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A two-stage procedure for the optimal sizing and placement of grid-level energy storage

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ABSTRACT

The economic benefit realized from energy storage units on the electric grid is linked to the control policy selected to govern grid operations. Thus, the optimal sizing and placement (OSP) of such units is also dependent on the operating policy of the power network. In this work, we first introduce economic model predictive control (EMPC) as a viable economic dispatch policy for transmission networks with energy storage. However, the numeric basis of EMPC makes it ill-suited for the OSP problem. In contrast, the method of economic linear optimal control (ELOC) can be easily adapted to the OSP problem. However, the relaxation of point-wise-in-time constraints, inherent to ELOC, will introduce a systematic underestimation of operating costs. Thus, we introduce a 2-step OSP algorithm that begins with the ELOC-based approach to determine the placement of energy storage units. Then, an EMPC-based gradient search is used to determine optimal sizes.

1. Introduction

It is generally recognized that the intermittent nature of renewable power (wind and solar) is a key barrier to its wider deployment on the grid. Grid-scale energy storage systems can alleviate this problem by accumulating and time-shifting excess power to periods of peak demand. These units also offer arbitrage opportunities since the variation of electricity prices in deregulated markets can be exploited. Hence, the question of the optimal sizing and placement (OSP) of storage units on the grid is critical to the viability of such endeavors. However, prerequisite to the OSP exercise is a definition of the operating (or control) policy for transmission networks with storage. Our goal is to present computationally tractable methods of addressing both of these questions.

Traditionally, the decision-making process that governs economic dispatch at the regional transmission organization level is deterministic. Uncertainty in consumer demand is handled by committing generating units with a total capacity that exceeds the load forecast so that fast reserves can then be regulated to maintain the supply-demand balance in real time. However, a higher proportion of intermittent renewable power on the grid magnifies the net load variability, which in turn requires a high level of expensive reserves. Stochastic analysis can be employed in this scenario to minimize the expected cost of power generation. Indeed, short and long term variations in wind speed have been described using the Weibull and Normal probability density functions respectively to develop stochastic economic dispatch models for systems with significant renewable resource (Arriagada et al., 2013; Hetzer et al., 2008; Keshmiri and Gao, 2010). Although these static optimization schemes are typically cast as two-stage stochastic programming problems, various simplifying measures including model modification (Ruiz et al., 2010), decomposition (Shiina and Birge, 2004) and scenario reduction techniques (Ruiz et al., 2009) have been proposed to ease the burden of computation. It is recognized that higher long term economic benefits can be obtained if the demand forecast over a time period is considered in the optimization process. This approach, termed dynamic economic scheduling (Bechert and Kwatny, 1972), takes into account the time-coupling constraints introduced by the limits of the generator ramp rates. Energy storage units introduce similar dynamic constraints and therefore also requires multistage analysis. Kim and Powell (2011) and Harsha and Dahleh (2015) applied dynamic programming (DP) as an energy storage management strategy for systems with supply and/or price uncertainty. However, since the necessary discretization of the inventory variable space makes DP prone to dimensionality problems, it is common to resort to heuristic alternatives (Qin et al., 2016).

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Our approach is to adopt economic model predictive control (EMPC), a look-ahead policy, as a control strategy for networks with storage. In-depth reviews of EMPC are provided in Ellis et al. (2014) and Rawlings et al. (2012). The main distinction between EMPC and the generic model predictive control (MPC) strategy is that the EMPC objective is an explicit profit or cost function, whereas MPC typically features a quadratic objective that penalizes set-point deviations. As with MPC, EMPC is implemented with a receding horizon. At each time step, an optimal sequence of actions is determined that minimizes the total anticipated costs within a horizon, subject to process constraints. Once the first control decision is implemented, the current state estimate and disturbance forecast are updated and a new set of actions is calculated. Thus, EMPC can be considered an audacious simplification of multistage stochastic programming in which only the expected scenario is considered per stage, followed by a re-optimization at each time step. Hooshmand et al. (2013) demonstrated the application of EMPC for power scheduling in systems with a high penetration of renewable sources and transmission congestion. Xie and Ilić (2009) also applied EMPC to the load-following problem while considering an environmental cost along with the traditional economic objective. In both studies, the authors demonstrated that a higher average economic benefit can be realized by exploiting technology advancements to regulate power output from renewable resources, compared to the traditional approach of simply treating the intermittent resources as negative load. In Adeodu and Chmielewski (2013), it was demonstrated that the addition of grid level energy storage devices on the power network allows a similar capability as it provides the freedom to charge up or discharge from the storage unit, depending on the available renewable generation potential. It was also shown that in such transmission networks with inventory holdup, EMPC performance improves with increasing horizon size.

In contrast to the extensive studies on energy storage management under uncertainty, few have focused on the OSP question. This is perhaps because the placement of pumped hydro systems, the most common large-scale energy storage technology, is dictated largely by geographical considerations. Denholm and Sioshansi (2009) explored the transmission-related value of placing ESS near the renewable source, but network topology was not considered. Sjödin et al. (2012) used chance constraints to describe a loss-of-load probability criterion for storage management and design under a direct current (DC) assumption. This was extended to an alternating current (AC) model in Bose et al. (2012). In both cases, the OSP question was addressed for a fixed storage budget. That is, the capital cost of the units which typically includes fixed installation costs and hence binary variables (thus significantly changing the nature of the problem) was not included in the objective. Most recently, Torchio et al. (2015) proposed a mixed integer semi-definite programming approach that handles fixed installation costs.

Our solution to the OSP problem will involve introducing a surrogate stochastic control policy with proven EMPC-like performance. Perhaps more importantly, this substitute control strategy termed economic linear optimal control (ELOC), can be solved efficiently to a global solution. These two properties make ELOC a good candidate for decoupling the OSP problem. As sketched in Fig. 1, our proposed 2-step solution strategy begins by solving the ELOC version of the OSP problem. Then, based on the similarity of both optimal control strategies, it is expected that the ELOC-based formulation will result in a solution close to a global solution of the EMPC-based problem. Thus, one can use the ELOC-based placement along with the size estimate as the initial point for an EMPC-based gradient search to determine the optimal storage sizes.

The outline of the paper is as follows. We start by describing our model of an electric power network with energy storage. It is important to reiterate that our goal is to demonstrate a tractable solution

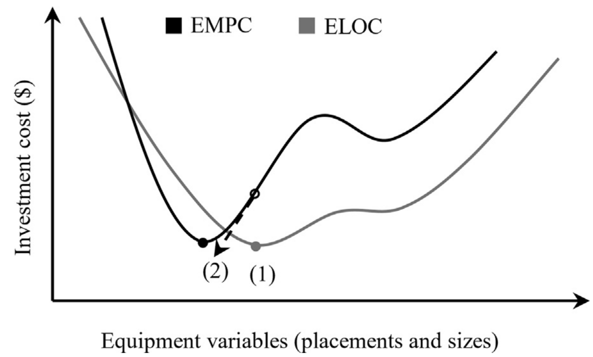

Fig. 1. Proposed 2-step OSP solution strategy.

method for the optimal sizing and placement of energy storage and an accompanying control strategy for such networks. As such, important power transmission features such as thermal losses, generator ramp rates and round-trip efficiencies will be ignored for the purpose of simplification without diminishing the applicability of the proposed method. Therefore, using a simple 5-bus network example, the application of EMPC for economic dispatch is shown to yield satisfactory performance on networks with energy storage. Then, we introduce the ELOC version of the dispatch problem and illustrate that its solution generates a feedback policy that is very similar to that of EMPC. Then, in Section 5, we return to the OSP problem and illustrate how EMPC and ELOC can be combined to arrive at a more efficient solution strategy, as compared to a purely EMPC-based approach.

2. System description

To develop a compact, dynamic model of a power network with storage, we assume that a storage device is present at each node, leaving the actual existence of such equipment to be reflected in its listed capacity (zero for no storage). Then, a power balance at each node m is given by

$$\dot{E}_{S,m} = P_{S,m} \tag{1}$$

$$P_{S,m} = P_{G,m} - P_{L,m} + \sum_{n \neq m} P_{n,m} \tag{2}$$

where $E_{S,m}$ is the energy in the storage unit at node m, $P_{S,m}$ is the power sent to the storage unit, $P_{G,m}$ is power generated from a conventional plant, $P_{L,m}$ is the consumer load and P_{nm} is the real power transmitted from node n to node m. If the direct current (DC) approximation is applied, then $P_{nm} = B_{nm}(\theta_n - \theta_m)$, where the constant B_{nm} is the susceptance of the transmission line, and θ_n, θ_m are the voltage angles at the two nodes. If the network is augmented with renewable power, then (2) will include the term $P_{R,m} - P_{C,m}$, where $P_{R,m}$ is the power available from the renewable source. Although engineering advances have been made in the control of renewable generation (Peña et al., 1996; Shimizu et al., 2001), we will assume $P_{R,m}$ can not be dispatched, but can be easily curtailed. This option is represented by the non-negative $P_{C,m}$ term. In essence, if $P_{C,m} > 0$, the situation is such that renewable power is available, but the system is unable (or unwilling) to consume it completely. Clearly, this is undesirable and a motivation for storage. In addition, there will be pointwise-in-time safety and capacity limits on the generators, transmission lines and storage units. Then, the network model can be described using standard linear, state space notation

$$\dot{s} = f(s, m, p) \tag{3}$$

$$q = h(s, m, p) \tag{4}$$