SAND2015-0222C

Potential Revenue from Electrical Energy Storage in ERCOT: The Impact of Location and Recent Trends

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Abstract—**This paper outlines the calculations required to estimate the maximum potential revenue from participation in arbitrage and regulation in day-ahead markets using linear programming. Then, we use historical Electricity Reliability Council of Texas (ERCOT) data from 2011-2013 to evaluate the maximum potential revenue from a hypothetical 32 MWh, 8 MW system. We investigate the maximum potential revenue from two different scenarios: arbitrage only and arbitrage combined with regulation. This analysis was performed for each load zone over the same period to show the impact of location and to identify trends in the opportunities for energy storage. Our analysis shows that, with perfect foresight, participation in the regulation market would have produced more than twice the revenue compared to arbitrage in the ERCOT market in 2011-2013. Over the last three years, there has been a significant decrease in the potential revenue for an energy storage system. We also quantify the impact of location on potential revenue.**

I. Introduction

With the advent of modern power electronics and an increased demand for renewable generation like wind and solar, there has been a renewed interest in grid-scale electricity storage devices. Potential uses of electricity storage include firming of variable renewable generation (e.g. wind and solar), shifting renewable energy from low demand periods to high demand periods, and increased grid reliability (e.g. voltage support and frequency regulation). Potential societal benefits include reduced fossil fuel use and reduced emissions. A complete discussion of potential benefits appears in [1], [2].

Regardless of the application or benefit, in deregulated electricity markets storage is ultimately only as valuable as the revenue stream generated by the storage device. This revenue stream comes from participating in markets for energy and ancillary services (e.g. frequency regulation, operating and contingency reserves) [3]. In regulated regions, vertically integrated utilities must invest in technologies that provide reliable electricity to the consumer at the lowest cost. In this scenario, electricity storage must be compared to the cost of competitive technologies that provide the capabilities required by the utility. An additional source of revenue is government incentives designed to guide future investment decisions based on the public good.

The two potential revenue streams considered in this paper are energy arbitrage and participation in the regulation market. Arbitrage involves purchasing (charging) energy when prices are low, e.g. during times of low demand, and selling (discharging) energy when prices are high, e.g. during times of peak demand.

Regulation up (RegUp) and down (RegDown), sometimes combined into a single regulation product, are ancillary services designed to maintain frequency stability. If the load increases while generation is held constant, the frequency will drop. In order to maintain tight tolerances on the frequency, generation must be constantly dithered so that load and generation are equal. Depending on the market, a balancing authority or vertically integrated utility will control generation on a second by second basis to track the load. The balancing authority must reserve enough regulation capacity to meet expected variations in load. Current practice is to reimburse regulation providers based mainly on capacity reserved along with compensation for any electricity that is purchased or sold.

Motivated by FERC order 755 [4], the industry is evolving towards "pay for performance" where compensation is based on the amount of work performed by a device, i.e., payment must reflect the device's accuracy when following a regulation signal. ERCOT, though not under the jurisdiction of FERC, is contemplating the introduction of a the Fast Responding Regulation Service (FRRS) in response to order 755 [5], [6]. A summary of the results of the pilot program are found at [7]. The analysis in this paper is based on the current renumeration methodology in ERCOT, but can be easily modified to accommodate compensation schemes arising from FERC order 755.

This paper outlines a framework for calculating the maximum revenue from an electricity storage system that participates in a day-ahead market, i.e., energy arbitrage, and in a regulation market. The approach is designed to calculate the "best-case" scenario using historical data to simulate operation with perfect day-ahead energy and reserve price 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 an storage facility.

Our approach formulates the revenue maximization problem as a linear program. The energy storage model and optimization formulation builds on the results in [8], where the authors present a stochastic framework for the valuation of electricity storage. Revenue from energy arbitrage and the regulation ancillary services market are only two of the potential benefits of electricity storage devices. A complete review of potential revenue streams is outlined in [1], [2]. An early summary of potential arbitrage revenue in various markets is found in [9].

TABLE I
STORAGE PARAMETERS

Symbol	Storage Parameter
τ	Time period length (e.g. one hour).
T	Number of time periods in optimization.
$\bar{q}^D$	Maximum energy sold in a single period (MWh).
$\bar{q}^R$	Maximum energy bought in a single period (MWh).
$\bar{S}$	Maximum energy storage capacity (MWh).
γ_S	Storage efficiency over one period (%).
γ_C	Conversion efficiency (%).

This report is organized as follows: Section II presents the energy storage model that is used throughout this paper. Section III provides the revenue maximization problem formulation. Section IV presents results for a hypothetical 32 MWh, 8 MW energy storage system located in each load zone. Concluding remarks are found in Section V.

II. Electricity Storage Model

Common energy storage mechanisms include mechanical, electrical, chemical, and thermal [1]. Examples of mechanical storage mechanisms are pumped hydro, compressed air, and flywheels. Superconducting magnetic energy storage and capacitors are examples of electrical storage mechanisms. Batteries are the most common type of chemical energy storage. The most prevalent form of thermal storage is ice.

The key parameters that characterize a storage device are:

1) Power Rating: [MW] The maximum power of the storage device (charge and discharge).

2) Energy Capacity: [Joules or MWh] The amount of energy that can be stored.

3) Efficiency: [%] 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, γ_C, and storage efficiency, γ_S. Conversion efficiency describes the losses encountered when input power is stored in the system. Storage efficiency describes the time-based losses in a storage system.

4) Ramp Rate: [MW/min] the ramp rate describes how quickly the storage device can change its power level.

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. arbitrage or regulation). For arbitrage, the device will maintain a constant output power over each time period. For regulation, it is assumed that the device is capable of tracking the regulation signal. We also assume the ramping time is negligible (i.e., energy storage ramp rates are high). If the ramp rate is slow compared to the time period this approximation does not hold and a model that incorporates ramp rate must be employed.

The parameters in Table I are those involved in storage system constraints. Thus, the maximum quantity that can be sold/discharged in a single period is equivalent to:

$$\bar{q}^D = (\text{Maximum discharge power level}) \times \tau \qquad (1)$$

Likewise, the maximum quantity that can be bought/recharged in a single period is equivalent to

$$\bar{q}^R = (\text{Maximum recharge power level}) \times \tau \qquad (2)$$

For a storage device that provides only one service there are two decision variables in the optimization: the energy sold q_t^D (discharged) at time t, and the energy purchased q_t^R (recharged) at time t in MWh. They are assumed to be non-negative quantities. In this case, the state of charge (SOC) S_t at any time t is given by:

$$S_t = \gamma_s S_{t-1} + \gamma_c q_t^R - q_t^D \ \forall t \in T \qquad (3)$$

which states that the SOC at time t is the SOC at time $t-1$ adjusted for storage losses plus any net charging (adjusted for conversion losses) minus the quantity discharged during t. Additional constraints include:

$$0 \leq S_t \leq \bar{S}, \ \forall \, t \in T \qquad (4)$$

$$0 \leq q_t^R \leq \bar{q}^R, \ \forall \, t \in T \qquad (5)$$

$$0 \leq q_t^D \leq \bar{q}^D, \ \forall \, t \in T \qquad (6)$$

For a device that is participating in arbitrage and the regulation market, a few additional parameters must be added into the storage device model. Additional decision variables to handle separate RegUp and RegDown markets are: the energy offered into the RegUp market q_t^{RU} at time t, and the energy offered into the RegDown market q_t^{RD} at time t in MWh. These decision variables are assumed to be non-negative quantities. In regulation markets, there is no guarantee that the capacity reserved will actually be deployed. Fortunately, since frequency regulation is concerned with the short-term balance of load and generation to maintain system frequency, actual regulation signals are usually zero mean over longer time periods. This time period varies depending on the market characteristics. In CAISO, the regulation deployed can have a non-zero mean for up to several hours while the PJM regulation need is zero mean over most 1-hour intervals.

In order to quantify the change in SOC from participation in the regulation market, it is useful to define the RegUp efficiency γ_{ru} as the fraction of the RegUp reserve capacity that is actually deployed in real-time (on average). Similarly, the RegDown efficiency γ_{rd} is the fraction of the RegDown reserve capacity that is actually deployed in real-time (on average). Another assumption is that the regulation signal is allocated equally among participating regulation resources, e.g. over any given time period the regulation signal for each resource is proportional to the total regulation need. The scale factor is the quantity offer by that resource divided by the total quantity procured. Thus, the SOC at time t for a device participating in arbitrage and regulation is given by:

$$S_t = \gamma_s S_{t-1} + \gamma_c q_t^R - q_t^D + \gamma_c \gamma_{rd} q_t^{RD} - \gamma_{ru} q_t^{RU} \qquad (7)$$

And it is complemented by the following constraints:

$$0 \leq S_t \leq \bar{S},\ \forall\, t \in T \tag{8}$$

$$0 \leq q_t^R + q_t^{RD} \leq \bar{q}^R,\ \forall\, t \in T \tag{9}$$

$$0 \leq q_t^D + q_t^{RU} \leq \bar{q}^D,\ \forall\, t \in T \tag{10}$$

Participating in RegDown provides the opportunity to increase the SOC subject to the RegDown efficiency and the conversion efficiency. Participation in RegUp provides the opportunity to decrease the SOC subject to the RegUp efficiency. The quantities allocated to RegUp and RegDown reduce the maximum potential quantities allocated to arbitrage subject to the charge/discharge constraints of the device.

III. Maximizing Storage Revenue

The problem of maximizing revenue from an energy storage device is naturally formulated as an LP optimization problem [10]. Next, the energy storage model presented above is combined with a cost function to maximize the revenue in two different scenarios: arbitrage and arbitrage combined with participation in the regulation market.

A. Arbitrage

The objective function when the storage unit participates only in arbitrage is given by:

$$\max \sum_{t=1}^{T} \left[(P_t - C_d) q_t^D - (P_t + C_r) q_t^R \right] e^{-rt} \tag{11}$$

where P_t is the price of electricity (LMP) at time t in (\$/MWh), C_d is the cost of discharging at time t in (\$/MWh), C_r is the cost of recharging at time t in (\$/MWh) and r is the interest rate over one time period. This model assumes continuous compounding. For this analysis, the cost terms are assumed to be 0. If there are costs associated with charging or discharging (e.g. the system has a limited cycle life so the cost of charging or discharging can be quantified), this term may be non-zero.

This objective function in combination with the storage energy conservation model presented in (3) and variables bounds presented in (4)-(6) form the optimization model that maximizes revenue for the energy storage.

B. Arbitrage and Regulation

The objective function when the storage device participates in arbitrage and regulation is given by:

$$\max \sum_{t=1}^{T} [(P_t - C_d) q_t^D + (P_t^{RU} + \gamma_{ru}(P_t - C_d)) q_t^{RU} + (P_t^{RD} - \gamma_{rd}(P_t + C_r)) q_t^{RD} - (P_t + C_r) q_t^R] e^{-rt} \tag{12}$$

where P_t^{RU} is the price of RegUp at time t and P_t^{RD} is the price of RegDown at time t. In many areas, the net energy for regulation is settled at the real-time price. This provides an additional arbitrage opportunity between the day ahead price and the real-time price. We assume that the price P_t represents both, the regulation and energy prices in the day ahead and do not take into account real-time revenue. While this does not reflect the actual settlement process, it keeps the optimization from incorporating any arbitrage between the day ahead and the real-time market.

Constraints shown in (7)-(10) complete the optimization problem for maximizing revenue from arbitrage and regulation. The solution is the energy bought and sold at each time step as well as the amount offered into the RegUp and RegDown markets that maximizes the storage unit revenue. For this analysis, we consider RegUp and RegDown as two separate markets. When both types of RegUp and RegDown are combined into a single product, the analysis is simplified.

When offering regulation services, some fraction of the RegUp/RegDown offers are accepted. This is captured by defining the RegUp efficiency γ_{ru} and the RegDown efficiency γ_{rd}. There are some constraints on γ_{ru} and γ_{rd} that must be observed, and are discussed in more detail in [11], [12]. Typically, the optimization solution is not sensitive to the choice of γ_{ru} and γ_{rd}, so the uncertainty in these parameters does not significantly impact the accuracy of the results. A sensitivity analysis is presented in [11].

The next section applies these optimization techniques to estimate the maximum potential revenue for a hypothetical 32 MWh, 8 MW energy storage device at each load zone in ERCOT using historical data from 2011-2013.

IV. Results

The ERCOT day-ahead market for energy generates settlement point prices (SPP's) for each load zone, hub bus, and resource node. A resource node is the electrical bus where a physical generator is connected. A load zone consists of a group of electrical buses that have been assigned to a load zone for settlement purposes. A map illustrating the approximate regions covered by each load zone is shown in Figure 1. A hub bus is a group of electrical buses that have been assigned to a hub (typically a 345 kV line). Hub buses are used for trading purposes only. A list of the current hub buses and load zones appears in Table II. This section presents results for every load zone for the following scenarios:

TABLE II
Summary of ERCOT Hub Buses and Load Zones

Hub Buses	Load Zones
North 345 kV Hub	North Load Zone
South 345 kV Hub	South Load Zone
Houston 345 kV Hub	Houston Load Zone
West 345 kV Hub	West Load Zone
ERCOT Hub Average 345 kV Hub	Rayburn (RAYBN) Load Zone
ERCOT Bus Average 345 kV Hub	Lower Colorado River Authority (LCRA) Load Zone
	CPS Energy (CPS) Load Zone (San Antonio)
	Austin Energy (AEN) Load Zone

- arbitrage based on perfect knowledge: 2011, 2012, and 2013
- arbitrage and regulation based on perfect knowledge: 2011, 2012, and 2013

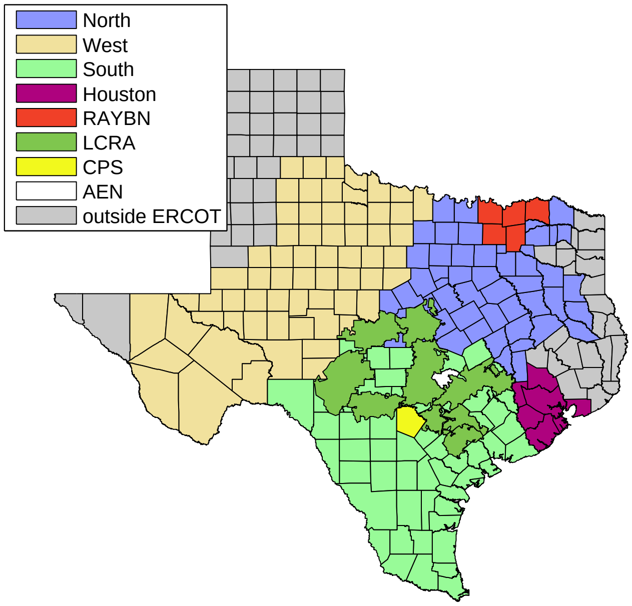

Fig. 1. Illustration of ERCOT load zones.

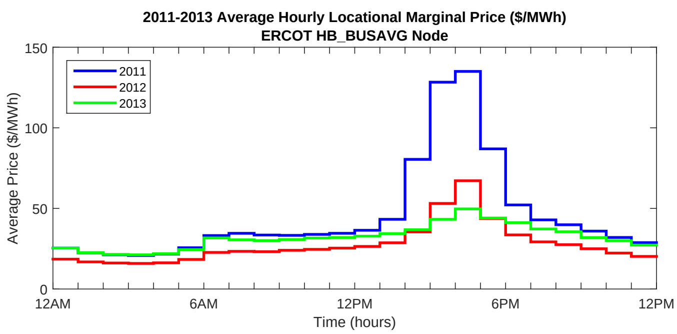

Fig. 2. Average hourly LMP prices for the ERCOT hub bus average (HB_BUSAVG), day-ahead market, 2011-2013.

Financial data for the analysis was obtained from the ERCOT website [13]. Average hourly LMP prices for 2011-2013 are shown in Figure 2 for the hub bus average. The parameters for a hypothetical energy storage system are shown in Table III. These parameters are consistent with a state-of-the-art energy storage facility and are loosely modeled after the ARRA (American Reinvestment and Recovery Act) funded Tehachapi Wind Energy Storage Plant in California.

TABLE III
ENERGY STORAGE SYSTEM PARAMETERS.

Parameter	**Value**
$\bar{q}^D$	8 MWh
$\bar{q}^R$	8 MWh
$\bar{S}$	32 MWh
γ_S	1.0
γ_C	0.8
γ_{ru}	0.5
γ_{rd}	0.5

A. Arbitrage with Perfect Knowledge

The arbitrage results for each load zone using perfect knowledge for 2011-2013 data are summarized in Table IV. The revenue was significantly higher for 2011, but this can be largely attributed to two factors that significantly increased energy prices. First, ice storms in February resulted in a loss of generation and rolling blackouts that disrupted service and resulted in a large price increase. Second, record heat over the month of August, coupled with record load levels, yielded extremely high wholesale prices. The larger diurnal swings in 2011, as shown in Figure 2, can be attributed to these two events. It also should be noted that the location of the energy storage system impacts maximum potential revenue. The West load zone offered the most revenue opportunity, while the remaining zones are roughly comparable. In all three years and across all load zones, the system was charging or discharging approximately 40 percent of the time to participate in energy arbitrage (and idle the rest of the time).

TABLE IV
ARBITRAGE OPTIMIZATION RESULTS USING PERFECT KNOWLEDGE, 2011-2013.

Load Zone	**Year**	**Revenue**	% Discharging	% Charging
North	2011	$1,063,599.54	18.90%	23.62%
	2012	$382,066.41	18.00%	22.50%
	2013	$254,605.18	18.81%	23.52%
South	2011	$1,076,180.49	18.78%	23.47%
	2012	$426,627.76	17.69%	22.11%
	2013	$289,562.01	18.62%	23.28%
West	2011	$1,182,502.88	20.00%	25.00%
	2012	$733,646.82	17.95%	22.44%
	2013	$517,344.45	18.49%	23.11%
Houston	2011	$1,063,385.41	18.84%	23.56%
	2012	$381,959.28	17.91%	22.38%
	2013	$280,054.47	18.78%	23.48%
RAYBN	2011	$1,057,443.51	18.91%	23.63%
	2012	$373,162.63	17.96%	22.45%
	2013	$250,356.83	18.78%	23.48%
LCRA	2011	$1,055,417.81	18.89%	23.62%
	2012	$449,793.75	17.97%	22.46%
	2013	$276,481.46	18.84%	23.55%
CPS	2011	$1,061,561.72	18.82%	23.53%
	2012	$391,876.86	17.99%	22.48%
	2013	$287,515.07	18.89%	23.62%
AEN	2011	$1,043,716.52	18.76%	23.45%
	2012	$368,224.91	17.92%	22.40%
	2013	$289,537.70	18.84%	23.56%

B. Arbitrage and Regulation with Perfect Knowledge

The arbitrage and regulation results for all load zones using perfect knowledge for 2011-2013 data are summarized in Table V. Again, the revenue for 2011 was significantly higher for the same reason discussed in the previous section (February ice storm and August heat wave in 2011 increased energy and ancillary service prices). In all three years across all regions, the system was performing very little arbitrage (q^D and q^R are both less than 3%) and participating in the regulation market the majority of the time. This is consistent with results observed in the CAISO market [11]. There is less differential in maximum potential revenue over regions compared to the arbitrage-only case. The West load zone still had the largest potential revenue, but not by a significant margin. This is due to the regulation services having a single price across all of ERCOT at each time period in the day ahead market, eliminating the impact of location on the regulation revenue stream. Hence, differences in revenues can be attributed to the arbitrage services only.

TABLE V
ARBITRAGE AND REGULATION OPTIMIZATION RESULTS USING PERFECT KNOWLEDGE, 2011-2013.

Year	Revenue	% q^D	% q^R	% q^{RU}	% q^{RD}
North Load Zone					
2011	$2,370,777.09	0.11%	0.87%	69.63%	85.62%
2012	$933,260.45	0.11%	0.83%	63.59%	78.12%
2013	$843,543.43	0.10%	1.38%	62.77%	75.98%
South Load Zone					
2011	$2,369,779.67	0.26%	0.99%	69.32%	85.36%
2012	$955,300.23	0.44%	0.94%	61.95%	76.67%
2013	$858,726.34	0.10%	1.35%	61.23%	74.11%
West Load Zone					
2011	$2,438,594.42	0.010%	2.23%	69.01%	82.16%
2012	$1,163,443.68	1.86%	2.57%	51.25%	63.61%
2013	$1,007,779.09	0.98%	2.57%	54.16%	65.03%
Houston Load Zone					
2011	$2,363,966.11	0.15%	0.85%	69.31%	85.37%
2012	$931,141.19	0.089%	0.78%	63.53%	78.09%
2013	$854,588.16	0.089%	1.30%	61.09%	73.99%
RAYBN Load Zone					
2011	$2,367,663.02	0.11%	0.84%	69.71%	85.78%
2012	$928,295.59	0.11%	0.83%	63.73%	78.31%
2013	$840,455.24	0.10%	1.44%	62.92%	76.02%
LCRA Load Zone					
2011	$2,362,665.58	0.17%	0.88%	69.24%	85.23%
2012	$982,249.28	0.61%	0.81%	61.34%	76.59%
2013	$853,824.74	0.10%	1.23%	61.40%	74.55%
CPS Load Zone					
2011	$2,359,793.64	0.14%	0.87%	69.32%	85.31%
2012	$938,393.86	0.23%	0.84%	63.38%	78.14%
2013	$856,761.94	0.17%	1.43%	60.95%	73.77%
AEN Load Zone					
2011	$2,355,535.66	0.14%	0.85%	69.73%	85.86%
2012	$925,236.23	0.10%	0.87%	64.26%	78.86%
2013	$862,277.62	0.12%	1.26%	60.38%	73.28%

V. CONCLUSION

In this paper we have outlined a linear programming optimization approach for estimating the maximum potential revenue from an energy storage system participating in arbitrage and the regulation market. If cost data is available, the same approach can be used to estimate net revenue. Using 2011-2013 price data for the all ERCOT load zones (North, South, West, Houston, RAYBN, LCRA, CPS, and AEN), we calculated the maximum potential revenue from arbitrage and arbitrage combined with regulation using perfect knowledge. These estimates serve as an upper bound on revenue from the two strategies. By looking at data from all load zones over several years, we were able to identify several trends. First, the increase in potential revenue in 2011 can largely be attributed to ice storms in February and a heat wave in August which resulted in price spikes for energy and ancillary services. The potential revenue for 2012 and 2013 are on the same order of magnitude and likely better represent a typical year. Location has a significant effect on potential revenues from energy arbitrage, with the West load zone offering the most potential. When offering arbitrage and frequency regulation services, the optimum strategy is to focus on frequency regulation. Since there is one price for ancillary services in the ERCOT day ahead market, and this is more profitable than arbitrage alone, the impact of location is greatly reduced. The maximum potential revenue in each load zone was roughly comparable, with the West still offering slightly more opportunity.

ACKNOWLEDGMENT

The authors would like to thank Dr. Imre Gyuk and his colleagues at the Energy Storage Program at the U.S. Department of Energy for funding this research. The authors would also like to thank Marcus G. Ollington who provided the LCRA shape files used in Figure 1. Sandia National Laboratories is a multi-program laboratory managed and operated by Sandia Corporation, a wholly owned subsidiary of Lockheed Martin Corporation, for the U.S. Department of Energys National Nuclear Security Administration under contract DE-AC04-94AL85000.

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