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Opportunities for Energy Storage in CAISO: Day-Ahead and Real-Time Market Arbitrage

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***Abstract*—Energy storage is a unique grid asset in that it is capable of providing a number of grid services. In market areas, these grid services are only as valuable as the market prices for the services provided. This paper formulates the optimization problem for maximizing energy storage revenue from arbitrage (day-ahead and real-time markets) in the CAISO market. The optimization algorithm was then applied to three years of historical market data (2014-2016) at 2200 nodes to quantify the locational and time-varying nature of potential revenue. The optimization assumed perfect foresight, so it provides an upper bound on the maximum expected revenue. Since California is starting to experience negative locational marginal prices (LMPs) because of increased renewable generation, the optimization includes a duty cycle constraint to handle negative LMPs. Two additional trading algorithms were tested that do not require perfect foresight. The first sets a buy price threshold and a sell price threshold (e.g., limit orders) for participation in the real time market, subject to the constraints of the energy storage system. The second uses the day-ahead prices as an estimate for the real time prices and performs an optimization on a rolling time horizon. The simple threshold algorithm performed the best, but both fell well short of the potential revenue identified by the optimization with perfect foresight.**

I. INTRODUCTION

Energy storage is a unique grid asset in that it is capable of providing a number of grid services. These services can be broken into two categories based on the characteristics of the charge/discharge profile required to provide the service. Energy applications typically transpire over long periods of time, often up to several hours. On the other hand, power applications happen on a much quicker time scale, seconds to minutes, and are often aimed at maintaining grid stability. A summary of energy and power applications appears in Table I. A detailed description of potential benefits from energy storage is found in [1].

TABLE I
SUMMARY OF ENERGY STORAGE APPLICATIONS.

Energy Applications	Power Applications
Arbitrage	Frequency regulation
Renewable energy time shift	Voltage support
Demand charge reduction	Small signal stability
Time-of-use charge reduction	Frequency droop
T&D upgrade deferral	Synthetic inertia
Grid resiliency	Renewable capacity firming

In market areas, energy storage is only remunerated for activities associated with market products. The common services include energy arbitrage and providing ancillary services. Arbitrage refers to purchasing energy (charging) when prices are low, and then selling (discharging) energy when prices are high. An early study identifying the potential arbitrage benefit is presented in [2]. While arbitrage is the most well known service that can be provided by energy storage, it rarely offers the most potential revenue [3], [4], [5], [6], [7], [8]. A study which evaluates potential arbitrage revenue in PJM using 2014 data is found in [9]. The study considered arbitrage in the day-ahead market and arbitrage in the real-time market, but not arbitrage between the two markets. The conclusion was that the real time market offered greater arbitrage opportunities because of the increased price volatility, but that the increased volatility also created forecasting challenges. A stochastic optimization formulation of a storage owner's arbitrage profit maximization problem under uncertainty in day-ahead and real-time market prices is presented in [10].

The most common ancillary service is frequency regulation, which is the second by second adjustment of output power to maintain system frequency. In some market areas like PJM, there is a single product for frequency regulation and the device must have a bidirectional capability. In other markets like CAISO and ERCOT, there are separate products for regulation up (inject power to the grid) and regulation down (pull power from the grid). Pay-for-performance was mandated by FERC Order 755 [11], [12], so all Independent System Operators (ISOs) in North America, with the exception of ERCOT, have adopted pay-for-performance mechanisms. Typically, this includes some type of mileage measurement combined with a performance score. The remuneration is a function of the capacity and mileage price, as well as the performance score. Potential revenue from frequency regulation is often 2-3 times the potential revenue from participating in arbitrage in the day-ahead energy market [3], [4], [5], [6], [7], [8].

This paper outlines a framework for calculating the maximum revenue from an electricity storage system that participates in the CAISO day-ahead and real-time markets for energy arbitrage. The approach is designed to calculate the best-case scenario using historical data to simulate operation with perfect day-ahead and real-time energy forecasts. This best-case scenario calculation is critical because it provides an upper bound on the revenue that can be collected by a storage facility and can be used to score other trading strategies. Hence, it is useful in estimating an upper bound for the value of a storage facility. Cost data is required to perform a cost-benefit analysis for a particular system and location. Information on the capital and operational costs of different energy storage technologies may be found in [13]. It should also be noted that this approach is only valid for scenarios where the size of the storage is such that it does not impact market prices. For large systems that might impact the market, a production cost modeling approach must be implemented.

The approach in this paper formulates the revenue maximization problem as a linear program. The energy storage model and optimization formulation builds on the results in [14], where the authors present a stochastic framework for the valuation of electricity storage. Previous results using a similar approach (without pay-for-performance) were presented in [3], [4], [5]. The algorithm, results for CAISO data (including a sensitivity analysis for each parameter), and results for several implementable trading algorithms appear in [3]. ERCOT results for a single node, two years of data, and implementable trading algorithms are presented in [4]. All nodes in ERCOT were analyzed over a three year period to look at the impact of location and to identify longer term trends in [5]. The pay-for-performance optimization for PJM, along with results for a representative flywheel plant are found in [5]. The pay-for-performance optimization for MISO is presented in [8]. The optimization formulation for the ISO-NE market along with expected results for a 2 MW, 3.9 MWh system deployed by the Sterling Municipal Light Department (SMLD) are found in [6]. This paper extends the optimization approach to include arbitrage accross the day-ahead and real time energy markets. Results are presented for three years of historical data at 2200 nodes to provide insight into the impact of location on potential revenue.

This report is organized as follows: Section II provides an overview of the CAISO energy markets. Section III presents the energy storage model that is used throughout this paper as well as the revenue maximization problem formulation. Section IV presents results for 2200 CAISO nodes for the 2014-2016 period. Concluding remarks are found in Section V.

II. CAISO Energy Markets

CAISO employs a day-ahead and a real-time energy market. The day-ahead market is composed of three market processes that run sequentially. The three steps are listed below [15]:

1) The ISO runs a market power mitigation test. Bids that fail the test are revised to predetermined limits.
2) The integrated forward market establishes the generation needed to meet forecast demand.
3) The residual unit commitment process designates additional power plants that will be needed for the next day and must be ready to generate electricity. Market prices set are based on bids.

The CAISO market utilizes a full network model, which considers active transmission and generation resources to identify the lowest cost energy to meet load. The model produces prices that show the cost of producing and delivering energy from individual nodes. The locational marginal price at each bus has three components: the marginal cost at the reference bus; the marginal cost of transmission losses from the reference bus to bus i; and the marginal cost of transmission congestion due to binding constraints. The day-ahead market opens for bids and schedules seven days before and closes the day prior to the trade date. Results are published at 1:00 p.m. the day prior. A description of the mixed integer programming (MIP) security constrained unit commitment is found in [16].

The real-time energy market is a spot market in which load serving entities can buy power to meet the last few increments of demand not covered in their day ahead schedules [15]. The market opens at 1:00 p.m. prior to the trading day and closes 75 minutes before the start of the trading hour. The results are published about 45 minutes prior to the start of the trading hour. The hour-ahead scheduling process (HASP) generates nodal prices on a 15-minute interval.

III. Energy Storage Model

The key parameters that characterize a storage device are [17]:

- Power Rating [MW]: the maximum rated power of the storage device (charge and discharge). It is possible to have a different power rating for charging and discharging.
- Energy Capacity [MWh]: the amount of energy that can be stored.
- Efficiency [percent]: the ratio of the energy discharged by the storage system divided by the energy input into the storage system. Efficiency can be broken down into two components: conversion efficiency and storage efficiency. Conversion efficiency describes the losses encountered when input energy is stored in the system. Storage efficiency describes the time-based losses in a storage system.
- Ramp Rate [MW/min or percent nameplate power/min]: the ramp rate describes how quickly a storage system can change its input/output power level.

An energy flow model is often employed to model market interactions. The simplest formulation is a discrete linear time invariant model given by [14]:

$$S_t = S_{t-1}\gamma_s + q_t^R\gamma_c - q_t^D \tag{1}$$

where S_t is the state of charge at time t, γ_s is the storage efficiency over one time period, γ_c is the conversion efficiency, q_t^R is the quantity of energy charged over one period, and q_t^D is the quantity of energy discharged over one period. This model assumes constant storage and conversion efficiencies.

For the analysis in this paper, we are concerned with the quantity of energy charged or discharged during each time period for each potential activity (e.g., buying and selling energy in the day-ahead and real-time markets).

The following parameters capture the storage system constraints:

t	time period (e.g. one hour)
$\bar{q}$	maximum discharged/recharged energy in one period (MWh)
$\bar{S}$	maximum storage capacity (MWh)
$\underline{S}$	minimum storage capacity (MWh)

For a storage device that provides only one service, e.g. arbitrage in one market, there are two decision variables: q_t^D and q_t^R, where q_t^D is the amount of energy discharged at time interval i and q_t^R is the amount of energy procured at time interval i. The decision variables are assumed to be non-negative quantities. Additional constraints include:

$$\underline{S} \leq S_t \leq \bar{S}, \forall t \quad (2)$$

$$0 \leq q_t^D + q_t^R \leq \bar{q}, \forall t \quad (3)$$

Note that the constraint in Equation (3) is required if negative LMPs are present to guarantee that simultaneous charging/discharging is within the constraints of the system. For a device that is participating in arbitrage and the regulation market, a few additional quantities must be incorporated into the storage device model.

Since we are concerned with both the day-ahead and real-time energy markets, we will define the following decsision variables:

q_t^{D-DA}	energy sold in the day-ahead market at interval i (MWh)
q_t^{D-RT}	energy sold in the real-time market at interval i (MWh)
q_t^{R-DA}	energy purchased in the day-ahead market at interval i (MWh)
q_t^{R-RT}	energy purchased in the real-time market at interval i (MWh)

The state of charge model can then be expressed as

$$S_t = S_{t-1}\gamma_s + (q_t^{R-DA} + q_t^{R-RT})\gamma_c - q_t^{D-DA} - q_t^{D-RT} \quad (4)$$

subject to the following constraint

$$0 \leq q_t^{D-DA} + q_t^{D-RT} + q_t^{R-DA} + q_t^{R-RT} \leq \bar{q}, \forall t \quad (5)$$

For CAISO, the objective function that maximizes potential revenue from participating in the day-ahead energy and real-time energy markets is given by

$$\max \sum_{t=1}^{T} \Big[(P_t^{DA} - C_d)q_t^{D-DA} + (P_t^{RT} - C_d)q_t^{D-RT} - (P_t^{DA} + C_r)q_t^{R-DA} - (P_t^{RT} + C_r)q_t^{R-RT}\Big] e^{-rt} \quad (6)$$

where P_t^{DA} represents the day-ahead price for energy ($/MWh) in interval i, P_t^{RT} represents the real-time price for energy ($/MWh) in interval i, C_d is the cost associated with discharging ($/MWh), C_r is the cost associated with charging, and r is the discount rate assuming continuous compounding.

IV. CAISO Results

For this study, three years (2014-2016) of CAISO day-ahead and real-time energy market data was analyzed for 2200 node locations. A notional 1 MW, 4 MWh system with the following parameters was employed for the analysis. Potential revenue was estimated for the following scenarios: day-ahead energy market arbitrage with perfect foresight; day-ahead and real-time arbitrage with perfect foresight; real-time arbitrage with preset buy/sell thresholds and no foresight; and real-time arbitrage using the day-ahead prices as a forecast of real prices, optimization over a sliding 24 hour time horizon, and no foresight. The results for each case are presented in the following sections.

TABLE II
Energy storage system parameters

parameter	**value**
γ_c	0.80
γ_s	1.0
$\bar{q}$	1.0 MWh
$\bar{S}$	4.0 MWh
$\underline{S}$	0.0 MWh

A. Day-Ahead Arbitrage with Perfect Foresight

First, an optimization was performed using only day-ahead energy prices. The optimization was run on hourly market data for each node assuming perfect foresight one month at a time over the three year period. The arbitrage results are summarized in Figure 1. The distribution of potential arbitrage revenue is shown in Figure 2. The monthly revenue profile for the minimum node, the median node, and the maximum node are found in Figure 3. The highest/lowest ten revenue nodes are listed in Table III. The maximum potential 3-year total arbitrage revenue ranges from $53.87K (SYLMARDC_2_N501 node) to $145.87K (ELCAPTN_1_N001 node), with an average of $81.05K. There are relatively few "high revenue" nodes, as noted in the distribution and heat map. The majority of the difference between the maximum node and the median node can be attributed to a few months with extremely high potential revenue opportunities.

B. Day-Ahead and Real-Time Arbitrage with Perfect Foresight

Next, an optimization was performed assuming participation in the day-ahead and real-time energy markets. The optimization was run on 15-minute data (hourly day-ahead market data was upsampled to create 15-minute data, the real-time market data is 15-minute data) assuming perfect foresight, one month at a time over the three year period. The arbitrage results are summarized in Figure 4. Note that the potential revenue

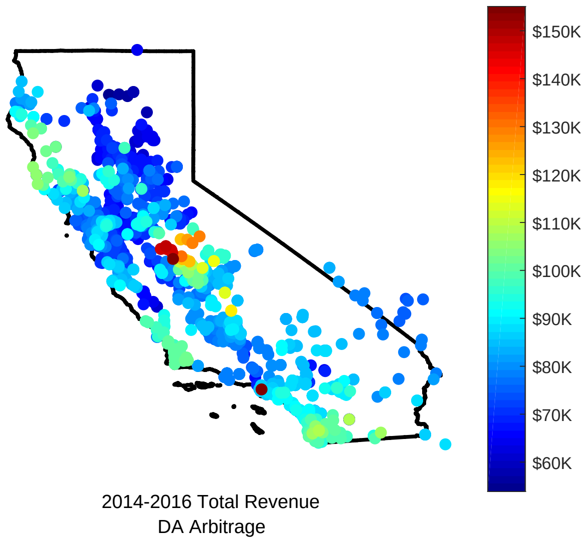

Fig. 1. Maximum potential day-ahead arbitrage revenue 2014-2016 ($K).

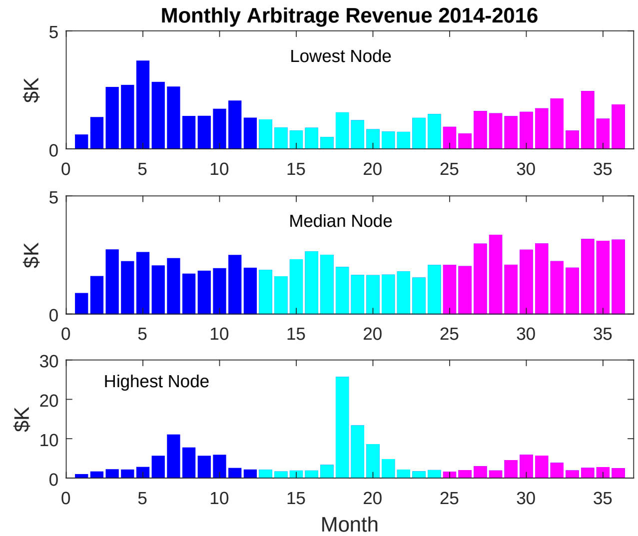

Fig. 3. Monthly day-ahead arbitrage revenue profile for the minimum node, the median node, and the maximum node 2014-2016.

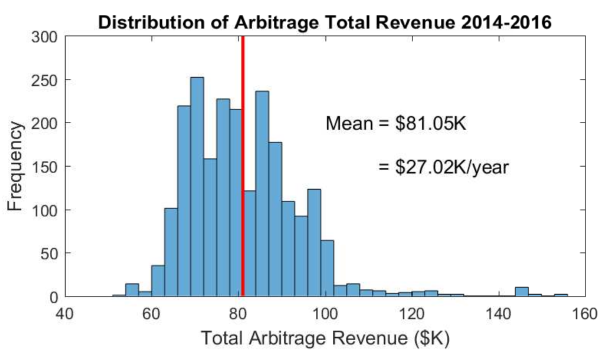

Fig. 2. Distribution of maximum potential day-ahead arbitrage revenue 2014-2016 ($K).

TABLE III
HIGHEST AND LOWEST POTENTIAL DAY-AHEAD ARBITRAGE REVENUE NODES.

Node	Revenue	Node	Revenue
SYLMARDC_2_N501	$53.87K	ELNIDO_1_N004	$155.05K
JBBLACK1_7_B1	$54.42K	ELNIDO_1_N001	$155.05K
JBBLACK2_7_B1	$54.65K	CRESSEY_1_N003	$147.44K
PIT3_7_N001	$55.83K	CRESSEY_1_N001	$147.44K
PIT6U2_7_B1	$56.02K	LIVNGSTN_1_N001	$146.52K
PIT5_7_N001	$56.22K	ELCAPTN_1_N004	$146.38K
PIT5_7_B1	$56.22K	ATWATER_1_N001	$146.28K
PIT6U1_7_B1	$56.34K	ATWATER_1_B2	$146.28K
PIT3_2_B1	$56.41K	MERCED_1_N001	$146.12K
PIT1U1_7_B2	$56.65K	ELCAPTN_1_N001	$145.87K

from arbitrage in the day-ahead plus real-time markets is significantly higher than potential revenue from participating in only the day-ahead market. Figure 5 illustrates the distribution of potential arbitrage revenue. The average potential revenue from participating in day-ahead and real-time arbitrage is $229,767.82, or $76,589.27/year for the three year period. This is almost three times the potential revenue from participating in only the day-ahead market. The distribution of the ratio of potential revenue, day-ahead plus real-time compared to day-ahead only, is found in Figure 6. The average improvement factor is 2.83. The node with the highest potential revenue is INDNFLT_6_N001, with a maximum potential total revenue of $541,035.85 over the three year period. Some statistics that characterize the optimal behavior for the maximum revenue node are summarized in Table V. The majority of the charging occurred through the real-time market, which takes advantage of negative prices when they occur. About 5.87% of the time, the system simultaneously charged in the real-time market and discharged in the day-ahead market, subject to the constraints of the system. This type of behavior would be very hard to replicate without perfect foresight because it would involve entering into the day-ahead market to discharge assuming some confidence of negative prices in the period of interest.

C. Optimal Dispatch Using Day-Ahead Prices as a Forecast for the Real-Time Market

Focusing on the market data from the maximum potential revenue node, INDNFLT_6_N001, two different trading algorithms were tested that did not require perfect foresight. The first algorithm uses the day-ahead market prices as a forecast for the real-time prices, and is described in Algorithm 1. Using data from node INDNFLT_6_N001, this algorithm resulted in a total revenue of $113K for the three year period, which is substantially less than the $541,035.85 maximum potential revenue with perfect foresight.

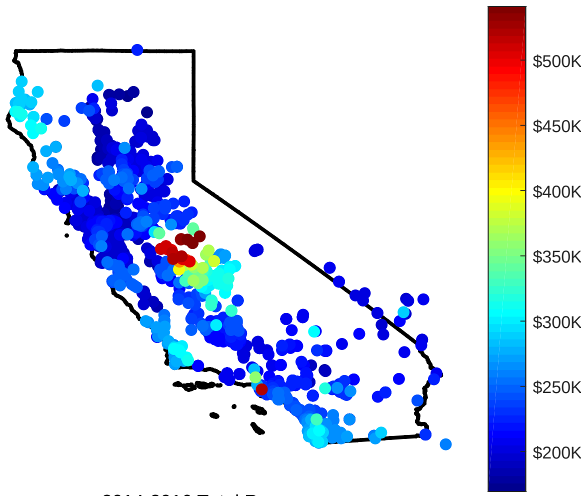

Fig. 4. Maximum potential day-ahead and real-time arbitrage revenue 2014-2016 ($K).

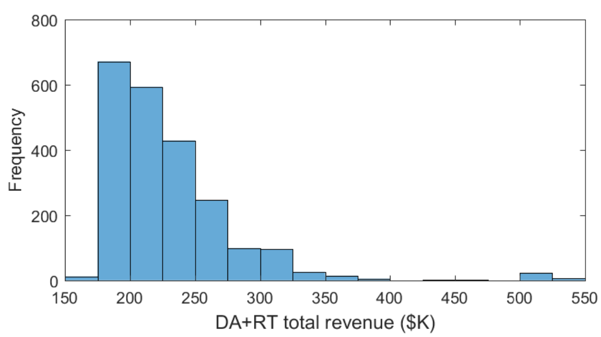

Fig. 5. Distribution of maximum potential day-ahead and real-time arbitrage revenue 2014-2016 ($K).

D. *Price Thresholds for Buying/Selling Energy in the Real-Time Market*

The second algorithm tested that did not require perfect foresight was buying/selling in the real-time market based on a price threshold (e.g., a limit order). Once again, data from node INDNFLT_6_N001, was employed for the analysis. A sweep of buy/sell thresholds generated the surface shown in Figure 7. The maximum revenue was generated with a buy threshold of $70/MWh and a sell threshold of $80/MWh (approximately $230K). There is a range of buy/sell thresholds that resulted in revenue greater than $200K for the three year period. While disappointing relative to the maximum potential revenue of $541,035.85, this relatively simple algorithm handily beats the maximum potential revenue from participating in only the day-ahead market ($129K).

Algorithm 1 Optimal dispatch using day-ahead market prices as a forecast for real-time prices

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for Each market day **do**
  1. Run optimization for 24-hour period using day-ahead prices
  2. Trade the quantities identified by the optimization in the real-time market
end for

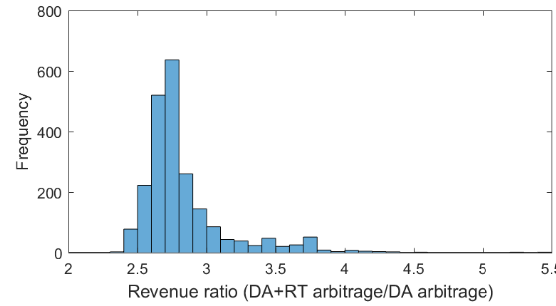

Fig. 6. Distribution of the ratio of maximum potential revenue, (day-ahead and real-time)/(day-ahead), 2014-2016.

TABLE IV
HIGHEST AND LOWEST POTENTIAL DAY-AHEAD PLUS REAL-TIME REVENUE NODES, RELATIVE TO DAY-AHEAD ONLY.

Node	DA ($)	DA+RT ($)	Ratio
EBMUDGRY_1_N001	$94,235.10	$224,593.29	2.38
CALISTGA_6_N001	$88,691.72	$212,577.50	2.40
GUALALA_6_N001	$91,374.96	$219,734.66	2.40
SOUTHBAS_1_N001	$90,819.80	$218,607.46	2.41
LAKEWOOD_1_N009	$92,159.73	$222,571.35	2.42
SEGS2G_7_B1	$87,360.28	$211,968.66	2.43
CLAYTN_1_N030	$87,982.69	$214,220.14	2.43
CLAYTN_1_N001	$87,982.69	$214,220.14	2.43
CLAYTN_1_N029	$87,982.98	$214,221.15	2.43
MEDWLNE_1_N001	$91,738.45	$223,629.49	2.44
MERCEDFL_7_N002	$124,710.46	$516,831.58	4.14
MERCEDFL_7_N001	$124,710.46	$517,638.12	4.15
INDNFLT_6_N001	$129,071.10	$541,035.85	4.19
MARIPOS2_6_N003	$128,469.67	$539,897.66	4.20
MARIPOS2_6_N001	$128,462.06	$540,021.40	4.20
BERVLLY_6_N001	$125,862.96	$535,814.84	4.26
EXCHQRTP_7_B1	$121,978.50	$533,175.58	4.37
EXCHQUER_7_B1	$121,525.31	$532,702.53	4.38
CRAGVIEW_1_N101	$61,458.74	$281,385.47	4.58
SYLMARDC_2_N501	$53,869.57	$280,612.88	5.21
MONA_3_N501	$65,793.67	$355,897.56	5.41

TABLE V
CHARACTERISTICS OF OPTIMAL CHARGE/DISCHARGE PROFILE FOR INDNFLT_6_N001 NODE, DAY-AHEAD PLUS REAL-TIME MARKET ARBITRAGE, 2014-2016.

Statistic	**Value**
Percentage of DAM discharging, q^{D-DA}	18.49%
Percentage of RTM discharging, q^{D-RT}	17.39%
Percentage of DAM charging, q^{R-DA}	9.23%
Percentage of RTM charging, q^{R-RT}	35.69%
Periods recharge RT, discharge DA, (6175/105216)	5.87%
Periods recharge DA, discharge RT, (1254/105216)	1.19%
Periods recharge RT alone, (34474/105216)	32.76%
Periods discharge RT alone, (17781/105216)	16.90%
Periods recharge DA alone, (9224/105216)	8.77%
Periods discharge DA alone, (16721/105216)	15.89%

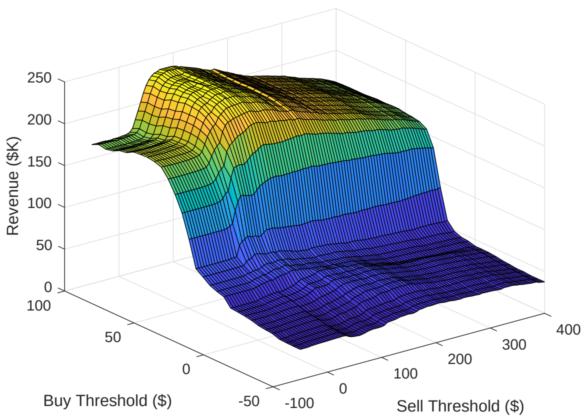

Fig. 7. Total real-time arbitrage revenue as a function of buy/sell price, 2014-2016.

V. CONCLUSION

This paper formulates the revenue maximization problem for energy storage participating in the CAISO day-ahead and real-time energy markets. Then, three years of historical market data for 2200 nodes was analyzed to identify the impact of location on potential revenue. The analysis considered participation in the day-ahead market as well as participation in the day-ahead and real-time markets. Two heuristic trading algorithms that did not require prefect foresight were also evaluated. The main takeaways are:

- Potential arbitrage revenue is highly location dependent in CAISO
- Participation in the day-ahead and real-time energy markets offers significantly more potential revenue than the day ahead market (2.83 times better on average)
- Using the day-ahead prices for a forecast of real-time prices did not perform well for the three year period (2014-2016)
- A relatively simple trading algorithm of buy/sell thresholds for the real-time market easily outperforms the maximum potential revenue from the day-ahead market, but falls well short of the maximum potential revenue from the day-ahead and real-time energy markets

Future research will focus on developing more sophisticated algorithms to participate in arbitrage in the day-ahead and real-time markets, as well as providing the newly introduced flexible ramping product.

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