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Market-Driven Energy Storage Planning for Microgrids with Renewable Energy Systems Using Stochastic Programming

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Abstract: Battery Energy Storage Systems (BESS) can mitigate effects of intermittent energy production from renewable energy sources and play a critical role in peak shaving and demand charge management. To optimally size the BESS from an economic perspective, the trade-off between BESS investment costs, lifetime, and revenue from utility bill savings along with microgrid ancillary services must be taken into account. The optimal size of a BESS is solved via a stochastic optimization problem considering wholesale market pricing. A stochastic model is used to schedule arbitrage services for energy storage based on the forecasted energy market pricing while accounting for BESS cost trends, the variability of renewable energy resources, and demand prediction. The uniqueness of the approach proposed in this paper lies in the convex optimization programming framework that computes a globally optimal solution to the financial trade-off solution. The approach is illustrated by application to various realistic case studies based on pricing and demand data from the California Independent System Operator (CAISO). The case study results give insight in optimal BESS sizing from a cost perspective, based on both yearly scheduling and daily BESS operation.

Keywords: Optimal operation and control of power systems, Smart grids, Control of renewable energy resources

1. INTRODUCTION

The need for a Battery Energy Storage System (BESS) to serve as a buffer for electric energy is palpable for microgrid systems that have a large penetration of intermittent renewable energy sources. A BESS may be economical for both islanded microgrids and a for grid-connected system, as a BESS increases reliability during outages and provides revenue or grid services such as peak shaving, voltage regulation, and arbitrage power trading during normal operation (Lasseter, 2002; Donadee, 2013; Kousksou et al., 2014) .

Applications of a BESS can be found in various settings to assist with renewable power integration. It has been applied to the problem of harmonic distortion, generally known as voltage regulation, which may occur in standalone operation (islanding) of a microgrid (Yang et al., 2014; Hanley et al., 2008). Specifically, a BESS can be used to reduces the effects of Photo Voltaic (PV) and wind energy production variability (Teleke et al., 2010; Zheng et al., 2015) by different control strategies such as a rule-based control and a model predictive control (MPC). A BESS in conjunction with PV and demand forecasting can help shift renewable generation to times of higher power demand or lower electricity price via an MPC technique (Sevilla et al., 2015). A mathematical model for a large BESS system was performed in Zhang et al. (2015) as a reduced four state space equations to model the relation between the bulk power grid and a BESS.

The benefits of BESS in coping with variable renewable energy production are evident, but the costs associated with financing and installing BESS are often prohibitive. In particular for residential settings (Holbert and Chen, 2015), a BESS may not produce sufficient revenue from energy arbitrage to achieve investment payback without government incentives to fund the BESS. At the same time, BESS costs are anticipated to drop in the near future and investment banks are expecting the payback time for unsubsidized investment in electric vehicles (EV) combined with rooftop solar and BESS (Houchois et al., 2014) to reduce to around six to eight years. Also, the economies of scale due to the adoption of EV and rapid improvement of battery technologies will likely reduce BESS prices. As a result, the projected reduction in pricing of BESS is expected to lead to a return on investment within a time frame of three years by 2030 (Nykvist and Nilsson, 2015; Sachs, 2014).

Optimal BESS sizing from an economical perspective must find the optimal trade-off between critical design parameters that include BESS sizing, BESS life expectancy due to battery degradation and total revenue from utility bill savings due to energy arbitrage. Holistic BESS scheduling models that aim to capture all cost aspects were developed

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in Nguyen et al. (2012) to maximize the overall profit of an existing wind-storage system. Economic models were used in Ornelas-Tellez et al. (2014) to predict the market price to optimize the operation of existing energy resources in a microgrid, but no future investments were considered. Operational stochastic control and optimization in Zachar and Daoutidis (2016) were designed as an MPC to ensure sufficient energy as an economic dispatch problem.

Motivated by the need to find the optimal BESS investment as a function of time considering capital and O&M costs, as well as operational revenues, this paper proposes a stochastic optimization approach that leverages mixed integer and real (convex) optimization to formulate financially optimal BESS sizing solutions. The stochastic optimization is used to address the variability in prediction and forecasting of energy and BESS pricing to determine when is the optimal time to invest in a BESS. The convex optimization is used to compute globally optimal solutions for BESS sizing parameters, given the operational model and the price variability in the day-ahead market.

The paper is outlined as follows. First, the problem formulation and the system topology for financial optimization are summarized in Section 2. The mathematical framework is summarized in Section 3, explaining the optimization techniques, objective functions and the constraints. Different operating scenarios are discussed and compared in Section 4 to cover cases of extreme high/low power variability in solar, wind and demand patterns. In Section 5, different BESS installation cases and optimal BESS sizing for a case study of a real microgrid are presented.

2. SYSTEM TOPOLOGY AND PRICING

2.1 Microgrid and Market Structures

Fig. 1 illustrates the structure of power market and microgrids used in this paper. The microgrid is modelled as a subset of the market $\mu G \subset \mathcal{N}$, and demand, renewable generation, and BESS power in both market (m) and microgrid (μ) are denoted by P_d, P_{RE}, and P_b, as illustrated in Fig. 1.

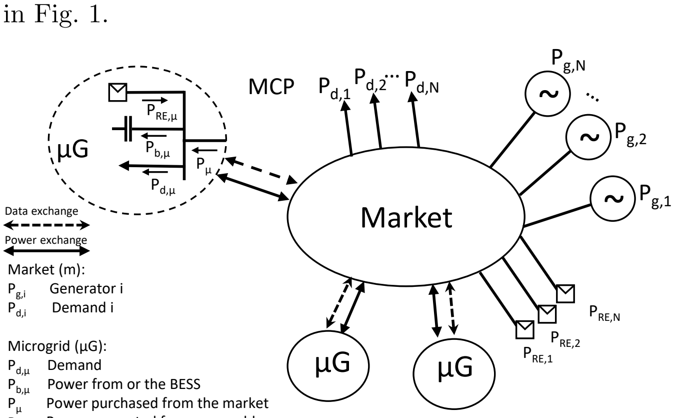

Fig. 1. Power market system architecture.

The net demand P_{net}, which is the actual market demand (including all microgrids' demand) minus the total renewable power available in the market, is computed via

$$P_{net} = \Sigma_{i\in\mathcal{N}} \left(P_{d_i} - P_{RE_i}\right) = \Sigma_{i\in\mathcal{N}} P_{g_i} \tag{1}$$

where P_{g_i} indicates power provided by generator i and

$$P_{\mu} = \Sigma_{j\in\mu G} \left(P_{d_j,\mu} + P_{b_j,\mu} - P_{RE_j,\mu}\right) \tag{2}$$

2.2 Market Clearing Price Modeling

Assuming that the microgrids will pay the hourly market clearing price (MCP) in the future instead of predefined constant or time-of-use (TOU) rates, a price model is required to anticipate the MCP at different times for optimal operation of microgrids.

Typically, Independent System Operators (ISO) aggregate the bids received from generators and cross it with the net demand hourly profile of the market to define hourly MCP. It is assumed that the MCP is solely a function of the net demand in that λ_P is linearly correlated with the market net demand P_{net} via

$$\lambda_P = \alpha\ P_{net} + \beta. \tag{3}$$

This pricing modeling has been validated in the literature (Huang et al., 2015; Verzijlbergh et al., 2014). It is assumed for simplicity that the parameters of the MCP model (α, β) remain constant throughout the 15 year modeling horizon. However, the optimization could consider more detailed and dynamic models where the pricing model parameters vary as generators are added or removed.

To model the effects of different generators' bidding strategies and maintenance schedules on different days of the week (weekdays and weekend) and different seasons (summer and non-summer) on MCP, four distinct MCP models are fit from historical CAISO demand and pricing data.

2.3 Microgrid and Power Market Growth

For realistic financial predictions and optimal sizing of the BESS, the financial model considers the annual growth of both the market and the microgrid. The growth of the market and the microgrid takes into account all components, i.e. demand, solar and wind.

For simplicity, we assume a fixed annual solar growth (ASG) defined by

$$ASG = \frac{S_{t+1y} - S_t}{S_t} \times 100\%$$

where S_t represents the vector of hourly solar profiles of the current year. Hence, with a fixed ASG, the net solar power S_{t+1} contribution is predicted to grow exponentially as

$$S_{t+1} = \left(\frac{ASG}{100} + 1\right) S_t$$

with $ASG > 0$. Similarly, we assume a fixed annual wind growth (AWG) as

$$AWG = \frac{W_{t+1y} - W_t}{W_t} \times 100\%.$$

The CAISO historical demand data shows different rates of increase at different hours of the day, specifically power demand at the peak hour has grown faster than at off-peak hours. to account for this effect, we define an annual demand growth profile (ADGP) that varies by hour of the day as

$$ADGP = (D_{t+1} - D_t) \oslash D_t \times 100\%,$$

where D_t is the vector of hourly power demand at year t and $\oslash$ denotes element-wise division.