Network-aware Participation of Aggregators in NEM Energy and FCAS Markets

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ABSTRACT

The integration of distributed energy resources (DER) has created a demand-side flexibility which can be traded in the electricity market by aggregators. However, generating bids that accurately represent the flexibility of consumers while maintaining the network limits is a challenging task–especially since the aggregators typically do not have access to the network data nor the bids of other aggregators. To overcome these challenges, we propose a price-generating bidding strategy enabling aggregators that share the same distribution network to participate in the energy and FCAS (frequency control ancillary service) markets. Complying with the Australian National Electricity Market (NEM), we develop energy-FCAS trapeziums that represent aggregators' energy and FCAS bid interdependency across their fleet of flexible consumers. We also obtain the prices at which the aggregators should submit their energy and FCAS bids. Moreover, to ensure network feasibility for any market clearing output, we obtain the network feasible region using three sets of optimal power flows (OPFs). Aggregators' trapeziums are then restricted to be within the network feasible region, making them ready to submit to the NEM. We illustrate the effectiveness of our proposed approach using 207 consumers being served by three aggregators in a 69-bus distribution network. The results show that our approach could increase aggregators' benefits by 18%, on average, compared to a price-taking approach.

CCS CONCEPTS

• **Computing methodologies** → *Artificial intelligence.*

KEYWORDS

Bidding strategy, Electricity Market, FCAS, NEM, OPF

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1 INTRODUCTION

The soaring uptake of distributed energy resources (DER), such as rooftop PV and batteries, has shifted a significant proportion of electricity generation away from the big generating companies and into the hands of the consumers in the distribution networks. Most of these flexible resources are equipped with energy management systems (EMS) with smart controllers and smart meters, allowing consumers to respond to the real-time prices and participate in the electricity markets [1]. However, managing this huge number of DER directly within the wholesale electricity market, if it was at all possible, would be a very difficult task. Therefore, aggregators have emerged, as mediators, to group together such DER and participate in the electricity market on their behalf.

A plethora of research works have focused on the market participation of aggregators in energy (and frequency) markets, e.g., [2–10][1]. These research works mainly assume that the aggregators are price-taking participants of the electricity market; meaning that they optimise their consumers' resources according to a price forecast and bid the aggregated generation and load capacities respectively at zero and the market cap price. This ensures that for any market clearing price, their bids, either generation or load, are accepted by the electricity market. This simplification makes the operating state of the DER and thus the distribution network crystal clear, i.e., aggregators can assume they will be dispatched.

However, consumers have a range of flexibility that can be offered to the electricity market for different prices. Price-taking approaches restrict DER bidding to a single point within the range, leading to poor management of their flexibility. In addition, in case the market clearing price (MCP) notably deviates from the forecast, the schedules obtained by the price-taking approaches are no longer optimum and may even lead to economic loss for both aggregators and the DER owners.

Another simplification, adopted in the literature, is to neglect the distribution network constraints [5–10]. However, the synchronised action of numerous consumers in response to electricity prices can exceed the distribution network limits and lead to infeasibility.

To overcome the above-mentioned challenges, we propose a bidding strategy that enables aggregators to bid their whole flexibility in both energy and FCAS markets. Since the participation in one market would limit the bids in another, we develop a feasible region showing aggregators energy and FCAS interdependency for their available flexibility. Moreover, we calculate the marginal prices at which the aggregators need to submit their flexibility across their feasible region.

[1]We go into greater detail of these approaches in the related work section.

To ensure the network feasibility for any market output, our approach uses three sets of OPFs to calculate the biggest region within which the network constraints are not violated. The aggregators' feasible regions are then shaped to be within the network feasible region which then can be submitted to the wholesale electricity market.

Note that the aggregators and the grid solve their respective subproblems sequentially. Therefore, neither aggregators nor the grid need to know each others' private data / constraints. This ensures the independent role of aggregators and the distribution system operator (DSO).

To take the forecasts uncertainty into account and obtain higher quality results, we implement our proposed approach within a receding horizon framework which moves forward every five minutes and uses the latest and the most accurate uncertainty information in every horizon.

Note that we develop our approach under NEM regulations, operated by the Australian energy market operator (AEMO) in Australia. Despite this focus, we expect our approach to be widely applicable to aggregators participating in other electricity markets, to co-optimise the energy and reserve capacities of their consumers. Moreover, we assume the aggregators only participate in the energy and contingency raise FCAS markets. While providing some insights on how to include the lower FCAS market, we leave the detailed study of such a case to our future work.

The rest of this paper is organised as follows: Section 2 reviews the related work and compares our contributions with the state-of-the-art. Section 3 provides a brief introduction on the NEM and AEMO. Section 4 provides an upfront overview on the proposed approach. Section 5 and 6 respectively present the aggregator and network subproblems. Section 7 numerically illustrates the effectiveness of the proposed approach using 207 consumers. Finally, Section 8 concludes this paper.

2 RELATED WORK

DER flexibility has been used for different purposes such as improving the voltage profile [11], peak shaving / valley filling [2]; and / or frequency response [3–10]. These research works schedule their DER using either the retail tariffs or the electricity market prices. When the DER are scheduled through the electricity market prices, a bidding strategy is required to obtain the DER schedules and the bids to the electricity market.

Since the power system frequency is mainly handled through trading raise and lower reserves in the wholesale electricity markets, our approach belongs to the second group of approaches. Unlike our proposed price-generating approach, almost all bidding strategies for residential DER follow a price-taking policy, for which we provide a brief literature review in the following.

In contrast to our approach, [3] and [4] only participate in the energy market and neglect the frequency markets. However, as Oudalov and et all showed in [12], the highest performance of DER is achieved when they provide frequency response.

Those works that consider both the energy and frequency markets [5–10], typically neglect the distribution network constraints. Assuming that their bids do not violate the distribution network constraints, [5–10] co-optimise their DER in the energy and frequency markets and submit the obtained bids to the associated markets. However, as we also show in our numerical results section, such an assumption can lead to infeasibilities. The reason is that the synchronised action of many DER in a distribution network can exceed its limits, e.g., when all DER are simultaneously responding to a price spike / drop or during peak PV production. Our approach overcomes the network infeasibility issue of [5–10] by appropriately including the distribution network constraints.

In addition to the above mentioned downsides, all [4–10] assume that the residential DER are price-taking participants of the wholesale electricity market. This means that they schedule their appliances according to a price forecast and assume that their bids, either generation or load, are accepted by the electricity market. This assumption makes the operating state of the network clear. Thus, the very few works that consider the distribution network constraints e.g., [13, 14], use this assumption and solved OPFs for this pre-specified operating point to ensure the network feasibility.

Note that the schedules obtained using price-taking approaches (with or without network) is optimum as long as the MCP is similar to the forecasted prices (an assumption that rarely holds in the real-world markets). In other words, limiting the range of energy-FCAS flexibility of DER to one point, might lead to poor results. To address this problem, our approach obtains a whole range of DER flexibility and bids them with different prices to the electricity market. This process makes sure that the aggregators take better actions when the electricity price deviates from the forecast (for example, moves from charge mode to discharge or visa versa in response to the electricity price).

On the other hand, when bidding a range of flexibility in the electricity market, the operating state of DER, and thus of the grid, depends on the market output. This makes including the network constraints more complicated than just solving one OPF (as in price-taking approaches [13, 14]). To meet this challenge, our approach uses three sets of OPFs to obtain the largest feasible region for the network. The aggregator bids are then restricted to be within the network feasible region, creating aggregator network-aware bids. This ensures that for any market clearing output, the network constraints are not violated.

To the best of our knowledge there is no price-generating approach for residential DER in the literature. For grid scale DER however, [15–17] first determine the effect of DER on the market prices and then use the obtained modified prices to schedule their DER. Similarly to the price-taking approaches, [15–17] bid one point to the electricity market (generation at zero and load at the market cap price).

Not only are [15–17] not able to bid a range of flexibility, but also they only consider the effect of their own DER on the electricity market prices. However, the price might change according to the behaviour of other participants (e.g., a generation company might trip leading to a sudden price increase) i.e., there are frequent real-world scenarios that [15–17] do not take into account. On the contrary, by submitting different capacities at different prices, our approach takes advantage of any price change in the electricity market (either due to its own DER or caused by other participants).

Given the above literature review, this paper contributes to the state of the art as follows:

- Proposing a novel price-generating bidding strategy for DER aggregators which can create a range of energy and FCAS capacities as well as the marginal prices at which the aggregators can provide these capacities.
- Obtaining the network feasible region using three sets of OPFs, and restricting the aggregator bids to be within the network feasible region. This ensures the network feasibility for any market clearing output across the aggregators' flexibility.

3 NATIONAL ELECTRICITY MARKET

The NEM is a five-minute real-time market which is operated by AEMO. Under NEM frequency standards, AEMO must ensure that following a credible contingency event, the frequency deviation remains within the contingency band (e.g., 49.5 to 50.5 Hz) and returns to the normal operating threshold (e.g., 49.85 to 50.15 Hz) within 5 minutes[2]. To do so, AEMO uses raise and lower FCAS markets to trade the required reserves in every 5-minute settlement.

Currently, the NEM includes 8 different FCAS markets: 2 regulation and 6 contingency FCAS markets. While the regulation FCAS includes a raise and a lower market, the contingency FCAS market is categorised into three main groups according to their response time: raise and lower 6-second, 60-second, and 5-minute FCAS markets. In the NEM, energy and all FCAS markets are fully co-optimised on a single real-time platform known as NEMDE (national electricity market dispatch engine). NEMDE clears the Australian market every 5 minutes to obtain the energy and FCAS prices as well as the dispatch of the participants.

Note that there is no day-ahead market in the NEM [19], however, to smoothly run the real-time market, AEMO requires participants to submit their pre-dispatch bids (capacity and price) the day before. In the NEM, the prices stay fixed for the next day but the capacity in each 5 minute period can be adjusted by the participants.

To bid in the NEM, participants need to submit their energy-FCAS "trapezium" as well as up to 10 price-bands for energy and each FCAS market. The trapezium of a generating unit for a raise FCAS market[3] is shown in Figure 1. In this example, the raise FCAS capacity is first limited by the ramp rate (i.e., R) of the unit (the flat top section); moving towards the maximum output of the unit on the energy axis (i.e., P^{max}), the capacity of the generating unit becomes more constraining than the ramp rate (i.e., $P + F \leq P^{max}$).

The NEM enables participants to break down their available capacity up to 10 *capacity bands* per market, and submit them at 10 different prices (known as *price bands*). To be in the market, a non-zero capacity should be allocated to at least one of these price bands. Given the capacities and price bands, NEMDE can dispatch the participants at any point of their trapezium (highlighted by yellow in Figure 1) to obtain the least-cost operating point. Co-optimising over participant feasible regions helps AEMO to find the lowest overall operating costs. This is why the average FCAS costs in the NEM are very low compared to the international markets such as the ones in California, Germany, and the UK [19].

[2]According to the event and/or location, contingency frequency band and the recovery time might differ [18].

[3]Participants need to submit either another trapezium for the lower FCAS market or a more generic trapezium accounting for both their lower and raise FCAS capacities.

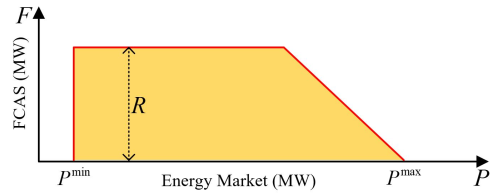

Figure 1: Energy-FCAS trapezium

Having NEM cleared, FCAS providers get paid their accepted bids regardless of whether or not a contingency actually occurs. In the case that a contingency does occur, they must respond up to their market accepted capacity to correct the frequency deviation. In this paper, we assume the DER is equipped with the necessary metering and control systems to be able to enact the required responses.

3.1 Market Simplification / Assumption

Here, we do not solve the day-ahead pre-dispatch part of the problem, but focus on the operational update of the capacity component of bids. These updates allow aggregators to put their best offer forward as they can account for how their actual dispatch and changes in uncertain renewable generation has affected their operating state. Note that the same technique can be used to obtain the pre-dispatch bids but with the day-ahead forecasts for the PV power, demand and market prices. However, since the aggregators can change their bids in real time and our distributed approach makes it possible to solve the problem within the time frame of the real-time market, we do not focus on the pre-dispatch problem.

Moreover, we allow aggregator price bands to be updated in real time in addition to capacity. So, we have opted to investigate a case that is more real-time than the existing NEM structure. We will discuss how our approach could fit in the more strict NEM requirements in Section 5.4.

4 THE OVERALL APPROACH

Markets can operate most efficiently (maximise system-wide social welfare), when participants provide bids that represent their true operating capabilities and associated costs. Unfortunately, the bids that NEM and most other markets accept have limited expressiveness, so in general, aggregators will not be able to exactly represent their characteristics through bids. Nonetheless, we develop an approach to generating bids that provides a good approximation of an aggregator's characteristics. For the overall capacity limitations of an aggregator this can be made exact, but it will only ever be approximate for the aggregator cost function estimate due to the time coupled behaviour of DER.

In addition, the distribution network bounds might limit aggregators' action. However, it is difficult (if at all possible) for aggregators to directly include the distribution network constraints. The reason is that aggregators mainly do not have access to the grid data / constraints. Even if they did, still their grid share depends on how their competitors (other aggregators) are acting. Unsurprisingly, aggregators do not have access to their competitors' information.

Given the limitations described above, our goal for each 5-minute market settlement is to obtain the energy-FCAS feasible region as well as price bands for each aggregator that are network compatible.

To do so, we decompose our problem into aggregator and network subproblems and generate the final bids by communicating between the two subproblems. In the following, we provide some overall explanation for aggregator and network subproblems which are then detailed in the next section.

4.1 Aggregator Problem Overview

In the aggregator subproblem, each aggregator calculates their energy-FCAS feasible region as well as their price bands. Since aggregators only have fast responding inverter-based DER, according to AEMO [20], their energy-FCAS feasible region is in the form of a triangle as shown in Figure 2. Unlike a general trapezium (e.g., Figure 1), the ramp rate is no longer limiting for fast-responding participants. This means that at each point the capacity that can be allocated to the energy or FCAS markets is interchangeable and thus the triangle in Figure 2 is an isosceles right triangle. Therefore, to characterise an aggregator's feasible region, we only need two points (A and B) or (A and C) or (B and C).

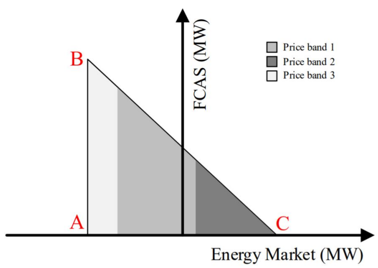

Figure 2: Energy-FCAS Triangle of Aggregators

Regarding the prices, we obtain 3 price bands representing the most important transitions that can happen to the aggregators (shown by different grey levels in Figure 2). These three dispatch transitions are: 1) moving from neutral battery status (neither charging nor discharging) to charge mode, shown by price band 1 in the figure. 2) Moving from neutral battery status to discharge mode, shown by price band 2. 3) Moving from a no-PV-curtailed point to a fully-PV-curtailed point, shown by price band 3. Note that since aggregators' problems are linear, these transitions (especially over a 5 minute settlement) makes sense. Yet, more discretisation (up to 10 bands) could be used to increase accuracy.

Without loss of generality, we fix the raise FCAS price bands to zero and instead just use the energy market prices to reflect an aggregator's preferences. Note that even though the bids for each market are separate, in practice, the markets are coupled in the NEMDE optimisation process. Therefore, as we show in section 5.3.2, the dispatch of aggregators will be the same.

To give an intuition on how we obtain the prices, imagine a half-full battery that is being scheduled for the next 24 hours. If the price of the first time-step is zero (or negative), the battery should charge at the first time-step in order to discharge at the later hours. The maximum charging price is the price at which the aggregator will stop charging in the first time step. We obtain this price and bid it as the maximum price that the battery can go to charge mode and provide the associated capacity band. If we keep increasing the price of the first time-step, then the battery stays neutral; by further increasing the price, from a point onward, the battery will go to discharge mode. This price is the minimum discharge price. We obtain this price and bid as the minimum price that the battery can discharge and provide the associated capacity band.

Having obtained aggregators energy-FCAS regions and prices, aggregators submit their bids to the DSO to have their feasible regions shaped according to the network operating limits.

4.2 Network Problem Overview

In our network subproblem, at each node, the DSO sorts aggregators bids according to their energy prices (the FCAS price is zero). Note that since aggregators triangles have the same angles (aggregators' feasible regions are isosceles right triangles), the network polygon is also a triangle. To apply the network effect on the aggregators' energy-FCAS feasible regions, we solve OPFs for the extreme points of the overall triangle A, B and C. As a result of this step, we obtain the network feasible region (network triangle). An example of the network feasible region when there are 3 aggregators, each providing 3 price bands, is given in Figure 3.

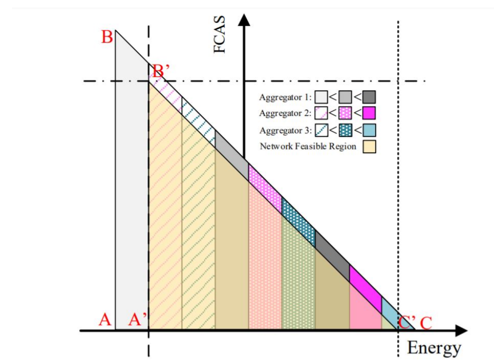

Figure 3: Network energy-FCAS feasible region

As shown in Figure 3, the bids are sorted increasingly from left to right (i.e., the first capacity band of aggregator 1 has the lowest price while the last capacity band of aggregator 3 has the highest price). If the network constraints were not limiting, the network feasible region would be the same as the original triangle A, B, C. However, in case of a network violation, the network limits the most expensive generation or the least expensive load (most extreme prices) to ensure network feasibility. This will lead to a feasible region smaller than the original feasible region (shown by A', B' and C' in Figure 3). In this example, aggregator 2 will not be limited, so it can submit its whole triangle to the NEM. However, the third capacity band of aggregator 1 as well as a significant part of the second capacity band of aggregator three cannot be submitted to the NEM. The DSO then sends aggregators their shaped energy-FCAS feasible regions which can be submitted to the NEM.

Every five minutes, the same process is repeated (in a receding horizon framework) to generate aggregators' network-aware bids. Note that since the NEM is cleared one time step at a time, the aggregators only use the energy-FCAS feasible region and their prices for the next five minutes. Yet, they account for multiple future time steps when determining their bids, to avoid shortsighted decisions. In the following, we explain the aggregator and the network subproblems of the proposed approach in detail.

5 AGGREGATOR SUBPROBLEM

Here, we first model a price-taking aggregator in Section 5.1 and then we use the price-taking model to obtain aggregators' feasible region as well as their prices respectively in Sections 5.2 and 5.3.

5.1 A Price-taking Aggregator

We use $i \in N$ for the network nodes; $t \in T$ for the time horizon; $c \in C^a$ for consumers being served through aggregator $a \in A$, where C_i^a is the set of such consumers located at node i. Total generation, demand and FCAS raise of aggregator a at node i are respectively given by $G_{i,t}^a$, $D_{i,t}^a$, and $F_{i,t}^a$. The generation, demand and raise FCAS capacity of consumer $c \in C^a$ are $g_{c,t}$, $d_{c,t}$ and $f_{c,t}$. We represent the internal variables of consumer c at time t (such as their PV and battery variables) with X. Finally, $h_c(d_c, g_c, f_c, X)$ and $h'_c(d_c, g_c, f_c, X)$ model any equality and inequality constraints of consumer $c \in C^a$. Given the energy and raise FCAS price forecasts, π_t^e and π_t^{fcas}, the aggregator a solves the following energy and FCAS co-optimisation problem:

$$\min_{D,G,F} \sum_{i \in N} \sum_{t \in T} \delta_t \cdot \left(\pi_t^e \cdot \left(D_{i,t}^a - G_{i,t}^a \right) - \pi_t^{\text{fcas}} \cdot F_{i,t}^a \right) \tag{1a}$$

$$D_{i,t}^a = \sum_{c \in C_i^a} d_{c,t} \qquad \forall i \in N, t \in T \tag{1b}$$

$$G_{i,t}^a = \sum_{c \in C_i^a} g_{c,t} \qquad \forall i \in N, t \in T \tag{1c}$$

$$F_{i,t}^a = \sum_{c \in C_i^a} f_{c,t} \qquad \forall i \in N, t \in T \tag{1d}$$

$$h_c(d_c, g_c, f_c, X) = 0 \qquad \forall c \in C^a \tag{1e}$$

$$h'_c(d_c, g_c, f_c, X) \leq 0 \qquad \forall c \in C^a. \tag{1f}$$

where δ_t is the time step duration in hours; the objective function (1a) minimises the cost of co-participation in the energy and raise FCAS markets. (1b)–(1d) obtain the aggregated demand, generation and raise FCAS bids of aggregator a. Constraint (1e) represents any consumer equality constraints e.g., battery SoC. Finally, (1f) models consumers inequality constraints e.g., charge / discharge rate of battery. An example for the extended $h_c(d_c, g_c, f_c, X)$ and $h'_c(d_c, g_c, f_c, X)$ can be found in [10].

Since the electricity market is cleared one time-step at a time, having (1a)–(1f) solved, only the values of the first time step are submitted to the electricity market. Note that the rest of the horizon is added to ensure that the aggregators' decisions are not shortsighted. Therefore, when neglecting the distribution network, the values: $\sum_{i \in N} G_{i,(t=1)}^a$, $\sum_{i \in N} D_{i,(t=1)}^a$ and $\sum_{i \in N} F_{i,(t=1)}^a$ are what aggregator a submits to the electricity market. The same co-optimisation problem is repeatedly shifted forward, on a receding horizon framework, to obtain the bids for the next market settlement.

In the following we use (1a)–(1f) to obtain aggregators' energy-FCAS feasible region as well as their price bands.

5.2 Generating Aggregator Triangles

The solution we are seeking is an isosceles right triangle which is obtained by finding any two corners of the triangle in Figure 2. Here, we use (1a)–(1f) to find corners B and C.

5.2.1 *Corner B.*

As can be seen in Figure 2, corner B has the minimum value on the energy axis (i.e., maximum load), and maximum value on the raise FCAS axis. Therefore, to get this corner, we run one optimisation problem that not only minimises the total costs of the aggregator but also maximises the load and raise FCAS participation of the first time step. The objective function of this case is given in (2) which is also subject to (1b)–(1f):

$$\min_{D,G} \sum_{i \in N} \sum_{t \in \{2,\ldots,T\}} \delta_t \cdot \left(\pi_t^e \cdot (D_{i,t}^a - G_{i,t}^a) - \pi_t^{\text{fcas}} \cdot F_{i,t}^a \right) - \gamma \cdot \sum_{i \in N} (D_{i,t=1}^a + F_{i,t=1}^a) \tag{2}$$

The first term of the objective function minimises the cost of co-participating in the energy and FCAS markets for $t \in \{2, \ldots, T\}$; the second term includes the demand and the raise FCAS participation of the first time step, which is subtracted with a large enough multiplier $\gamma \geq 0$, so that it is maximised as a priority before the other term. The solution of this time step provides corner B for the first time step as well as the optimum energy and FCAS participation for the other time steps i.e., $T \in \{2, \ldots, T\}$.

5.2.2 *Corner C.*

As can be seen in Figure 2, corner C has the maximum value on the energy axis (i.e., max generation). Therefore, to obtain the coordinates of corner C, we run one optimisation problem that not only minimises the total costs of the aggregator but also maximises the generation of the first time step. The objective function of this case is given in (3) which is also subject to (1b)–(1f):

$$\min_{D,G} \sum_{i \in N} \sum_{t \in \{2,\ldots,T\}} \delta_t \cdot \left(\pi_t^e \cdot \left(D_{i,t}^a - G_{i,t}^a \right) - \pi_t^{\text{fcas},a} \cdot F_{i,t}^a \right) - \gamma \cdot \sum_{i \in N} G_{i,t=1}^a \tag{3}$$

The solution of this time step provides corner C and thus the triangle. The next step is for an aggregators to obtain their prices.

5.3 Generating Aggregator Price Bands

Finding representative prices for aggregators is challenging as the market only clears 5 minutes at a time, but the outcome for an aggregator depends heavily on the prices and dispatch over time. This is because their stateful DER (e.g., batteries) primarily make money through energy arbitrage. So, what we need to do is to estimate how dispatch in the first interval will impact an aggregator's costs over time.

To get the cost function, here, we assume different dispatches across aggregators' energy-FCAS feasible regions and use forecast market prices over a forward horizon to capture the estimated forward cost associated with different first-time-step dispatch points. To get the price bands out of this, we compare the cost of operating at each point of an aggregator's triangle with a base case where no battery response is provided in the energy market. In the following we first obtain the base case and then step by step make a transition from this base case to another triangle point and obtain the associated price (until the whole triangle is covered).

To clearly explain our approach, we take an aggregator, who has an aggregated 1 MW of fixed load, 3 MW of PV power, and 5 MW / 10 MWh half-full battery, as an example. We explain what would happen to this aggregator at each step of our proposed approach.

5.3.1 Base Case. For the base case, we assume aggregators are dispatched at a point where the batteries are neutral in the energy market (i.e., neither charging nor discharging) and the whole PV power is used in the energy market (i.e., no PV power curtailment). To enforce this, we add the following constraints to (1a)–(1f).

$$P^{Ch}_{c,t=1} = 0, \qquad \forall c \in C^a \tag{4a}$$

$$P^{Dis}_{c,t=1} = 0, \qquad \forall c \in C^a \tag{4b}$$

$$P^{PV}_{c,t=1} = PV^{forecast}_{c,t=1}, \qquad \forall c \in C^a, \tag{4c}$$

where $P^{Ch}_{c,t} \geq 0$ and $P^{Dis}_{c,t} \geq 0$ are the battery charge and discharge power of consumer c at t; $P^{PV}_{c,t} \geq 0$[4] and $PV^{forecast}_{c,t}$ are the scheduled PV power and the PV power forecast of consumer c at t. Since we generate the triangle and price bands for the first time step of every horizon, (4a)–(4c) is only added for the first time step; meaning that the rest of the horizon can be scheduled according to the forecast. Let G^{base}, D^{base} and F^{base} denote the generation, demand and raise FCAS dispatch in the first time-step of the base case, and C^{base}_{exp} its expected future cost.

For the aggregator of our example, this means bidding 2MW (3MW PV − 1MW load) in the energy market at the first time step of the horizon and since the battery is half full, the aggregator can also provide 5 MW raise FCAS support. In the following, we add the capacity bands that DER can contribute to the triangle and calculate their prices with respect to C^{base}_{exp}.

5.3.2 Battery Charge. Here, we obtain the price for which the dispatch of aggregator can move from the base case to a triangle point in which the batteries are charging. This can be obtained by solving a similar optimisation problem as in (2), (1b)–(1f) s.t. (4c).

For the aggregator of our example, this means going to charge mode and bidding -3MW in the energy market (2MW base case − 5MW charge power) and providing 10 MW raise FCAS support (5 MW reducing charge + 5 MW going to discharge mode) in the first time step of the horizon. Such an operating point means that in the normal condition the battery is charging and the aggregator is injecting -3MW to the grid. However, in case of a contingency the aggregator can increase its output by 10MW i.e., the aggregator increase its injected power from -3MW to 7MW. To be able to do so, the aggregator needs to stop charging and go to discharge mode.

Let G^{Ch}, D^{Ch} and F^{Ch} respectively denote the generation, demand and raise FCAS dispatch in the first time-step of such a case; and C^{Ch}_{exp} the expected cost for the rest of the horizon ($t \in \{2, \ldots, T\}$) associated with such a first-time-step dispatch. The aggregator will operate at this new operating point only if the new benefit (given the expected future costs) is more than the base case (because otherwise it is better for the aggregator to dispatch at the base case). Let π^I_e and π^I_{fcas} be the energy and FCAS price variables for the first time step, we can write:

$$\delta_t \cdot \Big(\pi^I_e(D^{Ch} - G^{Ch} - D^{base} + G^{base}) - \pi^I_{\text{fcas}}(F^{Ch} - F^{base})\Big) + C^{Ch}_{exp} \geq C^{base}_{exp}. \tag{5}$$

Note that in the marginal case where the above equation is satisfied as equality, π^e_1 and π^I_{fcas} denote the prices for which charge or neutral status of batteries (in the first time-step) leads to the same benefit (i.e., the maximum prices for which the battery should still charge). We use such prices for the added capacity bands (with respect to the base case). However, in the equality case, equation (5) represents a line $\mathbf{aX} + \mathbf{bY} = \mathbf{c}$; meaning that several energy and FCAS price combinations (**X** and **Y**) would lead to cost **c**. To limit this infinite number of combinations, we assume the FCAS price to be zero and find the maximum energy price that it is beneficial for the aggregator to charge and provide the additional FCAS support. The aggregator finally bids FCAS at zero price and the additional MW power at π^I_e, in our example (-5MW, 5MW) at (π^I_e, 0). Note that in the price-taking approach, the aggregator would submit the load (i.e., -5MW) at the market cap price. Therefore, -5MW would be accepted at any MCP. However, as we observe, for MCPs higher than π^I_e, the aggregator should not charge at the first time step (this is ensured in our approach by bidding this capacity band at π^I_e).

Note that bidding FCAS at zero price does not mean that the aggregator is a price-taking participant in the FCAS market since the price of each FCAS capacity band has already been captured into the energy prices. Note that in a co-optimisation problem, the combination of energy and FCAS prices matters and thus when NEMDE solves its linear co-optimisation problem, for any energy and FCAS price combination leading to a higher benefit than the one aggregators have bid, the aggregators will be in the market.

5.3.3 Battery Discharge. Here we obtain the price for which the dispatch of aggregator can move from the base case to a point of the triangle in which the batteries are discharging. This can be obtained by solving a similar optimisation problem as in (3), (1b)–(1f) subject to (4c).

For the aggregator of our example, this means going to discharge mode and offering 7MW in energy market (2MW base case + 5MW discharge power) and 0 MW raise FCAS.

Let G^{Dis}, D^{Dis} and F^{Dis} respectively denote the generation, demand and raise FCAS dispatch in the first time-step of such a case; and C^{Dis}_{exp} the expected cost for the rest of the horizon ($t \in \{2, \ldots, T\}$) associated with such a first-time-step dispatch.

Similarly to the previous case, we can obtain the price of operating at such a point. Assuming a zero price for the FCAS market and π^{II}_e the variable representing the energy price, we can write:

$$\delta_t \cdot \Big(\pi^{II}_e(D^{Dis} - G^{Dis} - D^{base} + G^{base})\Big) + C^{Dis}_{exp} \geq C^{base}_{exp}. \tag{6}$$

When the above equation is satisfied as an equality, π^{II}_e represents the minimum price for which the aggregator can operate at this new dispatch point. In our example (5MW, 0MW) at (π^{II}_e, 0).

So far, we have calculated the capacity and price bands that the battery can add to the energy-FCAS triangle. In the following, we calculate the capacity bands that solar PV can add to our triangle, i.e., removing constraint (4c) from our base case.

5.3.4 Solar PV. In our base case, we assumed no PV curtailment, yet here, we remove that assumption and run one optimisation problem similar to (2), (1b)–(1f) subject to (4a)–(4b) to obtain the additional FCAS that the solar PV can contribute to our triangle[5]. For the aggregator of our example, this means curtailing PV power

[4]The variables $P^{Ch}_{c,t} \geq 0$, $P^{Dis}_{c,t}$ and $P^{PV}_{c,t} \geq 0$ are part of $X_{c,t}$ in (1e) and (1f).

[5]PV power should be curtailed to be able to be provided in the raise FCAS market.

and providing -1MW in energy market (2MW base case − 3MW PV which is curtailed) and 8 MW raise FCAS (5 MW the base case + 3 MW added by PV). A similar process will produce the maximum price for which the aggregator should curtail all the PV power and contribute to the FCAS market, we call this price π_e^{III}. Therefore, the aggregator bids FCAS at zero price and the additional MW power at π_e^{III}, in our example (-3MW, 3MW) at (π_e^{III}, 0).

Having solved the above steps, the capacities and price bands of the aggregator's triangle is ready. Since our FCAS prices are zero, we only need to sort capacities according to the obtained energy prices. Typically, $\pi_e^{III} < \pi_e^{I} < \pi_e^{II}$, so, the triangle for our example can be constructed, as shown in Figure 4.

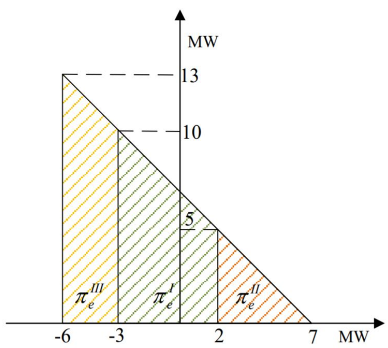

Figure 4: Energy-FCAS triangle

Note that here we obtained the whole operating range of aggregators in both energy and raise FCAS markets. As we mentioned in Section 3, the FCAS markets are activated sequentially. Thus, the obtained energy-FCAS feasible region can be submitted to any or all 6-second, 60-second and 5-minute FCAS markets, depending on the aggregators' business model.

5.4 Fitting to the NEM Requirements

Here, aggregators only participate in the raise FCAS market. However, a similar process can be used to construct the energy-FCAS triangle as well as the price bands for the lower FCAS market. However, we leave the detailed study of such a case and its combination with the raise FCAS triangle to future work.

We also assume that prices can be updated for every 5-minute settlement. However, as described in Section 3 according to the current NEM regulations, participants are required to submit a constant 10-band price for the whole day prior to the market day. To fit into the current structure of the NEM, aggregators could use historical prices to calculate their 10 price bands in advance, and then in real-time use the closest match to the prices they determine. We also leave the detailed study of such a case to future work.

6 NETWORK SUBPROBLEM

In this section, we introduce our network subproblem and shape the aggregator bids according to the network constraints. The aggregators will then submit their network-aware bids to the NEM.

Given the aggregator triangles and price bands at each node, our goal here is to make the biggest triangle for the network. The proposed network subproblem consists of the following steps:

1) At each node, the bids of the aggregators are sorted according to their energy prices (their FCAS price is zero). This creates a range of bids on the energy axis, starting from a minimum value (point A in Figure 3) and ending on a maximum value (point C in Figure 3). Note that Since 1) aggregators feasible region is a triangle (due to their fast responding inverter-based DER [21]), and 2) the triangle showing the inter-dependency between the maximum raise FCAS and energy market participation forms an isosceles right triangle[6], the polygon obtained from merging aggregators' feasible regions is also a isosceles right triangle.

2) The network aims to have the highest total bids in the energy and FCAS markets, i.e., maximising the energy and FCAS participation. Since we have sorted out the energy and FCAS bids according to the energy prices, such a maximisation is equivalent to maximising the energy and FCAS participation while minimising the total expected cost. Note that, here, the cost minimised by the network problem is not real (since it is obtained through the price bids submitted by the aggregators and not the MCP). However, it helps the network to limit the most expensive generation or the least expensive (the least important) loads, in case there is a network violation. This step needs to be solved for all the extreme points of the overall triangle A, B and C. The reason why we only solve the problem for the extreme points is that the network aims to increase the aggregators participation at each node i.e., be as close as possible to the extremes of the triangles.

We model the network constraints, using the *Distflow* equations [22]. Since the network should be feasible for any operating case, we duplicate the *Distflow* equations, each accounting for one network operating condition i.e., I) *Normal* in which only energy is traded and II) *Contingency* in which FCAS also gets called.

To model the distribution network we use $i, j, k \in N$ for nodes in a tree network; P_i^e, Q_i^e and I_i^e are the active power, reactive power and the current flowing into node i from the parent node k, where the line has resistance r_i, reactance x_i and impedance z_i. C_i represents the children nodes of node i; $G_i'^e$, $D_i'^e$ and F_i' are respectively the maximum generation, demand and FCAS bids accepted by the network at each node. $g_{b,i}^e$, $d_{b,i}^e$ and $f_{b,i}$ are the segment b of the sorted bids at each node i (obtained in step 1). We replace the superscript e (standing for energy) with FCAS to create the variables when aggregators are providing raise FCAS support.

$$\max_{i=1} P_i^e + P_i^{\text{FCAS}} \tag{7a}$$

$$P_i^e - r_i I_i^e + G_i'^e - D_i'^e = \sum_{j \in C_i} P_j^e \quad \forall i \in N \tag{7b}$$

$$P_i^{\text{FCAS}} - r_i I_i^{\text{FCAS}} + G_i'^e - D_i'^e + F_i' = \sum_{j \in C_i} P_j^{\text{FCAS}} \quad \forall i \in N \tag{7c}$$

$$Q_i^e - x_i I_i^e = \sum_{j \in C_i} Q_j^e \quad \forall i \in N \tag{7d}$$

$$Q_i^{\text{FCAS}} - x_i I_i^{\text{FCAS}} = \sum_{j \in C_i} Q_j^{\text{FCAS}} \quad \forall i \in N \tag{7e}$$

[6]Let $X_1 \in \mathbb{R}$ denote aggregator's total energy bid and $X_2 \in \mathbb{R}_{\geq 0}$ aggregator's total FCAS bids. According to Figure 2, $X_1 + X_2 \leq C$ Aggregators biggest energy-FCAS feasible region is obtained when the inequality is satisfied as an equality, i.e., $X_1 + X_2 = C$. This means that X_1 and X_2 are interchangeable which is only the case when the line makes an isosceles right triangle (45°, 45°, 90°).

$$V_i^e = V_k^e - 2\Big(r_i P_i^e + x_i Q_i^e\Big) + z_i^2 I_i^e \qquad \forall i \in N \quad (7f)$$

$$V_i^{\text{FCAS}} = V_k^{\text{FCAS}} - 2\Big(r_i P_i^{\text{FCAS}} + x_i Q_i^{\text{FCAS}}\Big) + z_i^2 I_i^{\text{FCAS}} \quad \forall i \in N \quad (7g)$$

$$v_{min}^2 \leq V_i^e \leq v_{max}^2 \qquad \forall i \in N \quad (7h)$$

$$v_{min}^2 \leq V_i^{\text{FCAS}} \leq v_{max}^2 \qquad \forall i \in N \quad (7i)$$

$$P_i^{e\,2} + Q_i^{e\,2} = V_i^e I_i^e \qquad \forall i \in N \quad (7j)$$

$$P_i^{\text{FCAS}^2} + Q_i^{\text{FCAS}^2} = V_i^{\text{FCAS}} I_i^{\text{FCAS}} \qquad \forall i \in N \quad (7k)$$

$$0 \leq I_i^e \leq i_i^{max\,2} \qquad \forall i \in N \quad (7l)$$

$$0 \leq I_i^{\text{FCAS}} \leq i_i^{max\,2} \qquad \forall i \in N \quad (7m)$$

$$0 \leq G_i'^e \leq \sum_{b \in B^T} g_{b,i}^e \qquad \forall i \in N \quad (7n)$$

$$0 \leq D_i'^e \leq \sum_{b \in B^T} d_{b,i}^e \qquad \forall i \in N \quad (7o)$$

$$0 \leq F_i' \leq \sum_{b \in B^T} f_{b,i} \qquad \forall i \in N. \quad (7p)$$

The objective function is to increase the participation of the distribution network in energy and FCAS markets by maximising the connection point power of the distribution network to the transmission network (i.e., $i = 1$). Active and reactive power flow equations are given through (7b)–(7e); The voltage of each node is calculated through (7f)– (7g) and is enforced to be within its safe limits (v_{min}^2 and v_{max}^2) through (7h)–(7i). The complex power, flowing in each line, is given in (7j)–(7k); and (7l)–(7m) limit the current of each line to the maximum line capacity $i_i^{max\,2}$. Finally, the bids accepted by the network (at each node) is limited to the summation of all bids at the node through (7n)–(7p). If there is no network violation, (7n)–(7p) would be satisfied as equalities (i.e., the network accepts all the bids of the aggregators). Yet, if the network constraints are violated, (7n)–(7p) are satisfied as inequalities, i.e., the network cannot accept all the bids of the aggregators.

Note that the network subproblem (7a)–(7p) needs to be solved for all the extreme points A, B and C of Figure 2. For vertices A and C of Figure 3, the right hand side of constraints (7n)–(7p) is using the values associated with the vertices, while for the optimisation of vertex B, $D_i'^e$ in (7o) is fixed on the obtained value in the maximisation of vertex A (i.e., A') in Figure 3.

Having solved (7a)–(7p), the network feasible region is obtained. The DSO then sends back the aggregators their network-aware feasible region which can be submitted to the NEM by the aggregators. Note that the final network operating state needs to be obtained through a comprehensive cooptimisation problem solved by NEMDE. The minimum information to run such a co-optimisation problem is the bids of all participants as well as the overall FCAS requirements–the information that is available for AEMO. However, since the bids to the market are within the network trapezium, any final operating state that AEMO chooses satisfies the network constraints.

Having the electricity market cleared, the operating state and thus the batteries SoC are known. Using the new SoCs, the same process is repeated to obtain the network-aware bids for the next time step.

7 NUMERICAL RESULTS

7.1 Setup and Data

To illustrate the effectiveness of our proposed approach, We use a 69-bus distribution network [23] modified with 207 consumers (3 consumers at each node). To obtain a more realistic case, one third of the consumers are equipped with a rooftop PV and a battery (PV-BAT consumers); another third of the consumers are equipped with just a rooftop PV but not a battery (PV consumers); and the remaining third of the consumers do not own any DER (NoDER consumers). We used 5 kW / 10 kWh batteries with the round trip efficiency $\eta^2 = 85\%$ and 5 kW rooftop PV to make our PV-Bat and PV consumers. We used anonymised solar and background load for 27 consumers in Tasmania, Australia, provided by Reposit Power [24], and randomly assigned this data to the consumers in our networks. We take the dispatch energy and FCAS MCPs as well as their pre-dispatch forecasts from AEMO[7].

The 207 consumers in our network are served by 3 aggregators. The aggregators have customers at different nodes of the system and even multiple aggregators have consumers at the same node. Aggregator 1 aggregates 30 PV-Bat and 40 PV consumers; aggregator 2 aggregates 21 PV-Bat, 25 PV and 32 NoDER consumers; and aggregator 3 aggregates 18 PV-Bat, 4 PV and 37 NoDER consumers.

We use the Gurobi and IPOPT solvers in JUMP, Julia [25] to respectively solve the aggregator and network subproblems on a laptop computer with a 2.50 GHz Intel(R) Core(TM) i7 and 8 GB of memory.

7.2 Comparative Approaches

To illustrate the effectiveness of our proposed price generating approach, we compare the results of four different approaches as follows:

- *Price-Taking*: in which the aggregators use a price forecast to schedule their consumers according to their expected benefit. The aggregators then submit their generation bids with zero price and their load bids with the market cap price to the wholesale electricity market. We use the market clearing price (MCP) to calculate the real benefit of the aggregators.
- *Perfect*: this approach does not use any forecasts. Instead, it assumes that the energy and FCAS prices are known for the whole horizon (288 future time steps) and thus, it can obtain the highest benefit possible.
- *Semi-Perfect*: this approach is a compromise between the *Price-Taking* and *Perfect* approaches in which only the first time step of every horizon is using the perfect information while the rest of the horizon is still using the forecasts.
- *Price-Generating*: in which the aggregators use the proposed approach to build their energy-FCAS triangles as well as the prices for each bid bands. The aggregators submit their bids to the wholesale electricity market which are then dispatched according to the MCP.

Note that although both the *Perfect* and *Semi-Perfect* approaches are unrealistic and unachievable, *Semi-perfect* is closer to our setting. Similarly to *Semi-perfect*, our approach uses forecast information for all future time steps (except the first time step). Yet, instead of using

[7] Both predispatch prices and MCPs are available at: https://www.aemo.com.au/

the perfect information for the first time step, we provide capacity and price bands to bid in the market. Even though unrealistic, we report the results of the *Perfect* and *Semi-Perfect* approaches, as these baselines enable us to assess and bound the potential for improvement to our approach.

7.3 Market Clearing

Since the *Price-Taking*, *Perfect* and *Semi-Perfect* approaches bid one (energy, FCAS) point to the electricity market, we calculate their obtained real benefit by multiplying their capacity bids with the MCPs[8]. For the proposed *Price-Generating* approach we first need to determine whether or not the market chooses to dispatch the aggregators, and by how much. Instead of replicating the full market dispatch, we use historical MCPs to dispatch aggregators and calculate their obtained benefits. Since NEMDE solves a linear problem, the aggregators are dispatched at band b as long as:

$$\pi_e^b \cdot P_e^b + \pi_{FCAS}^b \cdot P_{FCAS}^b \leq \pi_e^{cleared} \cdot P_e^b + \pi_{FCAS}^{cleared} \cdot P_{FCAS}^b$$

where P_e^b and P_{FCAS}^b are the energy and FCAS bids associated with the capacity band b which are submitted at the prices π_e^b and π_{FCAS}^b; the energy and the FCAS markets are cleared at $\pi_e^{cleared}$ and $\pi_{FCAS}^{cleared}$, respectively. In other words, the aggregators are dispatched at a point where the benefit they obtain through their bids, is less than or equal to the benefit they obtain by the market prices. Note that evaluating the effect of aggregator bids (either price-taking or price-generating) on the electricity market is out of scope of this paper and we leave its detailed study to future work. However, in general, such an effect ultimately leads to errors in the forecasts and we expect forecast errors to have less impact on the aggregators' benefit in our price-generating approach, compared to a price-taking approach. The reason is that price-taking approaches submit their bids at either zero or market cap prices, therefore, no matter how much the real price deviates from the forecasts, their bids is accepted by the market. However, our price-generating approach bids different capacities for different prices, So, in case the real price deviates from the forecast, our approach can act differently to ensure that the highest benefit is achieved. Moreover, our receding horizon framework implementation enables us to update the prices every five minutes and use the latest (most accurate) forecast which also increases the accuracy in our work.

In the following, we report the aggregators' benefit, when using the above approaches, first when the distribution network is neglected and then when the distribution network is included.

7.4 Network Neglected

In this case, we directly submit the bids obtained by each approach to the wholesale electricity market without applying the distribution network limits. The obtained benefit for each aggregator as well as the overall benefits of all aggregators are reported in Table 1.

As it is seen in Table 1, the proposed approach managed to obtain 32% higher benefits in total compared to the conventional price-taking approach. However, since the network constraints are neglected, the results obtained by all cases are infeasible and violate the distribution network constraints.

[8]As they bid energy at zero and load at market cap price, their whole (energy, FCAS) capacity is accepted.

Table 1: Overall benefit of aggregators neglecting network

Approach	Benefits (Thousand AUD)				Status
	Agg 1	Agg 2	Agg 3	Total	
Price-Taking	191.9	47.4	3.4	242.6	infeasible
Price-generating	225.2	71.1	23.8	320.2	infeasible
Semi-Perfect	229.6	74.6	26.9	331.1	infeasible
Perfect	275.4	106.7	54.3	436.5	infeasible

7.5 Network Included

Similarly to the previous section, we run the approaches in this section within a receding horizon framework but here we include the network subproblem. Thus, the aggregators first calculate their bids and send them to the DSO. The network operator then uses OPFs (one OPF for Price-Taking, Semi-Perfect and the Perfect approaches; and three OPFs for the proposed price-generating approach as explained in section 5) to find the network-aware bids. Then the aggregators submit their shaped bids to the electricity market. As in the previous section we calculate the total benefits of aggregators according to the MCP.

The total benefit of the aggregators as well as the overall benefits of all aggregators are given in Table 2.

Table 2: Overall benefit of aggregators including network

Approach	Benefits (Thousand AUD)				Status
	Agg 1	Agg 2	Agg 3	Total	
Price-Taking	187.6	19.2	3.3	210.1	feasible
Price-Generating	213.5	31.9	23.8	269.2	feasible
Semi-Perfect	224.4	44.1	26.9	295.3	feasible
Perfect	267.5	58.2	54.3	380.0	feasible

Comparing the results of Table 2 with the ones reported in Table 1, we conclude that less benefit is obtained (on average 13%) when network constraints are included. The reason is that in our experiments, the network constraints were active, so, the feasible region of aggregators was more limited, leading to feasible results at the expense of less benefit for the aggregators.

The final accepted bids of a PV-Batt consumer when using the Perfect, Semi-Perfect, Price-Taking, and Price-Generating approaches are shown in Figure 5.

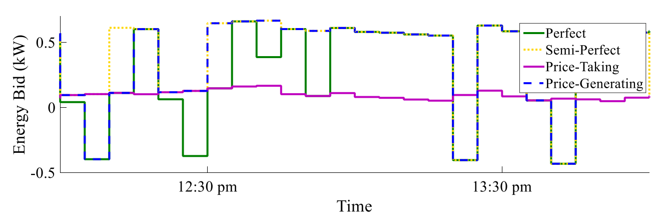

Figure 5: Bids of a PV-Batt consumer

The voltage of bus 27 for the proposed price-generating approach, once for the energy case and once when raise FCAS is called, are shown in Figure 6 and 7, respectively (the voltage is assumed to be safe when it is between 0.95 p.u. and 1.05 p.u.). To obtain these voltages, we bid the triangles with and without network effect to the wholesale electricity market; having the market cleared, we run two PFs (one when only energy is traded and another assuming the FCAS capacity is called upon) to obtain the real voltages of the network.

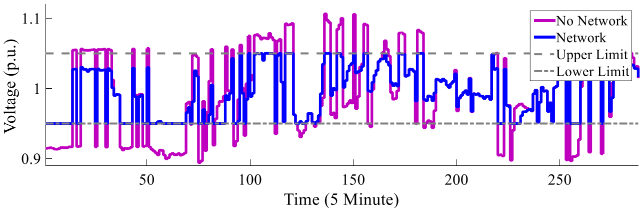

Figure 6: Voltage of bus 27 in energy case

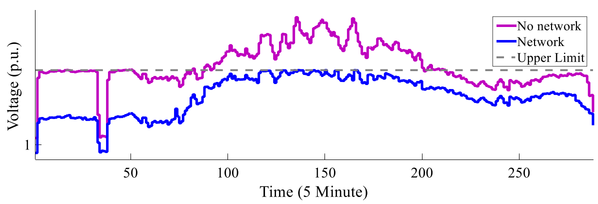

Figure 7: Voltage of bus 27 when raise FCAS is called

As it is seen in Figures 6 and 7, in both cases the proposed approach managed to keep the voltage of the distribution network within the safe limits

7.6 A longer Term Experiment

Table 3 reports the benefits of a PV-Batt consumer when using our proposed price-generating (PG) approach vs the price-taking (PT) approach over months September, October and November 2019 in New south wales (NSW), Australia. For both approaches, we have used AEMO's predispatch price forecast and then used MCP to calculate the real benefits of consumers: As reported in Table 3, the

Table 3: Overall benefit of a PV and a PV-Batt consumer

Approach	Benefit (AUD)			Rel. to PT
	Energy	FCAS	Total	
Price-Taking	651	1965	2616	–
Price-Generating	1194	1892	3086	+18%

PV-Batt consumer obtained 18% higher benefit (over three months) when using the proposed price-generating approach.

7.7 Computational Performance of the Proposed Approach

In our implementation, we solved both aggregators and the network subproblem sequentially and one after another on a single machine. However, the aggregators are working separately and neither the aggregators nor any two consumers of an aggregator have coupling constraints. Thus, the aggregator problem is decomposable at the level of every consumer. Moreover two out of three sets of OPFs of the network subproblem are independent and can be solved separately and in parallel (i.e. the OPFs of points A and C in Figure 4), which can reduce the computational burden.

We report the total computational time of our sequential implementation, and the expected fully parallel time (considering the slowest separated time to solve each subproblem) for both price-taking (PT) and price-generating (PG) approaches. In a real setting, we expect a compromise outcome with overall solve time somewhere between these two, and an additional overhead due to any communications latency. Table 4 reports the model size and solve time for the subproblems in a single horizon, and their contribution to the overall solve time in both sequential and parallel cases.

Table 4: Problem size and computational time.

Approach	Subprob.	#Var.	#Cons.	Time (Parallel)
PT	Aggregators	775k	656k	15.3s (0.09s)
	Network	964	755	0.7s (0.7s)
PG	Aggregators	1,428k	1,967k	40s (0.2s)
	Network	2.5k	3.0k	1.53s (0.9s)

8 CONCLUSION

We developed a price-generating bidding strategy in the distribution networks to enable the residential consumers to participate in both energy and raise FCAS markets. In our approach, the aggregators bid the flexibility of their consumers in the form of an energy-FCAS triangle. We also obtained the prices at which the aggregators need to submit their flexibility to the electricity market. Moreover, to ensure the distribution network feasibility, we shaped the aggregators bids to be within the network feasible region using three sets of OPFs.

We illustrated the effectiveness of our approach using 207 consumers, being served through three aggregators, within a 69-bus distribution network. Our results show significant improvements over the case in which aggregators use a price-taking bidding strategy. Moreover, through a voltage analysis, we compared the voltages on the network when the obtained bids neglect the network constraints with the proposed network-aware approach. The results revealed that neglecting the distribution network constraints can lead to infeasible solutions, violating the voltage safe limits at different times of the day.

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