A Great Location: Optimal Siting and Sizing of Energy Storage for Temporal Arbitrage

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Abstract

Electricity grid operators are turning to energy storage as a way of balancing demand with variable and intermittent renewable energy sources, but have little guidance on how to design and locate energy storage systems to maximize their value. This paper proposes a linear program that simultaneously optimizes the sizing and dispatch of a storage system used for temporal arbitrage on a wholesale energy market. Results are presented for a variety of efficiencies and battery costs, and are simulated for 2247 transmission nodes on the California electricity grid. The relationship between storage system cost and optimal reservoir size is examined, and systems with over 4 hours of storage capacity are found to not be cost-effective with most current battery technologies. The analysis demonstrates that the arbitrage value of storage is not normally distributed but rather shows a long tail of high-value nodes, and demonstrates a wider range of values a much wider range of values than previous reported. This distribution is found to be robust to price elasticity in the wholesale energy market, suggesting that a small set of high-value nodes hold the highest value for development by utilities or storage operators.

Keywords: Energy Storage, Energy Markets, Renewable Energy, Batteries, Optimization, Mathematical Programming

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1. Introduction

1.1. Motivation

The production of electricity from wind and solar energy has become a key element of climate change mitigation strategies, and 29 US states currently have set renewable energy procurement targets through Renewable Portfolio Standards [1]. However, intermittency and variability in these energy sources may lead to curtailment of renewable generation during peak hours and to increased reliance on peaker plants [2] - two outcomes that are environmentally and economically undesirable. Energy storage has been proposed as a technology that can help accommodate the intermittency of the renewable energy systems, while also providing other services such as increasing reliability, deferring upgrade costs, and providing ancillary services [3][4]. To promote development of new storage systems, the California Public Utility Commission has mandated that Californian utilities purchase 1.3 GW of storage by 2020 [5], and other regions are considering similar policies.

While many researchers are working on developing low-cost battery chemistries and storage technologies [6], less work has focused on how to design, site, and dispatch this new wave of storage systems.

This study characterizes the optimal sizing and siting of storage over an electricity grid in order to guide policy makers, utility operators, and energy developers. Rather than studying a specific site or technology, we are interested in understanding the impact of location, system efficiency, and reservoir sizing on the profitability of transmission-scale storage.

1.2. Prior Literature

The value of energy storage services can be assessed using a variety of methods, including engineering estimates, system economic dispatch models, and simulation of optimal bidding. For vertically integrated utilities, engineering estimates and economic dispatch models can be used to calculate the savings associated with owning storage systems [3, 4, 7, 8]. However, in regions where the energy industry has been restructured to allow open competition, the profitability of a storage system can be calculated using mathematical programming models. These tools can optimize bidding in wholesale energy markets [9, 10], ancillary service (AS) markets [11, 12], and bidding across multiple nodes in a network [13].

Current storage installations are dominated by large pumped-hydro facilities which are limited to favorable geographic sites, but new technology development has focused on modular systems that can be sited wherever the grids needs are greatest [2, 3, 6, 14]. While this flexibility promises to be an asset to the new storage technologies, the impact of site selection on system profitability has only been examined in [10] and [9], both of which considered a small number of nodes in the PJM market.

The sizing of a storage systems energy reservoir is another important design decision. Unlike conventional generators, the output of a storage system is limited by the capacity of its reservoir (typically described as the number of hours of storage available at peak output, e.g. a 1MW/4h system). While large reservoir capacities are seen in pumped-hydro storage systems due to economies of scale, new storage technologies typically have constant marginal cost, making such large reservoirs much more expensive [15].

Prior literature on sizing storage systems has focused on behind-the-meter installations. In these applications, storage is installed to reduce demand charges [3] in a commercial facility, or to smooth intermittency in a renewable energy plant such as a wind farm [16, 17, 18], photovoltaic array [19], or concentrated solar power system [20]. When storage is combined with these renewable energy sources, optimal sizing of the storage reservoir allows the plant operator to guarantee contractual energy delivery in the face of uncertain wind or solar forecasts [16, 18, 19].

By contrast, an independent storage system bidding into restructured energy markets would be sized to maximize profits (or minimize utility costs). The impact of reservoir sizing on arbitrage profits is explored through iterative simulation in [10] and [9], but an optimal size was not identified, and no prior literature has shown a method for endogenously optimizing the reservoir capacity of an independent storage system.

1.3. Novel Contributions

This paper builds on prior literature by examining the optimal sizing of a storage system bidding into wholesale energy markets. We examine the arbitrage value for transmission nodes across the grid operated by the California Independent System Operator (CAISO), allowing us to assess the statistical and geographic distribution of storage profits.

This paper addresses gaps in prior literature by introducing the following novel contributions:

1. Simultaneously optimizing reservoir size and system dispatch for energy arbitrage
2. Demonstrating the dependence of optimal reservoir size on storage reservoir cost
3. Presenting storage values for all nodes on the transmission network of an Independent System Operator (ISO)
4. Demonstrating that the storage profits are not uniform or normally distributed across transmission nodes, but rather show a significant tail of high-value nodes
5. Introducing a visualization tool for graphically describing nodal profits

1.4. Outline

In Section 2, we outline the assumptions of our model, based on findings in the literature described above. In Section 3 we propose a linear program (LP) that simultaneously optimizes the dispatch and reservoir size for a storage system, and then introduce the data that will be used for our analysis. In Section 4 we present results, first for a sample of nodes in order to validate the models output, and then for all nodes of the CAISO grid. We examine the impact of system efficiency and reservoir cost on the profitability of the system, relax the assumption that the storage operator acts as a price-taker, and test the statistical distribution of profits across nodes. We conclude by noting limitations to our work.

2. Modeling Assumptions

In the formulation proposed below, we examine the sale of energy in the wholesale energy market, and do not consider ancillary services (regulation up/down, capacity reserves, etc.). Other authors have examined the co-optimization of arbitrage and ancillary services [12, 9, 21, 20, 22], and the current results could be similarly extended. We limit ourselves to energy arbitrage for several reasons: (i) not all ISOs operate ancillary service markets; (ii) the ancillary service markets are traded at the regional level and would not affect comparisons between nodes; and (iii) the ancillary services markets have smaller trading volume than the wholesale energy market, and thus prices are more likely to be affected by the addition of storage [3, 10].

We assume that the cost of constructing the storage reservoir can be represented as a constant marginal cost, and that for accounting purposes it can be amortized across the lifetime of the storage system, as $/kWh/year. This follows the approach outlined in [15], and is representative for the electrochemical battery systems which have seen the bulk of recent development [14]. Economies of scale (decreasing marginal cost of reservoir capacity) are seen in pumped-hydro systems, flow batteries, and underground compressed-air energy storage, and could be integrated into the current formulation as an affine decreasing cost function (resulting in a convex quadratic program).

We report results for a storage system normalized to 1kW power capacity, and consider a variety of reservoir capacities, e.g. 2, 4, or 8 hours of storage. This allows results to be presented on the basis of kWh capacity for comparison with other studies. We assume that our results would scale up to a large-scale system (MW of power and MWh of capacity).

We assume that the storage operator has perfect foresight of energy prices.

While this assumption appears generous, it allows us to compute an upper bound on storage profits, which is useful for system planning. We initially assume that the storage system is a price-taker, i.e. that it is too small for its actions to affect the energy price at its trading node. This assumption is then relaxed in Section 4.5 by allowing market prices to respond to the actions of the storage operator. The assumptions of perfect foresight and price-taking behavior have been examined for individual nodes in [13] and [10].

3. Formulation

In the following sections we outline the mathematical formulation of our optimization problem, and the data used in our simulations.

3.1. Mathematical Formulation

The parameters and variables used in this analysis are defined below. Note that energy flow $c(k)$ into the battery is defined as negative, and energy flow out of the battery to the grid $d(k)$ is defined as positive, consistent with accounting for energy purchases as costs and sales as revenues.

k	Time index, from 0 to time horizon N
Δt	Time step size (hours)
$c(k)$	Energy flow into the battery at time k (charging)
$d(k)$	Energy flow out of the battery at time k (discharging)
P_{charge}	Maximum charge power capacity of the system (kW)
$P_{\text{discharge}}$	Maximum discharge power capacity of the system (kW)
$c_{\text{grid}}(k)$	Nodal electricity clearing price ($/kWh)
η_{in}	One-way system efficiency when charging
η_{out}	One-way system efficiency when discharging
$E(k)$	Energy level in reservoir at time k
E_{min}	Minimum allowable energy level as portion of capacity
E_{max}	Maximum allowable energy level as portion of capacity
E_{init}	Starting energy level of the storage system
h	Reservoir capacity (kWh)
γ	Annualized cost of constructing/purchasing one kWh of reservoir capacity ($/kWh/yr)

Asymmetry in the power limits and efficiencies can be accounted for by adjusting the appropriate parameters. Using these variables, the optimization problem can be stated as maximizing the net profit from buying and selling energy on the wholesale market, after considering the cost for constructing h hours of storage capacity:

$$\max_{c(k),d(k),E(k),h} \sum_{k=1}^{N} c_{\text{grid}}(k)\Delta t\,(c(k)+d(k)) - h\gamma P_{\text{discharge}} \tag{1}$$

Subject to the following constraints:

$$P_{\text{charge}} \leq c(k) \leq 0 \quad \forall k = 1...N \tag{2}$$

$$0 \leq d(k) \leq P_{\text{discharge}} \quad \forall k = 1...N \tag{3}$$

$$hE_{\text{min}} \leq E(k) \leq hE_{max} \quad \forall k = 0...N \tag{4}$$

$$E(k) = E(k-1) + c(k)\Delta t\eta_{\text{in}} + d(k)\Delta t/\eta_{\text{out}} \quad \forall k = 1...N \tag{5}$$

$$E(0) = hE_{\text{init}} \tag{6}$$

$$h \geq 0 \tag{7}$$

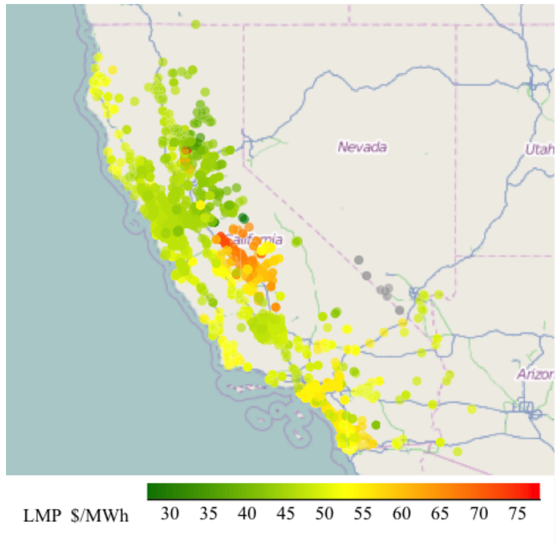

Figure 1: Example of Location Marginal Price (LMP) distribution on the CAISO grid. Each circle represents an LMP node on the the CAISO grid. Data from 4PM PDT, August 18 2013

In this formulation, the signs of the optimization variables $c(k)$ and $d(k)$ are constrained in order to accommodate the inefficiency in the system while preserving linearity in the constraints. Although it is compact, this model advances prior literature by simultaneously calculating both optimal reservoir size h and the optimal storage dispatch pattern $E(k)$.

As the objective and all constraints are affine in the optimization variables $c(k)$, $d(k)$, $E(k)$, and h, this optimization can be solved with standard solvers for linear programs, allowing for rapid simulation of thousands of scenarios.

3.2. Data

Data on the day-ahead location marginal price (LMP) of energy in the CAISO power grid for calendar year 2013 was collected from the web portal of the of the California Independent System Operator [23].

These LMPs reflect the clearing price at which energy sales are settled on the CAISO grid, and would be the price at which a transmission-connected storage system would buy and sell energy. In the day-ahead market, participants bid in on-hour blocks, and all participants bidding at a node receive the hourly clearing price for that node. Data was collected for the 2247 LMP nodes for which location information (latitude and longitude) is available, as shown in Fig. 1.

We set $P_{\text{charge}} = -1$ and $P_{\text{discharge}} = 1$ to represent 1kW of power capacity. For ease of presentation, we will assume that the depth of discharge is not constrained, i.e. $E_{\min} = 0$ and $E_{\max} = 1$. While many storage technologies have depth-of-discharge constraints due to electrochemical or physical constraints, the constraint has the simple effect of adjusting the effective size of the storage reservoir: a 5h reservoir with an 80% depth-of-discharge constraint would show the same optimal trading behavior as a 4h system with no depth-of-discharge constraint. Except where otherwise noted, all simulations were conducted with a round-trip efficiency of 90%, which is assumed to be the product of symmetric charging and discharging inefficiencies ($\eta_{\text{in}} = \eta_{\text{out}} \approx 0.95$).

4. Results

Because we assume the storage system acts as a price-taker and has perfect price foresight, the results below represent best-case arbitrage profits for a given power-to-energy ratio. For a merchant storage operator to be profitable, the arbitrage profits would need to cover average costs, which we expect will be dominated by the annualized costs of the battery and power system [15]. For this reason, we will refer to the value of the objective function as the long-run profits. We refer to the trading profits excluding the costs of the reservoir construction as the short-run trading profits [24]. Both are presented as \$/kWh/year. For electrochemical batteries that degrade as the system is repeatedly charged and discharged, an important performance metric is profit per cycle (expressed here as \$/kWh/1000 cycles). This is calculated by dividing the short-run trading profits by the number of charge/discharge cycles during the year, and normalizing to 1000 cycles.

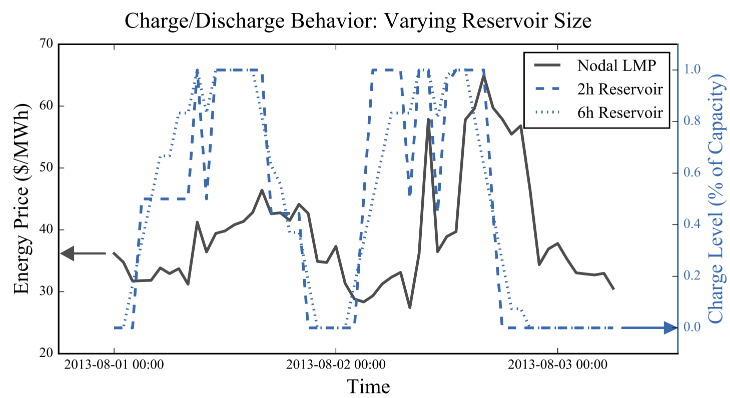

Figure 2: Example of the impact of reservoir size on optimal charging behavior, while system efficiency is held constant. The smaller system is able to capture peak price swings, but a larger reservoir allows the system to take advantage of sustained price differences- increasing profits but increasing construction costs.

4.1. Validation

We validate the output of the linear program by evaluating simulation output against the charge/discharge behavior and system size which would be predicted by microeconomic principles, to check that the reported behavior is both economically efficient and profit-maximizing.

As the optimization variables $c(k)$, $d(k)$, and $E(k)$ are linked through the constraints 2, we can capture the full system behavior by examining just the reservoir level $E(k)$. In Fig. 2 and Fig. 3 we plot the charge level for a randomly chosen LMP node from the CAISO dataset (BARRY_6_N001 is shown). Two days in August 2013 are shown, chosen for exhibiting periods of both low and high price volatility.

In Fig. 2, the two reservoir sizes are illustrated, obtained by fixing h in the optimization problem and examining the resulting values of $E(k)$. We see that the 6h system charges throughout the morning low-price period, and discharges throughout the evening high-price hours. The smaller system is able to more selectively charge and discharge at extreme price events, but is limited in its ability to capture value from sustained price differences.

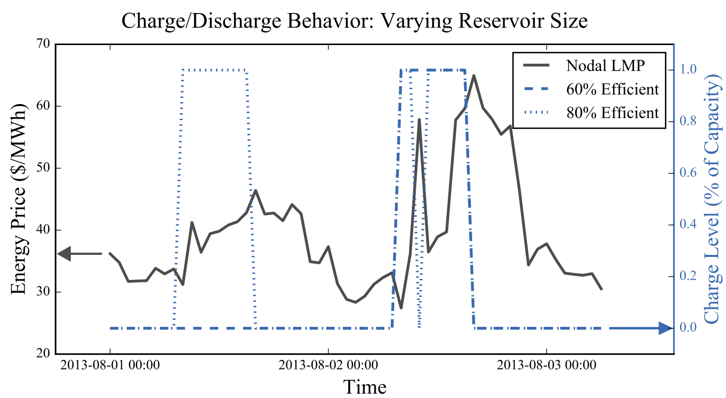

Figure 3: Example of the impact of storage system round-trip efficiency on optimal charging behavior, assuming a constant reservoir size. The storage system will only discharge when price differences are greater than the cost of efficiency losses, leading the high-efficiency system to cycle more often.

In Fig. 3 we examine the impact of changing the round-trip efficiency while fixing the reservoir capacity at one hour of storage ($h = 1.0$). At the lowest efficiency (60%), the system only charges once (during the second day), as price differences during the first day are not great enough to outweigh the round-trip efficiency losses. As efficiency increases to 80%, the system is able to take full advantage of diurnal price differences, and begins to arbitrage morning/midday price swings.

This reflects the economically efficient behavior of as charging whenever the price difference between two local extrema is greater than the energy loss, $1/(\eta_{\mathrm{in}}\eta_{\mathrm{out}})$, i.e. when the short-run trading profits are greater than the transaction cost created by round-trip inefficiencies [24].

In Fig. 4 the annualized storage price γ is held constant at \$5/kWh/year while the reservoir size h was constrained to take on a range of values as in Fig. 2. The long-term operator profits (including reservoir cost) are plotted against reservoir size h, and are shown to peak at a value of $h = 2.0$, which coincides with the optimal solution of the linear program when h is unconstrained.

At low reservoir sizes in Fig. 4, the operator charges and discharges the sys-

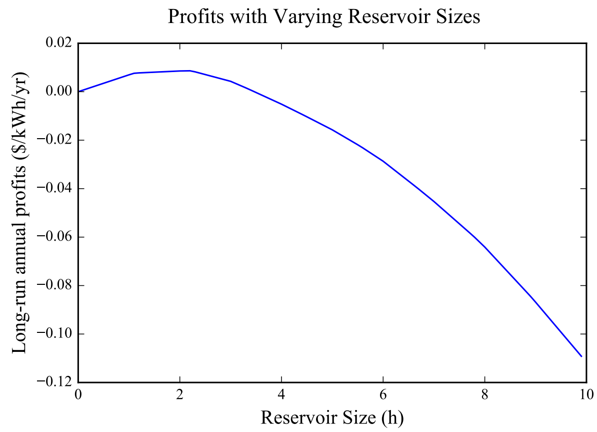

Figure 4: Example of the impact of reservoir sizing on long-run operator profits (including the cost of constructing the reservoir). At low reservoir sizes, the operator is not able to take advantage of all arbitrage opportunities. At large reservoir sizes, construction costs outweigh arbitrage benefits. At optimum, the marginal benefit of additional reservoir capacity is balanced by construction costs. Data is shown for the BARRY_6_N001 node in 2013 and assumes an amortized reservoir cost $5/kWh/year.

tem at the hours with the most extreme price events (similar to the 2h system in Fig. 2). As reservoir capacity increases the operator is able to capture off-peak price differences, but because price differences are smaller the marginal benefit of this additional reservoir capacity decreases. When the reservoir is below optimal size, the increase in trading profits is greater than the annualized costs of constructing the additional reservoir capacity. At optimum, the marginal benefits of adding capacity are precisely equal to the annualized costs of construction the additional capacity, and the operator's profits are maximized [24]. If the reservoir size is increased beyond the optimum, the annualized costs of storage construction overwhelm short-run trading profits, and the storage system may operate at a net loss.

The shape of this curve will differ for each node, as the returns to increasing storage size are determined by daily, weekly, and seasonal fluctuations in the location marginal price, which will depend on a node's local consumption and

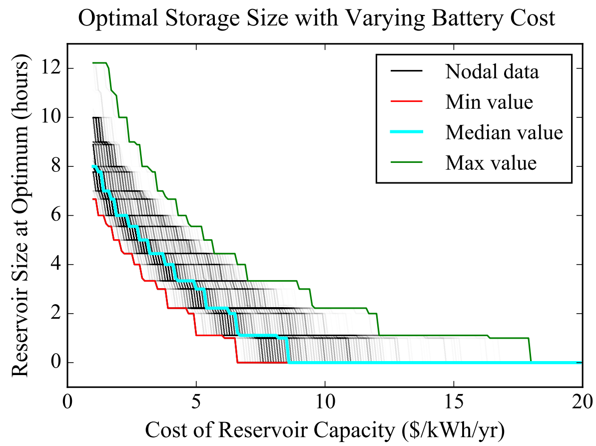

Figure 5: Optimal reservoir size in hours of storage capacity with varying annualized construction costs γ, across all CAISO LMP nodes. Optimal size of the storage system decreases when construction costs increase, as the marginal benefits from a larger reservoir are more rapidly offset by construction costs.

congestion patterns.

4.2. Sensitivity Analysis: Reservoir Construction Cost

This analysis can be extended by considering a range of reservoir costs, representing the variety of system costs associated with different storage technologies. In Fig. 5 the optimal reservoir size is plotted for each node over a range of annualized reservoir costs γ ranging from \$1-\$20/kWh/year, assessed at \$0.10/kWh/year intervals. Note that because the problem is formulated as an LP the resulting curves are not smooth, as the optimum jumps between vertices of the polyhedron defining the feasible region.

As storage price increases we see a monotonic decrease in optimal reservoir size. As shown in Fig. 4, the optimal reservoir size occurs when the marginal benefit equals the marginal cost of the additional reservoir capacity: as cost increases this optimum will come at lower reservoir sizes.

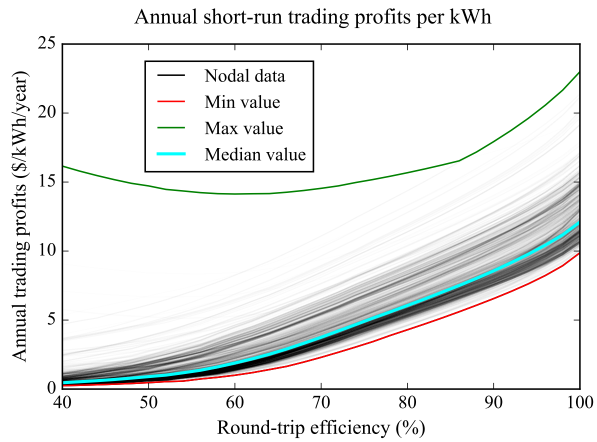

Figure 6: Short-run arbitrage profits for each node, plotted at varying efficiencies for a 1kW/1kWh system. Each node is plotted at 1% opacity to show the distribution of values at each efficiency.

4.3. Sensitivity Analysis: Storage System Efficiency

A key differentiator between storage technologies is round-trip efficiency, which also has an impact on the optimal dispatch schedule as was shown in Fig. 3. To explore the impact of system efficiency on system operation, the optimization was run for all nodes while varying round-trip efficiency from 40% to 100%. This reflects the full range of efficiency values seen in common storage technologies [6, 15].

We examine three metrics: short-run trading profits, number of charge/discharge cycles, and average profits per cycle. The latter two metrics are relevant for many electrochemical battery technologies which have a limited cycle life [15].

For clarity of presentation, in the results below the reservoir size was fixed at $h = 1.0$ (i.e. a 1kW/1kWh system), and results are presented as short-run arbitrage profits excluding reservoir costs. For each node and efficiency, an optimal size could be derived as in Section 4.2.

As efficiency increases, the storage system has fewer losses, increasing profits for a given temporal fluctuation in wholesale energy prices. Simultaneously, the

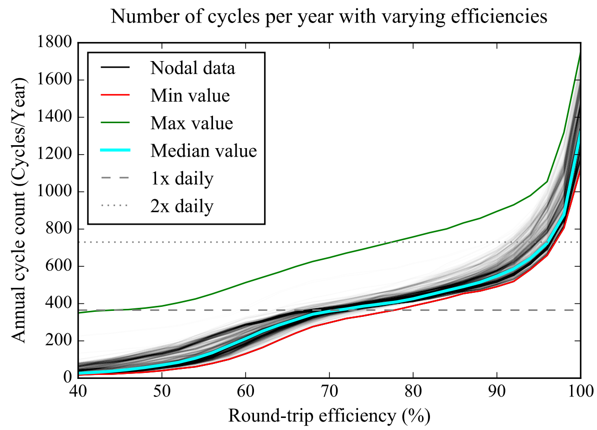

Figure 7: Annual cycle count at each node with varying efficiency, 1kW/1kWh system. Each node is plotted at 1% opacity to show the distribution of values at each efficiency.

storage operator makes more transactions because they can profitably arbitrage smaller price fluctuations. These effects combine to create a slightly nonlinear increase in profits with increasing efficiency, as shown in Fig. 6. A small number of nodes show high profits at low efficiencies due to significant negative price events, when inefficient loads would be paid for their ability to consume more energy.

In Fig. 7 the number of charge/discharge cycles is plotted, and shows a slight plateau around 365 charges/year from arbitraging diurnal price differences. There is a rapid increase in cycle count at high efficiencies because the optimization takes advantage of an increasing number of small variations in energy prices. While diurnal and midday/evening price differences occur very regularly, the more frequent trading seen above 95% efficiency is due to minor price fluctuations that may be difficult to predict without perfect foresight.

The per-cycle profits shown in Fig. 8 stay fairly constant over the range of 60-90% efficient systems, as the increase in profits is balanced by the increase in number of charge/discharge cycles. However, the per-cycle profits taper dramatically at high efficiencies as the operator chases the small profits associated

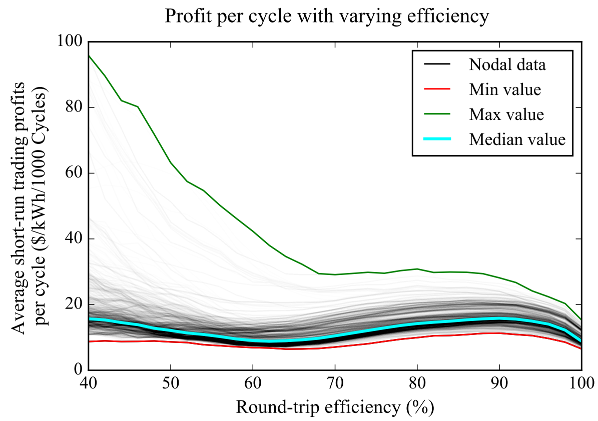

Figure 8: Profit per cycle for each node under varying efficiencies, assuming a 1kW/1kWh system. Each node is plotted at 1% opacity to show the distribution of values.

with frequent hourly price swings.

4.4. Comparison with Prior Results

Previous literature estimated the arbitrage value of storage on the CAISO grid to be in the range of $3-10/kWh/yr [3, 12]. These results are consistent with the median values shown above, but miss the long tail of high-value nodes. By assessing all LMP nodes, we see that there is a much wider range than previously reported, and that reporting a single value does not sufficiently characterize the distribution of storage value.

Comparing our per-cycle profitability results with the storage system cost and lifetime estimates reported in [15] we find that arbitrage-only profits at high-value nodes could cover the capital costs of pumped-hydro storage, underground compressed-air energy storage, lead-acid batteries with carbon electrodes, and the DOE long-term electrochemical battery cost target. These findings are consistent with existing deployments, which are mostly comprised of pumped-hydro storage [14].

While previous literature has not examined the optimal sizing of a transmission-scale storage system, the optimal sizes found here can be compared with current storage installations. Consistent with our results, high-capacity (8+ hour) reservoirs are only observed in pumped-hydro storage systems, while electrochemical battery systems are most frequently installed in 1-hour or smaller reservoir capacities [14].

4.5. Relaxing the Price-Taker Assumption

The model presented above in 1 assumes that the LMP values are not impacted by the storage operator's decision, but in reality a storage system used for arbitrage would smooth prices by providing additional supply when prices are high and additional demand when prices are low [4, 24]. In the following section we introduce a method for relaxing this price-taker assumption and show that the relaxation reduces profits for each node, but does not affect the relative distribution of profits across the grid.

The impact of market elasticity on arbitrage profits in the PJM market was assessed in [10], using regional trading quantities and clearing prices. However, expanding this approach to nodal LMP calculations is difficult: transaction quantities are not available for individual LMP nodes on the CAISO grid, and local congestion creates nonlinear price elasticity [25].

To overcome these challenges, we propose a simple method to approximate the impact of the storage system on local prices, without assuming that we have a linear elasticity or residual demand curve. We assume that buying energy will drive the market price up by a factor α, and selling energy will decrease prices by the same factor α, regardless of the quantity sold. For example, when $\alpha = 0.10$, we assume that the LMP increases by 10% whenever the storage system is charged, and the LMP decreases by 10% whenever the storage system discharges.

This does not affect the constraints 2 and only requires a linear modification to the objective function 1, which becomes:

$$\max_{c(k),d(k),E(k),h} \sum_{k=1}^{N} c_{\text{grid}}(k)\Delta t \left((1+\alpha)\, c(k) + (1-\alpha)\, d(k) \right) - h\gamma P_{\text{discharge}} \qquad (8)$$

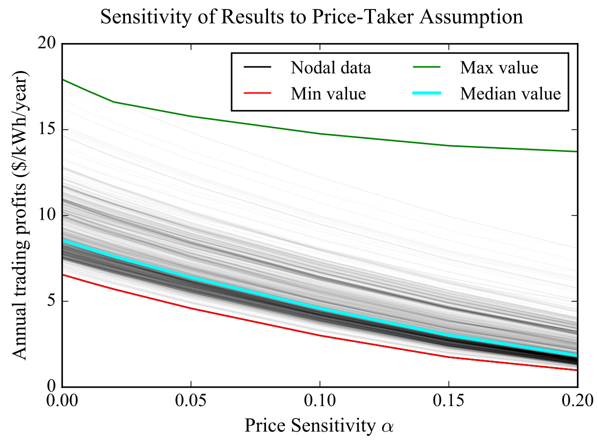

Figure 9: Impact of price responsiveness on storage operator profits. We assume that the market price of energy is depressed by a factor α whenever the storage operator sells energy, and is increased by α when the storage system buys energy. While profits decrease, the distribution of the profits across nodes is preserved.

For a given value of α, the linearity of the problem is preserved. Because each node faces different transmission constraints and supply curves, no single value of α can be applied for all nodes- at each node, α would need to be estimated from supply disruptions, a study outside of the scope of the present work. Instead, we evaluate a range of values for α in Fig. 9, to see the impact of price sensitivity to the price-taker assumption on the profitability of a storage operator under a variety of conditions. As in Section 4.3, we present short-run profits for a 1kW/1kWh system at each LMP node.

As α increases, the arbitrage potential decreases as price variations are smoothed out. However, the relative ordering and distribution of nodes is largely unaffected: our prior conclusions about the distribution and normality of nodes remain unaffected. If price/volume data were available, this assessment could be expanded to include a linear residual demand function at each node, resulting in a convex quadratic program as described in [10].

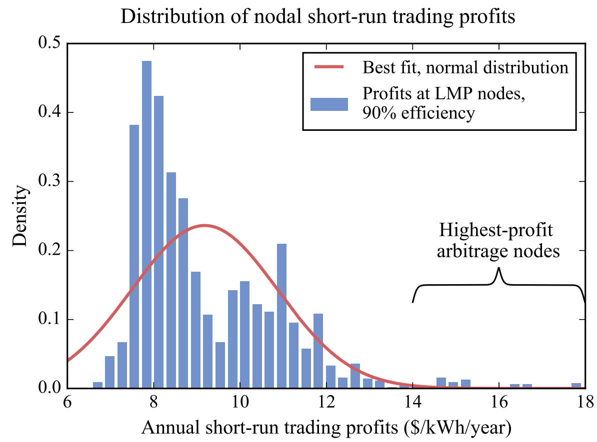

Figure 10: Histogram of nodal profits at 90% efficiency for 1kW/1kWh system, with best fit of a normal distribution (estimated with maximum likelihood estimation)

4.6. Distribution of Results

In the results above, storage profits are seen to not be uniform across nodes, but instead display a random component. If we were to *a priori* think of storage profits as the weighted sum of many uniform random variables (congestion, load, renewable energy intermittency, etc.), the Central Limit Theorem suggests that storage values would be distributed normally. However, in the results presented above and in Fig. 10, the distribution of storage profits appears to be significantly skewed.

Using both the Kolmogorov-Smirnov and Jarque-Bera normality tests [26] on each of the efficiencies and metrics above, we can reject at the 1% significance level the *a priori* hypothesis of normal distribution. These findings emphasize the significance of high-value nodes in understanding storage feasibility, and how storage site location dictates system profitability.

There appears to be a bimodal distribution in Fig. 10 which may indicate additional structure within this distribution; we plan to analyze this in future work.

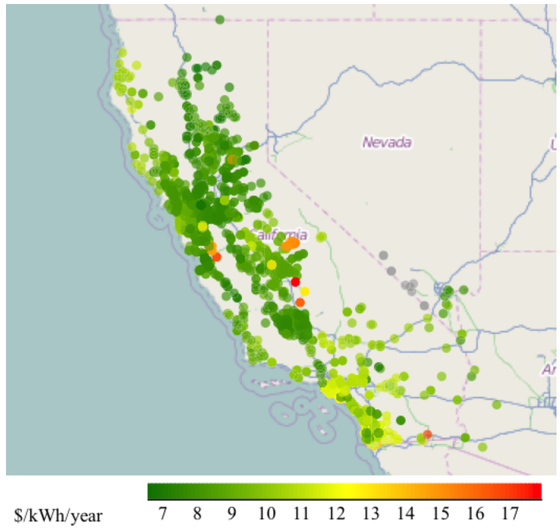

Figure 11: Plot of short-run trading profits from energy arbitrage of a 90% efficient 1kW/1kWh system at LMP nodes on the California ISO grid. Broad regions of high-value nodes in the Northern and Southern coastal regions suggest large regions of congestion where storage may have greatest impact.

4.7. Geographic Variation in Storage Value

The profitability of storage systems at each LMP was mapped out in a GIS-like web application which the authors built to allow researchers to visualize price data on the CAISO grid [27]. This allows for the geographic localization of high-value and low-value nodes, and assessment of spatial trends. An example of this mapping application is shown in Fig. 11, highlighting annual trading profits for the 90% efficiency scenario. Note the clustering of higher-value nodes in the Eureka region and the San Diego foothills, suggesting that congestion in these areas may be partly relieved by the deployment of storage.

5. Discussion

5.1. Limitations

By construction, this study has only examined transmission-scale storage bidding into the wholesale energy market. Under current regulations, these results do not apply to behind-the-meter storage or vehicle-to-grid services, but could be applied if aggregators were allowed to bid into the wholesale energy market [28].

We only consider bidding into the day-ahead energy market, but the results could be extended to cover sequential markets and ancillary services (AS), as has been done for single nodes in [11, 12, 22]. Since AS markets cover large regions (the CAISO grid has several thousand price nodes but only three ancillary service markets), the inclusion of AS markets would shift the profits of all storage operators in the AS market area without affecting their relative distribution.

The current results reflect a best-case scenario, since they are based on perfect foresight and price-taking behavior using historical market data. The significance of diurnal and morning/evening bidding in most efficiency levels was shown in Fig. 7, suggesting that profits are relatively insensitive to relaxing the perfect foresight assumption (as has been done in [10] and [13]). The price-taker assumption was discussed in Section 4.5 and [10] and does not affect our conclusions about optimal sizing, distribution of results, or geographic distribution of high-value nodes.

Only price data for 2013 was analyzed; the inclusion of a larger data set would increase the robustness of the results by introducing variance in natural gas prices, hydropower availability, and renewable energy deployment. The optimal siting of a new storage system would also require forecasting future energy prices under different scenarios of renewable energy penetration.

We have assumed that storage has a constant marginal cost, an assumption which could be relaxed for system which have significant economies of scale (pumped-hydro storage, flow batteries, and compressed-air energy storage) by replacing γ with an affine function of h, which would turn the problem into a convex quadratic program. We have also assumed that the impact of the storage system on energy prices can be represented by a constant factor, a convenient proxy in the absence of historical price/quantity curves. For a specific node, a linear price elasticity or residual demand function could be integrated and result in a convex quadratic objective function. These two modifications modifications (affine economies of scale and linear price elasticity) involve affine terms in separate variables, and thus can both be integrated while preserving the convexity of the formulation.

5.2. Conclusion

Using historic price data for 2247 price nodes on the California electricity grid, we utilized a linear program to simultaneously optimize the dispatch and reservoir sizing of a storage system for temporal arbitrage in the day-ahead wholesale energy market. We find that the optimal reservoir size is strongly dependent on installed costs, and that systems with 4 hours of storage or more are only optimal when annualized reservoir costs are below \$10/kWh/year. We explore the dependence of system profitability on efficiency, finding profits of \$7-17/kWh/year or \$10-27/kWh/1000 cycles for a 90% efficient storage system with 1 hour of reservoir capacity. We find a long tail of nodes that are of significantly higher value than have been reported in previous studies, and can reject the hypothesis that storage values are normally distributed. Our revenue estimates show that some existing technologies reported in [15] may be profitable in the highest-value nodes. These results will be of interest to policy makers, utility planners, and storage developers, and will help guide the design and siting of new transmission-scale energy storage systems.

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