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Scheduling distributed energy storage units to provide multiple services under forecast error

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ABSTRACT

When energy storage units (*ESUs*) within the distribution grid, such as batteries, provide local services such as supporting the integration of photovoltaics, peak shaving, and infrastructure upgrade deferral, they are inactive or only partially used most of time. Moreover, they are often not profitable because of their high investment costs. Their unused capacities could be used to provide power system services, such as frequency control, allowing them to generate additional revenues. However, individual units might not be available to provide system services over the entire frequency control contract duration, since they must also provide their local services. This paper shows how a set of distributed ESUs can simultaneously provide local services individually and system services in aggregate. Using a model predictive control approach, a central scheduler dynamically allocates parts of the energy and power capacities of each ESU to either the local or grid service with the objective of maximizing the profit of the aggregation. A key contribution of this paper is the development of an algorithm that handles both resource aggregation and optimal provision of multiple services. We find that multitasking can almost double an ESU's profits as compared with a single-service approach, and that the benefits from aggregation increase with the frequency control contract duration and with the forecast error.

Introduction

The number of energy storage units (*ESUs*) within the distribution grid is likely to increase since they can be used for a variety of local services including photovoltaic (*PV*) integration support, peak shaving, infrastructure upgrade deferral, and powering electric vehicles. However, the purchase cost of distributed ESUs, especially batteries, is expected to remain high in the near- to middle-term future [1]. A way to improve the economics of an ESU was described in [2]: when not fully used for its local service, an ESU could provide other services to power systems, such as frequency control. This so-called multitasking approach has been the subject of several recent publications, for example, [3] which analyzes storage capacity allocation under grid constraints, considering spot and intraday markets, and frequency control markets simultaneously; [4] where the focus is on peak shaving, electricity trading, frequency control, and uninterruptible power supply service; and [5] which considers energy arbitrage, frequency control, backup energy, and relief of distribution constraints.

A key challenge to power system service provision with ESUs is that individual units might not be available to provide the contracted service over the entire contract duration because they must also provide their local service. Therefore, there is a benefit to resource aggregation. Many papers have investigated the use of aggregations of distributed resources with limited energy capacities to provide both local and system services, for example, [6] develops methods to schedule/control electric vehicle charging to minimize charging costs and provide frequency regulation while minimizing negative network impacts, and [7] develops methods to schedule/control thermostatically controlled loads to provide frequency regulation in addition to actively managing the distribution network to increase PV energy absorption. However, these papers do not co-optimize the allocation of resources to the local and system services. Instead, they allocate a predefined power capacity to frequency control. Also, they focus on aggregations of resources providing the same local service, rather than resources providing diverse local services.

The contributions of this paper are fourfold. First, we develop an algorithm that dynamically co-optimizes the allocation of diverse ESUs' energy and power capacities over local and power system services with the aim of maximizing the cumulative profit from

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the different services. Our algorithm provides day- and hour-ahead allocation schedules that tell each ESU how much power and energy capacity to reserve for each service at each time step; our focus is not on real-time control. Second, through a case study, we investigate the benefits of combining aggregation and multitasking. Third, another case study compares the benefits of aggregation with the benefits of shorter frequency control contract duration. Finally, a last case study investigates the additional benefits of aggregation when there is forecast error. The present work is an extension of [8] which did not investigate forecast error.

We restrict our analysis to batteries as the sole energy storage technology; however, we consider batteries providing different local services. Since batteries have significant degradation costs (per kWh cycled), they are only attractive for local services when the alternative would lead to a higher cost per kWh. We therefore restrict ourselves to these types of local services:

- *PV-l*: minimization of PV curtailment when subject to line export limitation. If no battery were installed at this location, the alternative would be to either curtail the PV generator or to upgrade the line;
- *PV-t*: minimization of PV curtailment when the PV generator is connected to the grid through a transformer with limited thermal capacity. If no battery were installed at this location, the alternative would be to either curtail the PV generator or to upgrade the transformer;
- *Load-l*: customer load smoothing when the load profile sometimes exceeds the line import power. If no battery were installed at this location, the alternative would be to either curtail the load or upgrade the line;
- *Load-t*: customer load smoothing when the customer is connected to the grid through a transformer with limited thermal capacity. If no battery were installed at this location, the alternative would be to either curtail the load or upgrade the transformer.

The only power system service we consider is primary frequency control (*PFC*), since we found in [9] that it might soon become cost effective in Europe to provide this service with batteries. If secondary frequency control revenues increase or battery costs decrease, it could be considered as well, using the same methodology as for PFC.

Section 'Models and scheduling algorithm' describes the models and scheduling algorithm. Section 'Case study definitions' details the case studies, Section 'Results' discusses the results, and Section 'Conclusion' provides concluding remarks.

Models and scheduling algorithm

To model an ESU aggregation, we define a Local Area Control (*LAC*) as a building block. Each LAC, designated by the subscript i, represents one ESU and its local environment, and contains at least:

- One ESU, characterized by its energy and power capacities (E_i^{cap}, P_i^{cap}), its charge and discharge efficiencies (η_i^c, η_i^d), its self-discharge per time step $(1-\eta_i^{sd})$, and its linear and quadratic degradation costs $\left(d_i^l, d_i^q\right)$.
- One (aggregated) load profile.
- One electricity tariff profile (purchases) and one electricity feed-in tariff profile (sales).

Depending on the local service provided, the following options can also be present:

- One PV generation profile (local service: PV-l or PV-t).
- One line with limited export/import capacity, which creates a bottleneck between the grid and the LAC (local service: PV-l or Load-l).
- One transformer with limited thermal capacity that creates a bottleneck between the grid and the LAC (local service: PV-t or Load-t).

and the following decision variables:

- One PV curtailment profile (local service: PV-l or PV-t).
- One load curtailment profile (local service: Load-l or Load-t).

Since we focus on grid constraints associated with ESUs connected to the rest of the network through a bottleneck, we do not explicitly model power flow, as in [7]. In the future, our algorithm could be extended to explicitly include network constraints.

The goal of the scheduling algorithm is to maximize the profit of an existing ESU set. We do not consider investment costs, but we do consider ESU battery degradation costs as operational costs. The problem of how to attribute the benefits to all possible stakeholders is not considered here, nor do we address regulatory barriers to multitasking [3].

We use a Model Predictive Control (*MPC*) [10] approach to compute the allocation schedule. This receding horizon approach allows us to handle PV forecast error (detailed in Section 'Case study definitions') and the transformer plant-model mismatch described in Section 'Transformer overheating'. Furthermore, even when considering perfect forecasts, MPC is useful to handle limited-horizon, but perfect forecasts. We used YALMIP [11] to represent our set of equations and constraints, and to build our MPC controller. Since we aim to control large numbers of ESUs, we use linear and quadratic models within our controller, ensuring that the system model is computationally tractable.

In the following four subsections we describe our modeling approaches. Section 'Allocation of capacities' presents our ESU energy and power capacity allocation model, while Section 'Physical constraints, cost, and profits' describes our methods of modeling the cost/profit associated with buying/selling electricity from/to the grid, the cost of battery degradation, and the load curtailment penalty. Section 'Transformer overheating' describes our transformer model and overheating penalty, and Section 'Primary frequency control revenues and costs' details how we model the profit realized through PFC provision. Finally, Section 'MPC controller formulation' gives the full mathematical description of our MPC controller by bringing together the results of the previous sections.

Allocation of capacities

Our algorithm dynamically allocates fractions of the energy and power capacities of each ESU to either its local service or to frequency control, as shown in Fig. 1. For each time step k and each LAC, E_i^{cap} and P_i^{cap} are divided into a part that serves the local service ($E_{i,k}^l$, respectively $P_{i,k}^l$) and a part that serves PFC ($E_{i,k}^{pfc}$, respectively $P_{i,k}^{pfc}$):

$$SoC_i^l \cdot E_i^{cap} \leqslant E_{i,k}^l + E_{i,k}^{pfc} \leqslant SoC_i^u \cdot E_i^{cap} \tag{1}$$

$$0 \leqslant P_{i,k}^l + P_{i,k}^{pfc} \leqslant P_i^{cap} \tag{2}$$

where SoC_i^l and SoC_i^u are lower and upper State-of-Charge (*SoC*) limits (enforced to avoid operating areas associated with excessive degradation) and $P_{i,k}^l$ and $P_{i,k}^{pfc}$ represent the absolute value of the power that can be extracted or injected for the local service and