The Expected Revenue of Energy Storage from Energy Arbitrage Service Based on the Statistics of Realistic Market Data

Sadegh Vejdan, Santiago Grijalva
School of Electrical and Computer Engineering
Georgia Institute of Technology
Atlanta, Georgia, USA
vejdan@gatech.edu, sgrijalva@ece.gatech.edu

***Abstract*—The integration of intermittent renewable energy resources is increasing the volatility of electricity prices and is changing the way power systems are operated. Price volatility creates a unique business opportunity for energy storage owners to perform energy arbitrage: buying low cost energy and selling it back when the price is high. This paper provides a method to determine the expected revenue of energy arbitrage in the day-ahead energy market using the statistics of realistic market data. The proposed method uses an optimization model to calculate the maximum daily revenue from energy arbitrage. Clustering is used to differentiate among seasonal prices, and a regression model is used to fit the revenues to the price statistics for each cluster. The R-squared value for the goodness of fit is used to verify the observation. Results for the PJM market exhibit a linear correlation between the revenue and the price statistics of dispersion, mainly the price range and its standard deviation and hence the paper provides a straightforward method to estimate revenues. Winter prices provide more energy arbitrage opportunities due to their two-peak daily price data pattern with higher sensitivities to price statistics.**

***Index Terms*—Clustering, Energy arbitrage, Energy market, Energy storage, Linear optimization.**

I. Introduction

The intermittent nature of renewable energy resources is an important challenge in power system operation. This intermittency in generation translates into rapid net load changes resulting in electricity price volatility in power system markets. The reliable integration of renewable energy resources at high penetration levels requires flexible resources [1] such as energy storage systems. These resources provide rapid ramp rates that can compensate the intermittency of renewables. Privately-owned (merchant) storage systems can also benefit from the price volatility by buying energy when the price is low and selling it back when the price is high. This is known as the energy arbitrage service.

Energy storage systems are being deployed at a fast pace in the United States and worldwide [2]. With the estimated decrease in the investment cost up to 49% in the next five years [3], the private storage business model outlook is promising. Private storage systems can participate in energy and balancing markets and collect revenues, as well as to offer other services [4].The benefit analysis of energy arbitrage is not fully-understood, with few references addressing realistic data. This paper provides a method based on the statistics of realistic market data for the evaluation of the energy arbitrage service as a market-based revenue stream for privately-owned storage systems. No prior work has been found that analyzes the price data statistics to determine energy arbitrage revenue, which is the main contribution of this paper.

The evaluation of energy arbitrage service revenue is studied in the literature using different methodologies. One of the main assumptions is related to the market power of energy storage. If the operation of energy storage does not impact the market prices, the storage is a price-taker, and if it does, it is a price-maker. In price-maker models, the storage bids into the market, and the cleared price becomes a function of all the power suppliers' bids. Strategic bidding approaches are proposed to find the optimal scheduling of energy storage maximizing the revenue from energy arbitrage and other market-based services [5]–[10]. These approaches are based on bi-level optimization problems. The process of clearing the market is the lower level problem, and it requires the bidding information of the other market actors. Since the bids are not publicly available data, the actual applicability of these analyses for realistic storage service evaluation is limited.

Energy arbitrage service evaluation under a price-taker model is analyzed in [11]–[19]. The service revenue is optimized separately [11]–[13], or co-optimized with other market products, such as frequency regulation [14]–[19]. Linear and mixed integer optimization are used to determine the maximum revenue. Realistic market data of CAISO, ERCOT, PJM, and ISONE is used in [15]–[18], taking the market data as inputs to the optimization models. While the market prices contain valuable information about the potential revenue from energy arbitrage, no analysis is yet conducted on the price data statistics for the evaluation of energy arbitrage

978-1-5386-1006-0/18/$31.00 ©2018 IEEE

service. This research gap is investigated in this paper. In order to analyze the statistics, price data is clustered into summer and winter prices using a novel correlation-based algorithm. The proposed algorithm chooses the base price for each cluster and classifies the daily prices within a couple of iterations. A linear regression model is then deployed to fit the maximum daily revenue to the statistics of each cluster price.

The rest of the paper is organized as follows. Section II describes the problem that the private storage systems are facing. This problem is addressed in Section III, which is dedicated to the proposed methodology. A linear optimization model, a novel clustering algorithm for daily prices, and a linear regression model are introduced. Section IV provides the simulation results and suggests a linear correlation between the optimum daily revenue from energy arbitrage and the price statistics of dispersion. Finally, section IV concludes and discusses future work.

II. Problem Description

Analyzing the benefits of energy storage is very important for electric utilities, as well as private storage owners who need accurate estimates of revenues on their investments. Market-based services provide the means for private storage systems to participate and collect revenues. These services include energy arbitrage, which can be day-ahead and real-time. This paper focuses on the energy arbitrage service in the day-ahead energy market. We seek to understand the expected revenue from this service given a daily price data, and to gain insight on the correlation of the optimal revenue with respect to price data statistics. While it is known that the price changes would increase the revenue from energy arbitrage, no measure of "favorable" volatility is provided that can be used to determine the expected revenue. The proposed method can substitute the complex and computationally cumbersome calculations for this analysis, especially in the case of long time-horizon market data for multiple pricing nodes. The rest of this Section introduces the day-ahead energy arbitrage service and the energy storage market participation model.

Day-ahead energy markets are developed in restructured power systems so that market actors (power producers, consumers, and traders) buy/sell their consumed/produced energy for the next day. The independent system operator (ISO) operates the energy market by receiving the buyers' bids and sellers' offers. Maximizing the social welfare, the ISO clears the market and sets the electricity price for every hour of the next day. Both the demand and the cost of generation change during the day, and the resulting daily electricity price spread creates a unique business model for energy storage owners. They can buy low-cost energy during off-peak hours and sell it back at higher costs during peak hours.

Energy storage owners can participate in the day-ahead market to perform energy arbitrage and earn revenues. Since energy storage can operate both as generation and load, owners submit both bids and offers to the day-ahead market. Specifically, for the energy arbitrage, they submit bids for off-peak hours when they are expected to be charging, and submit offers for peak hours when they expect to be discharging. In order to maximize the energy arbitrage service revenue, storage owners forecast day-ahead prices, and optimize the dispatch using optimization models. To guarantee that the bids and offers will be cleared, they can submit zero prices for both. In this way, all the quantities are cleared in the market and will be paid or charged based on the market price of that hour. Traditional optimization modeling and calculation process is computationally demanding for long time-horizon price data and multiple pricing nodes. Moreover, there is little insight on the expected revenue with respect to the input price data. The proposed methodology described in the next Section overcomes these difficulties.

III. Proposed Methodology

In this Section, a linear optimization model is developed to calculate the owner's maximum revenue from the energy arbitrage given a price data. In order to analyze the revenue with respect to price statistics, a novel clustering algorithm that classifies the realistic price data is proposed. This step is necessary since seasonal prices are different in shape and their statistics. The algorithm determines when summer and winter start and when they end in terms of electricity prices.

A. Linear Optimization Model

The linear optimization model for the owner's maximum revenue from energy arbitrage is developed in (1)–(5). The optimization problem maximizes the energy storage owner's revenue from the energy arbitrage service given the day-ahead prices π_t. The storage is assumed to be price-taker, and its operation does not impact market prices. It is also assumed that prices are known with a perfect foresight. The analysis of forecast errors is out of the scope of this paper and is being studied by the authors. The time period is set to one hour, i.e. $\Delta t = 1hr$, and hence power and energy are used interchangeably. The charging and discharging powers, P_t^{chg} and P_t^{dis}, are limited by their minimum (both assumed to be zero) and maximum values $P_{\max}^{chg}, P_{\max}^{dis}$ as in (2) and (3). The energy level is also within its limits $E_{\min}, E_{\max}$ as in (4) to ensure a reliable operation. The net exchanged energy is zero during the time horizon, modeled by (5) where the final energy level E_T equals the initial one E_0. The charging and discharging efficiencies are denoted by η_{chg} and η_{dis}, respectively. The storage energy loss over time is modeled by the self-discharging efficiency denoted by η_s.

$$\max \sum_{t=1}^{T} \pi_t \left(P_t^{dis} - P_t^{chg} \right) \Delta t \tag{1}$$

$$\textbf{s.t.} \ \forall t \in \mathcal{T}$$

$$0 \le P_t^{dis} \le P_{\max}^{dis} \tag{2}$$

$$0 \le P_t^{chg} \le P_{\max}^{chg} \tag{3}$$

$$E_{\min} \le \eta_s E_{t-1} + \left(\eta_{chg} P_t^{chg} - P_t^{dis} / \eta_{dis} \right) \Delta t \le E_{\max} \tag{4}$$

$$E_T = E_0 \tag{5}$$

B. Price Clustering

The revenue from the energy arbitrage service is highly dependent on the input price data and its statistics. Seasonal prices have different patterns and statistics. This subsection describes the patterns in historical realistic price data of PJM used in this study, and proposes a novel clustering method.

The energy demand varies continuously creating temporal price spreads. One of the key factors is the seasonal weather change resulting energy demand and price variations. Figure 1 shows a 3D plot of annual prices of 2017 in the PJM market at the aggregate node [20]. Besides the daily changes, different price shapes are also seen for summer and winter seasons where the former has one peak in the evening, and the latter has two daily peaks: one in the morning and the other one in the evening.

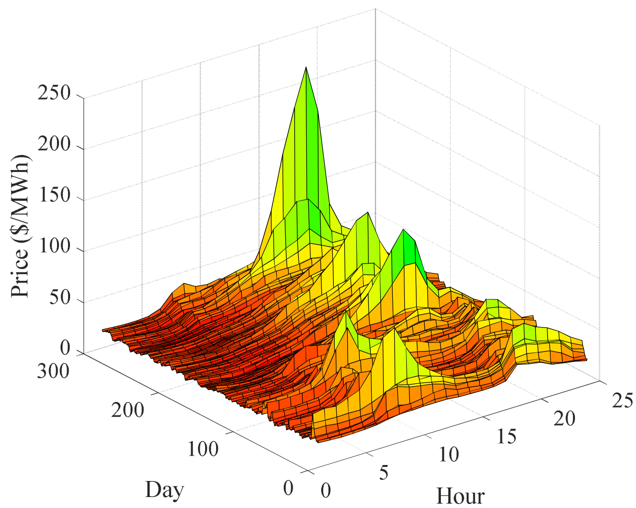

Fig. 1 Temporal price variations in the PJM market during 2017.

The optimization problem in (1) is expressed as a linear function of electricity prices. In other words, if the price is doubled while maintaining the same shape, so does the revenue while the charging/discharging pattern does not change. Leveraging on this fact, any set of daily price data with high linear correlation (i.e., similar shapes) would result in identical dispatch, and the revenues would be proportional to the correlation coefficient. Accordingly, based on the price pattern observation, we classify the prices into summer and winter prices using a novel clustering method. Specifically, we want to determine when each season starts (in terms of electricity prices) and how long it lasts. Thus, we developed a clustering algorithm inspired by the *k*-means algorithm used in machine learning [21]. In this algorithm, we used the Pearson correlation coefficient (PCC) to measure the linear correlation of two daily price data. Generally, for two data samples x and y with respective means of $\overline{x}$ and $\overline{y}$, the PCC is expressed as:

$$PCC = \frac{\sum_{i=1}^{n}\left(x_i - \overline{x}\right)\left(y_i - \overline{y}\right)}{\sqrt{\sum_{i=1}^{n}\left(x_i - \overline{x}\right)^2}\sqrt{\sum_{i=1}^{n}\left(y_i - \overline{y}\right)^2}} \tag{6}$$

The flowchart of the proposed clustering algorithm is illustrated in Fig. 2. The algorithm starts by choosing two initial base prices for the two seasons. In this paper, we chose Jan. 15th and July 15th for winter and summer initial base prices, respectively. This choice is arbitrary, however, in order to reduce the number of iterations, we chose distinct summer and winter prices rather than boundary prices in April and October. Then, the algorithm rolls on a daily basis, and for each day, it calculates the PCC of the price with the two base prices. The day is then added to the set with greater PCC (set $\mathcal{S}$ for summer and set $\mathcal{W}$ for winter). The total sum of PCCs

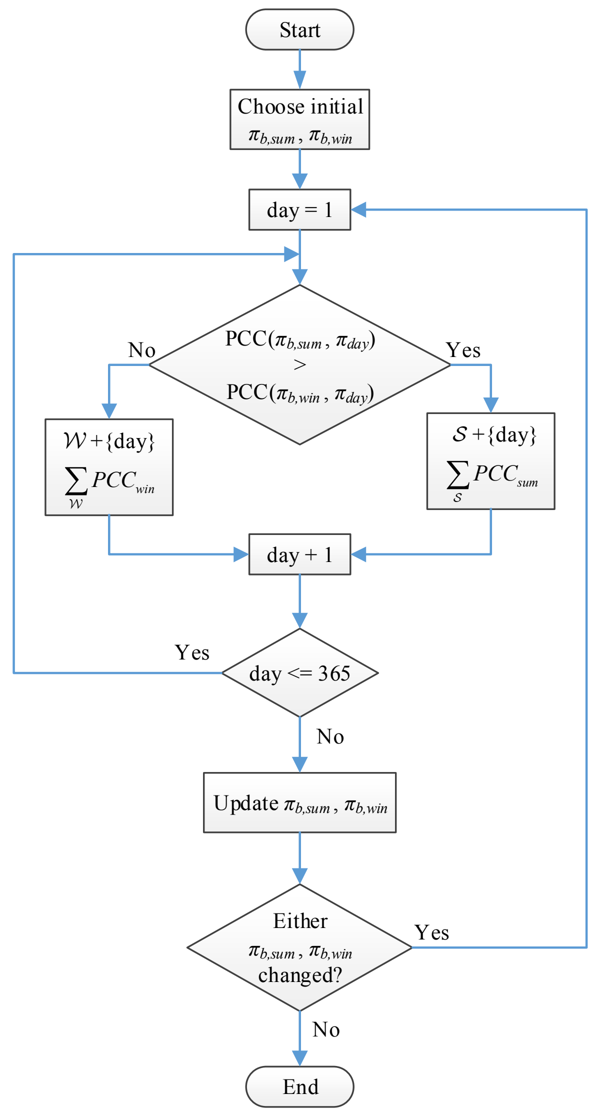

Fig. 2 The flowchart of the proposed clustering algorithm.

in each cluster is updated afterwards. This process iterates until all the days are clustered. After this process, all the two by two PCCs within each cluster are calculated and the daily price with the greatest sum of PCCs is chosen as the new base price. If either of the new base prices is different from the old ones, the algorithm reiterates from day 1, otherwise terminates. The final results are two clusters including summer and winter daily prices, as well as two base prices for each cluster.

C. The Linear Regression Model

In order to quantify the value of energy arbitrage with respect to price statistics, a first order polynomial (straight line) is fitted to the price data statistics of each cluster using the linear regression model:

$$y = X\beta + \varepsilon \tag{7}$$

where y is the vector of daily energy arbitrage revenues, X is the matrix of regressors with the first column of all ones and the second column of daily price statistics, β is a two-element parameter vector (intercept and slope), and ε is the error term. The best estimate of the β parameters that minimizes the squared errors is given by least-squares as in (8).

$$\hat{\beta} = \left(X^T X\right)^{-1} X^T y \tag{8}$$

Using these parameters, we can find the linear relationship between the daily price statistics (X) and the estimated daily revenues ($\hat{y}$).

$$\hat{y} = X\left(X^T X\right)^{-1} X^T y \tag{9}$$

The estimation error is given by:

$$e = y - \hat{y} = \left(I - X\left(X^T X\right)^{-1} X^T\right) y \tag{10}$$

where I is the identity matrix. The goodness of linear fitting models can be expressed by several measures. In this paper, the R-squared value (also known as coefficient of determination) is used. The R-squared value is calculated as:

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} \tag{11}$$

where

$$SS_{res} = \sum_i e_i^2 = \sum_i \left(y_i - \hat{y}_i\right)^2 \tag{12}$$

$$SS_{tot} = \sum_i \left(y_i - \bar{y}\right)^2 \tag{13}$$

IV. Simulation Results and Discussion

This Section provides the results of the proposed methodology. The storage owner's maximum revenue is calculated first. The clustering algorithm results are then provided. Prices statistics of dispersion are introduced next, and the results of the linear regression model are presented lastly.

A. Optimization Resuslts

Using the optimization model (1)–(5) and the PJM historical prices, the owner's revenue from the EA service is computed for the day-ahead market of the last five years. Hourly day-ahead market prices at the aggregate node were analyzed from 2013 to October of 2017 [20]. Data was cleaned, and the missing days without the price data were removed from the dataset. The missing hours are linearly interpolated using the adjacent hours. The simulation parameters corresponding to the energy storage device are $P_{\max}^{dis} = P_{\max}^{chg} = 100MW$, $E_{\max} = 100\,MWh$, $E_0 = 0.5E_{\max}$, $E_{\min} = 0$, $\eta_{chg} = \eta_{dis} = 0.95$, $\eta_s = 1$.

As an example, the day-ahead prices and the optimal dispatch for two sample days (1/9/2017 and 9/21/2017) are shown in Fig. 3. These two days result in maximum winter and minimum summer revenues in the year 2017 (until October 17th). The price shapes are different such that the winter day has two peaks, one in the morning and the other in the evening with the price range of 72$ during the day. However, the price shape of the summer day has only one peak during the evening with the price range of 8$. The charging and discharging patterns are different due to different price shapes. The revenue in the winter day is 7,785$ while the summer day provides only 490.5$, which is 6.3% of that for the winter day.

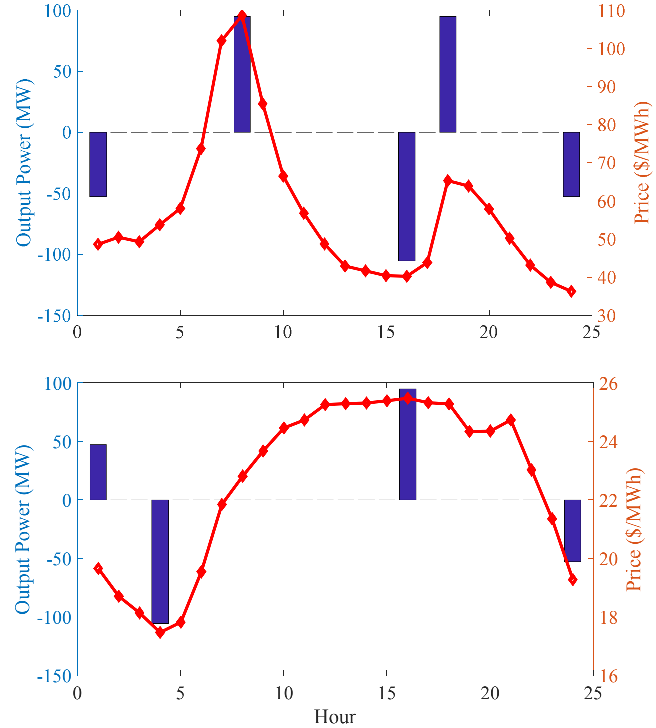

Fig. 3 Daily price and optimal dispatch for a) Jan. 9th and b) Sept. 21th 2017.

B. Clustering Results

The proposed clustering algorithm is run on the five-year historical price data of PJM and converged within 3, 2, 3, 3, and 4 iterations for 2013 to 2017, respectively. The results are shown in Fig. 4. It can be clearly seen that the proposed algorithm is capable of clustering seasonal prices based on their shapes. Fig. 4(a) and 4(b) show the sets of summer and winter prices. Final base prices in Fig. 4(c) show that the peak prices of the two clusters are almost equal while the minimum price of summer is lower than that of winter. Each of these prices has a favorable feature for energy arbitrage service. While the daily price spread is greater in summer, the winter prices have two peaks providing opportunities for two charging and discharging cycles in a day. The analysis of results provided later shows that the two-peak feature of winter prices is more favorable for energy arbitrage resulting in higher revenues in winter days.

Clustering results for each year are shown in Fig. 5. The range of the boxplots shows the middle 95% of the clustered summer days in each year. There are few days in summer and winter months with the price of the other shape. These days are considered outliers, and are not considered in determining the set of summer and winter days. Apart from 2017, the summer days for each year overlaps greatly. Using these results, we consider the set of summer days to include days 101 to 282. The set of winter days include the rest of the days in a year.

Once daily prices are clustered, we use each cluster's statistics to find a linear relationship with the maximum daily revenue calculated from (1)–(5). Therefore, the following daily price statistics of dispersion are tested:

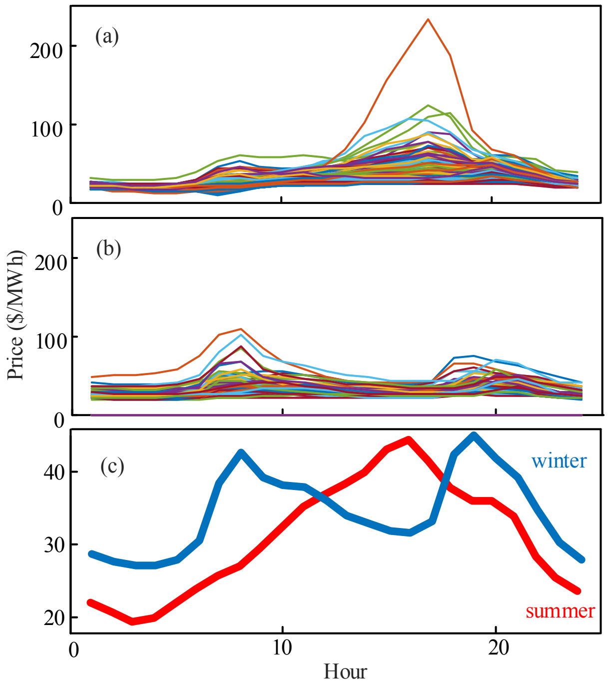

Fig. 4 Results of the proposed clustering algorithm: a) summer, and b) winter daily price clusters, and c) base prices of clusters.

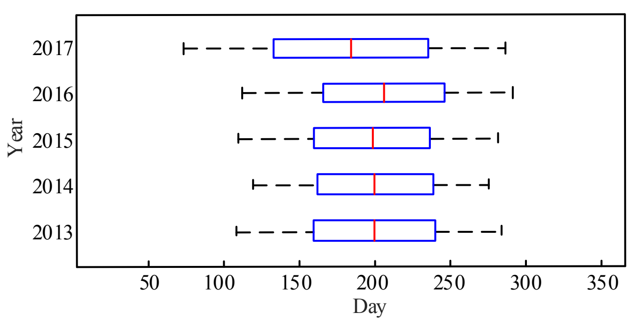

Fig. 5 Boxplot of summer days in each year clustered by the proposed algorithm.

- range: $\pi^{\max} - \pi^{\min}$,
- standard deviation: $\sigma = \sqrt{\frac{1}{N_T}\sum_{t=1}^{N_T}\left(\pi_t - \bar{\pi}\right)^2}$,
- mean absolute deviation (MAD):

$MAD = \frac{1}{N_T}\sum_{t=1}^{N_T}\left|\pi_t - \bar{\pi}\right|$, where $\bar{\pi} = \frac{1}{N_T}\sum_{t=1}^{N_T}\pi_t$. i.e. the average of absolute difference from the mean price.

C. *Linear Regression Results*

The linear regression model is applied to both summer and winter clusters for different price statistics. The tuples of revenue and statistics for each cluster are plotted in Fig. 6, as well as the fitted lines. In these plots, red crosses are for summer and blue circles are for winter. The estimated parameters of the fitted lines, and the R-squared values are reported in Table I for different clusters and price statistics.

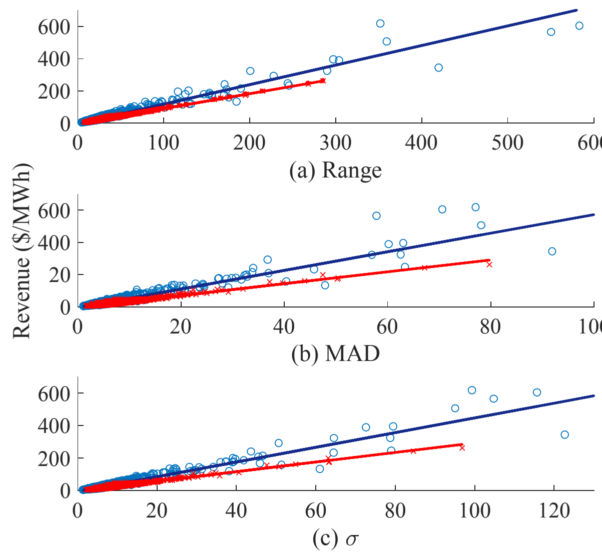

Fig. 6 Linear regression results: revenue vs. price a) range, b) MAD, and c) standard deviation.

TABLE I. LINEAR REGRESSION MODEL RESULTS

	Season	Range	MAD	σ
β0	summer	-2.55	-2.98	-1.77
	winter	-4.16	-5.01	-5.08
β1	summer	0.92	3.67	2.96
	winter	1.21	5.77	4.53
R-squared	summer	0.9868	0.9415	0.9619
	winter	0.9486	0.9253	0.9484

The results show that winter revenues are in general higher than summer revenues. The sensitivity of winter revenues with respect to price data statistics is always larger than those of summer. This is justified by the general price shape of winter daily prices. Because winter prices have two daily peaks, there is more opportunity for energy arbitrage in those days. Furthermore, the results reveal that the energy arbitrage revenue is linearly correlated with the electricity price data statistics of dispersion. Among the tested statistics, the revenue shows the best linear relationship with the price range. Therefore, given the electricity price data of a node, its expected revenue from the energy arbitrage can be easily expressed as a linear function of the price range. This simplifies the service benefit analysis for the utilities and investors. In addition, with the prices of different pricing nodes in a region, the problem of the optimal placement of energy storage in terms of the highest energy arbitrage value is simplified to finding the node with the highest sum of daily price ranges.

The results provided are for fixed energy storage parameters, such as efficiency and capacity. Sensitivity analysis can be performed within the same framework. While linear sensitivities change by varying energy storage parameters, the greater winter revenues and their sensitivities remain unchanged. Also, if the capacity of the energy storage is high enough to impact the energy market price (price-maker energy storage), the optimization model in [22] can again be used in our proposed framework to determine the service value. It is expected that higher extreme prices will emerge in the future energy markets with more renewables integrated into the grid. This adds to the value of energy arbitrage service from energy storage projects promising a unique business opportunity for the future grid.

V. CONCLUSION

A novel method is developed to determine the expected revenue of energy storage systems from the energy arbitrage service in the day-ahead market based on the statistics of realistic market price data. A machine-learning-based clustering algorithm is proposed to classify the prices into summer and winter clusters based on their correlation with a base price for each cluster that updates iteratively. The revenue in each cluster is fitted to the daily price statistics using a linear regression model. The proposed method was tested on the five-year PJM historical day-ahead energy market prices. The daily revenue is calculated using an optimization problem. It is observed that the service revenue is mainly determined by the price data shape. Using the clustering algorithm, two general price data patterns (summer and winter) are clustered in this market. The results of the linear regression model show that the clusters revenue is linearly dependent on the dispersion statistics of the price data, mostly the range. Winter prices result in higher revenues with more sensitivity to price dispersion. The results can benefit utilities and investors to analyze the energy arbitrage revenue in a straightforward manner using simple statistics of the energy market prices. The proposed clustering method is also a useful tool for other applications, such as an offline suboptimal dispatch and where there is no communication infrastructure so that ESS knows the actual day-ahead prices.

REFERENCES

[1] CAISO, "What the duck curve tells us about managing a green grid," *Calif. ISO, Shap. a Renewed Futur.*, vol. Fact Sheet, pp. 1–4, 2012.

[2] Greentech Media, "U . S . Energy Storage Monitor : Q3 2017 Executive Summary," June 2017.

[3] LAZARD, "Lazard's levelized cost of storage—version 2.0."

[4] J. Eyer, "Energy storage for the electricity grid : benefits and market potential assessment guide," *Sandia Natl. Lab.*, vol. 321, Feb. 2010.

[5] Y. Wang, Y. Dvorkin, R. Fernandez-Blanco, B. Xu, T. Qiu, and D. S. Kirschen, "Look-Ahead bidding strategy for energy storage," *IEEE Trans. Sustain. Energy*, vol. 8, no. 3, pp. 1106–1117, 2017.

[6] Q. Huang, Y. Xu, T. Wang, and C. Courcoubetis, "Market mechanisms for cooperative operation of price-maker energy storage in a power network," *IEEE Trans. Power Syst.*, doi: 10.1109/TPWRS.2017. 2762350.

[7] P. Zamani-Dehkordi, S. Shafiee, L. Rakai, A. M. Knight, and H. Zareipour, "Price impact assessment for large-scale merchant energy storage facilities," *Energy*, vol. 125, pp. 27–43, 2017.

[8] S. Shafiee, H. Zareipour, and A. M. Knight, "Developing bidding and offering curves of a price-maker energy storage facility based on robust optimization," *IEEE Trans. Smart Grid*, doi: 10.1109/TSG.2017. 2749437.

[9] E. Nasrolahpour, J. Kazempour, H. Zareipour, and W. D. Rosehart, "A bilevel model for participation of a storage system in energy and reserve markets," *IEEE Trans. Sustain. Energy*, doi: 10.1109/TSTE. 2017.2749434.

[10] S. Shafiee, H. Zareipour, A. M. Knight, N. Amjady, and B. Mohammadi-Ivatloo, "Risk-Constrained bidding and offering strategy for a merchant compressed air energy storage plant," *IEEE Trans. Power Syst.*, vol. 32, no. 2, pp. 946–957, 2017.

[11] H. Khani, R. K. Varma, M. R. D. Zadeh, and A. H. Hajimiragha, "A real-time multistep optimization-based model for scheduling of storage-based large-scale electricity consumers in a wholesale market," *IEEE Trans. Sustain. Energy*, vol. 8, no. 2, pp. 836–845, 2017.

[12] J. Liu, N. Zhang, C. Kang, D. S. Kirschen, and Q. Xia, "Decision-Making models for the participants in cloud energy storage," *IEEE Trans. Smart Grid*, doi: 10.1109/TSG.2017.2689239.

[13] H. Chitsaz, P. Zamani-Dehkordi, H. Zareipour, and P. Parikh, "Electricity price forecasting for operational scheduling of behind-the-meter storage systems," *IEEE Trans. Smart Grid*, vol. 3053, no. c, pp. 1–11, 2017.

[14] M. Kazemi, H. Zareipour, N. Amjady, W. D. Rosehart, and M. Ehsan, "Operation scheduling of battery storage systems in joint energy and ancillary services markets," *IEEE Trans. Sustain. Energy*, vol. 8, no. 4, pp. 1–1, 2017.

[15] R. H. Byrne, S. Hamilton, D. R. Borneo, T. Olinsky-Paul, and I. Gyuk, "The value proposition for energy storage at the sterling municipal light department," 2017.

[16] R. H. Byrne, R. J. Concepcion, and C. A. Silva-Monroy, "Estimating potential revenue from electrical energy storage in PJM," in *IEEE Power and Energy Society General Meeting*, Nov. 2016.

[17] R. H. Byrne and C. A. Silva-Monroy, "Estimating the maximum potential revenue for grid connected electricity storage: arbitrage and regulation," *Sand2012-3863*, p. 64, Dec. 2012.

[18] R. Byrne and C. Silva-Monroy, "Potential revenue from electrical energy storage in ERCOT: The impact of location and recent trends," in *in Proceedings of the 2015 IEEE Power and Energy Society (PES) General Meeting*, 2015, pp. 1–5.

[19] T. Zhang, S. X. Chen, H. B. Gooi, and J. M. Maciejowski, "A hierarchical EMS for aggregated BESSs in energy and performance-based regulation markets," *IEEE Trans. Power Syst.*, vol. 32, no. 3, pp. 1751–1760, 2017.

[20] "PJM Data Miner 2." [Online]. Available: http://dataminer2.pjm.com/ list.

[21] T. Hastie, R. Tibdjirani, and J. Friedman, *The Elements of Statistical Learning*, 2nd ed. Springer, 2013.

[22] J. Deboever and S. Grijalva, "Optimal scheduling of large-scale price-maker energy storage," *IEEE Power Energy Conf. Illinois, PECI 2016.*

Sadegh Vejdan (S'15) received the B.Sc. and M.Sc. degrees both in Electrical Engineering from The University of Tehran in 2013 and 2015, respectively. Currently, he is pursuing the PhD degree in Electrical and Computer Engineering at the Georgia Institute of Technology, Atlanta, GA, USA. His research interests include power system data analytics, applications of signal processing techniques in power systems, and power system protection.

Santiago Grijalva is the Georgia Power Distinguished Professor of Electrical and Computer Engineering and Director of the Advanced Computational Electricity Systems (ACES) Laboratory at The Georgia Institute of Technology. His research interest is on decentralized power system control, power system analytics and economics, and future sustainable energy systems. He has been principal investigator for research under the Department of Energy, ARPA-E, EPRI, PSERC, NSF and other industry and Government sponsors. From 2002 to 2009 he was with PowerWorld Corporation as a software architect and consultant. From 2013 to 2014 he was on assignment to the National Renewable Energy Laboratory (NREL) as founding Director of the Power System Engineering Center (PSEC). Dr. Grijalva is a Member of the Federal Smart Grid Advisory Committee of the National Institute of Standards and Technology (NIST). Dr. Grijalva's graduate degrees in Electrical and Computer Engineering, M.Sc. (99), Ph.D. (02) are from the University of Illinois at Urbana-Champaign.