model to allocate flexibility capacity considering their uncertainty. The capability of adjusting power from baseline is modeled in [16] to specify the remuneration of prosumers regardless of their uncertainty. The scope of these studies is limited to the energy market, and lacks a fair mechanism to consider uncertainties impact on the flexibility capacity and remuneration as mentioned before.

Regarding the aforementioned assessments, the need for a solution to resolve the drawback of remuneration issues for prosumers in the regulation market emerges. While the envisaged method must consider the uncertainty performance of prosumers, their data privacy concerns should also be observed. Distributed optimization methods have been employed to observe this concern in the bidding problem [17]-[19]. In these studies, the same obstacle of previous methods in contemplating the prosumers' uncertainty impact still exists. Also, these methods are not compatible to viably integrate valuing schemes of prosumers and implicit information sharing mechanism between prosumers and the aggregator.

In this paper, a new day-ahead (DA) distributed stochastic framework for the bidding strategy of an aggregator of smart homes is developed to participate in the regulation and energy markets. In this framework, the smart homes equipped with ESS and PV are valued based on their uncertainty characteristics affected by their local objectives. The developed distributed framework is linearly modeled based on Bender's decomposition approach. This study contributes to the current research as follows:

- Developing distributed bidding strategy for an aggregator valuing smart homes based on Bender's decomposition;
- Developing remuneration and bided power sharing schemes respecting the uncertainty characteristics of smart homes' provided power

The rest of the paper is as follows: Section II presents the overall developed framework, mathematical formulation, and the new rewarding scheme. In section III the case studies are introduced, and the implementation results of the developed method through these case studies are discussed. Finally, section IV concludes the paper by unveiling remarks and proposing future approaches to develop the method.

II. Developed Framework: Mathematical Formulation

A. Overall Framework

The developed framework aims at modeling the optimal DA strategy of an aggregator managing smart homes to participate in the regulation and energy markets. To implement the framework in a distributed manner, the Aggregator Management System that includes a model (ASM) communicates with Home Energy Management Systems (HEMSs) of smart homes to send bid power shares and to receive HEMSs' contribution response in realizing these shares. The ASM and HEMSs are modeled within the master and subproblems as depicted in Fig. 1 and iteratively solved by Bender's decomposition method introduced in [20], respectively. The HEMSs trying to reduce their operation cost, are responsible to tackle the uncertainty of their generation and consumption data. In each iteration, they calculate and send their optimality and feasibility cuts to the ASM. On the other hand, the ASM finds the optimal participation strategy in the markets and power bid shares of homes considering market price uncertainties and the received cuts from HEMSs. Also, to evaluate the flexibility performances of homes, ASM requests dual variables of the HEMSs' regulation capacity constraints realized in different scenarios for optimizing local objective functions. This information, besides preserving the privacy of homes' uncertainty characteristics, is employed to devise a valuing scheme. This scheme defines the fair remuneration mechanism for homes provided bid shares in the regulation up and down markets based on the standard deviation of the dual variables. So, the ASM using this valuing scheme can define the regulation revenue per provided power for the homes considering their uncertainty impact on local objectives.

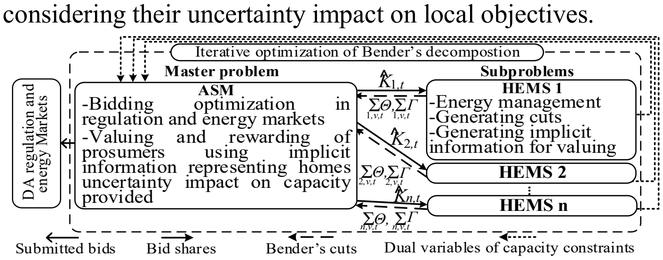

Fig. 1. Overall framework of the proposed method

B. Mathematical Model

The overall objective function of the framework F^{FW} including participation revenue in energy and regulation markets F^{ASM} and the sum of operation cost of homes F_h^{Home} specified by h is modeled by Eq. (1).

$$Min \quad F^{FW} = F^{ASM} + \sum_h F_h^{Home} \tag{1}$$

Eq. (1) is decomposed to ASM and HEMS problems which calculate the optimal solution of bidding strategy and operation cost of homes by the master problem and subproblems presented in the following subsections, respectively.

1) Subproblems: HEMSs

The HEMSs find the optimal DA operation scheduling of home h to reduce their operation cost according to Eq. (2)

$$Min \qquad F_h^{Home} = \sum_v \omega_{h,v}^H \left(\sum_t \rho_t^g P_{h,v,t}^g + C_{h,v}^{\deg}\right) \tag{2}$$

Subject to

$$C_{h,v}^{\deg} = 1000 Q_h^{bat} \left(-m_h^{bat} / 100 \right) \left(E_{h,v}^{tp} / C^{ESS} \right) \quad (3)$$

$$E_{h,v}^{tp} = \sum_t \left(P_{h,v,t}^{ESC} + P_{h,v,t}^{ESD} \right) \quad (4)$$

$$P_{h,v,t}^{g} + P_{h,v,t}^{PV} + P_{h,v,t}^{ESD} + \hat{P}_{h,t}^{Buy} = P_{h,v,t}^{L} + P_{h,v,t}^{ESC} + \hat{P}_{h,t}^{Sell} : \pi_{h,v,t}^{b} \quad (5)$$

$$P_{h,v,t}^{PV} \le P_{h,v,t}^{PV,\max} : \pi_{h,v,t}^{PV} \quad (6)$$

$$P_{h,v,t}^{g} \le P^{g,\max} + \hat{P}_{h,t}^{Sell} - \hat{P}_{h,t}^{Buy} : \pi_{h,v,t}^{g-} \quad (7)$$

$$P_{h,v,t}^{g} \ge -P^{g,\max} + \hat{P}_{h,t}^{Sell} - \hat{P}_{h,t}^{Buy} : \pi_{h,v,t}^{g+} \quad (8)$$

$$E_{h,v,t} = E_{h,v,t-1} + \xi^{ch} P_{h,v,t}^{ESC} \Delta t - \left(1 / \xi^{dch} \right) P_{h,v,t}^{ESD} \Delta t \quad : \pi_{h,v,t}^{E} \quad (9)$$

$$E_h^{\min} \le E_{h,v,t} \le E_h^{\max} \quad : \pi_{h,v,t}^{Ecap+}, \pi_{h,v,t}^{Ecap-} \quad (10)$$

$$P_{h,v,t}^{ESD} \le P_{h,v,t}^{ES,\max} \quad : \pi_{h,v,t}^{PDcap} \quad (11)$$

$$P_{h,v,t}^{ESC} \le P_{h,v,t}^{ES,\max} \quad : \pi_{h,v,t}^{PCcap} \quad (12)$$

$$\Delta t\, \hat{P}_{h,t}^{RGUH} \le E_{h,v,t} + \Delta t \left(P_{h,v,t}^{PV,\max} - P_{h,v,t}^{PV} \right) \quad : \pi_{h,v,t}^{RGU} \quad (13)$$

$$\Delta t\, \hat{P}_{h,t}^{RGDH} \le \left(E_h^{\max} - E_{h,v,t} \right) + \Delta t \left(P_{h,v,t}^{PV} + P_{h,v,t}^{g} \right) \quad : \pi_{h,v,t}^{RGD} \quad (14)$$

The subproblem takes into account the uncertain load and generation data with the probability of $\omega_{h,v}^{H}$ over scenarios of $v \in V$ in time $t \in T$ as well as received fixed variables of power bid shares set $\hat{K} = \left\{ \hat{P}_{h,t}^{RGUH}, \hat{P}_{h,t}^{RGDH}, \hat{P}_{h,t}^{Sell}, \hat{P}_{h,t}^{Buy} \right\}$ allocated by ASM. In Eq. (2), $P_{h,v,t}^{g}$ and $C_{h,v}^{\deg}$ calculated by equations (3)-(4) present the power bought from the grid at Time of Use (ToU) price of ρ_t^g and the degradation cost of the ESS of home *h* at time *t* in scenario *v*, respectively. Eq. (5) models the power balance at each time interval *t* in scenario *v*. $P_{h,v,t}^{PV}$, $P_{h,v,t}^{L}$, $P_{h,v,t}^{ESC}$, and $P_{h,v,t}^{ESD}$ stand for the power of PV, load, ESS charging, and ESS discharging, respectively. The capacity constraints of PV and the coupling point of the home with the grid are modeled by equations (6)-(8). The stored energy in ESS is calculated according to Eq. (9). The ESS capacity limitations on the state of energy, discharging power, and charging power are modeled by equations (10)-(12), respectively. Finally, the binding constraints of the regulation up and down power shares are denoted by equations (13) and (14), respectively. Regarding all of the constraints of a subproblem, the dual variables of constraints are denoted in front of that, which are used to generate feasibility and optimality cuts required by the master problem. These cuts are sent back to the ASM problem. Two key dual variables of regulation capacity constraints, $\pi_{h,v,t}^{RGU}$ and $\pi_{h,v,t}^{RGD}$, are utilized by ASM to perform valuing scheme based on the uncertainty characteristics of homes, which is presented in section B.3.

2) Master problem: ASM

The ASM aims at finding the optimal bidding strategy to participate in the regulation up and down as well as energy markets. Solving the ASM problem gives the power bid shares set $K = \left\{ P_{h,t}^{RGUH}, P_{h,t}^{RGDH}, P_{h,t}^{Sell}, P_{h,t}^{Buy} \right\}$ to be sent to the HEMSs. The objective function of the ASM is denoted in Eq. (15). Eq. (16) relates the master problem objective function to the bidding objective function in Eq. (17). In Eq. (17), R_s^{EM} and R_s^{RGM} stand for revenue obtained in the energy and regulation markets in the price scenario *s* with an associated probability of ω_s^M. The revenue of energy and regulation markets are modeled by equations (18) and (19), respectively. In these equations P_t^{EMS}, P_t^{EMB}, P_t^{RGU} and P_t^{RGD} present the power bids for energy selling, energy buying, regulation up, and regulation down at time *t*, respectively; where the $\rho_{s,t}^{EM}$, $\rho_{s,t}^{RGU}$, and $\rho_{s,t}^{RGD}$ are the uncertain market prices of energy, regulation up, and regulation down over the scenario $s \in S$ at time *t*, respectively. If ASM provides regulation up and down power at time *t*, the associated binary variables γ_t^{RGU} and γ_t^{RGD} should be activated which enforce the bids to obey the market minimum bid rules $P_{\min}^{RGU}$ and $P_{\min}^{RGD}$. This mechanism is modeled by equations (20)-(23). In these equations, *M* is a big number. Equations (24)-(27) denote that the power bids in the regulation and energy markets should be equal to the capacity provided by the homes. The power share of energy bids allocated to homes should be either selling or buying, which is modeled by equations (28) and (29), respectively. The equation sets (30) and (31) construct the optimality and feasibility cuts using the dual variables set $\pi_{h,v,t}$ found by subproblems, respectively.

$$Min \quad F^{FW} \quad (15)$$

Subject to

$$F^{FW} \ge F^{ASM} \quad (16)$$

$$F^{ASM} = -\sum_s \omega_s^M \left(R_s^{EM} + R_s^{RGM} \right) \quad (17)$$

$$R_s^{EM} = \sum_t \rho_{s,t}^{EM} \left(P_t^{EMS} - P_t^{EMB} \right) \quad (18)$$

$$R_s^{RGM} = \sum_t \left(\rho_{s,t}^{RGU} P_t^{RGU} + \rho_{s,t}^{RGD} P_t^{RGD} \right) \quad (19)$$

$$P_t^{RGU} \le M \gamma_t^{RGU} \quad (20)$$

$$P_t^{RGD} \le M \gamma_t^{RGD} \quad (21)$$

$$P_t^{RGU} \ge P_{\min}^{RGU} \gamma_t^{RGU} \quad (22)$$

$$P_t^{RGD} \ge P_{\min}^{RGD} \gamma_t^{RGD} \quad (23)$$

$$P_t^{EMS} = \sum_h P_{h,t}^{Sell} \quad (24)$$

$$P_t^{EMB} = \sum_h P_{h,t}^{Buy} \quad (25)$$

$$P_t^{RGU} = \sum_h P_{h,t}^{RGUH} \quad (26)$$

$$P_t^{RGD} = \sum_h P_{h,t}^{RGDH} \quad (27)$$

$$P_{h,t}^{Sell} \le M \left(1 - \delta_{h,t} \right) \quad (28)$$

$$P_{h,t}^{Buy} \le M \delta_{h,t} \quad (29)$$

$$F^{FW} \ge F^{ASM} + \sum_{h,v,t} \left(\Theta_{h,v,t} \left(K_{h,v,t} \right) \Big|_{\pi_{h,v,t}} \right) \quad (30)$$

$$\sum_{v,t} \left(\Gamma_{h,v,t} \left(K_{h,v,t} \right) \Big|_{\pi_{h,v,t}} \right) \le 0 \quad (31)$$

The developed framework allocates revenues in the regulation market for the homes based on their uncertainty characteristics. So, the new rewarding scheme is presented in the following which should be included in the ASM problem.

3) Rewarding Scheme

To attain an indication expressing the impact of homes' uncertainties imposed by the HEMSs local decision, on the capacity limitations for regulation power bid shares, the normalized inverse of the standard deviation of the regulation capacity constraints over scenarios *v* is considered. In order to calculate uncertainty valuing constants $u_{h,t}^{RGU}$ and $u_{h,t}^{RGD}$ the normalized inverse of the standard deviation of the dual variables $\pi^{RGU}_{h,v,t}$ and $\pi^{RGD}_{h,v,t}$ (derived from Eq. (13)-(14)), is used as formulated in Eq. (32) and (33) for regulation up and down, respectively. According to these equations, the lower the standard deviation of regulation capacity constraint over the scenarios, the higher uncertainty valuing constant.

$$u^{RGU}_{h,t} = \left(\sigma_{h,t}\left(\pi^{RGUH}_{h,v,t}\right) \Big/ \hat{P}^{RGUH}_{h,t} \right)^{-1} \tag{32}$$

$$u^{RGD}_{h,t} = \left(\sigma_{h,t}\left(\pi^{RGDH}_{h,v,t}\right) \Big/ \hat{P}^{RGDH}_{h,t} \right)^{-1} \tag{33}$$

To find the uncertainty valuing constants, the decomposed problems of sections *B.1* and *B.2* are executed. Then, these constants are calculated by the resultant dual variables of regulation capacity constraints of subproblems.

To devise a new rewarding scheme based on the uncertainty valuing constants, an assumption of allocating more revenue per power share to the low-uncertain home is adopted. To this end, for instance, the derivation of equations (34) and (35) for regulation up are considered. In these equations, a rewarding coefficient $U^{RGU}_{h,t}$ is added to the reward equation, $R^{RGUH}_{h,t}$, for home h in time t. Considering the binding equation of (35), which enforces equality of total revenue obtained from regulation up market and total revenue paid to the homes, the constraint of Eq. (36) can be derived. Applying the rewarding mechanism using the uncertainty valuing constants, the relation among $U^{RGU}_{h,t}$ for different homes should satisfy the constraint of Eq. (37). A similar derivation can be also performed for the regulation down to conclude equations (39) and (40). Consequently, equations (36)-(37) and (39)-(40) are added as additional constraints to the master problem, ASM.

$$R^{RGUH}_{h,t} = \left(U^{RGU}_{h,t}\rho^{RGU}_{s,t}\right)P^{RGUH}_{h,t} \tag{34}$$

$$\sum_h \left(\left(U^{RGU}_{h,t}\rho^{RGU}_{s,t}\right)P^{RGUH}_{h,t}\right) = \rho^{RGU}_{s,t}P^{RGU}_{t} \tag{35}$$

$$\sum_h \left(U^{RGU}_{h,t}P^{RGUH}_{h,t}\right) = P^{RGU}_{t} \tag{36}$$

$$U^{RGU}_{h,t}u^{RGU}_{h',t} = U^{RGU}_{h',t}u^{RGU}_{h,t} \tag{37}$$

$$R^{RGDH}_{h,t} = \left(U^{RGD}_{h,t}\rho^{RGD}_{s,t}\right)P^{RGDH}_{h,t} \tag{38}$$

$$\sum_h \left(U^{RGD}_{h,t}P^{RGDH}_{h,t}\right) = P^{RGD}_{t} \tag{39}$$

$$U^{RGD}_{h,t}u^{RGD}_{h',t} = U^{RGD}_{h',t}u^{RGD}_{h,t} \tag{40}$$

III. Case Studies and Discussion

A. System Data

For illustrative purposes, the developed framework is implemented on a system of an aggregator and two clusters of homes namely HC1 and HC2. The market and home data are taken from the ERCOT market [21] and homes of Austin, Texas in the spring of 2021, respectively. Each home cluster includes 400 homes. Fig. 2 demonstrates the average market prices of energy and regulation for 10 scenarios. The available PV power and daily load profiles for home clusters are illustrated in figures 3 and 4 [22]-[23], which consider 5 scenarios presented by hourly boxplot distributions. The scenarios were constructed through scenario generation and reduction processes based on Mont-Carlo and Fast-forward selection methods [24], respectively. Fig. 5 shows the TOU energy prices. TABLE I presents the specifications of the home clusters' ESSs [25].

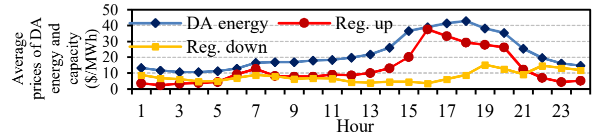

Fig. 2. Daily average capacity prices in energy and regulation markets.

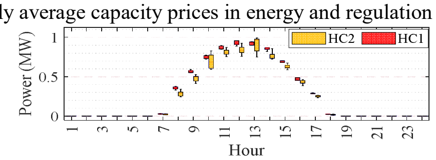

Fig. 3. Available PV power of home clusters with hourly distribution.

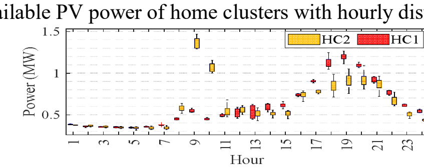

Fig. 4. Daily load profile of HCs with hourly distribution.

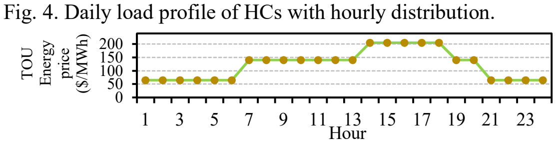

Fig. 5. TOU energy prices.

TABLE I. Specifications of ESSs

Parameter	Value	Parameter	Value
Capacity (MWh)	4.5	Max. SOC	0.9
Rating power (MW)	3	Min. SOC	0.1
Capital cost (Q) ($/MWh)	300	Initial Energy (MWh)	1
Life per cycle (m) (%)	-0.003	ξ^{ch}, ξ^{dch}	0.95

B. Case Studies and Results

To assess the performance of the developed framework and the rewarding scheme, two case studies are adopted as follows.

Case1: Bidding strategy for the aggregator without new rewarding scheme (Equations (1)-(31));

Case2: Considering the new rewarding scheme in the proposed aggregator bidding strategy (Equations (1)-(31), (36)-(37), (39)-(40))

The developed framework was implemented on General Algebraic Modeling System (GAMS), and was solved by CPLEX 12.5 in a system with a Core i7 2.3GHz CPU. The results of the case studies are discussed in the following.

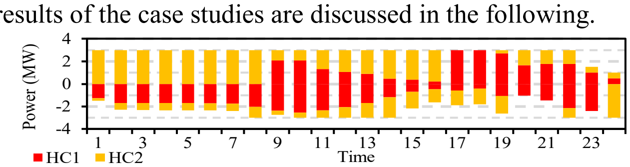

Fig. 6. Power bids and HCs bid shares in regulation up (positive) and down (negative) markets in Case1.

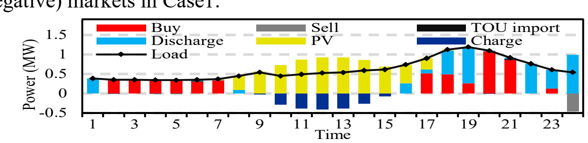

Fig. 7. HC1 power shares in Case1.

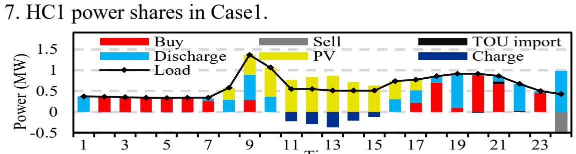

Fig. 8. HC2 power shares in Case1.

The bidding strategy and power shares of HCs for regulation up and down are illustrated in Fig. 6 for Case1. Also, figures 7 and 8 show local power shares among HC1 and HC2, respectively. According to these figures, the dependency of the regulation capacity provided by each HC to its local flexibility constraints realized by the HCs' load, generation, charging, and discharging patterns of ESS can be seen. For instance, the morning peak load of HC2 and the needed discharging energy limit the regulation up the capacity of midday hours for this HC when the ASM allocates more capacity to HC1. However, due to the high daily energy consumption of HC2, more regulation up power share is daily assigned to this HC to reduce its higher total cost. The higher uncertainty of HC2's load and generation in comparison with HC1, which can be seen in figures 3 and 4, is also involved in this cost reduction decision, constraining HC2's flexibility capacity more. So, HC1 contributes in these situations with lower uncertainty of flexibility capacity to increase whole aggregator profitability. TABLE II presents the numerical results of two cases. As it can be seen, the imposed standard deviation of HC2 on both regulation up and down capacity constraints is worse than HC1 in Case1. While, despite the healing behavior of HC1, it is rewarded with the same price with HC2 as the current framework of aggregators modeled in Case1 works. This approach creates no positive incentives for low-performance prosumers to improve their available flexibility capacity characteristics. Also, it discourages high-performance prosumers that better follow the scheduling of their resources.

TABLE II. COMPARATIVE NUMERICAL ANALYSIS OF CASE STUDIES

Point of comparison		Case 1 HC1	Case 1 HC2	Case 2 HC1	Case 2 HC2
Regulation up	Standard deviation of capacity	8.4	10.66	8.25	9.43
	Capacity share (MWh)	23.96	44.53	24.86	41.00
	Revenue ($)	401.6	458.2	436.7	407.5
	Mean revenue per capacity ($/MW)	16.76	10.3	17.56	9.9
	Mean rewarding Coeff. ratio (HC1/HC2)	-		1.13	
Regulation down	Standard deviation of capacity	18.92	18.94	14.07	17.50
	Capacity share (MWh)	36.00	21.29	29.48	25.10
	Revenue ($)	280.5	164.5	261.6	167.7
	Mean revenue per capacity ($/MW)	7.8	7.7	8.87	6.67
	Mean rewarding Coeff. ratio (HC1/HC2)	-		1.6	
Total regulation revenue of HC ($)		682.1	622.8	698.2	575.1
Energy revenue of HC ($)		-146.4	-134.5	-143.9	-134.1
Total profit of HC ($)		535.64	488.21	554.37	441.01

To remedy the incentivizing drawback in Case1, the developed rewarding scheme based on the obtained standard deviation of HCs' capacity constraints is applied in Case2. According to TABLE II, higher rewarding coefficients are realized for HC1 which has better flexibility performance due to the lower uncertainty of load and generation. The capacity standard deviations in Case2 are decreased for both HCs in regulation up and down, resulting in a total reduction of 13.6%. Because of the low exploitation of HC2 flexibility capacity in this case, the impact of that is less sensed in Case2, showing a more reduced standard deviation value. Regarding the rewarding goal of the developed framework, the mean revenue per capacity for better prosumer, which is HC1, is enhanced in Case2 for both regulation up and down, while this value is lowered for HC2 (highlighted in blue). As a result, the total regulation revenue (highlighted in green) reveals that the revenue share streams to HC1 more than HC2. Figures 9-11 demonstrate the illustrative results of Case2. For instance, higher rewarding coefficients make more revenue come from higher power shares for HC1 in peak-load time intervals with high prices of the regulation up capacity. Finally, preserving the energy procurement cost reduction objective for both HCs, in spite of decreasing total revenue for low-performance prosumer HC2, the corresponding value for HC1 as the high-performance prosumer is proliferated. Hence, this approach causes positive incentives for prosumers providing better and weak flexibility performances to keep and amend their flexibility characteristics in long-term, respectively.

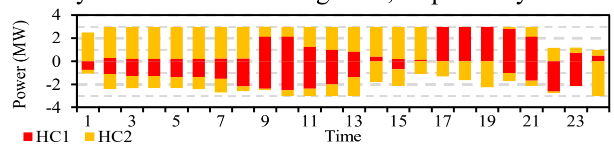

Fig. 9. Power bids and HCs bid shares in regulation up (positive) and down (negative) markets in Case2.

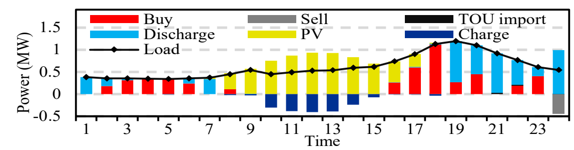

Fig. 10. HC1 power shares in Case2.

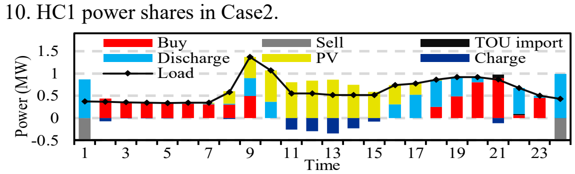

Fig. 11. HC2 power shares in Case2.

IV. CONCLUSION

A distributed framework for bidding of an aggregator valuing the performance of smart homes' flexibility uncertainty in energy and regulation markets was developed in this paper. This framework was linearly modeled based on the Benders decomposition method which, besides preserving the privacy of smart homes data, generates implicit information used to evaluate the flexibility capacity uncertainty of smart homes and to devise a new rewarding scheme. This rewarding scheme, evaluates the uncertainty impact arising from the local cost reduction objective of homes on provided flexibility capacity based on the standard deviation of capacity constraints. The numerical and illustrative analysis indicated that the new valuing and rewarding schemes induce positive incentives to improve flexibility capacity performance, resulting in higher revenue for high-performance prosumers and a lower uncertainty impact on the regulation bids share of all prosumers. To improve the developed method, it can be proposed to integrate valuing scheme based on the standard deviations of capacity constraints into a dynamic optimization process for finding rewarding coefficients instead of pre-calculating them.

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