Co-optimizing Energy, Grid Services and Voltage Support in Networks with Distributed Storage

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Abstract—This paper presents a framework for co-optimization of energy arbitrage, grid (ancillary) services, and network voltage support subject to real world cyberphysical constraints in an electric distribution network with high DER penetration, specifically distributed storage and solar generation. The framework uses a previously introduced 2-layer architecture, which is appropriately modified to minimize excess voltage deviations and total energy cost while simultaneously maximizing profit from participation in frequency regulation and ramping services. The global controller handles resource scheduling and grid service disaggregation while respecting network constraints. Each local controller attempts to maximize arbitrage profit while following the load profile and grid service schedule dictated by the global controller. Simulations using a benchmark distribution network show that: (i) the performance of the proposed controller is close to that of a perfect foresight controller and better than an opportunistic controller that does not plan for grid service events, (ii) the controller behaves as expected with the price signals, and (iii) it performs effectively across a wide range of solar and storage penetrations and configurations.

Index Terms—DER coordination, Distributed control

I. INTRODUCTION

The increasing penetration of distributed energy resources (DERs), such as rooftop photovoltaics, energy storage, electric vehicles, and load control opens the opportunity to engage in energy arbitrage and participate in grid (ancillary) services. At the same time, the increase in stochastic and distributed generation creates a need for improved network reliability. Coordination of a large number of DERs in a distribution network can increase their value to both the DER owners and the grid operators by simultaneously optimizing energy arbitrage, grid services participation, and network reliability.

In [1], [2], we introduced a 2-layer decentralized storage control architecture in which coordination is distributed between a global controller (GC) and local controllers (LC) that all operate in a model predictive control (MPC) fashion. Each storage system in the network is equipped with a local controller that has access to updated data only from the node it is connected to, but does not communicate with other nodes. The LCs communicate to the GC asynchronously and can have delays up to several hours. The GC is aware of the network model and makes decisions that aim to jointly maximize the revenue from energy arbitrage and provide voltage support by including a squared voltage deviation metric to the cost function [2]. Each LC uses its local data and the signals from the GC to minimize its individual costs. It was shown in [1], [2] that this 2-layer architecture is surprisingly robust to communication delays exceeding 24 hours due to the MPC and the ability of each LC to accurately forecast its future load and solar in the short term.

This paper builds upon the architecture in [2] by adding joint optimization of regulation signal following and ramp signal following to energy arbitrage and voltage support. Previous papers have addressed the co-optimization of energy and regulation signals or other services [3]–[6]; however, none of these have included ramp signals and considered network effects such as maintaining nominal voltages and communication delays. Additionally, our formulation includes a grid services feasibility phase designed to determine when and how much storage capacity to designate for grid services while maintaining tight voltage control, and a disaggregation phase that distributes the grid service power across the storage units in real time. Other papers only deal with the scheduling [4], or do not have a distributed collection of storage, thus not requiring disaggregation [3]–[6].

Regulation and ramp signals are two different types of grid services that storage can participate in and receive compensation for properly following. In contrast to regulation signals, ramps are not energy neutral over their duration, which is a minimum of 3 hours, and often require a significant amount of energy to be consumed or provided, see [7]. Furthermore, regulation signals are available at all times, but ramp signals occur only when there is a large unpredicted generation mismatch possibly due to wind changes or other factors. The compensation of ramp support is linearly increasing in both the positive and negative directions, hence the optimization over it leads to the maximization of a convex function. Furthermore, expressing the minimum 3 hour duration constraint is non-convex and makes the optimization even less tractable.

Our control algorithm overcomes these challenges by using heuristics and comparing the results to a perfect foresight controller which knows all of the ramp signals, solar generation, and power demand ahead of time. Future knowledge of the ramp signals removes the aforementioned issues of non-convexity and leads to the optimal solution. We also compare our control algorithm to one that does not plan to follow

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such events, but only opportunistically attempts to follow them as they occur. Finally, the disaggregation of ramp and regulation signals must occur rapidly in real time, especially for regulation signals. This precludes solving a full optimal power flow (OPF) problem during the regulation following event, hence we use a heuristic to disaggregate the signal while operating within feasible voltage bounds. We compare this disaggregating heuristic to an OPF disaggregator in order to determine the performance loss of using a faster algorithm.

II. MODELS AND ASSUMPTIONS

We adopt the same network formulation, storage model, OPF solver based on the SOCP relaxation in [8], and power quality metric based on the sum of squared voltage deviations as in [2]. The variables used in the optimization algorithms are given in Table I.

**Grid Services Markets:** The GC acts as a price taker in the grid services markets. We assume all bids at the market price are accepted, i.e., the market is always available to buy ramp and regulation capacity in either direction at a fixed value known ahead of time. This may lead to over scheduling ramps, which occur infrequently and mostly in one direction over the operation horizon. In order to account for this, we assume the market sets a low price for ramp signals they believe are unlikely to occur, and a higher price for ramp signals they think are more likely to occur. This ensures they have enough capacity to follow the ramps that are critical, but prevent over spending on unlikely ramps. It is not unrealistic to assume the market has some prior knowledge of ramp events, which influences their prices and is hinted at in [7]. However, the market does not have perfect knowledge of ramps and will still buy ramp capacity at times when no ramps occur. When this happens, the storage units remain idle and are compensated for the full market value of the ramp. The frequency response signals come from PJM regD designed for fast ramping systems such as batteries. It has a zero mean within 15 minutes, so the battery SOC does not change during the regulation following time [9].

Batteries in practice should not use part of their capacity for grid service signal following and part of their capacity for another purpose at the same time despite this being commonly seen in related papers [4]–[6]. These two uses can negate the purpose of the grid service signal (to be highly predictable and remove uncertainty from the system). However, including a binary decision variable for selecting between frequency response following and other uses makes the optimization problem non-convex. In the interest of being most energy efficient, we choose to execute the battery storage decision that uses excess solar generation over frequency response following when the controller has both options.

III. CONTROL ALGORITHMS

The control algorithm consists of a scheduling phase running on the GC and an operating phase split between the GC and LCs as illustrated in Figure 1. The scheduling phase takes place after each ramp event or every $\Delta_{GC}$ time steps, which ever occurs first. Its purpose is to determine available times intervals and storage capacity for voltage support, energy arbitrage, regulation services, or ramp following. To do so, two optimizations are performed: grid service feasibility optimization and load and storage profile optimization. The resulting schedules for regulation and ramp services are sent to the grid services market operator, who sends the final signals to be followed and compensates the storage units.

The operating phase runs every $\delta_{min}$, or in the event of a regulation signal, every 2 seconds. It consists of a local optimizer and a grid service signal power disaggregator, which operates only when a regulation or a ramp signal is received. The power disaggregator distributes the grid service signals directly to the storage units to follow in real time with negligible delay (major delay occurs only in the communication from the LCs to the GC due to limitations in the smart meter infrastructure [2]).

Upon receiving a new set of buffered and delayed data from the nodes (every $\Delta_{GC}$ time steps), the GC algorithms operate in MPC fashion with a lookahead time of $\Delta_F$ for a total horizon length of $\Delta_{GC} + \Delta_F$ time steps. The GC uses the buffered and delayed data to generate forecast scenarios of the future net loads for all the nodes as detailed in [2] (the equations given in this paper are for a single scenario for simplicity). The GC then solves the two scheduling phase optimizations sequentially over the forecast scenarios to determine both the grid service schedule and net load profiles for all the nodes over the next $\Delta_{GC} + \Delta_F$ time steps. The GC sends the energy and power capacity schedules to the grid service markets and the net load profile to each storage node.

We next detail the optimization problems for each phase.

**Grid services feasibility optimizer:** This optimization problem runs in the GC and determines profiles of the storage power injection to be used for ramps, regulation, and arbitrage while operating within the feasible voltage bounds. The cost function is an economic optimization over the three revenue sources (arbitrage, ramp following, regulation following) and has a large weight associated with voltage deviations to prioritize network reliability. The constraints are in order (and similar across the various optimizations): real and reactive power injection, storage model, storage charging and energy capacity, and power flow constraints. The optimization splits
the storage power injection capacity across the three revenue sources over the time horizon. The variable $u$ is the base storage profile that shows the power usage for both energy arbitrage and voltage support. The two variables $R_{\text{up}}$ and $R_{\text{down}}$ quantify the amount of power injection the controller wishes to allocate for up and down ramps. Splitting the ramp schedule across two variables is necessary to avoid maximizing over the convex ramp compensation function. In order to account for the minimum duration of 3 hours for ramps, we disregard portions of the signal with less than three consecutive hours of sufficient capacity. Finally, the variable $\epsilon$ gives the profile for regulation signal following capacity and times. The choice of providing regulation services during a time period is indicated by $u \approx 0$ and storage capacity $\epsilon > 0$. Figure 2 shows a sample of the 4 signals from the scheduler with high ramp prices. In this example the controller wishes to follow down ramps between hours 6 to 16 and 37 to 46, up ramp from hours 17 to 22, and regulation signals from hours 2 to 5. The energy bids for these ramps and the charging schedule between these periods is calculated in the next optimization.

\[
\text{minimize: } \sum_{\tau} \sum_{i \in Z} p_{\tau}(d_{\tau,i}^+ + u_{\tau,i}) + \sum_{\tau} \sum_{i \in Z} p_{\tau}(R_{\text{up}} + p_{\tau} R_{\text{down}} + p_{\tau} \epsilon_{\tau,i}) + \lambda_u \sum_{k=0}^{N} \sum_{i \in Z} (\max(w_{\tau,i}^{(k)} - V_{\text{tol}}^2, 0) + \max(V_{\text{tol}}^2 - w_{\tau,i}^{(k)}, 0))^{2}
\]

subject to: 
\[\mathcal{R}(s_{\tau}) = d_{\tau,i} + u_{\tau,i} + R_{\text{up}} + \epsilon_{\tau,i} \quad (1b)\]
\[\mathcal{R}(s_{\tau}) = d_{\tau,i} + u_{\tau,i} - R_{\text{down}} - \epsilon_{\tau,i} \quad (1c)\]
\[\mathcal{R}(s_{\tau}) = d_{\tau,i} + u_{\tau,i} \quad (1d)\]
\[\mathcal{R}(s_{\tau}) = d_{\tau,i} \quad (1e)\]

\[q_{\tau} = \eta(q_{\tau-1} + u_{\tau,i}) \quad \forall i \in Z \quad (1f)\]
\[u_{\tau,i} + R_{\text{up}} + \epsilon_{\tau,i} \leq u_{\tau,i}^{\text{max}} \quad \forall i \in Z \quad (1g)\]
\[u_{\tau,i} \leq u_{\tau,i} - R_{\text{down}} - \epsilon_{\tau,i} \quad \forall i \in Z \quad (1h)\]
\[0 \leq \epsilon, R_{\text{up}}, R_{\text{down}} \leq u_{\tau,i}^{\text{max}} \quad (1i)\]
\[q_{\tau,i} \leq q_{\tau,i}^{\epsilon,i}/4 \quad (1j)\]
\[q_{\tau,i} \leq q_{\tau,i}^{\epsilon,i}/4 \quad (1k)\]
\[q_{\tau,i}^{(k)} = \sum_{j \in \tau} (w_{\tau,i}^{(k)} - u_{\tau,i}^{(k)}) \beta_{ij} \quad (1l)\]
\[W\{i,j\}^{(k)} \geq 0 \quad \forall k \in [0, 1]. \quad (1m)\]

**Load and storage profile optimizer:** This optimization runs in the GC right after the grid services feasibility optimizer. It determines the amount of energy to hold on standby for ramps and the net load profile for each storage unit. The value of $q_{\text{red}}^k$ is calculated by summing up the power capacity for up or down ramps during the consecutive ramp hours determined by the scheduler and is bounded by the capacity of the storage unit. The cost function determines the charging profile for each storage node that allows them to get close to the energy requirement of the ramp while avoiding charging during regulation time periods, minimizing electricity costs, and respecting voltages. The net load profiles calculated based on the forecast scenarios and charging profile are sent to the LCs as in [2]. The battery charge during the ramp times calculated by this optimizer is the energy capacity given to the market for ramps, and is the level the local controllers would like to reach in preparation for ramp events.

\[
\text{minimize: } \sum_{\tau} \sum_{i \in Z} p_{\tau}(d_{\tau,i}^+ + u_{\tau,i}) + \sum_{\tau} \sum_{i \in Z} p_{\tau} R_{\text{up}} + \sum_{\tau} \sum_{i \in Z} p_{\tau} R_{\text{down}} + \sum_{\tau} \sum_{i \in Z} p_{\tau} \epsilon_{\tau,i} + \lambda_u \sum_{k=0}^{N} \sum_{i \in Z} (\max(w_{\tau,i}^{(k)} - V_{\text{tol}}^2, 0) + \max(V_{\text{tol}}^2 - w_{\tau,i}^{(k)}, 0))^{2}
\]

subject to: 
\[\mathcal{R}(s_{\tau}) = d_{\tau,i} + u_{\tau,i} \quad \forall i \in Z \quad (2a)\]
\[\mathcal{R}(s_{\tau}) = d_{\tau,i} + u_{\tau,i} \quad (2b)\]
\[u_{\tau,i}^{\text{min}} \leq u_{\tau,i} \leq u_{\tau,i}^{\text{max}} \quad \forall i \in Z \quad (2c)\]
\[q_{\tau,i}^{\text{min}} \leq q_{\tau,i} \leq q_{\tau,i}^{\epsilon,i} \quad \forall i \in Z \quad (2d)\]

**Local optimizer:** This optimization runs on the LCs during the operating phase every $\delta_{\text{min}}$ in a rolling horizon fashion. The output is the storage charging profile to be executed by the storage unit. The objective is to minimize local costs while following the GC signals which comprise a net load signal, frequency response schedule, and a required state of charge for ramp following. The optimization only uses the GC signal

\[
\text{minimize: } \sum_{\tau} \sum_{i \in Z} p_{\tau}(d_{\tau,i}^+ + u_{\tau,i}) + \sum_{\tau} \sum_{i \in Z} p_{\tau} R_{\text{up}} + \sum_{\tau} \sum_{i \in Z} p_{\tau} R_{\text{down}} + \sum_{\tau} \sum_{i \in Z} p_{\tau} \epsilon_{\tau,i} + \lambda_u \sum_{k=0}^{N} \sum_{i \in Z} (\max(w_{\tau,i}^{(k)} - V_{\text{tol}}^2, 0) + \max(V_{\text{tol}}^2 - w_{\tau,i}^{(k)}, 0))^{2}
\]

subject to: 
\[\mathcal{R}(s_{\tau}) = d_{\tau,i} + u_{\tau,i} \quad \forall i \in Z \quad (2a)\]
\[\mathcal{R}(s_{\tau}) = d_{\tau,i} + u_{\tau,i} \quad (2b)\]
\[u_{\tau,i}^{\text{min}} \leq u_{\tau,i} \leq u_{\tau,i}^{\text{max}} \quad \forall i \in Z \quad (2c)\]
\[q_{\tau,i}^{\text{min}} \leq q_{\tau,i} \leq q_{\tau,i}^{\epsilon,i} \quad \forall i \in Z \quad (2d)\]

(1d), (1e), (1f), (1l), (1m).
and local data allowing it to run frequently and with more accurate forecasts.

$$\begin{align*}
\text{minimize:} & \quad \sum_{\tau} \sum_{y} p_{\tau} \cdot z_{\tau y}^2 + \gamma \|z_{\tau}^2 - x_{\tau}\|_2 \\
& \quad + \gamma \sum_{\tau \in \mathcal{F}} |u_{\tau}| + \gamma \sum_{\tau \in \mathcal{R}} [R_{\text{sign}}(q_{\tau} - q_{\tau}^{\text{opt}})]^+
\text{subject to:} & \quad z_{\tau y}^2 = \hat{d}_{\tau y}^2 + u_{\tau} \\
& \quad (1f), (2d), (2c).
\end{align*}$$

**Power disaggregator:** The disaggregation optimization runs in the operating phase in the GC only when there is a ramp or regulation signal received from the grid operator. It must run fast, as it has to disaggregate the grid service power signal and send it to the LCs every 2 seconds. Therefore, the optimization makes use of the maximum charge and discharge profiles of the storage units from the grid services feasibility optimizer as bounds. These bounds act as a heuristic for the most power each storage unit can inject while remaining within the nominal voltage range. The optimization objective tries to operate the storage units within these bounds, while the constraints require the sum of all storage charging or discharging to equal the grid service signal request.

$$\begin{align*}
\text{minimize:} & \quad \sum_{\tau} \sum_{y} \left( (u_{\tau} - u_{\tau}^+\text{bound} + u_{\text{tol}}) + \\
& \quad + (-u_{\tau} + u_{\tau}^-\text{bound} + u_{\text{tol}}) + \right)^2 + \lambda_b |u_{\tau}| \\
\text{subject to:} & \quad \sum_{\tau \in \mathcal{E}} u_{\tau} = R_{\text{ramp}} \\
& \quad (1f), (2d), (2c).
\end{align*}$$

**Perfect foresight controller:** The perfect foresight controller has knowledge of the net power demanded and ramp signals ahead of time, and solves a single shot optimization over the MPC horizon. The performance of this controller is used to benchmark the performance of our controller. The cost function is the weighted sum over the three revenue sources with a large weight associated with voltage deviations to prioritize network reliability. If the perfect foresight controller cost function takes a penalty greater than the total value of the ramp for not following the ramp signal, the time period is rerun with that ramp signal removed. This is done to allow the controller to skip ramp events it does not think will maximize profit while avoiding the non-convexity of binary decision variables for selecting ramps.

**OPF Disaggregator:** The power disaggregator we use in our controller must run very fast, hence does not perform the full OPF. To benchmark its performance, we compare it to an OPF disaggregating optimization which uses the same objective function, but replaces the heuristic bounds; therefore, achieving possibly better voltage performance.

**Opportunistic Controller:** The opportunistic controller simply runs the cost minimization algorithm in [2] and only follows regulation signals when the batteries are idle, and ramp signals when the batteries have sufficient SOC. This is unrealistic, however, because the market requires scheduling ahead of time to ensure it has the proper reserves for the two events; thus, the purpose of this optimization is to act as a benchmark for the minimum expected performance of our algorithm.

**IV. Simulations and Results**

We evaluate our controller performance using the IEEE standard 123 bus feeder [10]. The time resolution is set to \(\delta_{\text{min}} = 1\) hour, and the global buffer delay, GC control horizon is \(\Delta_{\text{GC}} = 24\) hours, and the MPC lookahead horizon is \(\Delta_{\text{P}} = 24\) hours. The energy price follows a time of use model and is set to a peak price of 0.35 cents per KWh from 4pm to 9pm and to 25 cents per KWh for the rest of the day. The solar and storage penetrations are defined as percentages of the total network demand and are distributed as in [2]. The load data is provided by PG&E, the solar data is from NREL, and the forecaster is the ARIMA model used in [2].

The regulation signals come from PJM regD [11] and the ramp signals are extracted from wind data from NREL using the algorithm in [12]. Both signals are represented as percentages of the capacities selected in the scheduling phase. The price of regulation signals is set to a constant of 0.05 dollars per KW. Since they are available all the time, the price must be low to prevent the storage from only following regulation signals, rather, the storage units only follow regulation signals when they would otherwise be idle. The ramp prices are random between 0 and the maximum with a much higher probability of being near the maximum price during a ramp event. The maximum price varies in the simulations, but is typically 0.3 dollars per KWh.

The chosen metrics we use to evaluate the results are the various revenue streams (arbitrage, regulation, ramp signal following) as well as the squared voltage deviations compared to the perfect foresight controller. The results are also compared to the OPF disaggregator and the opportunistic controller to determine the efficacy of our heuristics. Each simulation takes place over the first 30 days of August and the results presented is the average of 10 random initializations of solar and storage deployments in the network.

**Solar and Storage Penetrations:** Figures 3, 4, 5, and 6 show total profit and voltage deviation for simulations run at a constant ramp price of 0.3 over a wide variety of solar and storage configurations. As solar increases, total profits increase since more energy is available for grid services and arbitrage; however, there is a point where the amount of solar saturates and more storage is required to capture additional profits. Our controller performance is worse with high DERs due to the amplification of forecast errors.

**Various Ramp Prices:** Figures 7 and 8 show profits based on category and ramp price for simulations at a solar penetration of 0.6 and a storage penetration of 0.4. The controller behaves exactly as expected when the values of ramps is increased. The controller shifts its focus away from arbitrage and achieves more profits from ramps. A similar behavior occurs in the perfect foresight controller. This demonstrates the predictability and controllability of our scheme based on price signals.

**Comparison of four controllers:** Table 9 summarizes the results of the four controllers (opportunistic, OPF disaggre-
control scheme is impractical in reality as grid service markets require bids to secure the proper amount of reserves. The OPF disaggregator only leads to a very minor improvement on voltage deviations over the much faster power disaggregator, indicating that the bounds are an effective heuristic. The perfect foresight controller represents the best achievable as it has perfect knowledge of all stochastic signals. The knowledge of future loads significantly improves the voltage support capabilities, since they are most effected by forecast errors. Also, knowledge of future ramps allows the storage units to avoid ramps that turn out to be less profitable than arbitrage or regulation signals.

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