Comparing Cycling and Opportunity Values of Long-Duration Energy Storage in United States

Ningkun Zheng, Bolun Xu
Dept. of Earth and Environmental Engineering
Columbia University
New York, NY, USA
{nz2343, bx2177}@columbia.edu

Abstract—The intermittency and seasonal pattern of renewable energy resources requires the ability to economically store the bulk of energy over long timescales. Long-duration energy storage is a promising solution to enable high renewable penetration in a low-emission electricity system, which can alleviate the long-term temporal mismatch of electricity demand and renewable resources abundant period. This paper analyzes how energy storage duration and location affect the cycling pattern and opportunity value of long-duration storage as a price taker in real-time market arbitrage. We use a dynamic programming approach to optimize the storage operation on an annual basis, and obtain the opportunity value of the energy stored. We perform the analysis over storage duration from one day to one month using historical data from California, New York, and Texas. Our results show significant locational differences among storage utilization that are jointly contributed by different resource mixes and congestion in the considered price zones. Long-duration energy storage is likely to be under-utilized in existing power systems, and deployment of long-duration energy storage must be carefully coordinated with renewable deployments.

Index Terms—Long-Duration Energy storage, Dynamic programming, Power system economics

I. INTRODUCTION

A net-zero carbon emission electricity system based on renewable energy resources (RES) faces challenges in system reliability and economical efficiency. With the ambitious renewable portfolio standard and carbon emission limitation targets, the RES capacity could surge exponentially to meet electricity demand and regional decarbonization targets [1],[2]. Long-duration energy storage (LDES) has the potential to store large quantities of renewable energy over a long time scale, which could be a solution to this problem. The capability of LDES to carry low-cost energy from a high RES availability period to a renewable “drought” season is valuable to lower the system cost. The U.S. Department of Energy aims at developing economical utility-scale LDES within one decade, reducing the production cost by 90% compared to current lithium-ion batteries for energy storage with more than 10 hours of duration [3].

Currently, pumped hydro storage (PHS) and compressed air energy storage (CAES) take on the function of sustaining electricity supply during multi-day periods of average demand exceeding average renewable supply [4]. Although these mechanical energy storage technologies are relatively mature, they suffer from several limitations and may not be the optimal choice for LDES [5]. The PHS and CAES are both geographically constrained from sitting in the desired location [6], while the PHS has more environmental concerns and the large-scale CAES designs combust non-renewable natural gas [7],[8],[9]. There is a multitude of possible LDES technologies available, including electrochemical, chemical, thermal, and previously mentioned mechanical options [6]. Each technology has its own set of cost and performance characteristics. Although the future technological pathway of LDES is still unclear, the value of LDES in the actual power grid is of guiding significance to the establishment of technology research goals.

However, the value of LDES is highly related to the share of RES in electricity system [10], as traditional power systems are dominated by daily variations with slight weekly patterns [11]. Install an utility-scale energy storage with excessive duration length in system may incur low utilization rate and high levelized cost of energy. It is essential to decide whether to install LDESs and further select suitable duration of LDES in different system conditions. In this paper, we investigate the cycling pattern and opportunity values of LDES of different duration in five locations covering California, New York, and Texas. These locations have unique generation mix, demand behavior, and climate pattern. The main contribution of this paper is listed as follows:

1) We use a dynamic programming approach to accurately optimize LDES real-time energy market arbitrage with hourly price data. Our proposed algorithm is able to solve an annual optimization problem with around 100,000 time steps within a few seconds. We implement our algorithm in five nodes of three ISOs with different electricity system conditions.

2) We show the opportunity values of LDES at 50% state of charge (SoC) level in different locations, which demonstrate the trend of price evolution if more storage were being integrated into the system. Longer storage duration can flatten the opportunity value, while the incidences of extreme opportunity value mitigation differ at investigated nodes.

3) We compare different storage duration LDESs cycling
patterns using the Rainflow algorithm. The result shows that the energy storage cycling utilization varies from different locations and storage duration.

II. METHODS

We introduce an analytical method to calculate the opportunity value of LDES in real-time energy market arbitrage. First, we present a formulation of dynamic programming for energy storage arbitrage in the energy market. Then we use an analytical method to evaluate opportunity value as a function of SoC level.

A. Energy market arbitrage formulation

We formulate energy storage arbitrage as a price response problem using dynamic programming. We assume energy storage is a price taker and the arbitrage is formulated as

\[ Q_{t-1}(e_{t-1}) = \max_{b_t, p_t} \lambda_t (p_t - b_t) - c p_t + Q_t(e_t) \]  

where \( Q_{t-1} \) is the maximized energy storage arbitrage profit dependent on the energy storage SoC at the end of the previous time period \( e_{t-1} \). This profit account from time period \( t \) till the end of the optimizing horizon \( T \). The energy market revenue is modeled as the product of the real-time market price \( \lambda_t \) and the energy storage dispatch decision \( (p_t - b_t) \) in the first term, where \( p_t \) is the discharge power and \( b_t \) is the charge power. The discharge cost is modeled in the second term of the objective function, where \( c \) is the marginal discharge cost. The end value function \( Q_t \) of the energy storage SoC \( e_t \) after time period \( t \) is modeled in the last term, which is a value-to-go function.

The objective function subject to the following constraints

\[ 0 \leq b_t \leq P, \quad 0 \leq p_t \leq P \]  

\[ p_t = 0 \text{ if } \lambda_t < 0 \]  

\[ e_t - e_{t-1} = -p_t / \eta + b_t \eta \]  

\[ 0 \leq e_t \leq E \]

where (1b) models the upper bound of storage power and lower bound (we assume as 0) of storage charge and discharge power. (1c) is a relaxed form of constraint that enforces the energy storage not to discharge and charge simultaneously. Limit the battery do not discharge at negative price periods is a sufficient condition for avoiding simultaneous charge and discharge (1d). (1e) models the energy storage SoC evolution constraint with efficiency \( \eta \). (1e) models the upper bound \( E \) and lower bound 0 of the storage SoC level.

B. Solution algorithm and opportunity value evaluation

We define \( q_t \) as the derivative of end value function \( Q_t \) in (1a), which represent the marginal opportunity value function of energy storage. It is evident that \( Q_t \) is valued and differentiable over the energy storage SoC level \( e_t \) within \([0, E]\). We can move the derivative operation into the expectation calculation in (1a). Then we can use an analytical formulation to calculate the opportunity value \( q_t(e) \) at any given energy storage SoC level.

Our prior work [15] proved \( q_{t-1} \) can be recursively calculated with next period value function \( q_t \), power rating \( P \), and efficiency \( \eta \). We rewrite this value function calculating using the deterministic formulation investigated in this paper as

\[ q_{t-1}(e) = \begin{cases} q_t(e + P \eta) & \text{if } \lambda_t \leq q_t(e + P \eta) \eta \\ \lambda_t / \eta & \text{if } q_t(e + P \eta) \eta < \lambda_t \leq q_t(e) \eta \\ q_t(e) & \text{if } q_t(e) \eta < \lambda_t \leq [q_t(e) \eta + c]^{+} \\ (\lambda_t - c) / \eta & \text{if } [q_t(e) \eta + c]^{+} < \lambda_t \leq [q_t(e - P \eta) / \eta + c]^{+} \\ q_t(e - P \eta / \eta) & \text{if } \lambda_t > [q_t(e - P \eta) / \eta + c]^{+} \end{cases} \]

which calculates the opportunity value function assuming the price follows a recursive computation framework. Thus we are able to get opportunity value function \( q_t(e) \) at any time period using backward calculation by stating an end period value function \( q_T \).

We further discretize \( q_t \) by equally spaced energy storage SoC level \( e \) into small segments, which is far smaller than power rating \( P \). For any SoC level \( e_t \), we can find the nearest segment and return the corresponding value. Note that \( Q_t \) in objective function is the integral of \( q_t \). Therefore, discretizing the derivative \( q_t \) is equivalent to approximate \( Q_t \) using piecewise linear functions.

III. SYSTEM DATA

We test the proposed opportunity value evaluation method using historical real-time locational marginal price data from New York ISO (NYISO), California ISO (CAISO) and Electric Reliability Council of Texas (ERCOT) [16], [17], [18], representing eastern interconnection, western interconnection, and Texas grid, respectively. To address various price patterns in different locations, we include prices from five nodes in the three ISOs. These nodes are NYISO_LONGIL (ZONE-D), NYISO_NORTH (ZONE-K), CAISO_WALNUT (WALNUT-6_N011), ERCOT_HOUSTON, and ERCOT_WEST.

We include 2017 to 2019 price data in our evaluation. To reduce computational cost and memory requirement, we downsample real-time price to hourly resolution. Note that ERCOT data has a 15-minutes resolution, while other ISOs data are in 5-minutes. Table I shows some price statistics in different nodes. In this table, we define a price over \$200/MWh as a peak price, and a price below \$0/MWh as a negative price.

Two nodes in ERCOT have significantly higher standard deviations because ERCOT’s price cap was \$90000/MWh from 2017 to 2019, which is almost ten-folds higher than other ISOs. Therefore, the average peak prices are also higher than other ISOs. NYISO_NORTH does not have many peak prices as other nodes. A 765kV transmission line made this node seldom has congestion and maintain a relatively low marginal price. While CAISO_WALNUT has more peak prices, as solar energy have periodically intra-day variation. NYISO_NORTH, CAISO_WALNUT, and ERCOT_WEST have considerably more negative price. These three nodes have substantially
TABLE I

| Location             | NYISO_LONGIL | NYISO_NORTH | CAISO_WALNUT | ERCOT_HOUSTON | ERCOT_WEST |
|----------------------|--------------|-------------|--------------|---------------|------------|
| Average Price        | 37.44        | 20.21       | 36.89        | 31.94         | 28.28      |
| Standard Deviation   | 41.75        | 41.14       | 52.39        | 141.68        | 138.95     |
| Average Normal Price | 34.96        | 23.06       | 33.52        | 24.89         | 23.27      |
| Average Peak Price   | 307.00       | 311.60      | 364.21       | 747.86        | 786.16     |
| # of Peak Price      | 254          | 54          | 422          | 261           | 210        |
| Average Negative Price | -30.74    | -31.86      | -9.38        | -3.39         | -2.57      |
| # of Negative Price  | 61           | 1644        | 1191         | 114           | 1110       |

Fig. 1. Duration curve of original hourly averaged real-time price and duration curve of opportunity value at 50% state of charge level over 3 years, unit are all $/MWh. The duration curves are clipped at the middle and represented by dash lines.

TABLE II

| Type       | NYISO | CAISO | ERCOT |
|------------|-------|-------|-------|
| Solar      | n/a   | 12.5% | 1.1%  |
| Wind       | 3.4%  | 9.8%  | 20.0% |
| Hydro      | 21.7% | 2.7%  | 0.2%  |
| Geothermal | n/a   | 8.9%  | n/a   |

higher renewable penetration. The average negative prices in NYISO is lower than other ISOs.

The renewable penetration rates of three ISOs are listed in Table II. In terms of the geographical distribution of resources, NYISO_LONGIL has a natural gas dominated fuel mix, while wind and hydro power almost account for all generation in NYISO_NORTH [12]. NYISO has a major congestion from north to south, hence the renewable energy generated upstate often cannot be delivered to New York City and Long Island. CAISO_WALNUT is located near Los Angeles, where bulk of solar PV and wind installed in the system [13]. Most wind generation in Texas located in ERCOT_WEST, and ERCOT_HOUSTION’s generation is mainly fossil fuel with relatively small scale off-shore wind [14], [19]. Notably, ERCOT also has moderate west-east transmission congestions that wind generation generated in West Texas may not delivered to East Texas demand centers like Houston.

IV. RESULTS

In this section, we show the effect of energy storage duration on opportunity value and storage cycle pattern at locations in Section III. All simulations are carried out using Matlab on an AMD Ryzen 7 3700x 3.60 GHz processor with 16 GB RAM. The opportunity value evaluation time is within 10 seconds, depending on the storage duration.

We assume a normalized 1 MW energy storage in these simulations with varying energy capacity durations. This energy storage has 80% one-way efficiency, no marginal cost, and no degradation. We examine four energy storage duration numbers: 1d, 3d, 7d (1w), and 30d (1m). As mentioned in Section III, we discretize energy storage SoC into segments, each segment is small enough to be regarded as continuous SoC change. A longer duration means a smaller power rate. In order to minimize the step error in valuation, the numbers of SoC segments are proportional to storage duration. To be specific, we set each day of storage duration to have 1500 SoC segments, i.e. in 30d cases, the SoC step is 1/45000 MWh.
In each case, we calculate opportunity values and implement hourly arbitrage for each year, and save the opportunity value function and SoC changes resulting from arbitrage.

A. Opportunity Value Analysis

The opportunity value of stored energy factors the cost for the energy storage to discharge, and provides a reference about the tendency at which the energy storage would flatten the electricity prices. We investigate the opportunity values of different duration storage at five nodes. We show original hourly averaged real-time price duration curve and price duration curves at 50% SoC level in Fig. 1. These 50% SoC price duration curves reflect the marginal value of energy at 50% SoC level. From these opportunity value duration curves, we can infer that energy storage with longer duration has a flatter duration curve. This property is evident at both end of the curves, whereas there are little difference in the middle at most nodes. Thus, we clip the price duration curves in the middle and use dash lines to represent the clipped parts.

Opportunity value curve in NYISO_LONGIL is the steepest among the five considered zones despite that its price data has the second-lowest standard deviation. With high renewable energy penetration, NYISO_NORTH has the most negative prices and lowest average negative price value within the time frame of the study. Energy storage with a duration longer than 3 days can significantly reduce negative opportunity values in NYISO_NORTH.

In CAISO_WALNUT, 30 days energy storage duration can significant reduce peak opportunity values and shorten the duration. Although the peak prices are lower than ERCOT, CAISO has more peak prices due to the intra-day solar energy variation. However, these peak prices are hard to be alleviated by short-duration storage. The solar energy generation and electricity demand has strongly seasonality pattern in CAISO, which lead to major renewable curtailment events happen in spring and peak net load happens in fall [20].

The average price in ERCOT is lower than the other ISOs. Although ERCOT has a higher peak price, the normal price is lower than other ISOs due to a longer clearing period and lower fuel price. The original price duration curve is very similar in two ERCOT nodes. Therefore, the energy storage opportunity value duration curve is homogeneous. The peak prices are usually happen in August, when the average wind output is the lowest during the year. Monthly duration energy
storage can mitigate the high opportunity value hours, but the utilization of the long-duration energy storage is limited due to the low curtailment of wind resources in ERCOT \[21\].

### B. Cycle Analysis

We use a rainflow-counting algorithm based on the ASTM E 1049 standard to analyze the energy storage cycle pattern \[22\]. First, we distinguish energy storage cycle according to cycle depth into 0-10% (shallow), 10-40% (light), 40-70% (moderate), and 70-100% (deep). Then we implement the rainflow-counting algorithm on yearly SoC changes resulting by energy market arbitrage, then average three-year cycle counting results for each node.

The energy storage cycle counting results is shown in Fig. 3. We log-scale the cycle counting results to narrow the order of magnitude differences. The figure shows that as storage duration increases, cycle number reduces except in shallow depth at all nodes as storage duration increasing. NYISO_LONGIL and NYISO_NORTH have similar energy storage cycle pattern. Seasonal wind resources capacity factor in NYISO_NORTH make more moderate cycles in this location \[23\]. We still have deep cycle in CAISO_WALNUT, due to the mismatch of major solar curtailment events and net load peak. Charge long-duration energy storage in spring and discharge in fall significantly reduce solar energy curtailment and shave net peak load, to highest profit compare to other locations in Fig. 2. In ERCOT_HOUSTON and ERCOT_WEST, the utilization of long-duration energy storage is low. The number of deep cycle diminish when storage duration longer than 7 days. Although ERCOT have high peak prices, the peak price duration is relatively short, while the wind resources capacity factor is stable year-round \[21\]. Thus, the long-duration energy storage is not substantially more profitable in Fig. 2.

### V. Conclusion

In this paper we investigated the opportunity value of cycle pattern of long-duration energy storage ranging from one day to one month duration using historical price data from California, New York, and Texas. Our opportunity value analysis results show that long duration storage mitigate price variations, but geographical differences remain significant. Storage has the most volatile opportunity value in LONGIL, despite that the price in LONGIL has the lowest standard variation. On the other hand, long duration energy storage will likely to be under-utilized in most scenarios based on the cycle analysis results. The weekly and monthly storage barely cycles deeply in all considered zones. In conclusion, the value and utility of long-duration storage is highly locational dependent and cannot be summarized only by renewable penetration or price deviations, deployments of long-duration energy storage must be accompanied with systematic analysis and coordinated planning with renewable deployments.

**References**

[1] M. R. Shaner, S. J. Davis, N. S. Lewis, and K. Caldeira, “Geophysical constraints on the reliability of solar and wind power in the united states,” *Energy & Environmental Science*, vol. 11, no. 4, pp. 914–925, 2018.

[2] N. A. Sepulveda, J. D. Jenkins, F. J. de Sisternes, and R. K. Lester, “The role of firm low-carbon electricity resources in deep decarbonization of power generation,” *Joule*, vol. 2, no. 11, pp. 2403–2420, 2018.

[3] U.S. Department of Energy, “Long duration storage shot,” 2021. [Online]. Available: https://www.energy.gov/eere/long-duration-storage-shot

[4] H. Safaei and D. W. Keith, “How much bulk energy storage is needed to decarbonize electricity?” *Energy & Environmental Science*, vol. 8, no. 12, pp. 3409–3417, 2015.

[5] J. D. Jenkins and N. A. Sepulveda, “Long-duration energy storage: A blueprint for research and innovation,” *Joule*, vol. 5, no. 9, pp. 2241–2246, 2021.

[6] N. A. Sepulveda, J. D. Jenkins, A. Edington, D. S. Mallapragada, and R. K. Lester, “The design space for long-duration energy storage in decarbonized power systems,” *Nature Energy*, vol. 6, no. 5, pp. 506–516, 2021.

[7] S. Kucukali, “Finding the most suitable existing hydropower reservoirs for the development of pumped-storage schemes: An integrated approach,” *Renewable and Sustainable Energy Reviews*, vol. 37, pp. 502–508, 2014.

[8] H. Blanco and A. Faaij, “A review at the role of storage in energy systems with a focus on power to gas and long-term storage,” *Renewable and Sustainable Energy Reviews*, vol. 81, pp. 1049–1086, 2018.

[9] E. Fertig and J. Apt, “Economics of compressed air energy storage to integrate wind power: A case study in ercot,” *Energy Policy*, vol. 39, no. 5, pp. 2330–2342, 2011.

[10] O. J. Guerra, J. Zhang, J. Eichman, P. Denholm, J. Kurtz, and B.-M. Hodge, “The value of seasonal energy storage technologies for the integration of wind and solar power,” *Energy & Environmental Science*, vol. 13, no. 7, pp. 1909–1922, 2020.

[11] A. J. Conejo, M. A. Plazas, R. Espinola, and A. B. Molina, “Day-ahead electricity price forecasting using the wavelet transform and arma models,” *IEEE transactions on power systems*, vol. 20, no. 2, pp. 1035–1042, 2005.

[12] Potomac Economics, “2019 state of the market report for the new york iso markets,” 2020. [Online]. Available: https://www.nyiso.com/documents/20142/2223763/NYISO-2019-SOM-Report-Full-Report.pdf

[13] Los Angeles Department of Water and Power, “Power content label,” 2019. [Online]. Available: https://www.energy.ca.gov/filebrowser/download/5234

[14] Electric Reliability Council of Texas, Inc. (ERCOT), “Grid information - generation,” 2021. [Online]. Available: http://www.ercot.com/gridinfogeneration

[15] B. Xu, A. Botterud, and M. Korpas, “Operational valuation for energy storage under multi-stage price uncertainties,” 59th IEEE Conference on Decision and Control, 2020.

[16] New York Independent System Operator, Inc. (NYISO), “Energy market & operational data,” 2021. [Online]. Available: https://www.nyiso.com/energy-market-operational-data

[17] California Independent System Operator, Inc. (CAISO), “California iso open access same-time information system (oasis),” 2021. [Online]. Available: http://oasis.caiso.com/mrioasis/logon.do

[18] Electric Reliability Council of Texas, Inc. (ERCOT), “Market prices,” 2021. [Online]. Available: http://www.ercot.com/mktinfo/prices

[19] U.S. Department of Energy’s Wind Energy Technologies Office, “Windexchange - wind energy in texas,” 2021. [Online]. Available: https://windexchange.energy.gov/states/tx

[20] California Independent System Operator, Inc. (CAISO), “Monthly renewables performance report,” 2021. [Online]. Available: http://www.caiso.com/Documents/MonthlyRenewablesPerformanceReport-May2021.htr

[21] LCG consulting, “2021 ercot electricity market outlook,” 2021. [Online]. Available: http://www.energyonline.com/reports/2021ERCOT_Outlook.pdf

[22] A. Standard, “E1049: standard practices for cycle counting in fatigue analysis,” 1985.

[23] Cameron McPherson, “Ny renewables – overview and ytd operation,” 2021. [Online]. Available: https://www.nyiso.com/documents/\%20Renewables\%20Presentation_FINAL.pdf/051c94d2-026a-fbd6-b7ad-ee1a2dc8a3d7