Robust Bidding Strategy for Aggregation of Distributed Prosumers in Flexiramp Market

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Abstract

Distributed prosumers (DPs) are the grid customers that own energy production/storage assets. Due to the flexibility and fast response of their assets, they can procure ancillary service products (ASP) in the wholesale market. An appealing ASP offered by California ISO in the real-time market (RTM) is flexiramp for which market participants do not submit direct offers, and the compensation is based on their energy opportunity costs. In this paper, we propose a bidding strategy model for DP aggregator participation in the RTM considering energy and flexiramp. First, we develop a risk-averse optimization to determine the optimal energy and reserve product to trade in day-ahead market while considering proper amounts of flexiramp to trade in the RTM. In the RTM, to obtain optimal amounts of energy and flexiramp, the aggregator must submit hourly multi-level price-quantity energy bids for multiple RTM intervals with 15-minute time-steps. On this basis, we propose a robust hourly economic bidding strategy model that determines the optimal energy bids in the RTM. We develop an adjustable robust counterpart of the model to address the RTM energy and flexiramp price uncertainties. The simulation results justify the efficacy of our proposed framework in gaining profits from the wholesale market.

Keywords: Aggregator, ancillary services, distributed prosumer, Electric vehicle, flexiramp.

Nomenclature

Parameters:

Λ_h	Forecasted marginal price in day-ahead market (DAM) at hour h.
Π_j	Probability of scenario j.
λ_h	Forecasted marginal price in real-time market (RTM) at hour h.
ρ^e	Penalty factor to limit the energy trade in RTM.
ϕ_h^{ch}, ϕ_h^{dis}	Charging and discharging prices of EVs.
PV	Photovoltaic power generation.
D^{nc}	Non-controllable demand.
ϑ	Expected portion of spinning reserve (SR) summoned for power generation.
σ	Parameter determining the limits of energy trades in RTM.
$\bar{P}$	Maximum power output.
$\underline{soc}$, $\overline{soc}$	Minimum and maximum limits of state of charge (SoC).
Δt	Time-interval.
ξ_b^{bs}	Round-trip efficiency.
$T_{j,k}^{arr}$, $T_{j,k}^{dep}$	Forecasted arrival and departure times of EV k in scenario j.
$soc_k^{ev,dep}$	The minimum state of charge at the time of departure set by the EV owner.
$\overline{L}_d^{th}$	Maximum power output of the air conditioner d.
$\underline{\theta}_d^{in}$, $\overline{\theta}_d^{in}$	minimum and maximum inside temperature limits set by the occupants.
B_d, R_d^{th}	Thermal constant and thermal resistance of the building.
$\theta_{j,h}^{amb}$	The ambient temperature.
COP_d	coefficient of performance of the air conditioner.
χ_d	The heat gains and losses due to occupants' activity, solar radiation and other loads.
LDE	Forecasted deferrable electric load (DEL).
dc_d	The duty cycle the building occupants set for their DELs.
PL_i, PG_i	Real load and generation in node i.
QL_i	Reactive load in node i.
ς^α, ς^β	Confidence level and risk parameter of CVaR ($0 < \varsigma^\beta, \varsigma^\alpha < 1$).
z_h	Binary determining the type of flexiramp provision in RTM at hour h (1: FRU, 0 FRD).
ν_h	Parameter determining the type of energy bid is RTM at hour h (1: selling, -1: purchasing).

$\mathbb{M}$	Parameter of big-$\mathbb{M}$ method.
ξ^e	Penalty associated with the error of the power level in the submitted energy bid to RTM.
Ψ^r, Γ^r	Adjustable parameters of the box and polyhedral uncertainty sets ($0 \leq \Psi^r \leq 1$ and $\Psi^r \leq \Gamma^r \leq \Psi^r \lvert J \rvert$).
$\lvert J \rvert$	The cardinality of the uncertainty set.
$\hat{\lambda}$	The constant perturbation of the uncertain real-time price forecast.

Continues Variables:

E	Energy traded in DAM.
SR	Spinning reserve (SR) traded in DAM.
e	Expected energy traded in RTM.
fru, frd	Expected total flexible ramp up and down provision in RTM.
psr	Expected total SR activation in RTM.
ϱ^e	Auxiliary variable limiting the expected energy trade in RTM.
p	Power output.
sr	SR of agent's asset.
ps	Expected SR activation of agent's asset.
l	Electric load.
ru, rd	Expected flexible ramp up and down provision by agent's asset.
soc	State of charge.
θ^{in}	The temperature inside the building.
pn_i^a, qn_i^a	Real and reactive powers of DPs connected to bus i.
pf_{ij}, qf_{ij}	Real and reactive power of line ij.
S_i, sf_{ij}	Apparent power injected in bus i and line ij, respectively.
V_i	Voltage at node i.
V_i^{sqr}	Variable corresponding to V_i^2 at node i.
ψ_j	Estimate of the cost of scenario j.
ς^ϕ	The value at risk in the CVaR measure.
$\pi_{i,h}$, $L_{i,h}$	Price and quantity of level i of the energy bid submitted to the RTM at hour h.
dum	Dummy variable.
ϖ^e	Error of the power level in the submitted energy bid to RTM.

w, v, u Auxiliary variables in the box and polyhedral uncertainty robust counterpart of the bidding model in the RTM.

Binary Variables:

x Binary denoting the operating mode of BESS and EVs (1: discharging mode, 0: charging mode).

$\alpha, \beta, \gamma, \delta$ Auxiliary binary variables used in the big-$\mathbb{M}$ method to linearize the energy bids to in the RTM.

Sets:

j Set of scenarios, $j \in \Omega$.

h Set of hourly time-steps in day-ahead optimization, $h \in H$.

t Set of 15-min time-steps in real-time optimization, $t \in T$.

k Set of EVs, $k \in \mathbb{K}$.

b Set of battery storage, $b \in \mathbb{B}$.

a Set of agents, $a \in \mathbb{A}$.

d Set of agents with controllable loads, $d \in \mathbb{D}$.

N^d, N^t Sets of nodes in distribution and transmission grids.

L^d, L^t Sets of lines in distribution and transmission grids.

i Set of levels of the energy bid submitted to the RTM, $i \in \mathbb{I}$.

Superscripts:

e Energy

sr, frp Spinning reserve and flexiramp

ru, rd Flexible ramp up and down

ev Electric vehicle

bs Battery energy storage system

ch, dis Charging and discharging modes

nc, th, de Non-controllable, thermal and deferrable loads

ua, fm Uncertainty award and forecasted movement

bid Submitted bid to the RTM.

1. Introduction

1.1 Problem Description

Impressive advancements in smart grid technologies in recent decades have brought about a variety of opportunities for power system owners, whether public- or investor-owned. Lower dependency on fossil-based energy resources, decarbonization through the use of renewable resources, more reliable electricity supply and higher engagement of distributed prosumers (DPs) are worth mentioning [1]-[3]. A DP is often considered in the literature as a building comprised of photovoltaic (PV) panels, a fixed battery energy storage system (BESS), electric vehicle (EV) charging stations, controllable thermal loads, deferrable electric loads (DELs), etc. [4]-[6]. Solely relying on the profit gained by supplying energy to the distribution grid may become cost-inefficient for such DP owners. In fact, due to the DP assets' high ramp capacity, one can make much higher profits by participating in multiple ancillary service products (ASPs) offered in the wholesale electricity market (WEM) [7]. Since these DPs are often too small for direct participation in the WEM, a load-serving entity or aggregator is required to aggregate their demand and participate in the WEM on their behalf—see Fig. 1. The appealing WEM ASPs for DPs include, but not limited to, spinning reserve (SR), regulation up and down, and flexiramp [8]-[10]. Flexiramp is a real-time market (RTM) product procured by reserving the ramp capacity of market participants to ensure the balance between supply and demand at the next time intervals [11], [12]. Unlike other ASPs, the participant cannot bid for the flexiramp directly, and its price is determined based on the energy opportunity cost of the market participants whose ramp capacities

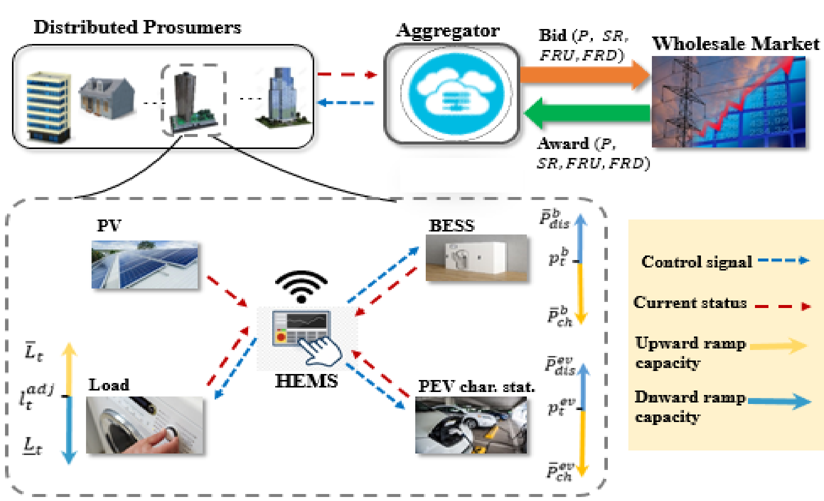

Fig. 1. The interaction of DPs, aggregator and WEM.

are reserved for flexiramp procurement [13], [14]. This paper proposes an optimal participation strategy for DP aggregators in the day-ahead and real-time markets, considering energy, SR and flexiramp.

1.2 Literature Review

Different research efforts have been conducted on the participation of DP aggregators in the WEM. They have focused on the strategic bidding of the aggregator considering the behavior of other market participants and profitability increase through the procurement of different ASPs [15]-[30]. In [15], the authors proposed a bi-level stochastic complementary model to capture strategic behavior and obtain its bidding curves in the energy market. To make the model computationally efficient, they employed a heuristic algorithm that considers one scenario at a time. They demonstrated that the aggregator can manipulate its bids to change pool prices to its own benefit. In [16], the bidding strategy of an active distribution company in the energy market was modeled as a bi-level optimization. The authors considered the uncertainties associated with the bidding of other market participants, market prices, and the production of DERs. The strategic interaction among the aggregator, DPs and WEM is modeled in [17]. The Stackelberg or Nash bargaining game is implemented to model the interactions of the aggregator and DPs, and a bi-level optimization is developed to model the interactions of the aggregator and market. This methodology can be used to improve the aggregator cost efficiency and to assess the value of demand flexibility such DPs introduce to power systems.

Additional increase in the profitability of such DPs is enabled by the provision of different ASPs in the WEM and grid support services [18]-[23]. The authors in [18] proposed a risk-averse bidding strategy model for the participation of DP aggregators in the day-ahead energy and frequency regulation market. They considered the battery degradation cost using a rainflow-cycle-counting algorithm. They managed the risks associated with energy and frequency regulation prices via the conditional value-at-risk measure. In [19], a distributionally robust optimization model was developed to propose a collaborative bidding strategy for participation of DPs in the day-ahead market (DAM). Since the proposed scenario-wise ambiguity set is based on the Wasserstein distance, it can include both distributional and statistical distance metric information. Two cases of collaborative and non-collaborative bidding strategies were compared, where the former led to less load curtailments. In [20], bi-level optimization for the DER aggregator participation in the energy and reserve markets was introduced where the wind forecast error was modeled by an ambiguity set. The information gap decision theory model was leveraged to enhance the risk that the aggregator can tackle for an expected payoff. The participation of such aggregators in the demand response (DR) program is discussed in [21]–[23]. An optimal bidding strategy method is proposed to reduce the risk of the aggregator's financial loss due to market price volatility in [21]. Further, a quantitative compensation mechanism is presented to encourage the DPs to participate in the DR program. In [22] a regret-based stochastic bi-level optimization for optimal participation of a DR aggregator in the short-term energy market was proposed. The aggregator offers energy prices to its DPs, aiming to maximize its own profitability. The DP reaction to the aggregators offered prices, and competition among the aggregators was considered. It was concluded that the regret-based algorithm results in efficient prices offered by the aggregator. In [23] the provision of DR by the aggregator of local energy systems was discussed. On this basis, stochastic mixed-integer linear programming was developed considering the uncertainties of DER power generation and DAM marginal prices. In this framework, the aggregator aims to satisfy the multi-energy demand of its customers with demand flexibility. In [24], a bidding strategy based on game theory was developed for a DR aggregator in the WEM, where the customer benefit function and price elasticity were utilized to derive an economic responsive load model. The robust counterpart of the original optimization was derived to address the price uncertainties. The non-cooperative game is solved by implementing the Nash equilibrium. An optimal bidding strategy for the day-ahead and real-time energy and reserve markets considering the uncertainties of DP resources was developed in [25]. The uncertainties of the DP information are modeled through a set of scenarios in a two-stage stochastic optimization, where the simulation results indicated a significant reduction in the energy cost of the DPs. In [26], the authors developed a two-stage bidding strategy for an aggregator with direct control of customers' AC thermostat. They derived the price bidding curves for the participation of thermal load aggregators in DAM and demand-only bids in the RTM. Moreover, they deployed the flexibility of the customer loads to address the uncertainties of weather and load forecasts. A hierarchical model predictive control was developed in [27] to deliver energy and ASPs in the RTM. This approach ensures the deliverability of multiple ASPs, enables arbitrage between multiple energy and ASPs, and enables the control of different flexible assets of DPs.

There are a few studies on DP participation in the WEM considering flexiramp [28]–[30]. The authors in [28] developed a participation strategy model for BESS aggregators in the DAM energy and flexiramp market. An optimization problem for the microgrids to participate in the DAM considering energy, spinning reserve, and flexiramp was developed in [29]. They implemented a hybrid stochastic/robust optimization (RO) approach to tackle the uncertainties in renewable generation and WEM prices. However, neither of them addresses the point that the flexiramp is an RTM product and market participants cannot directly bid for it. In other words, its procurement depends on the energy bid submitted by the market participant to the RTM. The authors in [30], on the other hand, proposed a two-stage bidding strategy for the participation of pumped hydro storage (PHS) in the RTM considering energy and flexiramp. They did not consider flexiramp in the day-ahead optimization, and they assumed that the PHS can submit bids at each 15-minute interval in the RTM process. In addition, they could not integrate the economic bidding price determination with the real-time optimization of the PHS; thus, one cannot ensure that the optimization results lead to the maximum profit.

1.3 Our Contributions

The literature on aggregator participation in the WEM has primarily focused on the participation in energy-only or joint energy and ASPs such as reserve and frequency regulation [15]-[27]. In this vein, scholars have mainly focused on uncertainty modeling, strategic participation, and bidding strategy approaches. However, the flexiramp is a novel market product with unique characteristics, e.g., it is procured for the next market time interval and the participants cannot submit direct bids for it. Hence, it calls for modified bidding strategy models to bring about higher profitability to the aggregators and DERs. There are a few studies on bidding for flexiramp; however, they have either neglected the fact that it is an RTM-only product and there is no direct bidding for it [28], [29] or they have failed to incorporate the hourly optimal price-quantity energy bids with the sub-hourly self-scheduling of the DP assets [30].

In this paper, we fill the gap in the research reported in the literature and propose a comprehensive framework for the participation of DP aggregators in WEM ASPs and flexiramp. On this basis, we first propose an optimal participation strategy for a DP aggregator in the DAM energy and SR markets while considering flexiramp profitability in the RTM. After the DAM clearance, we develop the RTM participation strategy by integrating a robust price-quantity bidding strategy model with a self-scheduling optimization objective. This approach enables one to reach the most rewarding participation in energy and flexiramp markets. We consider the aggregator as a third-party entity that does not have access to the distribution grid data. The aggregator can directly control some DPs' assets via the home energy management system (HEMS). The contributions of our study are threefold:

- A risk-averse two-stage scenario-based optimization is developed for the participation of a price-taker third-party DP aggregator in the DAM, considering the potential profitability in the real-time energy and flexiramp market ASPs. The conditional value at risk (CVaR) measure is employed to adjust the profitability risks that the aggregator may encounter imposed by the stochastic nature of the problem.

- An hourly price-quantity bidding strategy model for the participation of the aggregator in the RTM with 15-minute time intervals is proposed to maximize the profit gained from the energy and flexiramp market. The proposed model is linearized, and robust counterpart of the obtained MILP model is developed. The "box + polyhedral" uncertainty set is implemented to address the uncertainties of the RTM energy and flexiramp prices. On this basis, the aggregator modifies its hourly bidding to the RTM to reward the desired amounts of the flexiramp.

- Real-world data and test cases were implemented to assess the effectiveness of the proposed model in achieving profitability for DP aggregators. The simulation results justify that the flexiramp market provides a great opportunity for DP profitability if and only if a proper bidding strategy is adopted.

1.4 Paper Organization

The rest of the paper is organized as follows: The flexiramp features and the associated bidding strategy model are discussed in Section II. The mathematical formulation of the DAM and RTM optimizations are proposed in Sections III and IV, respectively. The case studies and simulation results are presented in Section V, and the discussion and concluding remarks are provided in Section VI.

2. Bidding For Flexiramp ASP

2.1 Aggregator Market Participation based on FERC Order 2222

Federal Energy Regulatory Committee (FERC) Order 2222 mandates the wholesale electricity markets (WEMs) across the US to provide for the participation of distributed energy resource (DER) aggregators in the market to trade energy and procure ancillary services products (ASPs) [31]. Our paper is based on realistic assumptions regarding the current situation of power systems in the US and develops an optimal bidding strategy model that a third-party aggregator can use in practice.

FERC defines a DER aggregator as: “an entity that aggregates one or more distributed energy resources for purposes of participation in the capacity, energy and ancillary service markets of the regional transmission operators and independent system operators [31].” The responsibilities of different entities based on the FERC Order 22 are provided in Table 1.

Table 1. The responsibilities of aggregator, ISO and distribution utilities based on FERC Order 2222 [31]

Entity	Responsibilities
Aggregator	• Meet the 100 kW minimum size requirement to participate in the WEM. • Provide to the data of physical parameters of the DER aggregation, including total capacity, minimum and maximum operating limits, ramp rate, the minimum run time and the default distribution factors. • Provide data regarding each resource’s capacity, location on the distribution grid and operating limits. • Provide telemetry data to the ISO so it can properly dispatch resources. Providing metering data for settlement purposes is not mandatory. • Disaggregate dispatch signals from the ISO and dispatch DER resources considering the constraints of the distribution grid.
ISO/TSO	• Periodic auditing for each resource in the DER aggregation. • Prevent compensation duplication for services where the same capacity by a DER is used for multiple ASPs. • Address coordination between the ISO, aggregator and distribution utility to ensure that the participation

	of these resources in ISO markets does not present reliability or safety concerns for the distribution or transmission system. • Revise its tariff to provide for coordination among the ISO, aggregator, and the relevant distribution utilities for (i) registering new DER aggregators, and (ii) operational coordination among the ISO, aggregator and distribution utilities. • Send dispatch signals to the aggregator.
Distribution Utility	• Review the DERs located in the distribution grid and enroll in a DER aggregation before the DER aggregator participates in the WEM. This review is performed to ensure all of assets of the aggregator are technically capable of providing ASPs to the WEM without posing significant risks to the distribution grid.

The aggregator is a third-party which does not have access to the distribution grid topology and data. Hence, in our approach, the technical constraints of the underlying distribution grid, such as voltage and thermal limits, are not included in the proposed bidding strategy. We still consider that all the DP energy transactions in real-time are subject to the grid constraints, but such constraints are coordinated between ISO and TSO/DSO, and hence are out of scope of this paper. In some other regulatory setting where the rules may be different, the grid constraints will have to be dealt with as the specific regulations require.

2.2 Flexiramp Structure

Based on the California ISO (CAISO) market, flexiramp product is procured by reserving ramp up and ramp down capacities from market participants at each RTM interval to deal with the net-load (load minus uncertain supply) uncertainties in the next time interval. The upward flexiramp is called flexible ramp up (FRU), and the downward one is called flexible ramp down (FRD). Market participants cannot directly bid for flexiramp, and the ISO determines their allocated flexiramp based on their submitted energy bids and compensates them according to the energy opportunity cost. The flexiramp is first procured in real-time unit commitment (RTUC) in 15-minute market intervals. Then, in the real-time dispatch (RTD) process, the marginal amounts are procured [32], [33].

The flexiramp allocated to each market participant comprises two parts: forecasted movement (FM) and uncertainty award (UA). The former refers to the ISO forecast for the change in the power output of the market participant. The latter refers to the ramp capacity of the participant reserved to deal with market uncertainties. These amounts are determined based on the bid submitted by market participants to the RTM

[32].

2.3 Bidding Strategy for Flexiramp

To better clarify how the energy bids may be modified to reward optimal amounts of flexiramp, an illustrative example is provided below. Assume the 3 generators whose data are given in Table 2. Generator 3 is assumed to be a price-taker to demonstrate how it can modify its bid for the flexiramp. Assume the load at the next interval is 480 MW, 100 MW of flexiramp is required, and generator 3 is unavailable:

- Without flexiramp constraint: $p_{g1} = 480$ MW, $p_{g2} = 0$ and locational marginal price (LMP) = 20 $/MWh.

- With the flexiramp constraint: 100 MW FRU is required. Generator 1 procures 50 MW of that; hence, $p_{g1} = 450$ MW. Another 50 MW of FRU is procured by generator 2. Thus, to supply the load, $p_{g2} = 30$ MW. In this case, LMP $= 30$ $/MWh and FRU price=$30 - 20 = 10$ $/MWh.

Now, assume that generator 3 desires to provide 5 MW of flexiramp and 10 MW of energy. If it bids, according to Table 2:

- Without flexiramp constraint: $p_{g1} = 470$ MW, $p_{g2} = 0$, $p_{g3} = 10$ MW, and LMP = 20 $/MWh.

- With flexiramp constraint: $p_{g1} = 450$ MW, $p_{g2} = 20$ MW, $p_{g3} = 10$ MW. Also, $\text{FRU}_{g1} = 50$ MW, $\text{FRU}_{g2} = 45$ MW, $\text{FRU}_{g3} = 5$ MW. Therefore, LMP $= 30$ $/MWh and FRU price = $30 - 20 = 10$ $/MWh.

As one can observe, if a bid submitted by a price-taker participant is in between the LMP and LMP minus the flexiramp price (30 $/MWh and 20 $/MWh, respectively), the participant is rewarded the flexiramp. If the bid is lower than the LMP minus the flexiramp price, the participant rewards energy. A similar justification can be made for the loads (negative generations). If their bid is between the LMP and LMP plus flexiramp price, they reward the flexiramp, and if it is higher than the LMP plus flexiramp price,

Table 2. The 3-Generator System Data

Gen	Initial power (MW)	Min power (MW)	Max power (MW)	Ramp rate (MW/h)	Bid amount (MW)	Bid price ($/MWh)
1	450	0	500	50	50	20
2	0	0	200	50	50	30
3	0	0	15	15	10	10
					5	25

they reward energy.

In the CAISO market, however, the participants submit hourly bids with up to 10 levels, which are used to run four RTUC processes, each with 15-minute time intervals. This is discussed further in Section IV.

3. Day-Ahead Optimization

The objective function the aggregator seeks to maximize for participation in the day-ahead energy and reserve market is envisioned as a two-stage scenario-based optimization problem. On this basis, $\mathrm{OF^{dam}}$ is developed in (1).

$$\begin{aligned}\mathrm{OF^{dam}} &= \max\left\{\mathrm{prof^{dam}} + \mathbb{E}\left(\sum_j \mathrm{prof}_j\right)\right\}\\ &= \max\left\{\sum_h (E_h \Lambda_h^e + SR_h \Lambda_h^{sr}) + \sum_j \Pi_j \sum_h \Big(e_{j,h}\lambda_{j,h}^e + fru_{j,h}\lambda_{j,h}^{ru} + frd_{j,h}\lambda_{j,h}^{rd}\right. \qquad (1)\\ &\left. + psr_{j,h}\lambda_{j,h}^e - \rho^e \varrho_{j,h}^e + \sum_k \Big((p_{j,k,h}^{ev,ch} - ps_{j,k,h}^{ev,ch})\phi_{k,h}^{ch} - (p_{j,k,h}^{ev,dis} + ps_{j,k,h}^{ev,dis})\phi_{k,h}^{dis}\Big)\Big)\right\}\end{aligned}$$

Note that parameters ϕ_h^{ch} and ϕ_h^{dis} show the charging and discharging prices of EVs according to their contract with the building owners (for residential customers $\phi_h^{ch}, \phi_h^{dis} = 0$). The first two terms of (1) show the first stage of the optimization, accounting for the expected profit gained by trading energy and SR in DAM, whereas the remaining terms represent the second stage of the optimization. Terms 3 to 6 evaluate the expected profit in real-time. By inserting term 7, high deviations from of the DAM power can be avoided. The last four terms represent the profits and payments to the EV owners by charging and discharging their EVs. Objective function (1) is subject to the following constraints.

3.1 Aggregated Constraints

The aggregated constraints are given below:

$$E_h + e_{j,h} = \sum_a p_{j,h}^a = \sum_a (PV_{j,a,h} - D_{j,a,h}^{nc}) - \sum_d (l_{j,d,h}^{th} + l_{j,d,h}^{de}) + \sum_b \left(p_{j,b,h}^{bs,dis} - p_{j,b,h}^{bs,ch}\right) + \sum_k \left(p_{j,k,h}^{ev,dis} - p_{j,k,h}^{ev,ch}\right) \quad \forall j,h \tag{2}$$

$$SR_h = \sum_a sr_{j,h}^a = \sum_b (sr_{j,b,h}^{bs,dis} + sr_{j,b,h}^{bs,ch}) + \sum_k (sr_{j,k,h}^{ev,dis} + sr_{j,k,h}^{ev,ch}) + \sum_d sr_{j,d,h}^{th} \quad \forall j,h \tag{3}$$

$$\vartheta_{j,h}.SR_h = psr_{j,h} = \sum_a ps_{j,h}^a = \sum_b (ps_{j,b,h}^{bs,dis} + ps_{j,b,h}^{bs,ch}) + \sum_k (ps_{j,k,h}^{ev,dis} + ps_{j,k,h}^{ev,ch}) + \sum_d ps_{j,d,h}^{th} \quad \forall j,h \tag{4}$$

$$fru_{j,h} = fru_{j,h}^{ua} + fru_{j,h}^{fm} \quad \forall j,h{:}\,(1,H-1) \tag{5}$$

$$frd_{j,h} = frd_{j,h}^{ua} + frd_{j,h}^{fm} \quad \forall j,h{:}\,(1,H-1) \tag{6}$$

$$fru_{j,h}^{fm} = \left(E_{h+1} + e_{j,h+1}\right) - \left(E_h + e_{j,h}\right) \quad \forall j,h{:}\,(1,H-1) \tag{7}$$

$$frd_{j,h}^{fm} = \left(E_h + e_{j,h}\right) - \left(E_{h+1} + e_{j,h+1}\right) \quad \forall j,h{:}\,(1,H-1) \tag{8}$$

$$fru_{j,h}^{ua} = \sum_a ru_{j,h}^a = \sum_b (ru_{j,b,h}^{bs,dis} + ru_{j,b,h}^{bs,ch}) + \sum_k (ru_{j,k,h}^{ev,dis} + ru_{j,k,h}^{ev,ch}) + \sum_d ru_{j,d,h}^{th} \quad \forall j,h \in [1,H-1] \tag{9}$$

$$frd_{j,h}^{ua} = \sum_a rd_{j,h}^a = \sum_b (rd_{j,b,h}^{bs,dis} + rd_{j,b,h}^{bs,ch}) + \sum_k (rd_{j,k,h}^{ev,dis} + rd_{j,k,h}^{ev,ch}) + \sum_d rd_{j,d,h}^{th} \quad \forall j,h \in [1,H-1] \tag{10}$$

$$\varrho_{j,h}^e \geq \sigma.E_h - e_{j,h} \quad \forall j,h \tag{11}$$

$$\varrho_{j,h}^e \geq e_{j,h} - \sigma.E_h \quad \forall j,h \tag{12}$$

Variables $p_{j,h}^a$, $sr_{j,h}^a$ and $ps_{j,h}^a$ are the power output, SR, and SR activation of DP a under scenario j, respectively. The power balance is enforced in (2), and the SR procurement and expected SR activation are set in (3) and (4). Based on (5) and (6), the total FRU and FRD are comprised of the associated FM and UA parts. The FM part of FRU and FRD are calculated using (7) and (8). The UA parts of FRU and FRD procured by reserving the ramp capacity of the DP assets are set in (9) and (10). To avoid losses due to RTM energy price uncertainties, (11) and (12) are enforced to limit the deviation of the RTM energy from the DAM energy.

3.2 Battery Energy Storage Systems

The constraints of BESSs are provided below:

$$p_{j,b,h}^{bs,dis} + ru_{j,b,h}^{bs,dis} + sr_{j,b,h}^{bs,dis} + ps_{j,b,h}^{bs,dis} \leq x_{j,b,h}^{bs}\bar{P}_b^{bs,dis} \qquad \forall j,b,h \tag{13}$$

$$p_{j,b,h}^{bs,dis} - rd_{j,b,h}^{bs,dis} \geq 0 \qquad \forall j,b,h \tag{14}$$

$$p_{j,b,h}^{bs,ch} - ru_{j,b,h}^{bs,ch} - sr_{j,b,h}^{bs,ch} - ps_{j,b,h}^{bs,ch} \geq 0 \qquad \forall j,b,h \tag{15}$$

$$p_{j,b,h}^{bs,ch} + rd_{j,b,h}^{bs,ch} \geq \left(1 - x_{j,b,h}^{bs}\right)\bar{P}_b^{bs,ch} \qquad \forall j,b,h \tag{16}$$

$$p_{j,b,h}^{bs,dis}, ru_{j,b,h}^{bs,dis}, rd_{j,b,h}^{bs,dis}, sr_{j,b,h}^{bs,dis}, ps_{j,b,h}^{bs,dis}, p_{j,b,h}^{bs,ch}, ru_{j,b,h}^{bs,ch}, rd_{j,b,h}^{bs,ch}, sr_{j,b,h}^{bs,ch}, ps_{j,b,h}^{bs,ch} \geq 0 \quad \forall j,b,h \tag{17}$$

Where, the binary variable $x_{j,b,h}^{bs}$ is used to ensure that the BESS does not operate in both operating states simultaneously. The total amount of power, FRU, SR, and SR activation are limited to the maximum discharging power in (13). The offered FRD in the discharging mode may not exceed the discharging power, according to (14). Since the BESS functions as a load in the charging mode, the summation of FRU, SR and SR activation in this mode cannot exceed the charging power output (15). The total power and FRD in the charging mode are limited to the maximum charging power in (16). The positivity of the variables is enforced in (17).

The state of charge (SoC) relationship is given below [28]:

$$soc_{j,b,h}^{bs} - soc_{j,b,h-1}^{bs} = \left((p_{j,b,h}^{bs,ch} - ps_{j,b,h}^{bs,ch}).\xi_b^{bs} - (p_{j,b,h}^{bs,dis} + ps_{j,b,h}^{bs,dis})/\xi_b^{bs}\right)\Delta t \qquad \forall j,b,h \tag{18}$$

$$\underline{soc}_b^{bs} \leq soc_{j,b,h}^{bs} \leq \overline{soc}_b^{bs} \qquad \forall j,b,h \tag{19}$$

$$soc_{j,b,H}^{bs} \geq soc_{b,0}^{bs} \qquad \forall j,b \tag{20}$$

The relationship between the SoC and output power is given in (18). The SoC is limited to its minimum and maximum levels in (19), and in (20), it is assured that the terminal SoC is greater than equal to its initial value.

To ensure that the SR and flexiramp of the BESS do not exceed the SoC capacity, the following constraints are enforced:

$$\left(ru_{j,b,h}^{bs,dis} + sr_{j,b,h+1}^{bs,dis}\right).\Delta t/\xi_b^{bs} \leq soc_{j,b,h+1}^{bs} - \underline{soc}_b^{bs} \qquad \forall j,b,h \tag{21}$$

$$rd_{j,b,h}^{bs,dis}.\Delta t/\xi_b^{bs} \leq \overline{soc}_b^{bs} - soc_{j,b,h+1}^{bs} \qquad \forall j,b,h \tag{22}$$

$$\left(ru_{j,b,h}^{bs,ch} + sr_{j,b,h+1}^{bs,ch}\right).\Delta t.\xi_b^{bs} \leq soc_{j,b,h+1}^{bs} - \underline{soc}_b^{bs} \qquad \forall j,b,h \tag{23}$$

$$rd_{j,b,h}^{bs,ch}.\Delta t.\xi_b^{bs} \leq \overline{soc}_b^{bs} - soc_{j,b,h+1}^{bs} \qquad \forall j,b,h \tag{24}$$

According to (21), the total FRU and SR offered by the BESS in the discharging mode may not exceed the available SoC. Note that the FRU at h is tied to the SR and SoC at h+1 because, unlike SR, the FRU at each interval accounts for the ramp capacity reserved at the next interval. The FRD in the discharging mode is limited to the available unused SoC at h+1 in (22). Likewise, (23) and (24) are enforced for the charging mode.

3.3 Electric Vehicles

The EV constraints are similar to the BESS, except that those constraints are only valid for the times the EVs are predicted to be connected to the charging station. Hence, for EVs, a set of constraints similar to (13)–(24) are enforced for $h \in [T_{j,k}^{arr}, T_{j,k}^{dep}]$ by replacing superscript bs with ev and setting b with set k. We also ensure that the SoC upon departure exceeds the minimum limit set by the EV owners:

$$soc_{j,k,T_{j,k}^{dep}}^{ev} \geq soc_k^{ev,dep} \qquad \forall j,k \tag{25}$$

3.4 Controllable Loads

The thermal considered in this study is the air conditioner (AC). The following equations model the AC constraints:

$$l_{j,d,h}^{th} - ru_{j,d,h}^{th} - sr_{j,d,h}^{th} - ps_{j,d,h}^{th} \geq 0 \qquad \forall j,d,h \tag{26}$$

$$l_{j,d,h}^{th} + rd_{j,d,h}^{th} \leq \overline{L}_d^{th} \qquad \forall j,d,h \tag{27}$$

The total FRU, SR and SR activation should not exceed the current power level, based on (26). The offered FRD should be limited to the maximum power minus the current power, which is enforced in (27). The relationship between the building temperature and AC power is given below [25]:

$$\theta_{j,d,h}^{in} - B_d\theta_{j,d,h-1}^{in} = (1 - B_d)\left(\theta_{j,h}^{amb} - COP_d.R_d^{th}.\left(l_{j,d,h}^{th} - ps_{j,d,h}^{th}\right)\right) + \chi_{j,d,h} \qquad \forall j,d,h \tag{28}$$

$$\underline{\theta}_d^{in} \leq \theta_{j,d,h}^{in} \leq \overline{\theta}_d^{in} \qquad \forall j,d,h \tag{29}$$

Note, the temperature range ($\underline{\theta}_d^{in}$, $\overline{\theta}_d^{in}$) is set by the building occupants.

To ensure that the offered ASPs do not exceed the temperature limits, the following equations are imposed:

$$\begin{aligned} &B_d\theta_{j,d,h-1}^{in} + (1 - B_d)(\theta_{j,h}^{amb} - COP_d.R_d^{th}.(l_{j,d,h}^{th} + rd_{j,d,h-1}^{th})) \\ &\qquad\qquad\qquad + \chi_{j,d,h} \geq \underline{\theta}_d^{in} \qquad \forall j,d,h \in [2,H] \end{aligned} \tag{30}$$

$$\begin{aligned} &B_d\theta_{j,d,h-1}^{in} + (1 - B_d)\left(\theta_{j,h}^{amb} - COP_d.R_d^{th}.\left(l_{j,d,h}^{th} - sr_{j,d,h}^{th} - ru_{j,d,h-1}^{th}\right)\right) \\ &\qquad\qquad\qquad + \chi_{j,d,h} \leq \overline{\theta}_d^{in} \qquad \forall j,d,h \in [2,H] \end{aligned} \tag{31}$$

Equation (30) enforces the FRD to be lower than the ramp capacity that if dispatched, the temperature falls below its minimum limit. In addition, by imposing (31), the FRU and SR offered by the AC ramp capacity, in case dispatched for energy, will not exceed the maximum temperature limit.

The DELs in a building are referred to any electric load that can be postponed to later hours, e.g., laundry and washing machine. To model such loads, these constraints hold [25]:

$$\sum_h l_{j,d,h}^{de} = \sum_h LDE_{j,d,h} \qquad \forall j,d \tag{32}$$

$$l_{j,d,h}^{de} \leq \sum_{n=\max(1,h-dc_d)}^{h} LDE_{j,d,n} \qquad \forall j,d,h \tag{33}$$

The total supplied DEL during the day equals the total forecasted amount per (32). The combination of (32) and (33) enforces each DEL to be supplied in its preset duty cycle.

3.5 Network Constraints

The distribution and transmission network constraints including voltage limits and line capacity can be incorporated into the proposed model. It must be noted that the aggregator can incorporate the network constraints only if the network data are provided by the ISO, TSO or DSO. Otherwise, the network constraints may be omitted. The power flow constraints in general format can be written as:

$$S_i = \sum_{j,j\neq i} sf_{ij} = V_i \sum_{j,j\neq i} (V_i^* - V_j^*) y_{ij}^* \qquad \forall i \in N \tag{34}$$

$$\underline{sf_{ij}} \leq sf_{ij} \leq \overline{sf_{ij}} \qquad \forall ij \in L \tag{35}$$

$$\underline{V_i} \leq V_i \leq \overline{V_i} \qquad \forall i \in N \tag{36}$$

Per (37), the apparent power injected to each bus is equal to the summation of apparent power of the lines connected to it. The minimum and maximum limits of the apparent power of each line and voltage requirement at each bus are enforced in (40) and (43).

A linear approximation of (34)-(36) distribution network can be implemented to model the distribution network constraints [34]:

$$pn_{i,h}^a - PL_{i,h} = \sum_{j,j\neq i} pf_{ij,h} \qquad \forall i \in N^d, h \in H \tag{37}$$

$$qn_{i,h}^a - QL_{i,h} = \sum_{j,j\neq i} qf_{ij,h} \qquad \forall i \in N^d, h \in H \tag{38}$$

$$qn_{i,h}^a = (QL_{i,h}/PL_{i,h}).pn_{i,h}^a \qquad \forall i \in N^d, h \in H \tag{39}$$

$$\underline{pf_{ij}} \leq pf_{ij,h} \leq \overline{pf}_{ij} \qquad \forall ij \in L^d, h \in H \tag{40}$$

$$\underline{qf_{ij}} \leq qf_{ij,h} \leq \overline{qf}_{ij} \qquad \forall ij \in L^d, h \in H \tag{41}$$

$$V_{i,h}^{sqr} - V_{j,h}^{sqr} = 2\left(r_{ij} pf_{ij,h} + x_{ij} qf_{ij,h}\right) \qquad \forall h \in H, ij \in L^d \tag{42}$$

$$\underline{V_i}^{sqr} \leq V_{i,h}^{sqr} \leq \overline{V_i}^{sqr} \qquad \forall h \in H, i = 1, \dots, N^d \tag{43}$$

According to (50) and (51), the total real and reactive powers injected to a node equal the corresponding values of the lines connected to that node. It is assumed that the DPs have the same power factor of other customers connected to that node as given in (52). The maximum and minimum limits of the real and reactive powers of each line are enforced in (53) and (54). The voltage requirement of each line is approximated in (55) and is enforced to stay in its limits in (56). Note that V_i^{sqr} is a new variable which is equal to V_i^2. It is used to linearize the above power flow model.

The power flow constraints of the transmission network are approximated using the concept of DC power flow. On this basis, the following is required:

$$P_{i,h}^{a} + PG_{i,h} - PL_{i,h} = \sum_{j,j\neq i} pf_{ij,h} = \frac{(\theta_{i,t} - \theta_{j,t})}{x_{ij}} \qquad \forall i \in N^t, h \in H \tag{44}$$

$$\underline{pf}_{ij} \leq pf_{ij,h} \leq \overline{pf}_{ij} \qquad \forall ij \in L^t, h \in H \tag{45}$$

$$\theta_{0,t} = 0 \qquad \forall h \in H \tag{46}$$

Based on (57), the injected power in each node equals to the summation of power in lines connected to it. The power of each line is enforced to stay within its limits in (58). The angle of the slack bus is set to 0 in (59).

3.6 Risk Measure

To manage the risk of the profitability in the day-ahead bidding optimization in a conservative approach, the CVaR measure is implemented to manage the profit uncertainty for a given confidence level ς^{α}. On this basis, CVaR is applied to objective function (1) as:

$$\max\left\{(1-\varsigma^{\beta})\mathrm{OF}^{\mathrm{dam}} - \varsigma^{\beta}(\varsigma^{\phi} + \frac{1}{1-\varsigma^{\alpha}}\sum_{j}\Pi_j\psi_j)\right\} \tag{47}$$

$$\mathrm{prof}_j + \varsigma^{\phi} \geq -\psi_j \ ; \qquad \psi_j \geq 0 \qquad \forall j \tag{48}$$

Where, $0 \leq \varsigma^{\beta}, \varsigma^{\alpha} < 1$. In real-world examples, a solution to stochastic optimization with a higher expected profit leads to a higher risk of larger profit loss in certain scenarios. Hence, applying the CVaR measure to predefined scenarios enables the management of the associated risk. Generally, the CVaR measure represents the expected profit of the $(1 - \varsigma^{\alpha}) \times 100\%$ of the scenarios with the lowest profit (highest cost). If the confidence level ς^{α} low, the CVaR only ignores the scenarios with the highest profits but unlikely possibilities. If $\varsigma^{\alpha}$is high, the CVaR emphasizes on the scenarios with the worst profits. To achieve a trade-off between the risk of profit uncertainty measured by the CVaR and the expected profit, the weighting coefficient ς^{β} is defined. The higher the value of ς^{β}, the higher the interest in profit risk management. The optimal value of ς^{ϕ} represents the value-at-risk (VaR). The VaR is the highest value the objective function can reach such that the probability that the realized profit is lower than equal to ς^{ϕ} is lower than equal to $(1 - \varsigma^{\alpha})$. The positive variable ψ_j measures the excess of the cost in scenario j over ς^{ϕ} ($\psi_j =$ 0, otherwise).

The day-ahead optimization is run using the objective function (47), and constraints (2)–(33), (37)–(46) and (48) to determine the optimal values of E_h and SR_h. If the network data are unavailable, constraints (37)–(46) may be omitted. The aggregator is assumed to be a price-taker and submits energy and SR capacity offers to the DAM. Hence, its rewarded energy and SR in DAM equals the optimal values of E_h and SR_h, which are used as inputs in the RTM.

4. Real-Time Bidding Strategy

4.1 Linearized Economic Bid

The aggregator first needs to decide whether to bid for FRU or FRD. Usually, only the price of one of them is non-zero because the shortage in FRU occurs when the system faces a sharp ramp up of net-load, and the shortage in FRD occurs when the net-load reduction is high. We assume:

$$z_h = \begin{cases} 1: & if \sum_{t,t\in h} \lambda_t^{fru} \geq \sum_{t,t\in h} \lambda_t^{frd} \\ 0: & O.W. \end{cases} \tag{49}$$

$$\lambda_t^{frp} = z_h \lambda_t^{fru} + (1 - z_h)\lambda_t^{frd} \qquad \forall t \in h \tag{50}$$

Where set t indicates the 15-minute RTM intervals, and set h indicates the current trading hour. Since the market participants must submit hourly bids to the RTM, the aggregator must decide for each hour to either submit energy purchase or energy sell bids.

Referring to Section II.B, the following happens for a bid submitted to sell energy in the market:

$$if \;\; 0 \leq \pi_{i,h} < \lambda_t^e - \lambda_t^{frp} \;\; \rightarrow \; L_{i,h} = p_{i,t} \qquad \forall i, t \in h \tag{51}$$

$$if \;\; \lambda_t^e - \lambda_t^{frp} \leq \pi_{i,h} \leq \lambda_t^e \;\; \rightarrow \; L_{i,h} = frp_{i,t} \quad \forall i, t \in h \tag{52}$$

$$if \;\; \lambda_t^e > \pi_{i,h} \;\; \rightarrow \; L_{i,h} = dum_{i,t} \qquad \forall i, t \in h \tag{53}$$

The non-negative variables $\pi_{i,h}$ and $L_{i,h}$ stand for the price and amount of bid level i at hour h, respectively. Based on (51), if the bid price is lower than the energy LMP minus the flexiramp price, the traded energy is equal to the submitted bid level. Per (52), if the bid is between the energy LMP minus the flexiramp price and energy LMP, the flexiramp is rewarded. Moreover, if the bid is greater than the energy LMP, it rewards nothing enforced in (53) ($dum_{i,t}$ is a dummy variable).

Likewise, in a bid submitted to purchase energy, we have:

$$if \;\; \lambda_t^e + \lambda_t^{frp} < \pi_{i,h} \;\; \rightarrow \; L_{i,h} = -p_{i,t} \qquad \forall i, t \in h \tag{54}$$

$$if \;\; \lambda_t^e \leq \pi_{i,h} \leq \lambda_t^e + \lambda_t^{frp} \;\; \rightarrow \; L_{i,h} = frp_{i,t} \quad \forall i, t \in h \tag{55}$$

$$if \;\; 0 \leq \pi_{i,h} < \lambda_t^e \;\; \rightarrow \; L_{i,h} = dum_{i,t} \qquad \forall i, t \in h \tag{56}$$

One can observe by converting $p_{i,t} \rightarrow -p_{i,t}$, $\pi_{i,h} \rightarrow -\pi_{i,h}$ and $\lambda_{i,t}^e \rightarrow -\lambda_{i,t}^e$, the model of sell energy bid (51)–(53) can be converted to purchase energy bid (54)–(56). Thus, we define:

$$v_h = \begin{cases} 1: & if \; selling \; bid \; is \; submitted \\ -1: & if \; purchasing \; bid \; is \; submitted \end{cases} \tag{57}$$

Using the big $\mathbb{M}$ method and parameter v_h, we merge and linearize (51) and (54):

$$v_h \pi_{i,h} - \left(v_h \lambda_t^e - \lambda_t^{frp}\right) \leq \left(1 - \alpha_{i,t}\right)\mathbb{M}_t^\lambda \qquad \forall i, t \in h \tag{58}$$

$$0 \leq v_h p_{i,t} \leq \alpha_{i,t}\mathbb{M}_t^e \qquad \forall i, t \in h \tag{59}$$

The binary variable $\alpha_{i,t}$ is used to linearize (51) and (54). The parameter $\mathbb{M}_t$ must be sufficiently large to relax its associated constraint.

To merge and linearize equations (52) and (55), using auxiliary binary variable $\beta_{i,t}$, we define:

$$v_h \pi_{i,h} - v_h \lambda_t^e \leq \left(1 - \beta_{i,t}\right)\mathbb{M}_t^\lambda \qquad \forall i, t \in h \tag{60}$$

According to the relationship between binary variables $\alpha_{i,t}$ and $\beta_{i,t}$, the following occurs:

$$\begin{array}{c} if\ \beta_{i,t} - \alpha_{i,t} = 1 \rightarrow frp_{i,t} \geq 0 \\ O.W. \rightarrow frp_{i,t} = 0 \end{array} \qquad \forall i, t \in h \tag{61}$$

Also, $frp_{i,t}$ based on (49) can be rewritten as:

$$frp_{i,t} = z_h fru_{i,t}^{bid} + (1 - z_h) frd_{i,t}^{bid} \qquad \forall i, t \in h \tag{62}$$

Based on (61) and (60)–(62) and using auxiliary binary variable $\gamma_{i,t}$, we can write:

$$\left(\alpha_{i,t} - \beta_{i,t} + 1\right) \leq 2\left(1 - \gamma_{i,t}\right) \qquad \forall i, t \in h \tag{63}$$

$$0 \leq fru_{i,t}^{bid} \leq z_h \gamma_{i,t}\mathbb{M}_t^e \qquad \forall i, t \in h \tag{64}$$

$$0 \leq frd_{i,t}^{bid} \leq (1 - z_h)\gamma_{i,t}\mathbb{M}_t^e \qquad \forall i, t \in h \tag{65}$$

To merge and linearize (53) and (56), using the binary variable $\delta_{i,t}$, we can write:

$$-v_h \pi_{i,t} + v_h \lambda_t^e \leq \left(1 - \delta_{i,t}\right)\mathbb{M}^\lambda \qquad \forall i, t \in h \tag{66}$$

$$0 \leq dum_{i,t} \leq \delta_{i,t}\mathbb{M}_t^e \qquad \forall i, t \in h \tag{67}$$

To ensure the total of $p_{i,t}$, $fru_{i,t}$, $frd_{i,t}$ and $dum_{i,t}$ for each bid level, equal the bid amount, the following is enforced:

$$L_{i,h} = v_h p_{i,t} + fru_{i,t}^{bid} + frd_{i,t}^{bid} + dum_{i,t} \qquad \forall i, t \in h \tag{68}$$

4.2 Real-Time Optimization Problem

In the RTM, the aggregator attempts to trade flexiramp and marginal amounts of energy needed for its agents. The objective function that the aggregator seeks to maximize is provided in (69).

$$\max \mathrm{prof}^{\mathrm{rtm}} = \max\Bigg\{\Delta t \sum_t \big(e_t \lambda_t^e + fru_t \lambda_t^{ru} + frd_t \lambda_t^{rd} \\ + psr_t \lambda_t^e - \xi_t^e \varpi_t^e + \sum_k \big((p_{k,t}^{ev,ch} - ps_{k,t}^{ev,ch})\phi_{k,t}^{ch} - (p_{k,t}^{ev,dis} + ps_{k,t}^{ev,dis})\phi_{k,t}^{dis}\big)\big)\Bigg\} \tag{69}$$

Parameter Δt in the RTM equals 0.25 hr. The OF in the RTM is similar to the OF in the DAM presented in (1), except that the time-steps are in 0.25hr.

In the following, the relationship between the energy bid and actual energy, FRU and FRD is enforced:

$$\varpi_t^e \geq e_t - \sum_i p_{i,t} \qquad \forall t \tag{70}$$

$$\varpi_t^e \geq \sum_i p_{i,t} - e_t \qquad \forall t \tag{71}$$

$$fru_t^{ua} = \sum_i fru_{i,t}^{bid}\,;\;\; frd_t^{ua} = \sum_i frd_{i,t}^{bid} \qquad \forall t \tag{72}$$

The error of the actual power output and the expected power out of the submitted hourly bid is evaluated in (70) and (71). The total provided FRU/FRD equals the total FRU/FRD expected to be rewarded from the energy bid, based on (72).

4.3 Robustness Against RTM Prices

The RTM energy and flexiramp prices are volatile and detecting the true underlying probability distribution function is difficult. To manage the aggregator profit against the uncertainties associated with the energy and flexiramp price forecasts conservatively, we develop the robust counterpart of the real-time optimization with the objective function (73). In this vein, we assume that the RTM uncertain prices $\tilde{\lambda}_t$ can be written as $\tilde{\lambda}_t = \lambda_t + \xi_t \hat{\lambda}_t$ where, λ_t is the nominal value of the parameter, $\hat{\lambda}$ is the constant perturbation, and ξ_t is an independent random variable distributed in the range $\xi_t \in [-1,1]$. The idea is to obtain a solution that is feasible against any value of ξ_t in the uncertainty set $\mathbb{U}$ such that:

$$\mathrm{OF}^{\mathrm{RTM}} = \max \mathbb{Z} \tag{73}$$

$$\mathbb{Z} - \text{prof}^{\text{rtm}} + \left\{ \max_{\xi_t^e, \xi_t^{ru}, \xi_t^{rd} \in \mathbb{U}_t} \Delta t \sum_t \left(\xi_t^e e_t \hat{\lambda}_t^e + \xi_t^{ru} fru_t \hat{\lambda}_t^{ru} + \xi_t^{rd} frd_t \hat{\lambda}_t^{rd} \right) \right\} \leq 0 \tag{74}$$

To cope with the random variables ξ_t^e, ξ_t^{ru} and ξ_t^{rd}, we apply the "box+polyhedral" uncertainty set. The box uncertainty set represents the ∞-norm of the uncertain data vector, i.e.: $\mathbb{U}_\infty = \left\{\xi \middle| |\xi_j| \leq \Psi^r, \ \forall j \in J_i\right\}$ where Ψ^r is the parameter controlling the size of the set such that $0 \leq \Psi^r \leq 1$. The polyhedral uncertainty set represents the 1-norm of the uncertain data vector, i.e.: $\mathbb{U}_1 = \left\{\xi \middle| \sum_{j \in J_i} |\xi_j| \leq \Gamma^r, \ \forall j \in J_i\right\}$ where Γ^r is the parameter controlling the size of the set such that $0 \leq \Gamma^r \leq |J|$ ($|J|$ is the cardinality of the set). Combining the two uncertainty sets provides higher flexibility in managing the robustness. The "box+polyhedral" uncertainty set is defined as: $\mathbb{U}_{1\cap\infty} = \left\{\xi \middle| \sum_{j \in J_i} |\xi_j| \leq \Gamma^r, |\xi_j| \leq \Psi^r, \ \forall j \in J_i\right\}$, where Ψ^r and Γ^r are the adjustable parameters, such that $0 \leq \Psi^r \leq 1$ and $\Psi^r \leq \Gamma^r \leq \Psi^r |J|$. Now, based on the definition of the box+polyhedral uncertainty set and using auxiliary variables ν, w_t^e, w_t^{ru} and w_t^{rd}, the robust counterpart of the optimization is derived as:

$$\mathbb{Z} - \text{prof}^{\text{rtm}} + \Psi^r \sum_t \left(w_t^e + w_t^{ru} + w_t^{rd} \right) + \Gamma^r \nu \leq 0 \tag{75}$$

$$\nu + w_t^e \leq \Delta t \hat{\lambda}_t^e u_t^e \ ; \ \ -u_t^e \leq e_t \leq u_t^e \qquad \forall t \tag{76}$$

$$\nu + w_t^{ru} \leq \Delta t \hat{\lambda}_t^{ru} u_t^{ru} \ ; \ \ -u_t^{ru} \leq fru_t \leq u_t^{ru} \qquad \forall t \tag{77}$$

$$\nu + w_t^{rd} \leq \Delta t \hat{\lambda}_t^{rd} u_t^{rd} \ ; \ \ -u_t^{rd} \leq frd_t \leq u_t^{rd} \qquad \forall t \tag{78}$$

$$\nu, w_t^e, w_t^{ru}, w_t^{rd} \geq 0 \qquad \forall t \tag{79}$$

The real-time OF in (73) is run on an hourly basis for bidding in RTM and is subject to (2)–(10), (13)–(33), (37)–(46), (58)–(60), (63)–(68), (70)–(72) and (75) –(79). Note that in the RTM for (2)–(10) and (13)–(33), index j for all variables and parameters is removed, and index h is replaced by index t. In addition, variables E_h and SR_h, which account for the energy and SR traded in the DAM, are used as parameters in the RTM optimization. Note, if the network data are unavailable, (37)–(46) will be removed.

The real-time optimization is run for each hour, and the optimal variables $\pi_{i,1}$ and $L_{i,1}$ $\forall i$ are determined. These values represent the hourly bids submitted by the aggregator to the RTM. Then, based on the RTM energy, FRU, and FRD prices, and the logic explained in Section II.B, the profit of the aggregator at each fifteen-minute market interval is calculated.

4.4 Solution Procedure

A flowchart of the proposed bidding strategy is presented in Fig. 2. The procedure starts with the participation in the DAM. First, based on the historical data, the aggregator derives the scenarios of uncertain parameters, including the RTM energy and flexiramp prices, DP loads, temperature, EV scheduling, and PV generation. These scenarios are then incorporated into the two-stage stochastic optimization modeled as an MILP. The output of the optimization is the optimal energy and SR the aggregator desires to trade in the DAM ($E_h, SR_h \quad \forall h$) which are submitted as quantity bids to the DAM. The ISO runs the DAM and notifies the aggregator regarding the traded energy and SR.

Next, the RTM process follows. At each hour, the aggregator must submit hourly bids to the RTM. On this basis, first, the aggregator receives the current status of each DP asset. Next, it forecasts the uncertain

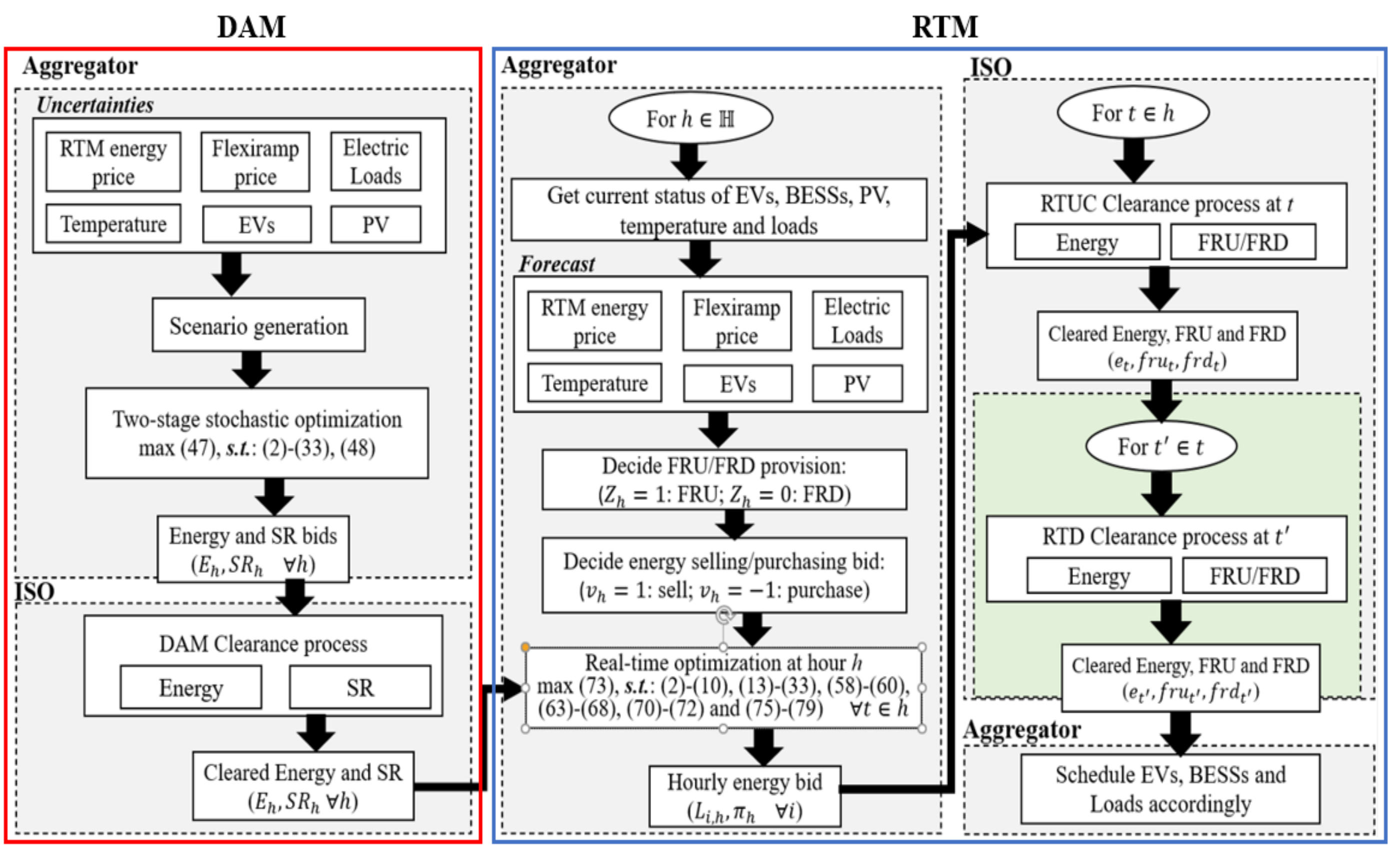

Fig. 2. The flowchart of the proposed bidding strategy model.

parameters. Then, based on its forecast of FRU and FRD prices, chooses the one with higher profitability ($z_h = 1$ for FRU and $z_h = 0$ for FRD). Next, based on its energy trade in DAM and forecasts of the loads and PV generation of DPs, the aggregator decides to either submit an energy selling or purchasing bid ($v_h = 1$ for selling bid and $v_h = -1$ for purchasing bid). The aggregator then runs its real-time optimization modeled as an MILP whose output is an energy price-quantity bid with $\mathbb{I}$ levels for hour h ($L_{i,h}, \pi_{i,h} \quad \forall i$) submitted to the RTM. In the RTM, the ISO runs four RTUCs each with 15-minute time-steps and notifies the market participants of the energy, FRU, and FRD results. During each RTUC, the ISO runs three RTDs each with 5-minute time-steps. The aggregator must comply with the RTM results by scheduling the DP resources accordingly; otherwise, it is penalized. The aggregator bidding in the RTM and the RTM process is run for each hour of the day.

In this study, the RTD process is neglected because the main focus is on hourly bidding to the RTUC process. However, incorporating the RTD process does not affect the bidding strategy model. The aggregator is assumed to be a price-taker whose bids do not impact the WEM LMPs. In addition, the impacts of other market participants on the market clearance process are reflected in the WEM LMPs.

5. Case Study and Simulation Results

5.1 Main Assumptions

The aggregator has a contract with 50 DPs, including 40 residential, 5 small commercial, 3 medium commercial and 2 large commercial buildings whose load data can be found in [35]. All buildings are assumed to have rooftop PV panels with power outputs driven by the PV solar radiance and temperature given in [36]. The expected building loads and PV power per $100m^2$are depicted in Fig. 3 (the forecast standard deviation is set to 5%). A total of 200 EVs are considered for the agents: 100 EVs for residential buildings and 100 for commercial buildings. The EV data and contract between the commercial agents and EV owners are adopted from [37]. The AC data and the associated building characteristics are taken from [27]. The DEL assumed is equal to 20% of the total load for residential agents and 0 for commercial agents.

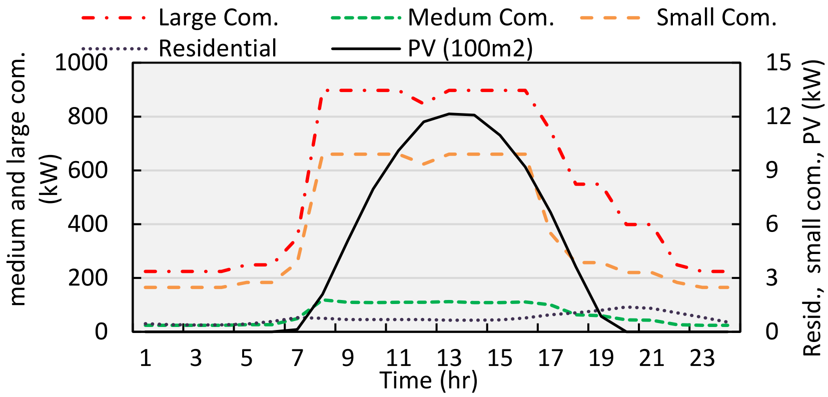

Fig. 3. Expected buildings loads as well as PV power per $100m^2$ [35]-[36].

The duty cycle for the DELs is assumed to be a random number between 0 and 4hr for each building. The price data are taken from the CAISO market in the PGE balancing authority area [38]. The historical data from 06/01/2020 to 08/28/2020 are used for price scenario generation, and the data of five business days, from 08/31/2020 to 09/04/2020, are used as the out-of-sample case study. It is assumed that the residential and commercial DPs are connected to nodes 611 and 625 of the IEEE 13-bus radial distribution system, respectively. The distribution system is connected to bus B in the PJM 5-bus test system, which is considered as the transmission system. The data associated with these test systems are given in [39], [40].

The simulations were performed in Python environment, and the IBM CPLEX optimizer API is employed to solve the problem on a PC with 2GB SSD hard drive and 64GB RAM. The minimum gap in the MILP was set to 0.1%. The computation time, on average, for the DAM optimizations was 3844s and for the hourly RTM optimizations was 463s.

Two cases are considered, and their simulation results are compared:

- Case I: Ignoring flexiramp in bidding strategy
- Case II: Considering flexiramp in bidding strategy

The aggregator is assumed to be a price taker, that is, it is a relatively small WEM participant whose bid does not affect the LMPs. For each of the five case days, we first run the day-ahead optimization, and we assume that it offers prices of 0 for SR and selling energy, and price equal to the associated cap for purchasing energy. Hence, it trades all the desired energy and SR based on the associated LMPs. Then, we run the real-time bidding optimization and compare the bids with the realized LMPs: the aggregator rewards the desired amounts if the bid goes through, and the bid is rejected otherwise.

5.2 Uncertainty Modeling and Scenario Generation

To capture the day-ahead scheduling uncertainties, 25 scenarios for each of the real-time price signals, PV generation, ambient temperature, EV scheduling, building loads, and heat gain and losses are generated as described in [25] and [27].

A Gaussian copula method is adopted to generate the ambient temperature scenarios used in the AC load constraints. The scenarios of the heat gain and losses are generated using a Gaussian white noise process with the following parameters: $\chi \sim N(0{,}1.10^{-6})°\mathrm{Cs}^{-\frac{1}{2}}$. The scenarios for the non-controllable load are generated using a seasonal naïve forecasting algorithm. The scenarios of PV generation are generated using a Gaussian copula method.

The scenarios of the EV arrival and departure times and the SoC at the time of arrival are generated using a seasonal naïve forecasting algorithm. The EV SoC at the time of departure ($\overline{soc}_k$) is set to the battery capacity of the EV.

A gradient-boosting algorithm was adopted to compute the RTM energy price scenarios. The RTM FRU and FRD price scenarios were generated using a seasonal naïve forecasting algorithm. Note that proposing novel forecasting algorithms for flexiramp prices is beyond the scope of this study.

5.3 Day-ahead Optimization Results

The effects of CVaR on the day-ahead optimization profitability for cases I and II in the five days of the case study are shown in Fig. 4. The value of ς^{α} is set to 0.95 and ς^{β} is increased from 0 to 1. As observed, the traded power in these two cases is not significantly affected by the flexiramp provision due to the relatively high price of energy. Flexiramp provision has affected the SR provision, and lower SR profit is gained in Case II. Indeed, considering flexiramp ASP lowers the profit out of SR in the DAM since the aggregator attempts to reserve the ramp capacity of DPs to provide flexiramp ASP in the RTM.

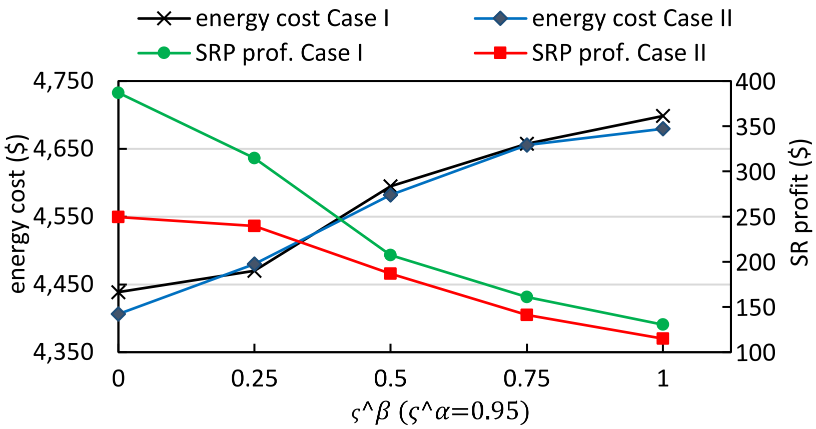

Fig. 4. The DAM costs versus the risk parameter for the 5 days of case study.

As the value of ς^{β} increases, the significance of the risk measure becomes more prominent. $\varsigma^{\beta} \approx 0.5$ gives proper results since (i) does not impact the costs drastically and (ii) does not marginalize the effects of CVaR measure. Hence, the results of the day-ahead optimization with $\varsigma^{\beta} = 0.5$ and $\varsigma^{\alpha} = 0.95$ are selected to use in the RTM. In this case, the traded power and SR in DAM along with the expected power, FRU and FRD to be traded in the RTM for the five days of the case study are depicted in Fig. 5 and Fig. 6, respectively.

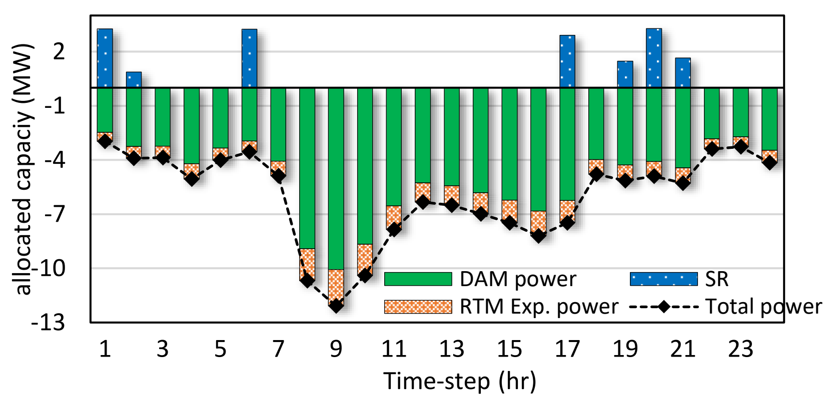

Fig. 5. The DAM traded and RTM expected energy and ASPs in Case I.

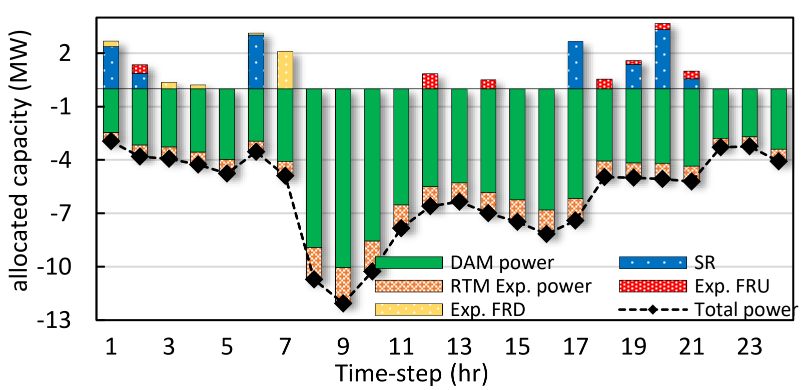

Fig. 6. The DAM traded and RTM expected energy and ASPs in Case II.

The flexiramp provision causes less capacity available for SR provision reducing 16.7 MW SR procured in Case I to 14.7 MW in Case II. In addition, procuring flexiramp in Case II affected the traded power, mainly by a slightly sharper increase in the total power curve at the time intervals in which FRU provision is expected.

5.4 Real-Time Optimization Results

The optimization horizon for each hourly bidding problem is 3 hours with 15-minute time-intervals. The ARIMA algorithm is implemented to forecast the real-time prices. The day with the least variance of hourly prices is selected as the exogenous input to ARIMA. The ARIMA parameters are set to (1,0,1) because they empirically demonstrated the best forecast fit. Proposing proper RTM price forecasting methods is beyond the scope of this study. The energy and flexiramp price forecast perturbations are set to 20% of the forecasted value.

The profit from energy, FRU, and FRD in the RTM based on parameters Ψ^r and Γ^r of the robust counterpart of the optimization are shown in Fig. 7. As observed, an increase in these parameters, particularly Γ^r, while reducing the profit from flexiramp, leads to more profit from energy trading by mitigating the impacts of the RTM price forecast uncertainties.

Considering $\Psi^r = 0.5$ and $\Gamma^r = 3$, the total procured FRU and FRD in the RTM for the five days of the case study are shown in Fig. 8. FRU procurement is higher because its marginal prices are much higher than those of the FRD. It can be observed in the profits gained from FRU and FRD in Fig. 7. The capacities

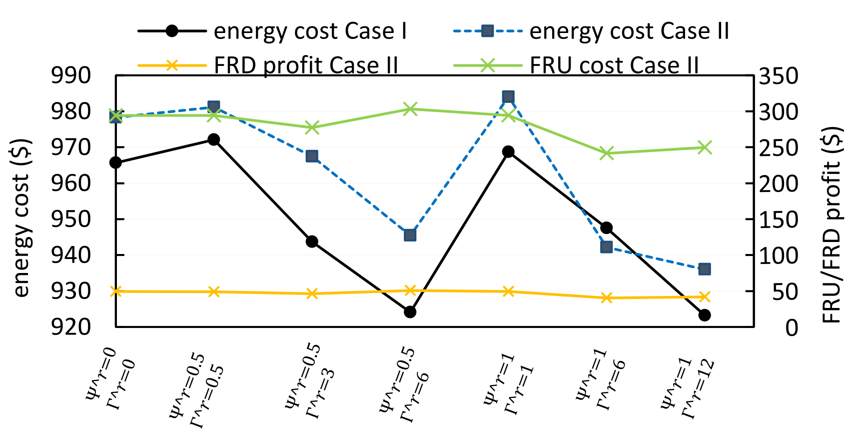

Fig. 7. Real-time profitability versus the robust counterpart parameters.

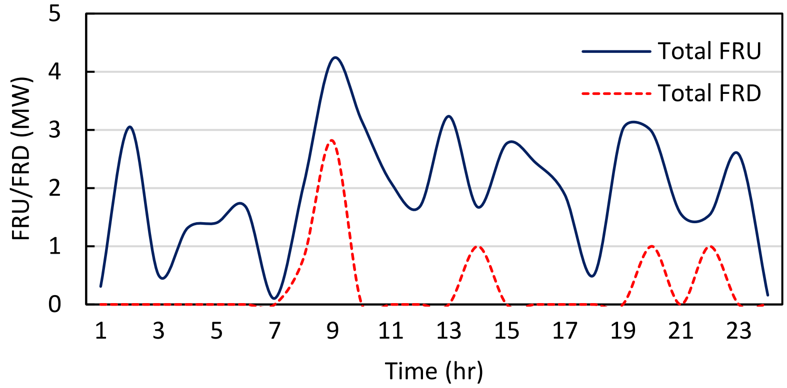

Fig. 8. Total FRU and FRD procured by the agents in the 5 days of case study in Case II with: $\Psi^r = 0.5$ and $\Gamma^r = 3$.

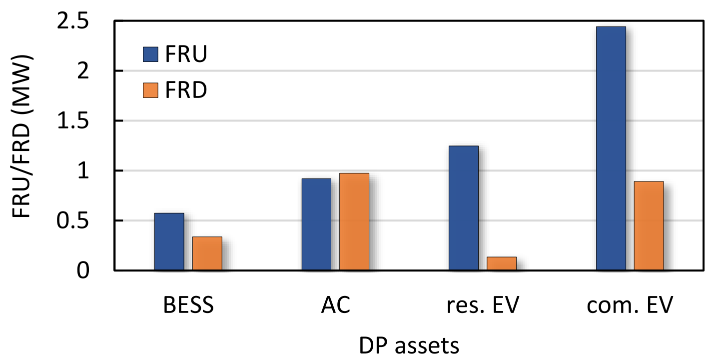

Fig. 9. The total provided FRU and FRD by different agent assets in Case II.

allocated to FRU and FRD by different assets of DPs are shown in Fig. 9. The BESSs procured the least amount of flexiramp owing to their smaller capacity. The ACs comparatively procured more FRD since they do not usually operate in full capacity and can allocate the rest of the power capacity to FRD. The EVs in commercial buildings procured the highest FRUs since they are mainly available for flexiramp provision in the periods when the system load increment and FRU prices are high. EVs connected to residential buildings are usually available during the night and early morning, and their contribution to FRU provision is comparatively low.

The simulation results for the DAM and RTM demonstrate that the operation of DPs did not cause any violation of the transmission and distribution system constraints including voltage limit and line capacity.

6. Conclusion

DPs have received increasing attention in recent years owing to their high ramp capacity and ability to participate in multiple ASPs in the WEM through their aggregators. In this study, their profitability of SR and flexiramp procurement is evaluated. Flexiramp is an RTM product offered in the CAISO market to which the market participant cannot submit direct bids, and the compensation is based on their energy opportunity costs. On this basis, a two-stage risk-averse optimization is developed for participation in the DAM energy and SR market while considering the profitability of DPs in RTM considering energy and flexiramp products. In the RTM, to obtain the optimal multi-level hourly bids submitted to the RTM with 15-minute time-intervals, a novel bidding strategy is developed and integrated with the DP optimization problem, which is robust against RTM price uncertainties. A 5-business day case study from the CAISO market and two cases without and with considering flexiramp (Cases I and II) were investigated. The simulation study demonstrated the following:

- The day-ahead optimization results indicate that the effects of considering the flexiramp on the energy trades of the aggregator in the DAM is trivial. On the other hand, it lowers the SR procurement by the aggregator (12% in our case study) because the aggregator attempts to reserve a portion of the ramp capacity of its agents for the flexiramp.
- The real-time robust optimization is affected by the uncertainty set control parameters, particularly Γ^r. An increase in these parameters lowers the profit gained from flexiramp procurement, but increases the profit from energy trading by mitigating the impacts of RTM price forecast uncertainties.
- The EVs connected to commercial buildings provided the highest flexiramp because they were connected during the times the flexiramp prices were relatively high. Next are residential EVs, AC and BESSs, respectively.
- Flexiramp provides a great opportunity to increase DP profitability from ASP procurement to the WEM by bidding for the flexiramp. Indeed, in the case study, the profit gained from the

ASPs in Case II almost doubled for the test day. The results show that Case II brings about savings in energy cost as well.

The following are the issues that should be explored in future work because they may have a significant impact on the evaluation of the proposed framework and on the profit gained from flexiramp procurement:

- Proper flexiramp price forecast algorithms.
- The competition of the aggregator and other market participants.
- DSO's ability to assure the technical constraints allowing DPs participation in the aggregated WEM ASPs.

7. Acknowledgment

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