FLEXIBILITY PROVISION BY DISTRIBUTED PROSUMERS IN WHOLESALE ELECTRICITY MARKET

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Abstract

The advancements in the smart grid flexibility is increasingly engaging the distributed prosumers (DPs), which are customer owned resources that can produce and consume energy while interacting with the grid. A particular characteristic of these prosumers which makes them suitable candidate for enhancing the grid flexibility is their high ramp rate. A new ancillary service product some USA independent system operators (ISOs) have launched, named flexible ramping product, enhances the flexibility of the grid by assuring sufficient ramp rates. This paper proposes a novel framework for the participation of the DPs through a mediator (aggregator) in the day-ahead energy and flexibility markets. The proposed interaction framework is a bi-level optimization, which by using the single-level mixed integer linear programming Karush-Kuhn-Tucker (KKT) conditions of the lower level optimization is converted to a single-level mixed integer linear programming (MILP) optimization. In order to encourage the DPs to participate in this framework, the aggregator must assure each agent that their profitability will be higher than the profit they could make by trading energy based on distribution level energy tariffs. The simulation results verify the participating DPs and grid market operator both benefiting.

1 Introduction

Renewable energy resources (RESs) have become an indispensable part of the grid during the past decades. However, their power generation uncertainty, mainly in wind and solar generation, if not integrated appropriately, may compromise the operation and planning of the power grid and may lead to unfavourable electricity prices or widespread load curtailments [1], [2]. To overcome this issue, some independent system operators (ISOs) have introduced a new flexible ramping product (FRP) which enhances the flexibility of the grid by assuring sufficient amounts of ramp up and ramp down rates to cover the uncertainties of the net-load. Such product capabilities are flexible ramp up (FRU) and flexible ramp down (FRD), respectively [3].

Among others, the advancements in the smart grid are toward engaging distributed prosumers (producer/consumer) which are becoming prominent nowadays. By defining appealing incentives and operation methods, the distributed prosumers (DPs) are encouraged to schedule their resources properly to help improve the grid conditions [4]. These resources include, but not limited to, battery energy storage system (BESS), photovoltaic panel (PV), plug-in electric vehicle (PEV), and adjustable and deferrable load [5]. Different incentive schemes aiming at further engaging DPs with the grid are discussed in the literature. In [6] a price-responsive model for the smart buildings' load to minimize the energy cost considering the comfort level of building occupants is proposed. The authors in [7] have leveraged the ability of DPs in distribution grid congestion management be designing a day-ahead market framework. In [8], the possible profits for DPs out of ancillary services provision for the grid, such as resilience enhancement and frequency regulation are discussed.

Most of the DPs' resources are fast-responding meaning they can meet the FRP procurement requirements properly [9]. Since DPs are relatively small capacity, they cannot directly participate in the wholesale electricity market (WEM). A mediator envisioned as the load serving entity (LSE) is required to aggregate their offers and participate in the market on their behalf—see Fig. 1. Since both the LSE and DPs (agents) are privately-owned, their efficacy is directly tied with their financial profitability. Hence, the aggregator attempts to make profit by offering optimal energy and FRP price sets to the agents. Likewise, each agent attempts to maximize its own profit by offering energy and reserve amount sets to the aggregator.

Each agent can also make profit if they are not engaged in this framework. Indeed, they can generally schedule and trade energy based on the distribution level energy tariffs [10]. Hence, in the aggregator/agent framework, the aggregator must assure each agent that their profitability will be higher if they participate in the WEM.

In order to cover the mentioned issues, in this paper we propose an aggregator/agent framework in which the aggregator provides the optimal model for the participation of agents in the day-ahead energy and flexibility ancillary service products. Also, it assures the agents that their expected profit will be higher than in the case where they trade energy individually and based on the distribution level energy prices. This framework is a bi-level non-linear optimization which based on the methods used in [11], can be converted to a single-level mixed integer linear programming (MILP) using Karush-Kuhn-Tucker (KKT) conditions of the lower level optimization.

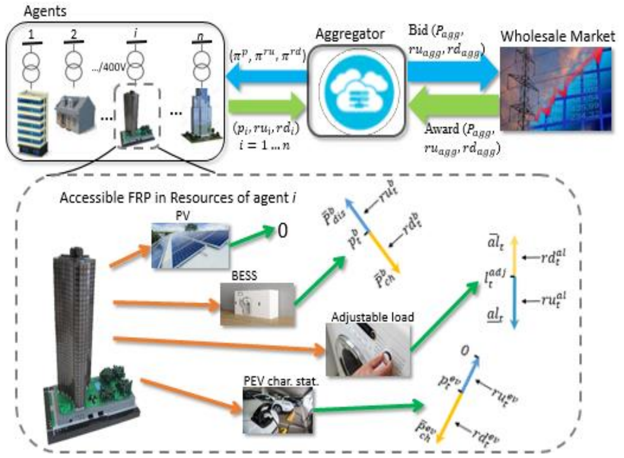

Figure 1 DP FRP capability and interaction with market

2 The Proposed Framework

Based on the FRP market product, the ISO requests for sufficient ramp capacities to assure the supply is able to follow the demand in real-time. The FRP providers are compensated for the provided ramp up and ramp down capacities leading to deviation from their optimal schedules. DPs' features properly fit the FRP market requirements. Figure. 1 shows a typical DP and the ability of its resources in FRU and FRD provision:

- The BESS can provide FRU and FRD up to $\bar{P}_{dis} - p_t$ and $p_t - \bar{P}_{ch}$, respectively.
- Each PEV during the time that is connected to the charging station can provide FRU up to p_t and FRD up $\bar{P} - p_t$.
- Lastly, the adjustable load is able to vary between its minimum and maximum comfortable ranges.

Note, the PEVs, due to technical and economic issues are only considered to work in charging mode. In case the discharging mode is available, they may procure FRU up to $|\bar{P}_{dis} - p_t|$.
A flowchart for the proposed framework describes the process. The process initiates the aggregator forecasting the DAM energy and FRP prices. Next the aggregator runs the self-scheduling optimization (the lower level optimization) of agent *i* with the distribution level energy prices. By doing so, it evaluates the profit the agent could make if it did not participate in the WEM framework and traded energy based on the distribution level prices. By adding the minimum profit constraint to the bi-level optimization, it assures each agent that its profit will be higher than trading energy with the distribution grid. Then, the aggregator runs the bi-level optimization and participates in the WEM.

Flowchart for the Aggregator's Participation in WEM	
1:	Forecast WEM energy, FRU & FRD prices.
2:	***for*** *a*=1 *: n*
3:	**Input:** Gather data of the resources of agent *a* including BESS, PEV, PV, Load data.
4:	Forecast day-ahead PEV schedule, PV generation and load level for agent *a*.
5:	Run self-optimization for agent *a* based on the distribution energy prices and set the evaluated profit as *min prof.*
6:	***end for***
7:	Run bi-level optimization converted to MILP and add the *min prof* constraint of agents.
8:	Participate in the day-ahead energy and FRP market.
9:	Send the awarded schedules to agents.

3 Mathematical Formulation

The proposed optimization problem consists of two levels as presented below. As this optimization is further simplified and converted to a MILP using KKT conditions of the lower level optimization, the lower level constraints are presented along with their Lagrange multipliers.

3.1 Upper Level Optimization (Aggregator)

At the upper level the aggregator attempts to maximize its own profitability (C^{agg}) by offering optimal energy and FRP prices to the agents:

$$C^{agg} = \max \sum_t \sum_a \{p^a_t \theta^p_t + ru^a_t \theta^{ru}_t + rd^a_t \theta^{rd}_t - p^a_t \pi^p_t - ru^a_t \pi^{ru}_t - rd^a_t \pi^{rd}_t\} \tag{1}$$

Where π and θ stand for the price offered by the aggregator to agents and the forecasted WEM prices, respectively. Notations p, ru, rd denote the output power, procured FRU and FRD of the agents. Also, indices t and a represent time-intervals and agents. The decision variables the aggregator may adjust to maximize its profit are:

$$DV_{agg} = \{\pi^p_t, \pi^{ru}_t, \pi^{rd}_t\}$$

3.2 Lower Level Optimization (Agents)

Each DP agent attempts to maximize its profit (C^{dpa}) by optimally scheduling its own resources using the following objective function:

$$C^{dpa} = \max \sum_t \left\{ p^a_t \pi^p_t + ru^a_t \pi^{ru}_t + rd^a_t \pi^{rd}_t + pru^a_t \pi^p_t - \varphi^l lc_t + \delta^{ev}_t \sum_k p^{ev}_{k,t} \right\} \tag{2}$$

In which p^a_t is the injected power to the grid. Parameters φ^l and lc_t stand for the value of lost load (VOLL) and the curtailed load. Variable pru^a_t denotes the portion of FRU expected to be summoned for energy generation under ancillary service. Lastly, δ^{ev}_t represents the contract with PEV owners and k is the set of EVs. In case the PEV and smart building owner is the same, the last term may be omitted. The Objective function (2) $\forall t$ is subject to the constraints below:

Power balance of the agent is enforced by:

$$p^a_t + pru^a_t - prd^a_t - p^b_t - p^{pv}_t + d_t + \sum_k p^{ev}_{k,t} = 0; \qquad \lambda^p_t \tag{3}$$

Where d_t denotes the agent's electric load. Also, pru^b_t and prd^b_t are the expected portions of FRU and FRU that may be summoned for energy dispatch in the real-time market (RTM). The BESS's power (p^b_t) is assumed positive in discharging mode. The PEV are assumed to only work in charging mode, that is, $p_{k,t}^{ev} \geq 0$. The PV power output is considered to be uncontrollable and all its energy is either consumed by the agent or injected to the grid.

The FRU and FRD the agent procures equal the summation of the amounts procured by BESS, PEVs and adjustable load:

$$ru_t^a = ru_t^b + \sum_k ru_{k,t}^{ev} + ru_t^{al}; \qquad \lambda_t^{ru} \tag{4}$$

$$rd_t^a = rd_t^b + \sum_k rd_{k,t}^{ev} + rd_t^{al}; \qquad \lambda_t^{rd} \tag{5}$$

In which notations *b*, *ev*, and *al* stand for BESS, PEV and adjustable load. The agent is committed to supplying and consuming energy under the FRU and FRD requirements in the RTM enforced by the following constraints:

$$pru_t^a = ps_t^{ru} \times ru_{t-1}^a; \qquad \lambda_t^{psu} \tag{6}$$

$$prd_t^a = ps_t^{rd} \times rd_{t-1}^a; \qquad \lambda_t^{psd} \tag{7}$$

$$pru_t^a = pru_t^b + pru_t^{ev} + pru_t^{al}; \qquad \lambda_t^{pru} \tag{8}$$

$$prd_t^a = prd_t^b + prd_t^{ev} + prd_t^{al}; \qquad \lambda_t^{prd} \tag{9}$$

Where ps_t stands for the portion of the procured FRP predicted to be called up for energy generation/consumption and pru and prd are the corresponding amounts of FRU and FRD. Worth noting in (6)-(7) is that unlike other ancillary services, e.g. reserve and regulation products, the procured FRP for time-interval *t* is anticipated to be committed as energy at *t*+1, i.e., the FRP is procured to cover the uncertainties of the net load at the next market interval.

The BESS's technical constraints along with its FRP procurement capacity are given below:

$$p_t^b - rd_t^b - prd_t^b \geq \underline{p}^{b,ch}; \qquad \mu_t^{b,pmin} \tag{10}$$

$$p_t^b + ru_t^b + pru_t^b \leq \overline{p}^{b,dis}; \qquad \mu_t^{b,pmax} \tag{11}$$

$$e_t^b - e_{t-1}^b = -p_t^b - pru_t^b + prd_t^b; \qquad \lambda_t^{b,e} \tag{12}$$

$$\underline{e}^b \leq e_t^b \leq \overline{e}^b; \qquad \lambda_t^{b,emin}, \lambda_t^{b,emax} \tag{13}$$

$$ru_t^b, pru_t^b, rd_t^b, prd_t^b \geq 0; \ \mu_t^{b,ru}, \mu_t^{b,rd}, \mu_t^{b,pru}, \mu_t^{b,prd} \tag{14}$$

In which, e_t^b is the SOC of the battery. Parameters $\overline{p}^{b,dis}$ and $\underline{p}^{b,ch}$ are the maximum discharging and charging power. Based on (10), (11), the power output of the BESS is limited to the amount of FRU and FRD the agent is offering as well as the predicted energy under FRP commitment. Equation (12) determines the variation in the SOC of the battery and (13) sets its boundaries. Lastly, in (14), the positivity of the procured FRP and energy under FRP are enforced.

For $\mathrm{t} \in [\mathrm{T_k^{in}}, \mathrm{T_k^{out}} - 1]$, the PEVs' FRP provision model is given below:

$$p_{k,t}^{ev} - rd_{k,t}^{ev} - prd_{k,t}^{ev} \geq 0; \qquad \mu_{k,t}^{ev,pmin} \tag{15}$$

$$p_{k,t}^{ev} + ru_{k,t}^{ev} + pru_{k,t}^{ev} \leq \overline{p}_k^{ev}; \qquad \mu_{k,t}^{ev,pmax} \tag{16}$$

$$e_{k,t}^{ev} - e_{k,t-1}^{ev} = -p_{k,t}^{ev} - pru_{k,t}^{ev} + prd_{k,t}^{ev}; \qquad \lambda_t^{ev,e} \tag{17}$$

$$\left.\begin{array}{l} \underline{e}_k^{ev} \leq e_{k,t}^{ev} \leq \overline{e}_k^{ev}; \ t \in [T_{\mathrm{k}}^{in}, T_k^{out} - 1] \\ \underline{e}_k^{leave} \leq e_{k,t}^{ev} \leq \overline{e}_k^{ev}; \ t = T_k^{out} \end{array}\right\} \begin{array}{l} \lambda_{k,t}^{ev,emin} \\ \lambda_{k,t}^{ev,emax} \end{array} \tag{18}$$

$$ru_{k,t}^{ev}, pru_{k,t}^{ev}, rd_{k,t}^{ev}, prd_{k,t}^{ev} \geq 0; \quad \mu_{k,t}^{ev,ru}, \mu_{k,t}^{ev,rd}, \mu_{k,t}^{ev,pru}, \mu_{k,t}^{ev,prd} \tag{19}$$

Parameters $T_{\mathrm{k}}^{in}, T_k^{out}$ are the forecasted arrival and departure time of PEVs. Based on (15), the procured FRD and the expected energy under FRD may not exceed the power level. Likewise, based on (16), the summation of power, FRU and energy under FRU cannot exceed the power limit. In (18), it is assumed that the PEV owner is able to choose the desired PEV energy level upon departure ($\underline{e}_k^{leave}$).

The agent's load (d_t) can be divided into two parts, namely fixed load (FL) and adjustable load (AL). The AL can participate for FRP provision in its comfortable levels:

$$d_t = al_t + fl_t; \qquad \lambda_t^d \tag{20}$$

$$al_t + rd_t^{al} + prd_t^{al} \leq \overline{al}_t; \qquad \mu_t^{al,max} \tag{21}$$

$$al_t - ru_t^{al} - pru_t^{al} \geq \underline{al}_t; \qquad \mu_t^{al,min} \tag{22}$$

$$ru_t^{al}, pru_t^{al}, rd_t^{al}, prd_t^{al} \geq 0; \quad \mu_t^{al,ru}, \mu_t^{al,rd}, \mu_t^{al,pru}, \mu_t^{al,prd} \tag{23}$$

The decision variables the agent may adjust to maximize its profit are:

$$DV_{dpa} = \{p_t^b, ru_t^b, rd_t^b, p_{k,t}^{ev}, ru_{k,t}^{ev}, rd_{k,t}^{ev}, ru_t^{al}, rd_t^{al}\}$$

4 Linearization and Profitability Assurance

4.1 Linearization

The proposed bi-level optimization is nonlinear which as described below is converted to a single-level mixed integer linear programming MILP using Karush-Kuhn-Tucker (KKT) conditions of the lower level optimization. The linearization procedure as described in [11] is as follows:

- Write the lower level optimization as a convex linear problem. Then, write it in its KKT conditions form.
- Applying the strong-duality theorem, linearize the non-linear terms appearing in the upper level objective function. In order to do so, one needs to form the gradient matrix obtained from the original and/or dual form of the lower level problem.
- Replace the nonlinear terms in the objective function of the upper level optimization with the equivalent linear terms attained from the lower level optimization.
- Linearize non-linear terms in the upper level constraints.
- Create the single-level MILP corresponding to the original optimization using the linearized upper level objective function and merging the upper and lower level constraints.

4.2 Profitability Assurance:

As mentioned before, in order to attract the agents to participate in this framework, the aggregator needs to assure their profitability is higher than in the case where agents trade energy with the distribution level energy prices. To achieve this, the aggregator runs first the self-scheduling optimization (the lower level optimization) of agent *i* in which it considers

$$\begin{aligned} \Psi^a = \sum_t \Big[& \lambda_t^p (p_t^{pv} - d_t) - \mu_t^{b,pmin} \underline{p}^{b,ch} + \mu_t^{b,pmax} \overline{p}^{b,d} + \mu_t^{b,emin} \underline{e}^b - \mu_t^{e,max} \overline{e}^b + \mu_t^{al,max} (al_t - \overline{al}_t) + \mu_t^{al,min} (\underline{al}_t - al_t) \\ & + pru_t^a \theta_t^p - \varphi^l lc_t + \sum_k \big(\delta_t^{ev} p_{k,t}^{ev} - \mu_{k,t}^{ev,pmax} \overline{p}_k^{ev} + \mu_{k,t}^{ev,emin} \underline{e}_k^{ev} - \mu_{k,t}^{ev,emax} \overline{e}_k^{ev} \big) \Big] - \lambda_1^{b,e} e_0^b - \sum_k \lambda_{k,T_{\mathrm{k}}^{in}}^{ev,e} e_{k,T_{\mathrm{k}}^{in}}^{ev} \geq Prof_{min}^{dpa} \qquad \forall a \end{aligned} \tag{24}$$

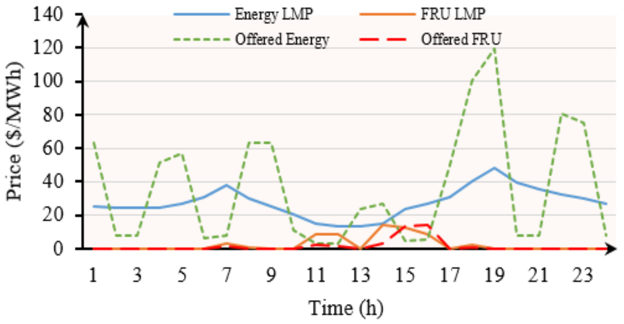

Figure 2 Market price signals and prices offered to agents

the energy prices equal to the distribution level electricity prices and considers the ancillary services prices equal to 0. Next, it adds this minimum profit as a constraint to the optimization. Thus, for each agent, (24) is enforced. The left-hand side of (24) is the equivalent of (2) which is linearized based on the mentioned procedure.

5 Case Study and Numerical Results

The aggregator deals with 4 types of agents with the following resource options: (i) commercial with (w) BESS (A1), (ii) commercial without (w/o) BESS (A2), iii) residential w BESS, (A3), (iv) residential w/o BESS (A4). All agents have 10 PEVs. The load, PV, PEVs and BESS data are given in [12]. The WEM under study is CAISO market summer day with relatively high FRU prices stemmed from lack of ramp up capacity on 07/15/2019 in Portland General Electric's area.

The market energy, FRU and FRD prices as well as the corresponding prices offered by the aggregator to the agents as a result of the proposed optimization are provided in Fig. 2.

The FRU and FRD provided by each type of agents at each hour with focus on the benefits of BESS is provided in Fig. 3.

As it is observed, the agents with fixed BESS (A1 and A3) are relatively more capable of FRP provision. Also, since the FRP provision is mostly during business hours, the BESS of A3 was more efficient in FRP provision compared to A2 which as an agent at work. The A4, which is residential, provided the least amount of FRP due to absence of BESS and the fact that most of its PEVs were not available during business hours.

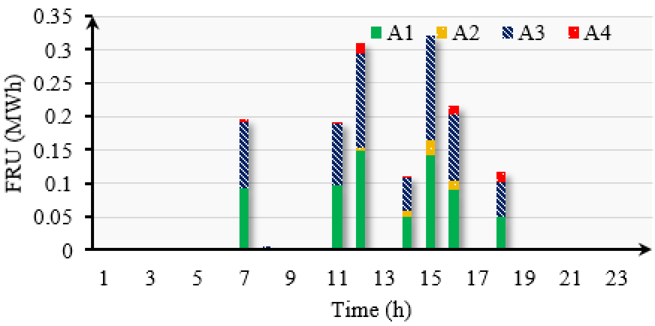

Figure 3 FRU procurement per agent type

The expected costs of each type of agents is given in Table I. The profitability of agents A1 and A3 compared to agents A2 and A4, is much higher benefiting from BESS.

Table 1 The cost/profit per agent type (prices are in $)

Agent	Energy prof.	FRU prof.	CS prof.	Total prof.
A1	3.8	4.0	5.4	7.7
A2	-25.8	0.5	4.2	-25.3
A3	34.8	4.3	4.5	40.1
A4	5.3	0.4	5.6	5.7

5 Conclusion

This paper proposes a bi-level optimization framework for the participation of DPs in the wholesale energy and FRP markets. The original optimization is non-linear which by using the KKT conditions of the lower level problem is converted to MILP. Case study is conducted on 4 types of agents. The 40 agents could procure 14.65MWh of FRU in total for the grid and make extra $92 profit out of it. The agents with BESS can provide more ramp capacity for FRP requirements; 46% of total FRU was procured by A1 which is commercial and 48% by A3 which was residential.

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