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 novel 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. While the current effort focuses on power networks, it is postulated that the proposed methodology can be extended to create a new paradigm for solving the generic integrated process design and control problem.

Keywords

Energy Storage, Renewable Power, Economic MPC, Economic Linear Optimal Control.

Introduction

It is generally recognized that the intermittent nature of renewable power generation is a key barrier to wider deployment on the grid. Grid-scale Energy Storage Systems (ESS) can alleviate this problem by accumulating and time-shifting excess power to periods of peak demand. ESS also offers arbitrage opportunities since electricity price variation in deregulated markets can be exploited. The issue of Optimal Sizing and Placement (OSP) of storage units on the grid will be critical to the success of such endeavors. However, prerequisite to the OSP activity 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.

Studies such as Harsha and Dahleh (2015), Rao et al. (2015), Keshmiri et al. (2010), have applied various stochastic methods to govern grid operations on networks with renewable power. These approaches are generally prone to computational issues since complexity increases exponentially with the dimensionality of the problem. As such, alternative policies (Qin et al., 2016) or model modifications (Ruiz et al. 2010) are often pursued. Our approach will be to adopt Economic Model Predictive Control (EMPC), as a control strategy for networks with storage. Xie and Ilić (2009) applied EMPC to economic dispatch while considering an environmental objective along with traditional generation costs. However, the inclusion of ESS was not examined.

In contrast to the extensive studies on storage control, 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

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largely by geographical considerations. Denholm and Sioshansi (2009) explored the transmission-related value of placing ESS near the renewable source, but network topology was ignored. Sjödin et al. (2012) used chance constraints to describe a loss-of-load probability criterion for storage management and design. 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 ESS – which typically will include fixed installation costs and hence binary decision 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 can handle fixed installation costs.

Our approach to the OSP problem will involve introducing a surrogate control policy with proven EMPC-like performance. This control strategy, termed Economic Linear Optimal Control (ELOC), can also be solved efficiently to a global solution. These properties make ELOC a good candidate for decoupling the OSP problem. As sketched in Figure 1, our proposed 2-step solution strategy begins by solving the ELOC version of the OSP problem to a global solution. Then, based on the similarity of both optimal control strategies, it is expected that both the EMPC and ELOC based formulations will results in identical storage unit placements. 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.

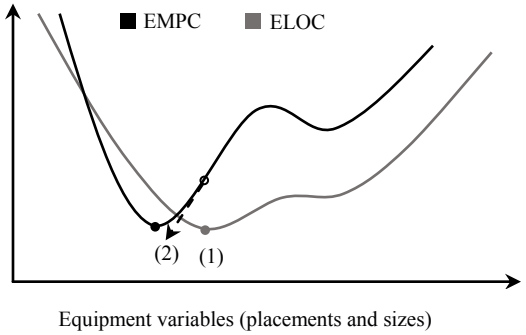

Figure 1. Proposed 2-step OSP solution strategy (1) ELOC-based solution (2) EMPC-based solution

The outline of the paper is as follows. We will start by describing our model of an electric power network with energy storage. Then, using a simple 5-bus network example, application of EMPC will be shown to yield satisfactory performance. Then, we will introduce the ELOC problem and illustrate that its solution generates a feedback policy that is very similar to that of EMPC. Then, we will return to the OSP problem to illustrate how EMPC and ELOC can be combined to arrive at a more efficient solution strategy, as compared to the original EMPC-based approach.

System Description

To develop a dynamic model of a power network with storage, we assume that a storage device is present at each node. Then, a power balance at each node m is given by

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

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

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 power consumed by the 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 Eq. (2) will include the term $P_{R,m} - P_{C,m}$, where $P_{R,m}$ is the power available from the renewable source. While this cannot be dispatched, it can be 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 process equipment. Finally, it is assumed that the marginal cost of renewable power generation is negligible, but the cost of conventional power produced takes the following quadratic form:

$$g(P_{G,m}) = \sum_m \left(c_{m,0} + c_{m,1} P_{G,m} + c_{m,2} \left(P_{G,m} \right)^2 \right) \tag{3}$$

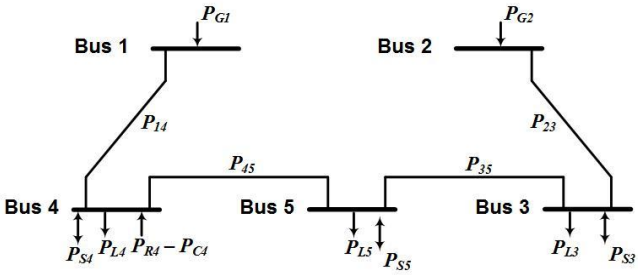

Figure 2. 5-bus Transmission Network with ESS

As an example, consider the 5-bus network of Figure 2 in which there is renewable energy generation at bus 4 and potential for energy storage installation at buses 3, 4 & 5. Accordingly, $[E_{S,3}, E_{S,4}, E_{S,5}]^T$ is the vector of state variables. Manipulated variables are selected as $[P_{G,1}, P_{G,2}, P_{14}, P_{23}, P_{35}, P_{45}, P_{C,4}]^T$. Generally, the voltage angles, θ_m, should also be used as manipulated variables since they dictate the power flows, P_{nm}. However, due to the topology of our example network, there is a one-to-one relationship between the angles and the power flows which indicates that we can work directly with the power flow variables. Lastly, consumer loads and renewable power, $[P_{L,3}, P_{L,4}, P_{L,5}, P_{R,4}]^T$ are considered as

disturbances. In state space notation, the vectors of state, manipulated and disturbance variables are defined as *s*, *m* and *p* respectively. Defining the vector of performance variables as $q = [s^T, m^T]^T$, the power network model can be described as

$$\dot{s} = A^{(p)}s + B^{(p)}u + G^{(p)}p \tag{4}$$

$$q = D_x^{(p)}s + D_u^{(p)}m \tag{5}$$

$$q^{\min} \le q \le q^{\max} \tag{6}$$

where $A^{(p)} = 0_{3\times3}$

$$B^{(p)} = \begin{pmatrix} 0 & 1 & -1 & 0 & 0 \\ 1 & 0 & 0 & -1 & -1 \\ 0 & 0 & 1 & 1 & 0 \end{pmatrix}, G^{(p)} = \begin{pmatrix} -1 & 0 & 0 & 0 \\ 0 & -1 & 0 & 1 \\ 0 & 0 & -1 & 0 \end{pmatrix}$$

$$D_x^{(p)} = \begin{pmatrix} D_{x1}^{(p)} \\ D_{x2}^{(p)} \end{pmatrix}, \quad D_{x1}^{(p)} = I_{3\times3}, \quad D_{x2}^{(p)} = 0_{3\times3}$$

$$D_u^{(p)} = \begin{pmatrix} D_{u1}^{(p)} \\ D_{u2}^{(p)} \end{pmatrix}, \quad D_{u1}^{(p)} = 0_{3\times5}, \quad D_{u2}^{(p)} = I_{5\times5}$$

$$q^{\min} = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 250 \\ 0 \\ -500 \\ -300 \\ -250 \\ -450 \\ 0 \end{pmatrix} \quad q^{\max} = \begin{pmatrix} E_{S,3}^{\max} \\ E_{S,4}^{\max} \\ E_{S,5}^{\max} \\ 500 \\ 500 \\ 500 \\ 300 \\ 250 \\ 450 \\ \text{Inf} \end{pmatrix}$$

The cost curve coefficients of the dispatch-capable generators are assumed to be $c_{0,1} = 2000$, $c_{1,1} = 10$, $c_{2,1} = 0.092$, $c_{0,2} = 450$, $c_{1,2} = 25$, $c_{2,2} = 0.3$.

Economic Model Predictive Control (EMPC)

If the network model is discretized, EMPC can be described in the following form

$$\min_{m_{k|i}} \sum_{k=i}^{i+N-1} g\left(q_{k|i}\right) \text{ s.t.} \tag{7}$$

$$s_{k+1|i} = A_d^{(p)}s_{k|i} + B_d^{(p)}m_{k|i} + G_d^{(p)}\hat{p}_{k|i} \tag{8}$$

$$q_{k|i} = D_x^{(p)}s_{k|i} + D_u^{(p)}m_{k|i} \tag{9}$$

$$q^{\min} \le q_{k|i} \le q^{\max} \tag{10}$$

where *k* and *i* are the predictive and actual time indices respectively and $s_{k|i}$ refers to the prediction of s_k made at time *i*. At a current time *i*, an estimate of the state $s_{i|i}$, along with a forecast of disturbances $\hat{p}_{k|i}$, $k = i,\ldots i+N-1$ should be available. Then, problem (7) is solved for the optimal sequence $m_{k|i}$*. Following a receding horizon framework, only the first input, $m_{i|i}$*, is implemented on the actual system $s_{i+1} = A_d^{(p)}s_i + B_d^{(p)}m_i + G_d^{(p)}p_i$. At time $i+1$, $s_{i+1|i+1}$ and $\hat{p}_{k|i}$ are updated based on new information and a new sequence $m_{k|i+1}$* is calculated. It is common to impose constraints on the final state, $s_{N|i}$, which if selected appropriately, will provide certain guarantees for closed-loop stability (Rawlings et al., 2012). It has also been noted that EMPC performance improves with horizon size, *N*, but this comes at the price of increased computational effort (Adeodu and Chmielewski, 2013; Mendoza-Serrano and Chmielewski, 2015).

In this work, the disturbance p_i is modelled as the output of a finite-dimensional linear shaping filter, driven by zero-mean white noise.

$$x_{i+1}^{(f)} = A_d^{(f)}x_i^{(f)} + G_d^{(f)}w_i \tag{11}$$

$$p_i = D_x^{(f)}x_i^{(f)} + \bar{p} \tag{12}$$

The superscript (*f*) serves to distinguish shaping filter matrices from process (*p*) matrices. Assuming that the internal state of the disturbance model is known (or estimated), a Zero Future Information forecast (Mendoza-Serrano and Chmielewski, 2014) can be simulated at each time step, using

$$x_{k+1|i}^{(f)} = A_d^{(f)}x_{k|i}^{(f)} \tag{13}$$

$$\hat{p}_{k|i} = D_x^{(f)}x_{k|i}^{(f)} + \bar{p} \tag{14}$$

where $x^{(f)}_{i|i} = x^{(f)}_i$ is the internal state at time *i*. The shaping filter matrices in continuous time form are defined as $A^{(f)} = \text{diag}\,(A_{11}, A_{22}, A_{33})$, $G^{(f)} = \text{diag}\,(G_{11}, G_{22}, G_{33})$, where

$$A_{11} = \begin{pmatrix} 0 & 0 & 0 \\ -\tau_c^2 & -2\chi w_c & -\tau_c^2 \\ 0 & 0 & -1/\tau_h \end{pmatrix}, A_{22} = -\text{diag}\begin{pmatrix} 1/\tau_l & 1/\tau_l & 1/\tau_l \end{pmatrix}$$

$$A_{33} = \begin{pmatrix} -1 & 0 & 0 \\ -\tau_{cw}^2 & -2\chi_w w_{cw} & -\tau_{cw}^2 \\ 0 & 0 & -1/\tau_h \end{pmatrix}$$

$$G_{11} = \begin{pmatrix} 0 \\ w_c^2 \\ 1/\tau_h \end{pmatrix}, G_{22} = \text{diag}\begin{pmatrix} 1/\tau_l & 1/\tau_l & 1/\tau_l \end{pmatrix}, G_{33} = \begin{pmatrix} 0 \\ w_{cw}^2 \\ 1/\tau_h \end{pmatrix}$$

$$D_x^{(f)} = \begin{pmatrix} 22.9 & 0 & 0 & 10.1 & 0 & 0 & 0 & 0 & 0 \\ 13.7 & 0 & 0 & 0 & 6.05 & 0 & 0 & 0 & 0 \\ 46.3 & 0 & 0 & 0 & 0 & 19.0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 100 & 0 & 0 \end{pmatrix}$$

$$\bar{p} = \begin{bmatrix} 200 & 150 & 250 & 200 \end{bmatrix}^T$$

The spectral density of the white noise driving the shaping filter is given as $S_w = \text{diag}\,[S_{w1}\ S_{w2}\ S_{w3}]$, where

$$S_{w1} = \frac{4\chi}{w_c}\left(\frac{w_c^2\tau_h^2 + 2\chi w_c\tau_h + 1}{w_c^2\tau_h^2}\right)$$

$$S_{w2} = \text{diag}\begin{bmatrix} 2\tau_l & 2\tau_l & 2\tau_l \end{bmatrix}$$

$$S_{w3} = \frac{4\chi_w}{w_{cw}}\left(\frac{w_{cw}^2\tau_h^2 + 2\chi_w w_{cw}\tau_h + 1}{w_{cw}^2\tau_h^2}\right)$$

and τ_h = 1h, τ_l = 1.5h, χ = 0.05, χ_w = 0.1, $w_c = 2\pi/24$ and $w_{cw} = 2\pi/72$.

Economic Dispatch with EMPC

The process and shaping filter models of the 5-bus example were discretized using the sample and hold method with a sample time of 0.5h. Figure 3 compares the closed-loop EMPC trajectories for the baseline case (without storage) with the scenario of $E_{S,3}^{\max}$ = 1500MWh, $E_{S,4}^{\max}$ = 0 and $E_{S,5}^{\max}$ = 0. The storage acts as a fast reserve, enabling the conventional generators to operate at steadier, inexpensive levels. It is also observed in Figure 4 that for the baseline case, the available renewable power is more likely to be underutilized, as indicated by the more frequent and larger non-zero values of $P_{C,4}$. These instances coincide with periods of low demand or limitations on the P_{45} transmission line. The economic motivation for ESS is apparent as the average operating cost is reduced from 20,613$/h to 19,336$/h (6.2%).

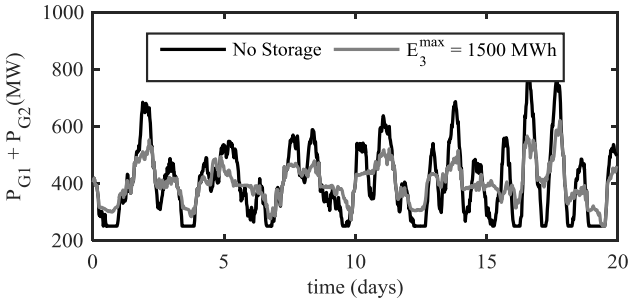

Figure 3. EMPC: Optimal power generated

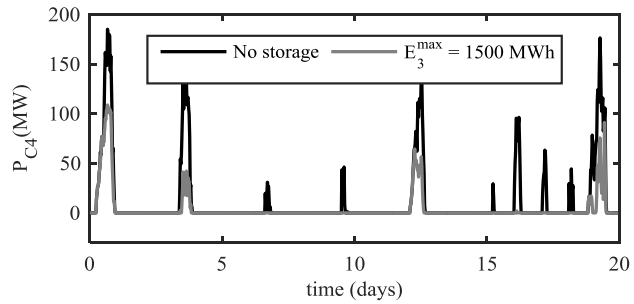

Figure 4. EMPC: Unutilized renewable power.

Economic Linear Optimal Control (ELOC)

In contrast to EMPC, where the sum of instantaneous operating costs within a finite horizon is minimized, the ELOC objective is the expected value of the operating cost (Peng et al, 2005). Typically, the optimal steady state operating point will be on a process boundary. This indicates that during dynamic operation, the disturbance is likely to cause constraint violations. This calls for the selection of a more conservative operating point, denoted as the Backed-off Operating Point (BOP). Essentially, some economic benefit is forfeited to reduce the likelihood of constraint violation. The central feature of ELOC is the determination of the BOP, $\bar{q}$, and a companion linear feedback gain, L, that will enable the average of the economic objective to be minimized, while the statistical constraints of (21) are observed. Thus, the ELOC problem is stated as

$$\min_{\bar{s},\bar{m},\bar{q},L} g_1(\bar{q},\sigma) \text{ s.t.} \tag{15}$$

$$\bar{s} = A_d \bar{s} + B_d \bar{m} \tag{16}$$

$$\bar{q} = D_x \bar{s} + D_u \bar{m} \tag{17}$$

$$\sigma_j = \sqrt{\rho_j \Sigma_z \rho^T{}_j} \tag{18}$$

$$\Sigma_x = (A_d - B_d L)\Sigma_x (A_d - B_d L)^T + G_d \Sigma_w G_d^T \tag{19}$$

$$\Sigma_z = (D_x - D_u L)\Sigma_x (D_x - D_u L)^T \tag{20}$$

$$\alpha\sigma_j \le q_j^{\max} - \bar{q}_j, \alpha\sigma_j \le \bar{q}_j - q_j^{\min} \tag{21}$$

where

$g_1(\bar{q},\sigma) = E[g(q)]$

$$A_d = \begin{bmatrix} A_d^{(p)} & G_d^{(p)} D_x^{(f)} \\ \mathbf{0} & A_d^{(f)} \end{bmatrix}, B_d = \begin{bmatrix} B_d^{(p)} \\ \mathbf{0} \end{bmatrix}, G_d = \begin{bmatrix} \mathbf{0} \\ G_d^{(f)} \end{bmatrix}$$

$$D_x = \begin{bmatrix} D_x^{(p)} & \mathbf{0} \end{bmatrix}, \; D_u = D_u^{(p)}$$

ρ_j is the jth row of the identity matrix with the same dimension as Σ_z and α is the number of standard deviations between the steady state target and process boundaries. Crucially, a globally optimal solution to Problem (15) can be efficiently obtained using the method provided in Zhang et al. (2015).

Economic Dispatch with ELOC

For our 5-bus example, the ELOC objective is

$$g_1(\bar{q},\sigma) = \sum_m c_{0,m} + c_{1,m}\bar{P}_{G,m} + c_{m,2}\left(\bar{P}_{G,m}^2 + \sigma_{G,m}^2\right) \tag{22}$$

The ELOC feedback policy, m_i - $\bar{m}$ = $L(s_i$ - $\bar{s})$, was obtained from the global solution of Problem (15) using $\alpha = 1$. From the inventory utilization trajectories in Figure 5, it is noted that both control strategies (EMPC and ELOC) yield similar performances and hence, similar costs. Expectedly, pointwise-in-time constraints are not enforced in the ELOC. Therefore, the ELOC is not implementable for operational purposes, although a method to re-introduce these constraints, dubbed 'Constrained ELOC' is described in Mendoza-Serrano and Chmielewski (2015). The guarantee of an analytic, global solution to the ELOC problem and the similarity between ELOC and EMPC are persuasive motivations for the ELOC to be utilized in the OSP problem.

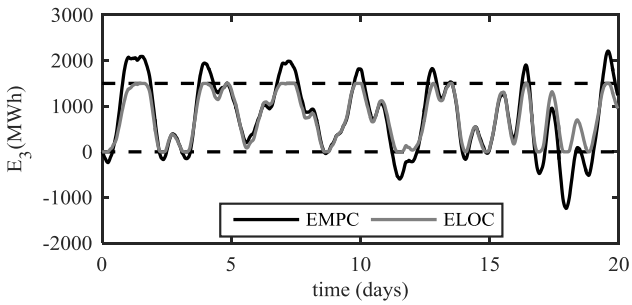

Figure 5. Comparison of EMPC and ELOC trajectories

Optimal Sizing and Placement of Energy Storage

The objective to be minimized in the OSP problem is the net present value, equal to the sum of the present value of average operating costs and the capital cost of storage. For the latter, we adopt the sixth-tenth rule to relate storage capacity to cost and also include a fixed installation cost:

$$\min_{E_{S,m}^{\max},\delta_m\in\{0,1\}} \gamma.E\left[g(q)\right]+\sum_m \delta_m\left(C_1+C_2\left(E_{S,m}^{\max}\right)^{0.6}\right) \tag{23}$$

The operating strategy selected will describe the implicit relationship between the average operating cost, $E[g(q)]$ and storage capacity, $E_{S,m}^{\max}$.

EMPC-based OSP

As illustrated in the first example, if given storage sizes and placements, EMPC can be used to numerically evaluate the average operating cost as

$$E\left[g(q)\right]=\frac{1}{M}\sum_i^M g(q_i) \tag{24}$$

where q_i is obtained from the EMPC simulation and M is a suitably large simulation period. Therefore, EMPC can be used as a black-box function in conjunction with a solver that can handle the discontinuities associated with the binary variables δ_m. However, such solvers, typically based on simulated annealing algorithms (Kirkpatrick et al. 1983), can be computationally expensive. Of course, the non-smooth form of Problem (23) precludes the use of standard gradient search methods since they cannot see beyond the discontinuity and may drive the search trajectory away from the true optimum. However, such methods may be applied if the storage placement is fixed. That is, the OSP problem can be decomposed into several sub-optimizations, each searching over a unique storage placement. This approach is obviously unwieldy as the number of placement possibilities increases combinatorially with network size.

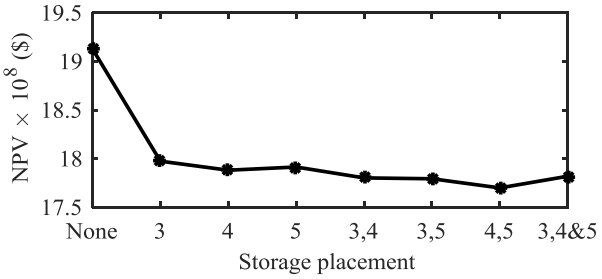

Figure 6. Optimal net present value for fixed storage placement scenarios

However, since the current example has only 8 possible placements, this approach is tractable and can be used to find the true global optimum. Using $C_2 = 10^5$, $C_1 = 20C_2$, $\gamma = 9.28 \times 10^4$ and EMPC to estimate $E[g(q)]$ with M = 1440h, the result of such an exhaustive search on the 5-bus network is summarized in Figure 6. It indicates that the global solution to the OSP problem is $E_{S,3}^{\max}=0$, $E_{S,4}^{\max}=1564\text{MWh}$, and $E_{S,5}^{\max}=1309\text{MWh}$ with a NPV of $\$1.77 \times 10^9$.

ELOC-based OSP

ELOC's similarity to EMPC and its attractive solution properties can be exploited to improve the likelihood and speed of convergence to a global solution. Two modifications to the original ELOC problem are required to construct the ELOC-based OSP problem. First, the elements of $q^{\max}$ in Eq. (21) that correspond to the storage capacities are considered as variables. Then, the objective Eq. (15) is replaced with Eq. (23), with the average operating cost calculated as

$$E\left[g(q)\right]=g_1(\bar{q},\sigma) \tag{25}$$

Due to the non-convexity introduced by the binary variables, it is worthwhile to discuss the solution methodology used for the ELOC-based OSP problem. Our solution method (Zhang et al., 2015), is based on the Generalized Benders Decomposition (Geoffrion, 1972). It involves successive iterations between the relaxed master problem and a variation of the primal problem known as problem Q as shown in Figure 7. An appropriate choice of complicating variables ensures that global solution to the former, with its nonconvex, nonlinear objective can be readily obtained using BARON (Tawarmalani and Sahinidis, 2005). Similarly, problem Q can be readily solved using a standard semi-definite programming (SDP) solver (MOSEK, 2015), since it contains only convex constraints.

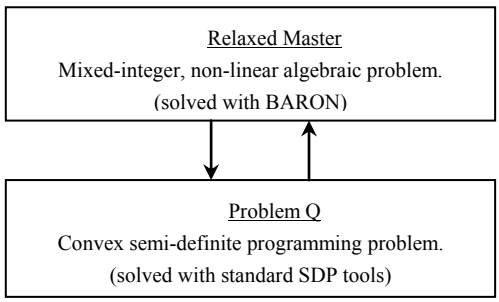

Figure 7. Solvers used in ELOC-based OSP solution procedure

It is expected that the ELOC-based OSP solution will lie in the neighborhood of the true optimum such that the ELOC unit placement solution, δ^*_m, is a global solution. Then, to correct for the statistical constraint assumption of the ELOC framework, a local EMPC-based search for the optimal sizing solution is conducted using the ELOC-based solution as the initial guess. Returning to the 5-bus example, the solution to the ELOC-based OSP problem

was found to be $E_{S,3}^{\max} = 0$, $E_{S,4}^{\max} = 3260\text{MWh}$, and $E_{S,5}^{\max} = 248\text{MWh}$. Using this as the starting point, the gradient search of the EMPC-based OSP scheme found a solution at $E_{S,4}^{\max} = 2090\text{MWh}$, $E_{S,5}^{\max} = 800\text{MWh}$, with a NPV of $\$1.77 \times 10^9$.

Conclusions

In this work, we have shown that the numeric based EMPC policy is capable of exploiting energy storage units within an electric power network. In addition, it was shown that the analytic based ELOC policy can achieve similar results by sacrificing with respect to the enforcement of inequality constraints. However, the analytic nature of the ELOC formulation indicates that extension to the OSP problem, which is in essence an integrated system design and control problem, will result in attractive computational properties. In fact, it was shown that a global solution to the ELOC-based OSP problem can be guaranteed with relatively little computational effort. In contrast, the numerically intensive EMPC-based OSP formulation will require black-box based solution methods (i.e., gradient search or simulated annealing) and is ill suited to address integer variables. The proposed 2-step procedure captures the benefits of both formulations. The first step uses the ELOC-based approach to select integer variable values, the energy storage locations, along with estimates of the optimal storage sizes. Then, a gradient based search using the EMPC-based approach is used to determine the optimal storage unit sizes.

Future studies will extend the operating mode of the electrical network from the economic dispatch case to the unit commitment scenario. While the EMPC approach can be easily adapted to address this change, the ELOC formulation requires a more creative set of modifications. Future efforts will also investigate use of the proposed 2-step approach for the problem of integrated design and control of chemical processes.

Acknowledgements

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