Economic Analysis of using Distributed Energy Storage for Frequency Regulation

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ABSTRACT

The need for a high ramping energy resource for frequency regulation is increasing due to the high penetration of intermittent and variable renewable energy sources, such as wind and solar, in the electricity grid. Traditionally, special generators have been used for frequency regulation. These generators can provide high capacity but have a very slow response time. Battery energy storage (BES) has gotten tremendous attention due to the advancement in technology. BES has a very fast response time, which makes it suitable for frequency regulation. In this paper, we perform an economic analysis of a distributed energy storage participating in the PJM and NYISO regulation markets. The distributed storage consists of many small consumers' installed batteries. A centralized entity at a microgrid level controls the distributed storage using our proposed algorithms. The economic analysis is performed from the perspective of individual storage owners. Our results show that the five-year *net-present-value* (NPV) of the consumers' investment is positive if the utility shares 30% (or above) of the regulation revenue with the storage owners and keeps the rest of the 70%.

CCS CONCEPTS

• **Hardware** → **Smart grid**; **Batteries**.

KEYWORDS

Energy storage, frequency regulation, electricity market

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1 INTRODUCTION

Due to demand/supply mismatch, system frequency deviates from the required frequency to run the system smoothly. Frequency regulation refers to the injection or removal of active power in the grid to bring the system frequency back to normal [14]. A frequency regulation resource can provide frequency regulation service by following *Automatic Generation Control* (AGC) signal that is sent by the system operator to the resource on a preset frequency.

Traditionally, special generators have been used for frequency regulation. Although these traditional generators can provide high capacity, their response time is slow. With the advancement in technology, flywheel and BES have been adopted for frequency regulation. Contrary to the traditional resources, energy storage resources have a limited energy capacity but their response time is very fast. In PJM [15], the regulation signal is divided into two components, *RegD* signal and *RegA* signal. *RegD* and *RegA* signals are meant for the energy-limited fast regulation resources and the traditional high capacity resources, respectively. *RegD* signal is a high-pass filtered component of the *Area Control Error* (ACE) whereas *RegA* is a low-pass filtered component of the same ACE. *RegD* has a high frequency but is balanced around zero. Therefore, it is suitable for fast but energy-limited regulation resources such as BES. On the other hand, *RegA* has low frequency but requires high capacity regulation resources and is suitable for traditional regulation resources.

Frequency regulation requires fast resources on a high priority basis due to the dependence of the power system stability on the frequency [12]. The energy storage system (ESS) is highly suitable for frequency regulation due to its fast ramp rate compared to traditional regulation resources. Recently, problems related to applications of energy storage to the frequency regulation has been addressed in the literature. These include energy storage control [4, 6, 7, 11, 16], simulation modeling [6, 7, 21], determining suitable type of energy storage system [8, 18] and economic analysis [11, 22]. Economic feasibility of energy storage participating in the frequency regulation has been studied in [10, 13, 17, 19, 20]. Energy storage control schemes have a large impact on the energy storage lifetime, the benefits of participating in frequency regulation and capacity allocation.

BES is suitable for frequency regulation due to it's fast response time. Previous studies have performed economic analysis for single, centralized energy storage participating in the frequency regulation. Aggregating a large number of consumers' batteries can make a large energy storage that can be used for frequency regulation. This requires efficient scheduling schemes that efficiently schedule the AGC signal among a large number of batteries. In this paper, we propose a centralized battery scheduling scheme and perform economic analysis from the perspective of the storage owners. Our results show that battery owners, that utility that centrally controls the batteries as well as the system operator itself obtain advantage of this distributed storage. Even if the regulation revenue is shared

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among the utility and the storage owner, the 5-years NPV of the storage owner's investment is positive. As far as the system operator is concerned, it obtains a new flexible and scalable fast resource for frequency regulation. This is a win-win situation for all the stakeholders.

The rest of the paper is organized as follows. We present the centralized battery scheduling scheme in section 2. We explain regulation payment mechanisms for frequency regulation in the PJM and NYISO regulation markets in section 3. Experimental results are given in section 4. Finally, the paper is concluded in section 5.

2 DISTRIBUTED STORAGE AND THE BATTERIES SCHEDULING ALGORITHMS

The proposed distributed storage consists of N households (HH) each of which has installed an ESS of a given capacity. Each of the ESSs is connected with a microgrid level central controller. The controller can centrally control the charging and the discharging of each of the ESSs.

2.1 Energy Storage System Model

We use the energy storage model that has already been used in previous studies [1–3, 9, 23]. Energy storage is characterized by the following parameters

- **Power Rating (kW/MW):** Maximum charge and discharge power of the ESS.
- **Energy Capacity (kWh/MWh):** Total energy that can be stored in the energy storage.
- **Efficiency:** This is the ratio of the total energy discharged from ESS to the total energy input to the system.

Let C, P_c, P_d and γ be the energy capacity, maximum charging power, maximum discharging power and round trip efficiency of the energy storage, respectively. Let P be the charge power (≥ 0) or discharge power (≤ 0) applied from time t to time $t + \Delta t$. Then the state of charge $\mathrm{SOC}^{t+\Delta t}$ at time $t + \Delta t$ can be calculated in eq. 1 as

$$\mathrm{SOC}^{t+\Delta t} = \begin{cases} \mathrm{SOC}^t + \frac{\gamma \times \Delta t \times P}{C}, & P > 0, \\ \mathrm{SOC}^t + \frac{\Delta t \times P}{C}, & P < 0. \end{cases} \tag{1}$$

In general, there is a loss of power both of the times during charging and discharging. Therefore a battery has both of the charging and discharging efficiencies. In simulations, we can use a round trip efficiency applied during charging or discharging. For convenience, we apply efficiency during charging only.

2.2 Batteries Scheduling Algorithm

Suppose a total charge or discharge energy x_t^{net} is to be distributed among N batteries. We need to find $\mathbf{x_t} = \left\{x_t^i : i = 1, 2, 3, ..., N\right\}$ such that $\sum_{i=1}^{N} x_t^i = x_t^{net}$, where x_t^i is the charge/discharge energy for i_{th} household's battery during time t given net charge/discharge energy x_t^{net}, battery capacities $\mathbf{C} = \{C_i : i = 1, 2, 3, ..., N\}$, battery maximum powers $\mathbf{P} = \{P_i : i = 1, 2, 3, ..., N\}$, current state-of-charge (SOC) of the batteries $\mathbf{SOC} = \{\mathrm{SOC}_i : i = 1, 2, 3, ..., N\}$, batteries efficiencies $\mathbf{\Gamma} = \{\gamma_i : i = 1, 2, 3, ..., N\}$ and SOC_LIMIT. Where $\mathbf{P}$ is array of charge (discharge) powers if $x_t^{net} > 0$ ($x_t^{net} < 0$). Similarly, SOC_LIMIT is the maximum(minimum) limit on the SOC of the batteries if $x_t^{net} > 0$ ($x_t^{net} < 0$). Algorithms 1 and 2 find $\mathbf{x_t}$ given states and parameters of the batteries.

Algorithm 1: Distribute Energy for Charging.

(1) Sort **SOC** in ascending order.
(2) Find minimum k such that the total energy required for charging first k batteries in sorted order up to $\mathrm{SOC_{k+1}}$ is greater than or equal to x_t^{net} (where $x_t^{net} > 0$).
(3) Set charge energy $x_j'(> 0)$ for j_{th} ($j = 1, 2, 3, ..., k-1$) battery in sorted order equal to the energy required to increase SOC of that battery up to $\mathrm{SOC_k}$
(4) Compute remaining energy $x_t^{remaining} = x_t^{net} - \sum_{j=1}^{k-1} x_j'$.
(5) Divide $x_t^{remaining}$ in first k batteries, in sorted order, proportional to their respective energy capacities and add it to their respective energies x_j' ($j = 1, 2, 3, ..., k-1$) computed in step 3.

Algorithm 2: Distribute Energy for Discharging.

(1) Sort **SOC** in descending order.
(2) Find minimum k such that the total energy required for discharging first k batteries in sorted order up to $\mathrm{SOC_{k+1}}$ is less than or equal to x_t^{net} (where $x_t^{net} < 0$)..
(3) Set discharge energy $x_j'(< 0)$ for j_{th} ($j = 1, 2, 3, ..., k-1$) battery in sorted order equal to the energy required to decrease SOC of that battery up to $\mathrm{SOC_k}$
(4) Compute remaining energy $x_t^{remaining} = x_t^{net} - \sum_{j=1}^{k-1} x_j'$.
(5) Divide $x_t^{remaining}$ in first k batteries, in sorted order, proportional to their respective energy capacities and subtract it from their respective energies x_j' ($j = 1, 2, 3, ..., k-1$) computed in step 3.

3 PAYMENT MECHANISMS AND THE REGULATION MARKETS

We use regulation signal data and price data from NYISO and PJM ancillary service markets. All RTOs/ISOs make payments to the regulation resources according to FERC Order 755. Under FERC Order 755 [5], the regulation resources should be compensated with respect to the capacity (MW) that the resources bid in the market and the regulation mileage (ΔMW). Suppose energy storage regulation resource bids capacity P_{max}^t during a given time interval, i.e. the maximum power that the energy storage can provide in both regulation-up and regulation-down is equal to P_{max}^t. The regulation payment for the time interval is calculated according to the regulation resource capacity P_{max}^t (MW), regulation mileage or movement M_t (Δ MW/MW) and regulation resource performance η_t.

- *Mileage (M)*: It is the sum of the absolute differences between the regulation signals and quantify the work done by the regulation resource over the time period. Suppose $\left\{P_k^t :\ k = 1, 2, 3, .., n\right\}$ is the regulation resource output over a time interval $[t, t + \Delta t]$. The mileage M_t for the time interval is defined as

$$M_t = \frac{\sum_{k=1}^{n} |P_k - P_{k-1}|}{P_{max}}. \tag{2}$$

- *Performance Score* η_t: Performance score lies between 0 and 1 and is calculated based on delay, correlation and precision. The delay is the time taken by the regulation resource in responding to the regulation signal, correlation is calculated using statistical correlation between the output of the regulation resource and the regulation control signal and the precision quantifies the error between the regulation control signal and the regulation resource output. A single performance score is calculated by averaging delay, correlation and precision scores.

A regulation resource bids in the regulation market by offering a capacity price and a mileage price. Regulation resources whose bids are accepted are credited according to the market capacity clearing price (CCP) R_C and market performance clearing price (PCP) R_M. A regulation resource has to maintain a minimum performance score to be eligible to bid into the regulation market. Regulation credit R_t for the regulation resource during time period t can be calculated using the following generic formula:

$$R_t = P^t_{max}\left(R^t_C + \eta M_t R^t_M\right). \tag{3}$$

Although eq. 3 can be used to calculate credits in NYISO real-time regulation market, but PJM uses a mileage ratio instead of mileage M in the credit calculation. PJM day-ahead regulation market offers two types of regulation signals to the regulation resources, namely, *RegA* and *RegD* signals. *RegA* and *RegD* signals are obtained by applying low pass filter and high pass filter to the ACE, respectively. Energy storage has high rampability and can quickly adjust its power output according to the regulation signal. But energy storage is limited by its energy capacity and therefore cannot respond to the regulation up or regulation down signals if the storage has reached its maximum or minimum energy capacity level, respectively. On the other hand, traditional regulation resources are slow in changing their power outputs. Therefore, PJM divides its ACE into *RegA* and *RegD*. *RegD* is energy neutral regulation signal having zero mean and is meant for fast but energy-limited resources such as energy storage. *RegA* signal which is low-pass filtered ACE is meant for traditional regulation resources. *RegD* signal changes very quickly and relatively has higher mileage than the *RegA* signal. Mileage ratio β_t, defined in eq. 4, is the ratio of the signal mileage (*RegA* or *RegD* for which regulation resource has made a bid) to the *RegA* signal mileage

$$\beta_t = \frac{M_t}{M_t^{RegA}}. \tag{4}$$

β_t is equal to one for the *RegA* signal and is greater than one for *RegD* signal. Therefore, fast regulation resources providing regulation for *RegD* signal are paid higher than the traditional regulation resources providing regulation for *RegA* signal. Eq. 5 for calculating regulation credits in the PJM regulation market is obtained by replacing M_t with β_t in the eq. 3 as follows:

$$R_t = P^t_{max}\left(R^t_C + \eta \beta_t R^t_M\right). \tag{5}$$

The distribution of CCP and PCP in NYISO and PJM regulation markets for the year 2018-2019 is shown in figure 1. It appears that PJM performance prices are much higher than the NYISO performance prices. But, it is obvious from eqs. 3 and 5 that NYISO uses mileage in its performance credit calculation whereas PJM uses mileage *ratio*. Mileage ratio is relatively a smaller number than the mileage itself therefore the higher PJM performance prices are accounted for by using mileage ratio.

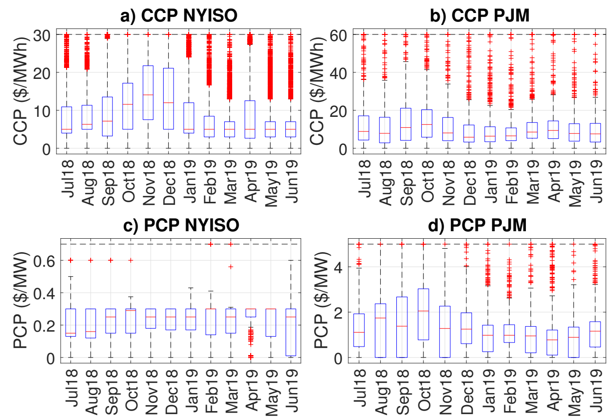

Figure 1: Regulation Prices Distribution in PJM and NYISO

PJM *RegA* and *RegD* command signals are 2-second resolution signals between -1 to 1 and a regulation resource calculates power by multiplying its capacity with the regulation signal. NYISO divides 6-second resolution ACE signal among all the regulation resources proportional to their respective capacity. Fig. 2 shows samples of PJM *RegA*/*RegD* signals and NYISO ACE. PDFs (Fig. 2 b) and d)) are obtained using a sample of 30 days signal data from both PJM and NYISO whereas the plot of regulation signals 2 a) and c)) are obtained using 4 hours and 12 hours of data from PJM (2 a)) and NYISO (2 c)), respectively. NYISO ACE is perfectly symmetric with zero mean. PJM *RegD* signal is also symmetric with zero mean but most of the density is concentrated at -1 and 1. PJM *RegA* signal does not seem to have a zero mean and consists of low-frequency components of the ACE.

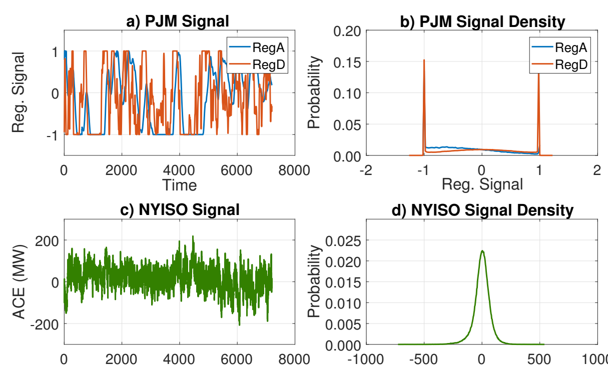

Figure 2: Regulation Signal Data

4 EXPERIMENTAL RESULTS

We created a simulation setup of a distributed energy storage consisting of 1000 small batteries of 1 kW and 2kW with half-hour energy capacity at maximum power, i.e. 1 kW and 2 kW batteries'

Table 1: Regulation revenue from PJM and NYISO regulation markets

	PJM		NYISO	
	Total	Avg. Daily	Total	Avg. Daily
Jul 2018	$27857.23	$928.57	$22813.64	$760.45
Aug 2018	$27480.05	$886.45	$25441.06	$820.68
Sep 2018	$33441.59	$1078.76	$30102.75	$971.06
Oct 2018	$33204.01	$1106.80	$31648.62	$1054.95
Nov 2018	$25134.32	$810.78	$39704.51	$1280.79
Dec 2018	$22201.81	$740.06	$36141.96	$1204.73
Jan 2019	$20579.02	$663.84	$26439.23	$852.88
Feb 2019	$19750.72	$637.12	$25740.16	$830.33
Mar 2019	$18637.96	$665.64	$21042.49	$751.52
Apr 2019	$23116.81	$745.70	$36111.97	$1164.90
May 2019	$17814.29	$593.81	$23301.15	$776.71
Jun 2019	$19980.35	$644.53	$18086.97	$583.45
Total	$289198.16	$792.32	$336574.52	$922.12

energy capacities are 0.5 kWh and 1 kWh, respectively. There are 482 and 518 consumers having 1 kW and 2 kW batteries, respectively. Table 1 shows monthly regulation revenue that the distributed storage obtains by participating in PJM and NYISO regulation markets for the year 2018-2019. Fig. 3 shows daily regulation revenue in both of the regulation markets for the same year. Daily minimum, mean and maximum revenues for the PJM regulation market are $300.57, $792.32 and $4019.80 and for NYISO regulation market are $339.78, $922.12 and $6134.30, respectively.

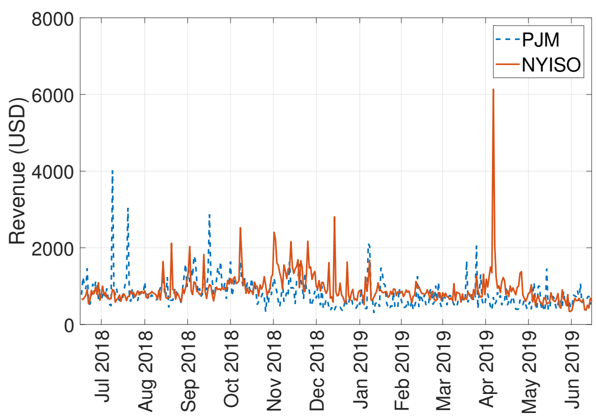

Figure 3: Daily regulation revenue in PJM and NYISO regulation markets for the year 2018-2019

As all the investment in the batteries is made by the batteries owners, we calculate NPV from the perspective of storage owners for the two types of consumers (1 kW and 2 kW). We calculate consumers NPV for ten cases where each case corresponds to a percentage of the total revenue that the utility shares with all of the consumers and keeps the rest of the revenue. We consider Li-ion batteries cost and lifetime data. Although li-ion batteries cost has decreased tremendously since the past many years, to be conservative we assume USD 400/kWh including all the installation and inverters costs. We calculate NPV for 5 years batteries lifetime with a 10% discount factor. Suppose x is the total revenue for a year that the utility obtains using all the 1000 batteries in a given regulation market. We calculate revenue x_i for the i_{th} consumer with a battery of capacity C_i as in eq. 6:

$$x_i = \frac{xC_i}{\sum_{j=1}^{N} C_j}, \quad i = 1, 2, 3, ..., N \tag{6}$$

where C_i is the battery's energy capacity. We assume the same yearly revenue for each of the 5 years period for the calculation of NPV. For example, total yearly regulation revenue in the PJM regulation market is equal to $289198.16 and suppose 50% is shared with the consumers. Therefore, a consumer with 0.5 kWh/1 kW battery obtains a yearly revenue of $\frac{0.5\times\frac{289198.16}{2}}{0.5\times482+1\times518} = \$95.26$ and a consumer with 1 kWh/2 kW battery obtains a yearly revenue of $\frac{1\times\frac{289198.16}{2}}{0.5\times482+1\times518} = \$190.51$. Costs of 0.5 kWh and 1 kWh batteries are $200 and $400, respectively. With 5 years lifetime of batteries and 10% discount factor, the NPV for 0.5 kWh and 1 kWh batteries' owners are $161.10 and $322.19, respectively. Table 2 shows NPV for both types of consumers in PJM and NYISO regulation markets for varying sharing percentages.

The NPV for 10% and 20% is negative for batteries of both capacities. However, the NPV is positive for 30% and above for both of the PJM and NYISO markets. This means that it is profitable for the storage owners to participate in the distributed storage when the sharing percentage is 30% or higher. However, this threshold is for the current example only and may vary in the other examples. The objective of the current paper is not to recommend or device mechanisms for incentivizing the storage owners, but to show the economic feasibility for the storage owners as well as for the utility companies that control the distributed storage centrally. Optimal sharing percentage threshold or incentive mechanisms for the participating storage owners can be done in a separate work.

5 CONCLUSION

We propose a distributed energy storage scheme and use it for frequency regulation in PJM and NYISO regulation markets. The total revenue obtained by the utility is shared among all the participating battery owners. We calculate NPV for different sharing percentages. Our results show that the NPV from the side of battery storage owners is positive when the utility shares greater than or equal to 30% of the total revenue with the participating consumers. This is a win-win situation for the consumers as well as for the utility companies. Apart from financial incentives, the need for large battery storage is increasing due to the high penetration of variable renewable energy sources in the electricity grid. Our proposed model can aggregate a large number of storages to provide services for the electricity grid.

In the current experimental example, results show that 30% sharing percentage is profitable for the storage owners. However, this threshold percentage may vary from market to market or for other data. Even if this threshold doesn't change significantly, this is a minimum borderline and may not be an optimal choice. The storage owners may not agree to accept small share and decline participating in the distributed storage. Future research should investigate

Table 2: Net present value for the storage owners

	PJM			NYISO		
Sharing Percentage	NPV 1 kW	NPV 2 kW	Utility Revenue	NPV 1 kW	NPV 2 kW	Utility Revenue
10%	$-127.78	$-255.56	$260278.35	$-115.95	$-231.90	$302917.07
20%	$-55.56	$-111.12	$231358.53	$-31.90	$-63.80	$269259.61
30%	$16.66	$33.32	$202438.71	$52.15	$104.30	$235602.16
40%	$88.88	$177.75	$173518.90	$136.20	$272.40	$201944.71
50%	$161.10	$322.19	$144599.08	$220.25	$440.50	$168287.26
60%	$233.32	$466.63	$115679.26	$304.30	$608.60	$134629.81
70%	$305.53	$611.07	$86759.45	$388.35	$776.70	$100972.36
80%	$377.75	$755.51	$57839.63	$472.40	$944.80	$67314.90
90%	$449.97	$899.95	$28919.82	$556.45	$1112.90	$33657.45
100%	$522.19	$1044.39	$0.00	$640.50	$1281.00	$0.00

the optimal or near-optimal incentive mechanism for the storage owners.

In general, the lifetime of a li-ion battery is much higher than 5 years. But a regulation signal deteriorates the batteries cycle lifetime very quickly compared to normal usage of the battery. Therefore, we assume a very small lifetime of 5 years for the batteries in calculating the NPV. Future research may calculate the NPV by using appropriate cycle aging algorithms that approximate the batteries cycle lifetime.

Further research may look into other applications of the distributed storage. These applications may include energy arbitrage, peak shaving, deferral of system upgrade and participating in the install capacity market.

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