Thesis Project

Emissions Mitigation Potential of Grid Scale Energy Storage Systems for Peak Load Shifting

By: Bhuvan Neema [a,b,c]

Advisor: Prof. Jeremiah Johnson [a,b,d]

Prof. Gregory A. Keoleian [a,b,c]

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[a] School for Environment and Sustainability, University of Michigan, Ann Arbor, Michigan
[b] Center for Sustainable Systems, University of Michigan, Ann Arbor, Michigan
[c] College of Engineering, University of Michigan, Ann Arbor, Michigan
[d] Department of Civil, Construction, and Environmental Engineering, North Carolina State University, Raleigh, North Carolina

Abstract

Cost of battery energy storage systems (ESS) has reduced significantly in recent years resulting in a marked increase in its use for power grid applications. Regulations by grid operators and state policies, such as energy storage mandates, have further accelerated their deployment in place of conventional generators for range of grid services. Majority of such policies and regulations are designed to compensate ESS based on their classification as a generator, transmission, or distribution assets. What is less acknowledged, and in many cases not accounted for, are the environmental benefits that ESS may provide when deployed for the grid services. Recognizing the environmental value of energy storage through policy measures can increase their relative attractiveness. This research presents a comprehensive analytical framework to evaluate the emissions abatement by ESS while providing resource adequacy service by shifting the peak load. Using a constrained optimization for ESS dispatch and least-cost economic principle, the marginal generation mix, and emissions rate were identified. The emissions mitigation potential is determined for shifting the peak load generation from inefficient natural gas based peaker units to the marginal generators during non-peak hours. Model determined the net avoided CO_2 emissions, capacity value, energy arbitrage gains, and net cost of ownership for ESS in order to estimate the cost of CO_2 abatement from the grid. We examined three grid regions (ERCOT, CAISO, and ISO-NE), selected for their high share of natural gas generation. Across all the grid regions, the first 100 MW of storage capacity on the grid provides the maximum emissions reduction and benefits from subsequent capacity additions diminish. The combustion emissions abatement potential across all the grid regions and technologies is between 30-42 tonCO_2/MWh of storage capacity. On life-cycle basis, net emissions avoided over emissions invested (EAOI) is higher for longer duration of storage capacity due to lower energy dependent production burdens for the storage system. The study also presents a framework to assess the capacity value of ESS on the grid for different storage duration. The energy arbitrage and capacity value streams identified with load shifting application are not enough to repay the capital and operation costs for the ESS. Hence, the total cost of avoided emissions with such application is considerably high: between \$750–3,200/ton-CO_2. The approach used to determine the CO_2 emissions benefits in this study can also be applied to other emissions to inform the environmental value of ESS to policymakers, grid operators and utilities.

Table of Contents

Abstract....1

1. Introduction....3

2. Methods....7

2.1 Economic Dispatch Model....8

2.2 Constrained Optimization Algorithm for ESS Dispatch....12

2.3 Environmental Impact Assessment....15

2.4 Cost of Emissions Abatement....18

2.4.1 Levelized Cost of Energy Storage....18

2.4.2 Energy Arbitrage Value....19

2.4.3 Capacity Value....19

3. Results....22

3.1 Emissions Abatement Potential....22

3.2 Capacity Value of Energy Storage Systems....24

3.3 Value Proposition and cost of emissions abatement....25

4. Discussion....28

Appendices....31

Appendix A: Hourly dispatch model....31

Appendix B: Model Validation....33

Appendix C: Emissions reduction and EAOI for other ESS technologies....34

Appendix D: Cost of Emissions Abatement with Energy Storage Systems....37

Appendix E: Levelized cost of Energy Storage Systems....38

References....39

1. Introduction

In the U.S., the power sector accounts for over 29% of total greenhouse gas (GHG) emissions and majority of these emissions are directly associated with the combustion of fossil fuels during the use phase.[1] To reduce the environmental impacts from the power sector, renewable resources such as solar photovoltaics (PV) and wind turbines are increasingly deployed at both utility and distributed scale across U.S. The intermittent characteristics of these renewables is affecting the power system reliability leading to more deployment of inefficiency combustion turbines on the grid. Energy storage is a promising technology to address this issue by improving the resource adequacy for the grid by shifting the peak load and displacing the inefficient units from the grid. The emissions reduction potential is dictated primarily by the heat rates of displaced and added generator units as well as the storage system characteristics such as round-trip efficiency and lifetime.

Large-scale integration of such variable renewable resources is quickly changing the power generation and management systems of the electricity grid.[2] Zahedi presented the new challenges with maintaining power quality and reliability of the grid due to intermittency and unpredictability nature of solar power generation, especially at large-scale solar energy systems.[3] Wang and Bertling demonstrated that incorporation of wind farms has very limited system reliability improvement.[4] Furthermore, higher penetration of wind resources degrade the grid voltage stability due to the surplus or shortage of power.[5]. In addition, low marginal cost of electricity generation for non-dispatchable renewable resources have reduced the energy margins for large-scale dispatchable thermal power plants in several wholesale markets.[6] This created the risk of early uneconomic retirements for several thermal assets and lower reserve margins on the grid. Insufficient capacity margins pose a critical challenge to grid operators for maintaining the reliability standards. On the other hand, behind the meter solar PV resources are further altering the net-load pattern by creating new late-evening peaks that demands flexible resources with higher ramp-rate.[7,8] With the growth of electric vehicles and advent of superchargers the need for the flexible grid resources is further amplified.[9] Traditionally, such new capacity needs are managed through operating reserves in short terms and through resource adequacy planning mechanisms in long term. The combustion turbine (CT) is generally viewed as the capacity resource to be used on the grid for addressing the needs during the limited number of peak hours on the grid. On the other hand, natural gas based combined cycle (NGCC) are used to provide the baseload generation requirements. . With higher heat rates, CT units not only increase the cost burden on electricity rate payers but also leads to higher GHG emissions from power sector. Energy storage systems (ESS) can potentially address such challenges through load-shifting application.

ESS are considered as an effective tool to enhance the flexibility and controllability of the entire grid and several studies have assessed the role of energy storage to enable high penetration of renewables on the grid.[10,11] CAISO's studies suggest that 22 GW / 186 GWh of energy storage would be needed in California by 2050 for 100% RPS target.[12,13] Denholm and Margolis evaluated the combination of PV and storage to effectively replace baseload generation in the system.[14] Zhao et. al provided a comprehensive review of potential applications for integrated ESS and renewable resources.[15] With the flexible charging–discharging characteristics ESS can play various roles for different stakeholders including generation-side roles: such as time-shifting & load smoothing and grid-operator side roles: including frequency regulation, voltage control and transmission congestion relief. Each of these applications have specific performance requirements and based on the technical characteristics of ESS technologies, suitability for grid applications are determined.[16,17] With the emergence of new technologies, hybrid energy storage systems are also thoroughly researched. Integrating storage technologies with supplementary operating characteristics can enable range of services offerings from a single ESS.[18] Energy storage technologies holds the key to high share of renewable energy on the grid, however its adoption is limited by high costs. Arbabzadeh et. al demonstrated this in the off-grid system where incorporating vanadium redox flow battery reduces both the renewable curtailment and life cycle carbon emissions, however it is not the most cost-effective solution for low emissions target scenarios.[19]

To address the need for grid balancing resources with use of ESS, policymakers and regulators are intensifying measures to incentivize cost-efficiency improvement for implementation of energy storage technologies in the market.[20,21,22] Three states: California, Oregon, and Massachusetts already have energy storage mandates in-place.[23,24] With the state directives to the Public Service Commission for developing an Energy Storage Deployment Program, New York is expected to join the list with storage procurement target for 2030.[25,26] FERC Order 755 guidelines mandates storage assets to be compensated with performance driven tariffs structure for grid services, but like other state mandates, it fails to acknowledge the environmental impacts of energy storage system integration for grid applications.[27,28] ESS inherently do not possess green characteristics and thus tracking their emission attributes is essential to formulate their future policies. In the load shifting application, ESS changes the net load profile by discharging during peak load hours and charging using non-peak hours. Such application provides an opportunity to avoid the emissions from the grid by displacing the conventional combustion turbines during peak hours with cleaner resource while charging.[29,30] In the natural gas dominated power grid regions unutilized capacity from marginal units during non-peak hours, , can potentially be dispatched on the grid to charge ESS. Compared to peaker units, the natural gas combined cycle units are 25-40% more efficient and have lower operational cost of electricity generation.[31] Due to this difference in operational costs, ESS can shift load to less expensive units while potentially mitigating emissions due to improved system generator efficiency. Lund et. al and Finnveden et. al have noted in their researches the need for estimating marginal GHG emissions from electricity generation to more accurately estimates the changes in emissions resulting from marginal changes in the net-load profile.[32,33] In this study we developed a dispatch model of electricity production to quantify GHG emissions from the marginal units on the grid that enables the evaluation of the environmental value for ESS with load shifting application.

Many studies have thoroughly investigated these ESS technologies for power systems applications and evaluated their benefits for the resource adequacy and grid reliability.[34,35,36] Capacity credit is usually adopted to assess the contribution of a generator unit to the resource adequacy. Majority of current work involving energy storage capacity benefits is centered around smoothing the output power profiles of renewable energy resource.[37,38] Today the effects of standalone energy storage on system reliability is negligible and majorly ignored. However, the load shifting application essentially improves the reserve margin by reducing the net peak load on the grid and hence contribute to system reliability. Models to optimize the ESS performance on the grid for peak load shaving are also abundant in the literature.[39,40,41] Majority of these optimization models are tested on IEEE standard bus systems, have thoroughly investigated the operational parameters of ESS, and determined the optimal configuration for technical and economic performance. However, there are very few studies that deployed the environmental impact as a part of their objective function in assessing the bulk ESS on the grid for load-shifting.[42,43] Bulk-ESS systems for load shifting application will affect how the existing systems operate and methods are necessary to examine the marginal effects and resulting change in CO_2 emissions. This study presents an analytical framework to compute the environmental impacts of integrating ESS to the grid for load-shifting applications. The model uses linear optimization approach to determine the hourly dispatch of energy storage units and identifying the displaced and added generation capacity from the grid. There are range of energy storage technologies available commercially that can be deployed for bulk-energy services like peak load shifting.[44] The model examined for Vanadium redox batteries (VRFB), Sodium Sulfer (NaS), Lithium ion (Li-ion), and Lead-Acid (PbA) battery energy storage technologies. Different penetration levels for ESS on the grid are studied to determine the incremental benefits and net cost of GHG abatement. Sensitivity analysis is also conducted to highlight the significance of each parameter in the dispatch model for ESS on environmental benefits.

The framework presented in this research work can be applied for any ESS technology to compute specific emission benefits associated with fuel consumption for displaced and added generation units. The outline of the report is as follows: Section II explains the methods to determine the ESS optimal operating strategy and its environmental benefits; Section III presents the simulation results for ERCOT grid case study; In Section IV the state policies and regulatory measures are discussed which can optimize the environmental benefits of ESS on the grid followed by conclusion in Section V.

2. Methods

Electricity is provided through a continuously changing mix of generation assets and power-grid complexity makes it extremely difficult to trace grid electricity consumption back to a specific generation asset.[45] Furthermore, energy storage shifts electricity production away from its consumption on the time-scale. Ryan et. al reviewed range of methods to compute the emission associated with the electricity load and found that several academic studies deployed economic dispatch model to determine both marginal unit and marginal emissions from electricity consumption.[46] Typically, marginal units are determined based on economic dispatch principle in which the last dispatched unit, with an economic production level, cost-effectively satisfy the load, power flow, and transmission constraints on the grid. In addition to this, the marginal units for a given period are also affected by the units providing baseload generation, ramp requirement on the grid for subsequent hours, as well as need for flexible capacity to address forecast and uncertainty movements on the grid load. In Load shifting service electricity is stored during times of low demand (Figure-4), increasing the dispatched capacity and associated emissions on the grid from marginal generator during non-peak hours. The stored energy is then discharged during the peak hours which reduce the net dispatched capacity requirement from marginal generator units and hence the associated emissions.

To assess the emissions mitigation potential of ESS used primarily for peak load reduction, we carried out the analysis in three steps: 1) Developing a baseline power system model based on fuel type and generator technology; 2) Using linear optimization model to determine ESS dispatch for minimizes daily peak load; and 3) Computing the net cost of emissions abatement using the average heat-rates of marginal units, cost of storage system, and revenue potential from energy and (when available) capacity markets for ESS. This study is novel because it assesses the environmental emissions abatement potential in the existing grid regions in U.S. through a historical load data and provides the cost of CO_2 abatement with this mechanism to compare it with other emissions mitigation approaches. The minimum and maximum size range studied for energy storage in this application is 100 MW to 1,000 MW, with storage capacity from 100 MWh to 6,000 MWh, each operated up to one cycle per day. The model is implemented for three grid regions: ERCOT, CAISO, and ISO-NE. The modeling approach is summarized in Figure-1.

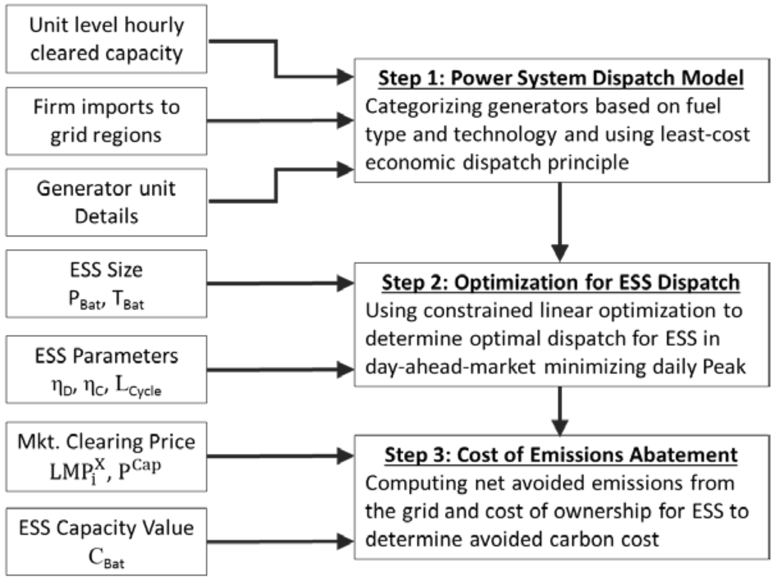


***Figure 1**: Modeling approach for evaluating the environmental impact of ESS on the grid with peak load shifting application*

2.1 Economic Dispatch Model

It was essential to develop an hourly baseline power system model to determine marginal power generating units. In current U.S. electricity markets, regional grid operators determine unit commitment and generator dispatch at varying time intervals (e.g., day-ahead, hour-ahead and real-time markets). In this study, the dispatched capacity of generator units is grouped together into categories based on the type of fuel used and generation technology. McCarthy and Yang used a similar approach in their effort to estimate the GHG emissions impact of plug-in hybrid electric vehicles in California.[47] The model uses a least cost-based ordering approach to establish a dispatch order where the generators are dispatched from low to high operational cost. The cost of generation for a resource depend on multiple factors including start-up cost, maintenance costs, unit type, fuel used, age, and load flexibility. To characterize the least cost principle in our simplified model, we used variable fuel cost for each category of power plant where the entire fleet is dispatched based on fuel consumption up to their maximum available capacity. Our dispatch model uses a simple merit-order approach to match supply with demand. The model moved through the queued set of plants types and dispatch the generation by fuel type until it meets the demand.

To develop a dispatch model the first step was to obtain the supply information. Power plants are represented in our models for each grid region are primarily based on the data from EPA

Clean Air Markets Program.[48] This database provides the unit level operating data for 2015 for each state. This database is supplemented with information from respective ISO's data archives for grid load, Energy Information Administration (EIA) Form 860 and EIA-923. [49,50] Table-1 provides a list of major input factors along with their respective data sources used in this work. The simulations presented here use the grid as it existed in 2014 for ERCOT and 2016 for CAISO and ISO-NE. Based on the type of fuel and technology, the generating units are categorized as: Renewables which include wind, solar, and biomass; hydropower; nuclear; coal; natural gas combined cycle (NGCC); natural gas steam turbines (NGST); natural gas combustion turbines (NGCT); and oil based combustion turbines. Non-dispatchable resources (typically renewable) are considered as firm dispatch on the grid and resulting net-load which is catered through dispatchable resources. The available capacity from dispatchable power plants are queued in same order as presented above for ascending variable cost. Due to low marginal cost nuclear resources assumed to appear lower in the dispatch order followed by coal and hydro resources. NGCC and NGST units provides the remaining generation capacity whereas the load ramp and peak capacity is provided by the less efficient NGCT and oil based combustion turbines.

Table 1: Summary of major datasets used in the economic dispatch model and their sources

Dataset	Source
Hourly demand	ISO's Data Archives[51,52,53]
Total annual imports	ISO's Data Archives
Unit prime mover type	Form EIA-860, 2016 U.S. EIA[54]
Unit prime mover fuel type	Form EIA-860, 2016 U.S. EIA[55]
Unit prime mover heat rate	Form EIA-923, 2016 U.S. EIA[56]
Unit hourly economic dispatch	Clean Air Markets Data Archives U.S. EPA[57]
Hourly nuclear production values	Power Reactor Status Reports, U.S. NRC[58]
Hourly renewable production values	ISO's Data Archives

In this study, we used a representative model for each of the following grid operator regions:

- **ERCOT**: It manages the production and distribution of electricity within a part of Texas which serves about 90% of the state and operates separately from the Eastern and Western Interconnections, with limited connectivity through five direct-current ties.
- **CAISO**: It constitutes about 80% of California's power grid which is divided into three sub-regions where exchange among the regions are limited due to transmission constraints.

- **ISO-NE**: It oversees the bulk electric power and transmission system primarily for six Northeastern states including Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, and Vermont.

***Figure 2**: Studied grid region. From left: (i) ERCOT; (ii) CAISO; (iii) ISO-NE*[59]

All three grid regions have significant natural gas capacity (ERCOT- 48%, CAISO- 32%, and ISO-NE- 53%) which allows charging constraint with NGCC units to be valid as marginal units.[60,61,62] ERCOT region has a peak load of 65GW and generates 347 TWh of electricity. Wind resources provide 11.7% of electricity used in ERCOT On the other hand, CAISO with the peak load of 45GW and annual electricity generation of 228 TWh, source 20% of its electricity supply from non-hydro renewable resources. In ISO-NE nuclear accounts for 26.3% of annual electricity use (105 TWh).[63,64,65] Given the interconnected nature of power grid, the spatial boundary of this study is limited to geographic extent of respective grid regions. Import and export transactions can represented a significant share of the capacity supply stack for studied areas. In 2016, CAISO imported about 26% of its electricity from other western grid regions and whereas ISO-NE met almost 17% of its electricity demand from Canadian sources.[66,67] Although in aggregate these regions reflect overall importing trends which can impact marginal units, the net flow of electricity from neighboring regions are assumed to remain constant in our analysis. Figure-3 summarizes the dispatch model results for January month in all the three grid region. It is observed that CAISO region has larger capacity of combustion turbines followed by ERCOT region. Whereas, natural gas based steam turbines accounts for higher marginal capacity in ISO-NE grid. Appendix-A shows the dispatch model results with the generation for summer, and winter months.

The simplifying, aggregate methods and the disparate data sources used for the model lead to some differences in generation and demand. To ensure that the model is a realistic representation of respective grid regions, dispatch results for generation capacity were compared to the historical grid load. As we do not model intra-zonal transmission and distribution (T&D), the losses associated with it are added to grid load based on historical average T&D loss rates of 7%.[68] The dispatch model needs to accurately capture the hourly variation on the grid load and difference in the unit type dispatch during off-peak and on-peak hours for determining the emissions from marginal units. On an average, the generated load profile by baseline model matches the demand on the grid. Modeled generation varies from historical load data by ±7.5% in some hours over the year, but is within 3.5% of the observed value when averaged over the year. The differences between the modeled results and historical values are also compared on annual generation mix. Appendix-B shows generation by fuel type for generators in each grid regions, showing close alignment of results for generator mix. The differences between the modeled results and historical values are modest and outweighed by year-over-year fluctuations in external trade through import/export.

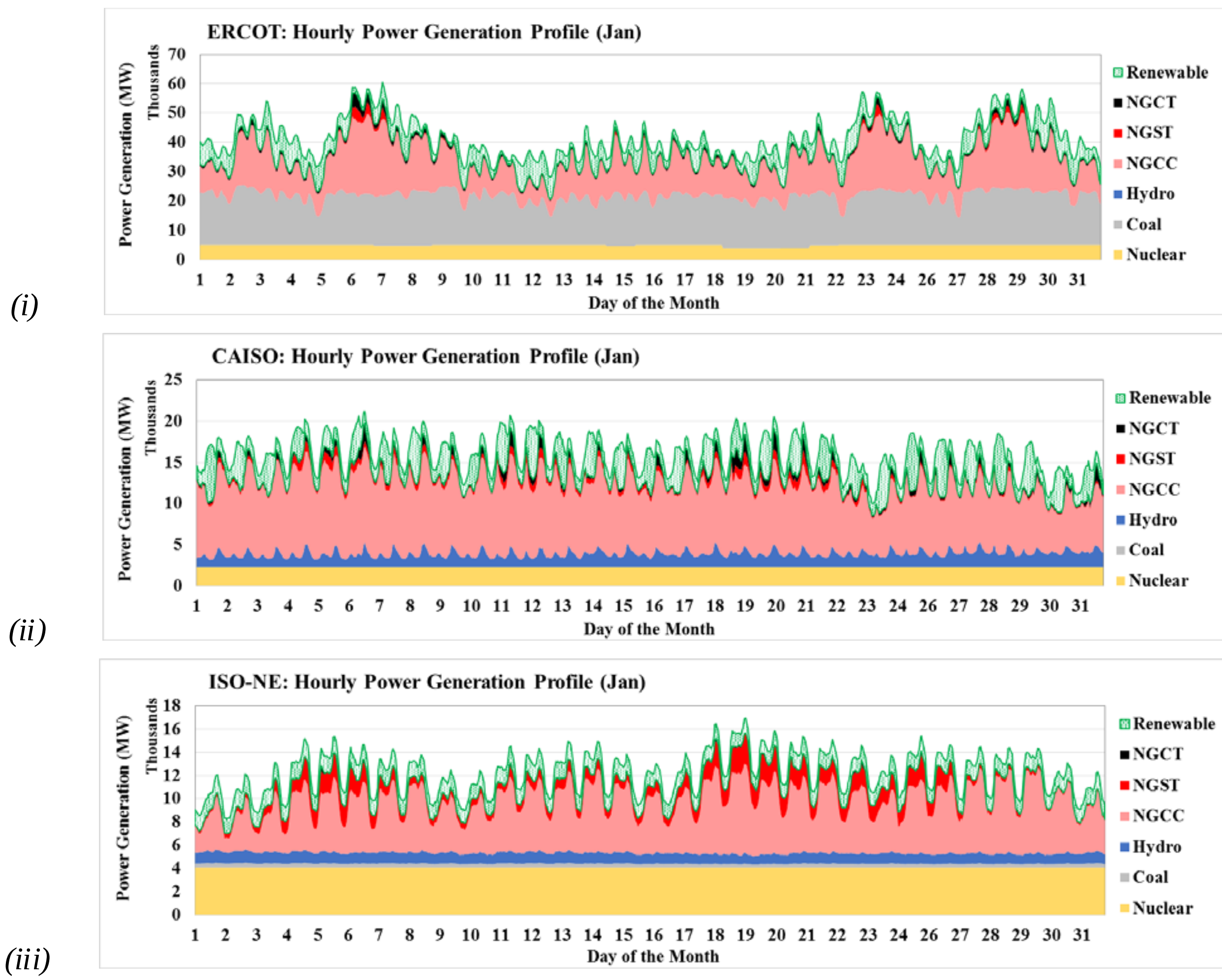


***Figure 3**: From top to bottom: Hourly resource mix stack from the economic dispatch model for the three grid regions (i) ERCOT; (ii) CAISO; (iii) ISO-NE*

2.2 Constrained Optimization Algorithm for ESS Dispatch

The net electricity demand (net-load[1]) is influenced by several factors such as temperature, renewable resource penetration, and variability of wind & solar resources. The hourly load shape is the dominant factor influencing the hourly dispatch of ESS. Therefore, for this study we modelled ESS to dispatch in the day-ahead energy market assuming perfect load forecast. In addition, ESS is constrained with one cycle per day starting from 12:00AM midnight. A MATLAB based linear program is developed to determine the optimal day-ahead hourly commitment for charging and discharging of ESS. The objective functions for the optimization model is to minimize the daily primary peak load [1-3] where the decision variables are the hourly discharging rate $P_{D,i}^{X}$, and hourly charging rate $P_{C,i}^{X}$, for each i^{X} hour of day X as demonstrated in Figure-4.

Objective Function:

$$\boldsymbol{f_1 = min \;\; PL^{X}} \qquad \forall \boldsymbol{X} \qquad \text{-----------} [1]$$

$$\boldsymbol{PL^{X} = max \;\; L_i^{X}} \qquad \forall \boldsymbol{X} \qquad \text{-----------} [2]$$

$$\boldsymbol{L_i^{X} = l_i^{X} - \left(P_{D,i}^{X} \times t\right) + \left(P_{C,i}^{X} \times t\right)} \qquad \forall \boldsymbol{X} \qquad \text{-----------} [3]$$

Decision Variables: $\boldsymbol{P_{D,i}^{X}}$ *and* $\boldsymbol{P_{C,i}^{X}}$

PL^{X} = *Peak load for day X (MW)*

L_i^{X} = *Net-grid load in i^th hour for day X with ESS dispatch model (MW)*

l_i^{X} = *Grid load in i^th hour for day X with baseline dispatch model (MW)*

$P_{D,i}^{X}$ = *ESS discharging rate in i^th hour on X day of the year (MW)*

$P_{C,i}^{X}$ = *ESS charging rate in i^th hour on X day of the year (MW)*

t = *Unit time step in the dispatch model (hr)*

ESS are typically measured in two dimensions: power rating (MW) and energy capacity (MWh). Power rating is represented by the maximum charging and discharging limit of the system. Power capacity is relevant for load-shifting because it represents the maximum potential by which an energy storage can reduce the peak load from the grid. Energy capacity of ESS determines the duration of potential displacement. The operation of the ESS is subject to both power and energy constraints. In addition, the charging and discharging efficiencies creates the ESS operational

[1] Net load on the grid is defined as = grid load – solar generation – wind generation

limits. Maximum hourly charging and discharging rate for ESS is constrained by the power rating of ESS as in eq. [4].

$$\mathbf{0} \leq \boldsymbol{P_{D,i}^{X}}, \boldsymbol{P_{C,i}^{X}} \leq \boldsymbol{P_{ES}} \qquad \forall\, \boldsymbol{i,X} \qquad \text{----------- [4]}$$

P_{ES} *= Power rating of ESS (MW)*

Similar to Rahimi's approach, our model uses a virtual discharging and charging bar on load shape to optimize ESS commitment in day-ahead market. We first identify the peak load PL^{X} and the peak load hour i_{P}^{X} for each X day and determines the adjacent hours for potentially discharging the ESS for minimizing the daily peak.[69] Likewise, the model determines the minimum grid load and off-peak hour before the daily peak for potentially charging the ESS. As shown in Figure-5, the model uses a discharge bar AB over the daily peak load and slide it down to determine displaced generation capacity from the grid for each hour. The length of shaved load for each hour $P_{D,i}^{X}$ is constrained by [4]. A similar charging bar is placed below minimum load hour occurring before the daily peak load where hourly charging rate $P_{C,i}^{X}$ is constrained by [4]. The total quantity of peak reduction and added capacity is governed by energy constraints [5-7]. The iterative process balances the charging and discharging of ESS determining the decision variables to optimize the primary objective function. In each iterative cycle the model monitors the state of charge (SOC) for ESS. The change in SOC affect the ability of ESS to meet the discharging or charging objective in the model. Compared to central station power plants, the lifetime of battery energy storage systems is quite short, and its replacement cost has great impact on it overall economic performance. To minimize the degradation caused by low SOC, the ESS are constrained to operate between a minimum and maximum SOC threshold [8]. The system is solved chronologically starting from January 1st with ESS at SOC_{Min}^{ES}. For each day the objective function utilizes upto maximum capacity of ESS SOC_{Max}^{ES} that satisfy all the constraints and discharge the unit to SOC_{Min}^{ES} level by end of each day [9].

$$\sum_{i=0}^{24}\left(\boldsymbol{P_{D,i}^{X}} \times \boldsymbol{t}\right) \leq \boldsymbol{\eta_{D}} \times \boldsymbol{E_{ES}} \times \left(\mathbf{1} - \boldsymbol{SOC_{Min}^{ES}}\right) \qquad \forall\, \boldsymbol{X}$$

----------- [5]

$$\sum_{i=0}^{24}\left(\boldsymbol{P_{C,i}^{X}} \times \boldsymbol{t}\right) \leq \frac{\boldsymbol{E_{ES}} \times \left(\mathbf{1} - \boldsymbol{SOC_{Min}^{ES}}\right)}{\boldsymbol{\eta_{C}}} \qquad \forall\, \boldsymbol{X}$$

---------[6]

$$\sum_{i=0}^{24}\left(\boldsymbol{P}_{D,i}^{X}\times\boldsymbol{t}\right)=\boldsymbol{\eta}_{D}\times\boldsymbol{\eta}_{C}\times\sum_{i=0}^{24}\left(\boldsymbol{P}_{C,i}^{X}\times\boldsymbol{t}\right)\qquad\forall\ \boldsymbol{X}$$

---------[7]

$$\boldsymbol{SOC}_{Min}^{ES}\leq\ \boldsymbol{SOC}_{i}^{X}\ \leq\boldsymbol{SOC}_{Max}^{ES}\qquad\forall\ \boldsymbol{i},\boldsymbol{X}\qquad\text{---------[8]}$$

$$\boldsymbol{SOC}_{0}^{X}=\ \boldsymbol{SOC}_{24}^{X}\ =\ \boldsymbol{SOC}_{Min}^{ES}\qquad\forall\ \boldsymbol{X}\qquad\text{---------[9]}$$

E_{ES} = *Energy rating of ESS (MWh)*

SOC_{Min}^{ES} = *Minimum State of Charge for ESS (%)*

SOC_{Max}^{ES} = *Maximum State of Charge for ESS (%)*

SOC_{i}^{X} = *State of charge in* i^{th} *hour and X day or the year (%)*

η_D = *ESS discharging efficiency (%)*

η_D = *ESS charging efficiency (%)*

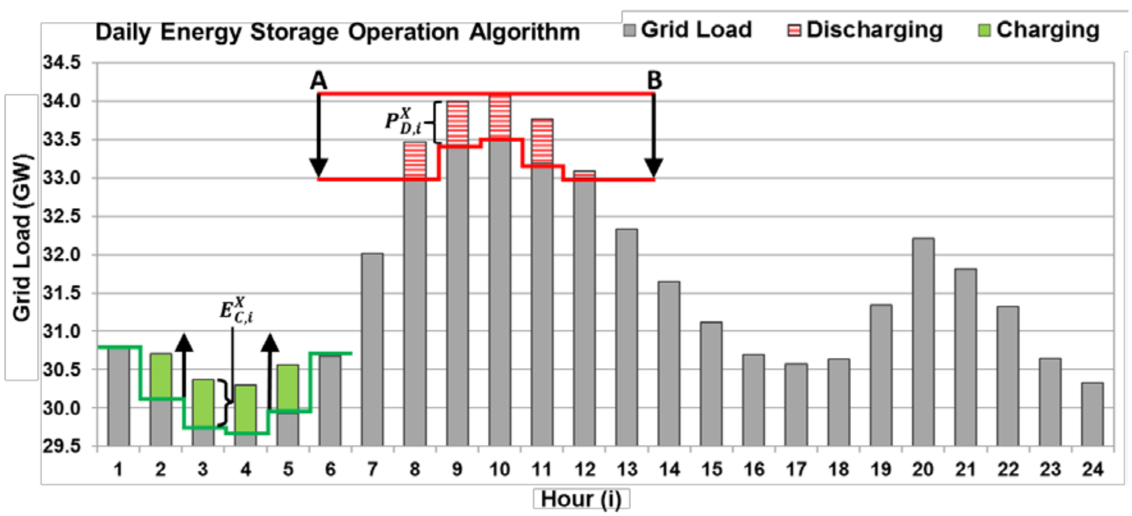


Figure 5*: Example results for peak load shifting*

The primary objective for ESS is to provide resource adequacy service on the grid by reducing the peak load and displacing the marginal generator capacity during the peak hours. Using the results from the constrained ESS dispatch optimization model, the new net-load profile is determined as in eq. [3] and the economic dispatch model from section 2.1 is deployed to identify the change in the required generator capacity.

For peak load shifting application, several energy storage technologies offer the most suitable characteristics including pumped-hydro storage, flow batteries, lead-acid batteries, lithium-ion batteries, and sodium-sulfur batteries. These advanced battery systems can be utilized with existing infrastructure, helping energy providers to meet peak demands while contributing towards the reserve margin targets. Table-3 list the potential energy storage technologies considered within this study and their respective system parameters for the optimization problem.

2.3 Environmental Impact Assessment

As identified by Arbabzadeh et al., a key principle in achieving environmental benefits from energy storage is to "charge clean, displace dirty. Factors that influence this include: the emissions from generators displaced, the emissions from charging generators and the round-trip efficiency of ESS technology.[70] During the operation of ESS for peak load shifting emissions from displaced marginal generators are avoided in exchange for emissions from additional marginal units brought online to charge the ESS. To evaluate the change in CO_2 emissions with use of ESS, we compared the baseline dispatch model from section 2.1 with the constrained ESS dispatch model in section 2.2 for a year-round to obtain the net displaced and added generator schedule for each hour. The generators that are attributed with charging the energy storage system are NGCC units in all the three grid regions because each region have high penetration of NGCC units which serves as the marginal units during the non-peak hours. The units that are displaced by the discharge of the ESS, are typically the marginal NGCT and NGST generators. However, for the high penetration cases of ESS, NGCC are also displaced to minimize the peak load. The emissions associated with thermal generators are defined by the heat rate (HR) and the avoided emissions are attributed to less fuel consumption on the grid for electricity generation by shifting the load units with lower HR. However, this comes at the cost of round-trip losses in ESS which is captured in the constrained dispatch of ESS and the net-load profile. Because we categorized the generator units based on fuel and technology type, we are using annual average heat rate (Btu/kWh) for generator type from U.S. EIA 2015 database instead of actual heat rate of individual generator unit. Although this introduces a small error into our model, we are primarily interested in annual marginal emissions changes, and therefore we expect the effect of this error to be relatively small. With the average heat rate for combustion turbines and combined cycle power plants, net CO_2 emissions avoided from the grid during the use phase of ESS, $\boldsymbol{NEA_{NG}^{Use}}$ is computed using eq [12].

In this study, we investigate CO_2eq emissions only, however this model can be applied to other impact factors as well.

$$\left(P_{D,i}^{X} \times t\right) = E_{di\_CT}^{X} + E_{di\_ST}^{X} + E_{di\_CC}^{X} \qquad \text{-----------} [10]$$

$$\left(P_{C,i}^{X} \times t\right) = E_{ci\_CC}^{X} \qquad \text{-----------} [11]$$

$$NEA_{NG}^{Use} = f_{NG}^{Comb} \sum_{X=1}^{365}\left[\left\{HR_{CT} \times \sum_{i=1}^{24} E_{di\_CT}^{X}\right\} + \left\{HR_{ST} \times \sum_{i=1}^{24} E_{di\_ST}^{X}\right\} - \left\{HR_{CC} \times \sum_{i=1}^{24}\left(E_{ci\_CC}^{X} - E_{di\_CC}^{X}\right)\right\}\right] \qquad \text{-----------} [12]$$

$EAOI$ = *Emissions avoided over emissions invested*
NEA_{NG}^{Use} = *Net CO_2 Emissions Avoided from NG combustion*
f_{NG}^{Comb} = *NG Combustion emissions factor*
HR_{CT} = *Heat Rate for NG Combustion Turbines (CT) Power Plants*
HR_{ST} = *Heat Rate for NG Steam Turbines (CT) Power Plants*
HR_{CC} = *Heat Rate for NG Combined Cycle (CC) Power Plants*
$E_{di\_CT}^{X}$ = *Displaced CT in i^{th} hour on X day of the year*
$E_{di\_ST}^{X}$ = *Displaced ST in i^{th} hour on X day of the year*
$E_{di\_CC}^{X}$ = *Displaced CC in i^{th} hour on X day of the year*
$E_{ci\_CT}^{X}$ = *Added CC in i^{th} hour on X day of the year*

In addition to emissions associated with combustion at power plants, we considered upstream and downstream emissions associated with natural gas production and battery materials, manufacturing, and disposal. Note that a complete comparative life cycle assessment of using ESS as an alternative to conventional peaker unit would also need to consider the materials and manufacturing burdens associated with the power plant itself. The production burdens for the avoided fuel use (NG) can be approximated using the fuel upstream emissions burden factor f_{NG}^{Up}. However, comparison of upstream and end of life emissions for ESS with the displaced peaker units is challenging because many units have been in service on the grim for over 2-20 years and some of them can potentially be deployed for alternative ancillary services instead of retirement. Allocation of these emission require thorough assessment of each individual unit. A systematic comparison of ESS are so far only available for either complete replacement of existing units or as an alternative option for new capacity. Energy returned on invested (EROI) metric has been commonly adopted in assessment of fuels and energy systems as it incorporates both the primary energy inputs to the system and the usable energy. [71,72] Barnhart and Benson presented a similar concept for evaluating the electrical ESS using the energy stored on energy invested (ESOI) metric.[73] The ESOI use the net energy stored over the life-time of an ESS system and accounts for the production burden in denominator to determine the effectiveness. Motivated by such analysis we present a novel method to assess the effectiveness of emissions abatement from ESS: emissions avoided on emissions invested (EAOI). EAOI, eq [13], is the ratio of net emissions avoided on life-cycle bases from the fuel combustion to the net emissions burden from the production of ESS. Similar to eq [11], net CO_2 emissions avoided from the production phase of fuel use $\boldsymbol{NEA_{NG}^{Up}}$ is computed using the upstream emissions factor $\boldsymbol{f_{NG}^{Up}}$ in eq [14]. We amortized the embodied emissions in the ESS to allocate the production burden for one year of operation [15].

$$\boldsymbol{EAOI = \frac{NEA_{NG}^{Use} + NEA_{NG}^{Up}}{NPB_{ES}^{Up}}}$$

----------- [13]

$$\boldsymbol{NEA_{NG}^{Up} = f_{NG}^{Up} \sum_{X=1}^{365} \left[\left\{ HR_{CT} \times \sum_{i=1}^{24} E_{di_{CT}}^{X} \right\} + \left\{ HR_{ST} \times \sum_{i=1}^{24} E_{di_{ST}}^{X} \right\} - \left\{ HR_{CC} \times \sum_{i=1}^{24} \left(E_{ci_{CC}}^{X} - E_{di_{CC}}^{X} \right) \right\} \right]}$$

----------- [14]

$$\boldsymbol{NPB_{ES}^{Up} = \left(\frac{f_{ES-P}^{Up} \times P_{ES} + f_{ES-E}^{Up} \times E_{ES}}{L_{ES-Life}} \right)}$$

----------- [15]

$\boldsymbol{NEA_{NG}^{Up}}$ = *Net CO_2 Emissions Avoided from NG production*
$\boldsymbol{NPB_{ES}^{Up}}$ = *Levelized Net Production Burden for ESS*
$\boldsymbol{f_{NG}^{Up}}$ = *NG Upstream emissions factor*
$\boldsymbol{f_{ES-E}^{Up}}$ = *Energy Storage production burden – Storage capacity dependent*
$\boldsymbol{f_{ES-P}^{Up}}$ = *Energy Storage production burden – Power rating dependent*
$\boldsymbol{L_{ES-Life}}$ =*Service life of energy storage system*

2.4 Cost of Emissions Abatement

The goal for this study was to help us investigate the cost-effectiveness of using energy storage primarily for CO_2 abatement from the grid. Emissions abatement policies like cap and trade or carbon taxes have significant consequences in electricity markets as they affect the operating margins for fossil fuel based generators. In order to compare the cost-effectiveness of energy storage, we computed the cost of ownership for the ESS and net revenue potential to determine the cost of CO_2 abatement $\boldsymbol{C_{CO_2}}$ from the grid in the use phase as \$/ton.CO_2 [16]. The regional electricity markets in U.S. typically encompass three classes of service: energy, capacity, and ancillary services. Energy service relates to the physical delivery of power, capacity service addresses the resource adequacy for the grid by ensuring the availability of sufficient generation capacity during peak load, and the ancillary service market provides remaining grid support services. The following section explains the revenue potential assessment methodology for evaluating ESS.

$$\boldsymbol{C_{CO_2}} = \frac{\boldsymbol{NCO_{ES}}}{\boldsymbol{NEA_{NG}^{Use}}} \qquad \text{----------- [16]}$$

Where $\boldsymbol{NCO_{ES}} = \boldsymbol{LCC_{ES}} - \boldsymbol{R_{EA}} - \boldsymbol{R_{CV}}$

$\boldsymbol{LCC_{ES}}$ = *Levelized capital cost of energy storage*

$\boldsymbol{R_{EA}}$ = *Annual revenue from Energy Arbitrage by ESS*

$\boldsymbol{R_{CV}}$ = *Annual revenue from capacity market by ESS*

2.4.1 Levelized Cost of Energy Storage

The estimated cost of ownership for ESS depends on several parameters including the net capital cost of the system and the revenue potential. There are several studies and reviews in the literature that provides the cost of ESS, however, there is hardly any consensus on the capital cost for any energy storage technology. Zakeri, and Syri in their comprehensive life cycle cost review found that the Li-ion cost assumption in the literate have been to between \$283-683/kW for power and \$470-1249/kWh for energy cost.[74] Schmidt et. al used the experienced based cost curves to predict the aggregated cost of utility scale Li-ion battery energy storage systems to be \$461/kWh by 2030.[75] The life of ESS also plays a critical role in determining the annual cost of ownership. The life-time of each energy storage technology is based on 365 operating cycles per year for peak-load shifting application. Using annual discount rate of 5 percent, the levelized capital cost is computed for ESS in eq [17]. In addition to the capital cost, a 1.5% additional annual operation and maintenance cost is assumed over the lifetime of ESS.

$$\boldsymbol{LCC_{ES}} = \left(\boldsymbol{P_{ES}} \times \boldsymbol{C_{ES}^{P}} + \boldsymbol{E_{ES}} \times \boldsymbol{C_{ES}^{E}}\right) \times (\boldsymbol{r_{CRF}} + \boldsymbol{r_{O\&M}}) \qquad \text{----------- [17]}$$

$$\boldsymbol{r_{CRF}} = \boldsymbol{I} \times \left[\frac{(\mathbf{1}+\boldsymbol{I})^{\boldsymbol{L_{ES-Life}}}}{\{(\mathbf{1}+\boldsymbol{I})^{\boldsymbol{L_{ES-Life}}}-\mathbf{1}\}}\right]$$

$\boldsymbol{r_{CRF}}$ = *Capital recovery factor*

$\boldsymbol{r_{O\&M}}$ = *Annual operation and maintenance cost (fixed as % of capital cost)*

$\boldsymbol{I}$ = *Discount Rate*

$\boldsymbol{C_{ES}^{P}}$ = *Power dependent capital cost of energy storage system*

$\boldsymbol{C_{ES}^{E}}$ = *Energy dependent capital cost of energy storage system*

2.4.2 Energy Arbitrage Value

Resource in energy markets are compensated with the locational marginal price (LMP) which is the marginal cost of supplying, at least cost, the next increment of electric demand at a specific location (node) on the electric power network. LMP's are typically higher during the peak hours due to lower HR for marginal units. With the load shifting application ESS capitalize on the energy arbitrage by charging at a cheaper rate and getting compensated with higher LMP for discharging during peak hours [18].

$$\boldsymbol{R_{EA}} = \sum_{\boldsymbol{X}=\mathbf{1}}^{\mathbf{365}} \sum_{\boldsymbol{i}=\mathbf{1}}^{\mathbf{24}} \left\{\left(\boldsymbol{E_{D,i}^{X}} - \boldsymbol{E_{C,i}^{X}}\right) \times \boldsymbol{LMP_{i}^{X}}\right\}$$

----------- [18]

$\boldsymbol{LMP_{i}^{X}}$ = *Historical clearing locational marginal price for i^th hour on X day*

2.4.3 Capacity Value

Generator assets are compensated in capacity market based on their capacity value, which is the capability of a resource to provide firm energy in the hour of need, typically during the peak load period or in a contingency event when adequate generation is not available. The capacity value is measured as the percentage of nameplate capacity for a generator resource. With peak shaving applications ESS can potentially obtain capacity credit and generate additional revenue for its resource adequacy service. However, the capacity and reliability benefits of ESS are less acknowledged by grid operators. Today some regions do account for capacity value of ESS which is the function of both the power rating and energy capacity. CAISO classify energy storage as a non-generator resource with effective flexible capacity (EFC) as the output power that can cater the grid load for 3 hours. The EFC of an ESS is qualified for capacity payment in the market. In other regions ESS are classified as a non-generator resource because they are limited by energy storage capacity and hence contribute to reserve margin on a discounted basis. Several studies in literature have established a capacity value for energy storage systems based on their duration of storage. However, there is no consistent and standardized approach across these studies to recognize the capacity benefits. In order to consider the appropriate incentive for the reliability service from peak load shifting application the capacity credit for an ESS system is computed using the dispatch model as the average daily peak load reduction over power rating of ESS [19]. This incorporates the incremental capacity benefits for the higher energy to power ratio in our model for catering the peak load. To compute the revenue potential from capacity market historical capacity prices are considered for respective grid regions [20]. Unlike CAISO and ISO-NE, ERCOT is energy only market. Hence, the capacity revenue are assumed to be zero for ERCOT.

$$\boldsymbol{Cap^{Cr}} = \frac{\mathbf{1}}{\mathbf{365}} \times \sum_{X=1}^{365} \frac{\boldsymbol{Max}\left(\boldsymbol{l_i^X}\right) - \boldsymbol{Max}\left(\boldsymbol{L_i^X}\right)}{\boldsymbol{P_{ES}}} \qquad \text{----------- [19]}$$

$$\boldsymbol{R_{CV}} = \boldsymbol{Cap^{Cr}} \times \boldsymbol{P_{ES}} \times \boldsymbol{P^{Cap}} \qquad \text{----------- [20]}$$

$\boldsymbol{Cap^{Cr}}$ = *Capacity Credit of ESS*

$\boldsymbol{Max}\left(\boldsymbol{l_i^X}\right)$ = *Peak Load for day X in baseline dispatch model*

$\boldsymbol{Max}\left(\boldsymbol{L_i^X}\right)$ = *Peak Load for day X in ESS constrained dispatch model*

$\boldsymbol{P^{Cap}}$ = *Capacity price*

Table 2: Grid Application Assumptions for ESS Model

Input parameters	Units	Variable	Values	Sensitivity Cases
ESS Power Rating	MW	P_{ES}	100 - 1000	--
ESS Capacity	Hr	T_{ES}	1 - 6	--
Number of ESS Full Cycles [a]	per Year	$L_{ES-Life}$	365	--
Study period [b]	Year	n	1	--
Natural Gas Emissions Factor				
Upstream [76]	kg of CO_2eq/MMBtu	f_{NG}^{Up}	13.63	± 10%
Combustion [77]	kg of CO_2eq/MMBtu	f_{NG}^{Comb}	53.07	--
Heat Rates [78]				
Natural Gas Turbines	Btu/kWh	HR_{CT}	11,302	± 10%
Natural Gas Steam Turbines	Btu/kWh	HR_{ST}	10,372	± 10%
Natural Gas Combined Cycle	Btu/kWh	HR_{CC}	7,655	± 10%
Discount Rate	%	I	5	± 2%

[a] *ESS are constrained to operate for one cycle per day to shave daily primary peak*
[b] *ESS system emissions abatement is studied for one annual cycle from Jan – Dec for each grid region*

Table 3: Energy Storage Systems Parameters

Parameter	Units	Variable	VRFB	PbA	NaS	Li-ion
Operation Parameter						
Round-trip efficiency	%	$\eta_D \times \eta_C$	82.5 [79]	80 [80]	80.5 [81]	85 [82]
Service life	Years	$L_{ES-Life}$	10	9	10	13
Production Burden [83]						
Energy Dependent	kg CO_2/MWh	f_{ES-E}^{Up}	104,400	114,933	67,820	35,700
Power Dependent [a]	kg CO_2/MW	f_{ES-P}^{Up}	160,000	160,000	160,000	160,000
Cost of ESS [84]						
Capital Cost- Power	$/kW	C_{ES}^{P}	490	378	366	463
Capital Cost- Energy	$/kWh	C_{ES}^{E}	467	463	298	795
O&M Cost [b]	% of CapEx	$r_{O\&M}$	1.5%	1.5%	1.5%	1.5%

[a]*This component of energy storage production burden is held constant due to the lack of data*
[b]*O&M costs are assumed to be same across all the energy storage technology type*

3. Results

3.1 Emissions Abatement Potential

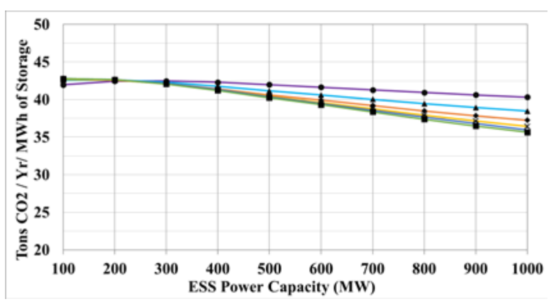
The net emission impact of using ESS on the grid for resource adequacy service depends on both the avoided emissions in the use phase and the upstream emissions burden. Figure-6 demonstrates the net emissions abatement potential of various ESS sizes with Li-ion battery technology. The results for other technologies are provided in Appendix C for respective grid regions. For each ESS size the avoided combustion emissions from the fuel use is normalized by the energy capacity (MWh) of the system to understand the net impact of incremental storage capacity on the grid. The first 100MWh of energy storage on the grid has the highest emissions reduction potential of 42 ton-CO_2/MWh as energy storage majorly displaces marginal combustion turbines across all the grid regions. As the capacity penetration of ESS increased to 6000 MWh, the annual emissions reduction potential reduces to 35 ton-CO_2/MWh in ERCOT and 30 ton-CO_2/MWh ISO-NE grid. Whereas, in CAISO region emissions reduction potential remains close to 40 ton-CO_2/MWh of storage even with 6000 MWh of ESS capacity because it has high higher share of peaker units (7.8%) in its energy mix. Round-trip efficiency of ESS technologies influence the displaced marginal unit capacity and the emissions abatement by avoided fuel use. Like in Figure-6, increased penetration on the grid across all the battery technologies lead to similar decremental trend in emissions abatement as for Li-ion batteries (Appendix C). However, with lower round-trip efficiencies their respective abatement potential is considerably lower than Li-ion ESS. These values are further used to determine the net cost of emission abatement.

Figure 6 and Appendix C also shows the EAOI for respective ESS technology, representing net environmental benefits relative to production burden of ESS. Across all the technology type EAOI is greater than one which means for all the ESS configurations the peak load shifting application result in net emissions reduction on life-cycle basis. EAOI for a given ESS technology depends of multiple parameters including energy dependent production burden factor, round trip efficiency, and life-time of the system. For all four ESS technologies studied and in all three grid regions, increased penetration of ESS (MW) leads to lower EAOI ratio. This is primarily due to diminishing emissions abatement potential with higher storage capacity because the production burden associated with the power rating is assumed to be consistent across all technologies.

Furthermore, among the all the four technologies Li-ion batteries have superior performance due to its higher efficiency, life-time, and lowest production burden associated with energy capacity. However, energy dependent upstream emissions burden is relatively lower across all the technologies when compared to power dependent burden. Hence, with higher storage capacity (hrs) the EAOI ratio is improved significantly in each grid regions. For all the three grid regions first 100 MW of ESS with 600 MWh capacity offers highest life-cycle environmental benefits relative to its production burden.

	Avoided CO_2 emissions from fuel combustion	Emissions avoided over emissions invested (EAOI)

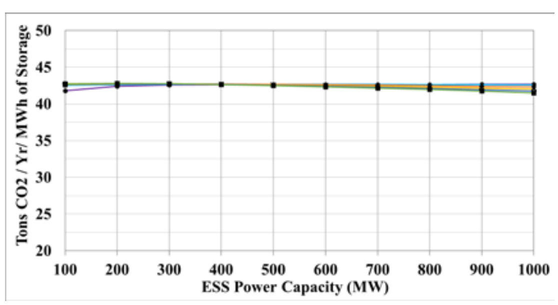
ERCOT



Power Rating (MW)

Energy Capacity (hr)	100	200	300	400	500	600	700	800	900	1000
1	3.5	3.5	3.5	3.5	3.5	3.5	3.4	3.4	3.4	3.4
2	6.0	6.0	6.0	5.9	5.8	5.7	5.7	5.6	5.5	5.4
3	7.8	7.8	7.7	7.6	7.5	7.3	7.2	7.1	6.9	6.8
4	9.2	9.2	9.1	8.9	8.7	8.5	8.4	8.2	8.0	7.9
5	10.3	10.3	10.2	10.0	9.7	9.5	9.3	9.1	8.9	8.7
6	11.2	11.2	11.0	10.8	10.5	10.3	10.0	9.8	9.6	9.3

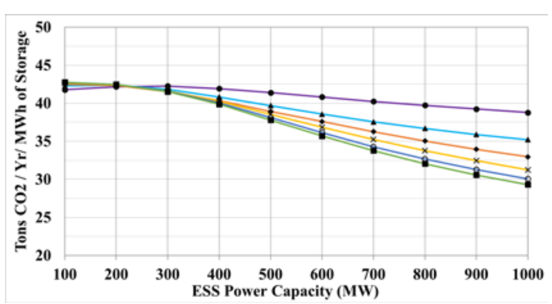
CAISO



Power Rating (MW)

Energy Capacity (hr)	100	200	300	400	500	600	700	800	900	1000
1	3.5	3.5	3.6	3.6	3.6	3.6	3.6	3.6	3.6	3.6
2	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0
3	7.8	7.8	7.8	7.8	7.8	7.8	7.8	7.8	7.8	7.8
4	9.2	9.2	9.2	9.2	9.2	9.2	9.2	9.1	9.1	9.1
5	10.3	10.3	10.3	10.3	10.3	10.2	10.2	10.2	10.1	10.1
6	11.2	11.2	11.2	11.2	11.1	11.1	11.0	11.0	10.9	10.9

ISO-NE



Power Rating (MW)

Energy Capacity (hr)	100	200	300	400	500	600	700	800	900	1000
1	3.5	3.5	3.5	3.5	3.5	3.4	3.4	3.3	3.3	3.2
2	6.0	6.0	5.9	5.8	5.6	5.4	5.3	5.2	5.1	5.0
3	7.8	7.8	7.6	7.4	7.1	6.9	6.7	6.4	6.2	6.0
4	9.2	9.1	9.0	8.7	8.3	8.0	7.6	7.3	7.0	6.7
5	10.3	10.2	10.0	9.7	9.2	8.7	8.3	7.9	7.5	7.3
6	11.2	11.1	10.9	10.4	9.9	9.3	8.8	8.4	8.0	7.7

1 Hr   2 Hr   3 Hr   4 Hr   5 Hr   6 Hr

EAOI	3.0	4.0	5.0	6.0	7.0	8.0	9.0	10.0	11.0	12.0

Figure 6*: Emissions avoided from the grid with the use of lithium-ion battery energy storage systems for peak load shifting application in three U.S. grid regions with variable power and energy storage capacity. Life cycle CO_2 emissions are represented using the EAOI ratio which*

incorporates both: upstream production burdens for batteries & fuel and use phase avoided emissions from fuel combustion

3.2 Capacity Value of Energy Storage Systems

Recognizing the capacity value contribution of ESS is important to ensure proper compensation for their resource adequacy service and incentivizing its deployment on the grid. The value of ESS capacity in this study is based on the degree to which it contributes to the reliability of the electric supply system by reducing the daily peak demand. The capacity credits computed for ESS sizes are summarized in Figure 7. Across all the grid regions, the first one-hour block of stored energy provides the maximum capacity benefits and the incremental benefits from subsequent blocks of stored energy begin to diminish. For example, in CAISO grid for a 1000 MW system the first one-hour block provides 45% capacity value, while the second one-hour block provides 24% additional capacity value (for a total of 69%). This is because the value of the first one-hour block of energy stored captured the maximum load reduction in peak hour. The subsequent block of storage operates in the shoulder hours and therefore provides lower reliability benefits than their rated capacity. Although, ERCOT do not have a capacity market, but it is observed that the ESS system with 4 hours of storage capacity can provides nearly 100% capacity benefits primarily by peak load reduction. A similar increasing capacity value trend is observed in CAISO and ISO-NE grid for longer duration of storage. CAISO and ISO-NE regions have relatively lower capacity value because these regions observe primary peak in earlier in the day limiting charging period for ESS, and have higher secondary peak load. Across all the three regions first 100 MW obtains higher capacity credit and as more storage capacity is integrated on the grid their capacity credit is reduced.

In addition to the resource adequacy services of ESS, the benefits from a grid planning perspective also play an important role in determining the correct incentives. As seen in section 3.1, ESS enables the use of efficient generators on the grid and this is demonstrated from the improvement in the grid load factor (LF) as shown in Figure 7. Load factor is defined as the average energy load on a system as compared to its peak load for a given period. A higher load factor is advantageous for grid operators because existing energy resources on the grid can be utilized more effectively leading to their higher capacity factor (CF). This essentially spreads the fixed costs of resources over more kWh of output, resulting in lower cost of electricity generation per unit ($/kWh). Shifting the peak load flattens the load duration curve by increasing the utilization of existing resources through charging and reducing the peak demand from the grid through discharging. The increase in load factor is because of both: improvement in the average load and reduction in peak load. Across all the three regions as the penetration of ESS capacity (MW) increases on the grid, higher storage duration (hrs) leads to greater improvement in the load factor. With the lowest annual peak load, ISO-NE regions observes the highest potential of over 4.3% improvement in LF with 6000 MWh followed by CAISO (2.45%) and ERCOT (1.5%).

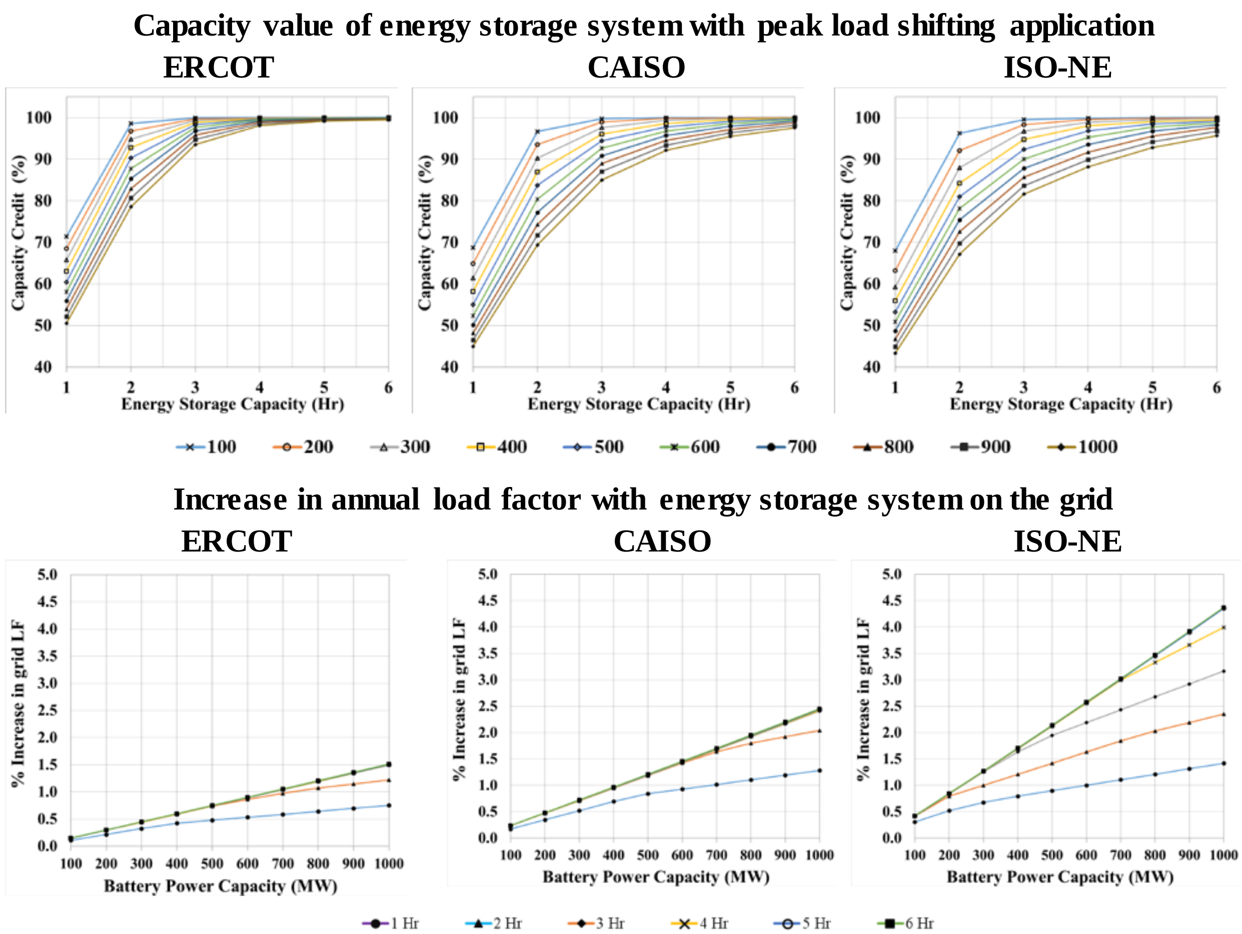


***Figure 7**: Capacity Value of battery energy storage system in the constrained economic dispatch model computed as average daily peak load reduction over the power rating on ESS. Impact on grid load factor is also summarized for the grid regions where shifting the peak load using ESS flattens the load duration curve and essentially increases the LF.*

3.3 Value Proposition and cost of emissions abatement

Figure-8 shows the results of the cost assessment for ESS in the three grid regions for peak load shifting with Li-ion battery technology. The results for VRFB, NaS, and PbA technology is provided in Appendix D. As shown in Figure-8, the net revenue potential for ESS increases with more deployment of storage systems on the grid. However, decreasing slope across all the storage capacity (MW) curves on the grid demonstrates that the marginal revenue reduces for longer duration of energy storage. Due to lack of capacity market ERCOT regions has higher marginal prices during peak hours and hence the highest energy arbitrage potential among all the three grid regions. In CAISO region resource adequacy mechanism offers additional revenue potential for ESS owners through bilateral contracts with load serving entities. Whereas, capacity payment through annual auctions in ISO-NE region provides the capacity value to ESS. Although, capacity credit is higher for longer duration of storage capacity (Figure-7), the net share of capacity value in total revenue reduces in both the regions and energy arbitrage becomes increasingly important.

The emissions abatement cost computed here incorporates all the parameters of grid and storage system through amortized cost of storage (shown in Appendix E), net revenue, and emissions abated in the use-phase from the grid. As shows in Figure-8, the cost of emissions abatement is lower with first 100 MW of storage on the grid across all the three regions. As the storage capacity is scaled up, the incremental cost of storage outweighs the increase in annual revenues and reduction in CO_2 emission. Longer duration of storage capacity improves the cost performance as the energy dependent cost component is compensated through higher capacity credits for storage systems. As seen in Appendix D, across all the technologies NaS batteries will result in lowest cost of abatement due to its lower investment cost and higher life-time.

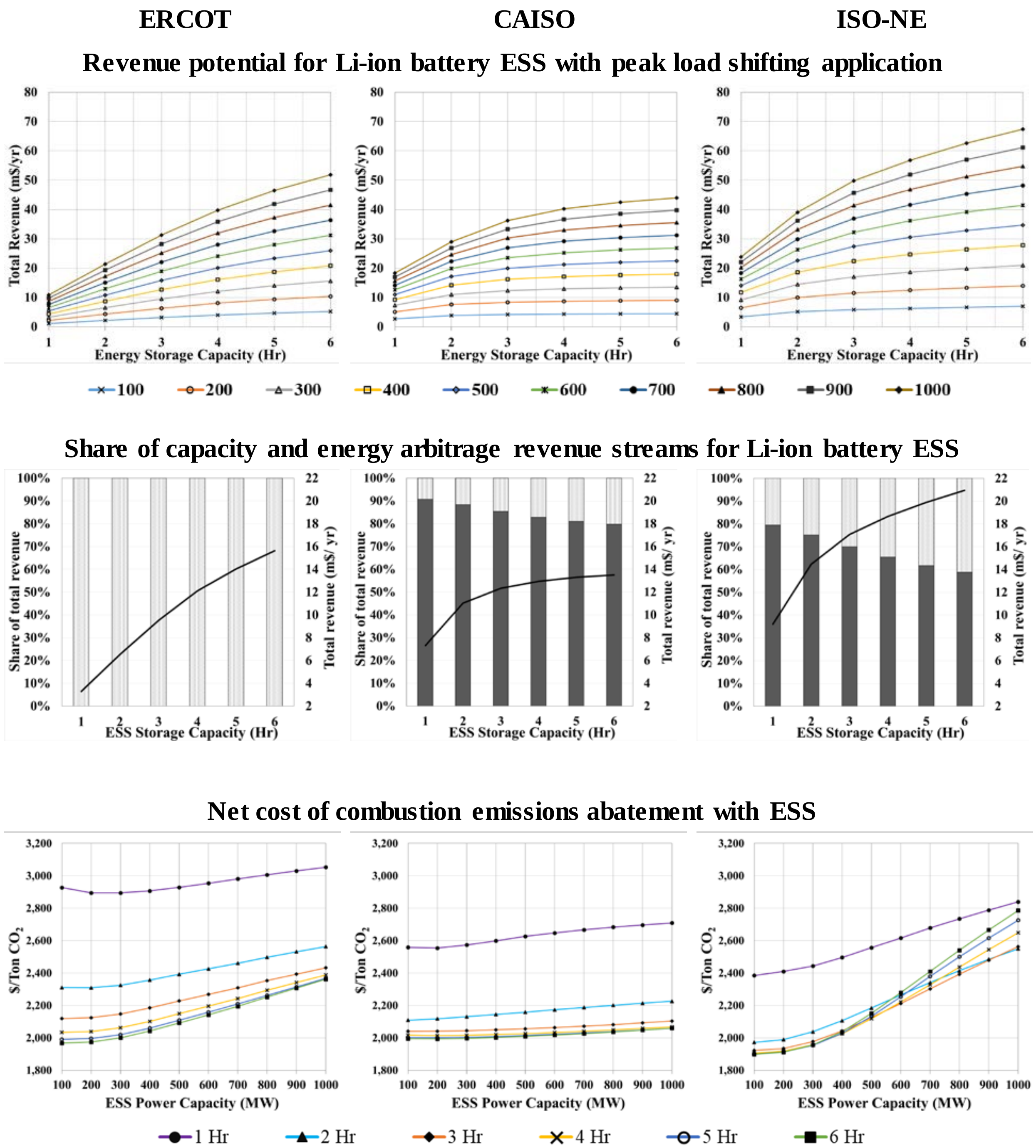


***Figure 8**: Net revenue potential for ESS across the grid regions based on capacity penetration and various duration of storage. Revenue breakdown is shown from energy arbitrage and capacity markets for 300MW ESS system. Using the emissions avoided in the use phase and levelized cost of storage, net emissions abatement cost trend is determined where each additional storage unit yielding higher marginal cost of CO_2 abatement from the grid*

4. Discussion

The integration of ESS into the grid can lead to a wide range of environmental impacts and understanding the net environmental impact of using ESS for power grid services requires the integration of LCA and power systems analysis. The marginal generator units are identified on the grid for determining the changes to the power system with integration of ESS. Linear optimization model is developed to determine the hourly dispatch of energy storage for minimizing the daily peak load. This research suggests that energy storage integration shows promise for lowering the total life cycle emissions with peak load shifting application. Results shows that energy storage can potentially reduce 30-42 tonCO_2/MWh of storage capacity from the studied grid regions. Although, the cost of the battery energy storage is quite high and can change the results significantly, the cost of avoided carbon emissions with peak load shifting application of energy storage is uneconomical compared to alternative mechanisms. The abatement cost only considers the avoided combustion emissions of the fuel, but the net cost of emissions abatement depends on marginal units on the grid during charging hours, production burden for battery system & fuel, and revenue potential from power markets.

The marginal generator unit on the grid is highly sensitive to number of parameters and the marginal emission factor may range from 525 gCO_2/kWh to 670 gCO_2/kWh.[85] Typically, these marginal emissions are lowest during early morning hours with low grid load and are highest in the afternoon with the mid-day peak load. In gas dominated grid regions generators operating on the margin are likely to be natural gas based CC and CTs, however, Siler Evans study found coal as marginal unit for over 14% period in Texas and 16% in Western Electricity Coordinating Council (WECC).[86] Mo et. al. determined that in MISO region coal accounts for over 55% of marginal generation during non-peak hours, while gas takes up almost all the marginal generation during peak load period.[87] Electricity generation system uses complex operating constrains to constantly balance supply and demand on the grid. The model developed in this study simplified the grid into one zone and under the most basic assumptions, all the marginal emissions for charging the energy storage are considered from NGCC plants. Natural gas is often more expensive than coal, however, due to system constraints some zones in the grid regions have coal as the marginal unit. To charge energy storage with coal and displace natural gas based peaker units leads to more net emissions during the operation of the energy storage system, fundamentally altering the objective of emissions abatement from the grid.

As more capacity of storage is integrated on the grid, upstream emissions associated with the energy storage and natural gas have more influence on EAOI in peak load shifting application. There are major uncertainties associated with the production burden for grid scale ESS and with constraint of one charge-discharge cycle in the load shifting application, ESS are underutilized. With the advancement in technologies ESS are capable of stacking range of grid services including frequency regulation, reserves, and voltage regulations. Considering multiple service application, ESS could mitigate more emissions from the grid when compared to single service case. For the life-cycle assessment, share of production burden for ESS would be attributed to secondary services by ESS, improving the EAOI for load-shifting application. In addition to environmental value, using energy storage asset for more than one function can potentially increase the storage profitability.[88,89] However, policy and market conditions remain the primary barriers to stacking energy storage services. On the other hand, there are uncertainties exist with the production burden of the displaced fuel use for peaker units. A small fraction of methane leakage occurring in the extraction, production, and transportation of natural gas could significantly impact the life-cycle emissions of the displaced fuel use from the grid.[90],[91] If both charging and discharging units are natural gas based, then the EAOI would have minimal impact whereas if the charging generators are other than gas, the results for EAOI will change significantly.

In addition to the environmental benefits, the economics also plays a key role is determining the cost-effectiveness of ESS for emissions abatement application. The levelized capital cost of ESS is a function of the use case and system specifications, e.g. power rating and energy capacity. The use case for a storage technology determine its lifetime in number of years that a storage technology will continue to operate. The cost of storage technologies is coming down very quickly and as the cost of storage is reduced the emissions abatement cost also decrease. Another consideration is the net revenues earned by ESS in energy and ancillary service markets. Energy arbitrage potential with load shifting service across all the region is volatile and is dictated by several parameters including gas price and renewable penetration on the grid. In addition, ESS provides capacity benefits by contributing towards system resource adequacy. In this study ESS operates on the well-established functionality of peak shaving through which it is available at maximum capacity during peak load hours. However, the true capacity value is computed as the capability of a resource to lower the risk of loss of load events (LOLE). Shioshansi and Madaeni et. al. estimation approach through dynamic programming use loss of load probability to determine the capacity value of storage as a function of the duration of stored energy. [92] Since the duration of stored energy dictates in which peak hours the storage system can mitigate the risk and provide reliability benefits, storage system with shorter duration of storage qualifies for partial capacity credit. The framework applied in this research only consider the peak-shaving due to which the capacity benefits are relatively higher than other studies. The role of capacity market based revenue in CAISO and ISO-Ne strengthens the argument that the capacity benefits of energy storage system should be recognized as per the level of stored energy duration to improve their economic performance.

The framework applied in this study presents a simplistic approach that can be used to refine the existing standards for considering the capacity contribution of energy storage for resource adequacy. This study further provides a structure to quantify the emissions abatement potential of using energy storage system across grid applications and evaluate its cost effectiveness for different storage technologies. As shown in the results, there is significant potential to deploy energy storage on the grid for reducing the emissions with resource adequacy service. However, on the cost side energy storage technologies proved to be an expensive strategy for emissions reduction. The energy arbitrage and capacity value streams are not enough to repay the capital and operation costs for the ESS. Hence, the environmental value quantified in this research presents an additional value stream which could be recognized through policy and market regulation for ESS. Furthermore, it is believed that by providing other services during the idle hours of storage systems the cost effectiveness of the proposal could be improved. Accordingly, a future study can be developed based on the results of this research to investigate how stacking multiple services shape the economic and life cycle environmental sustainability of energy storage systems on the gird.

Appendices

Appendix A: Hourly dispatch model

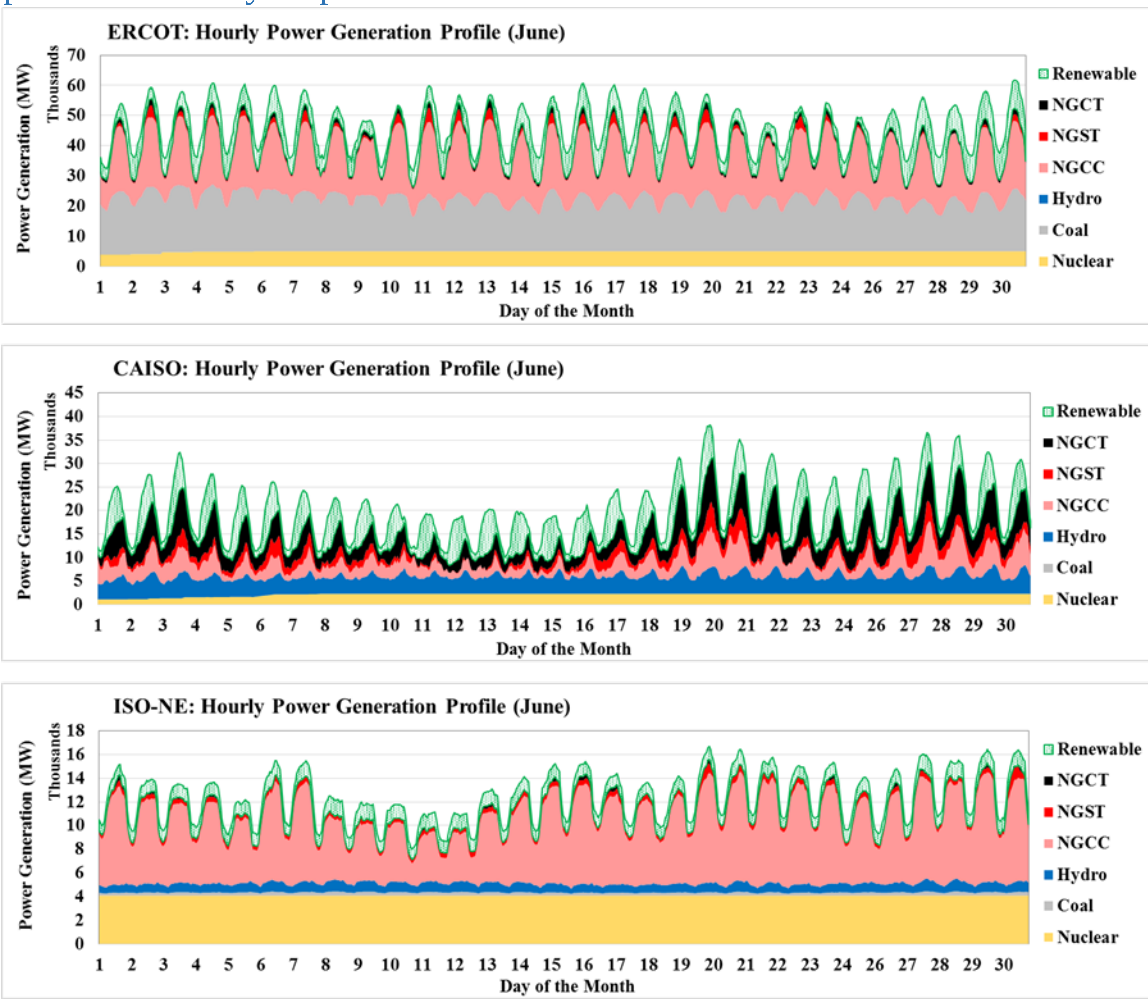


Figure 9*: Hourly resource mix stack from the economic dispatch model for the month of June in three grid regions. Higher daily peak is observed across all the three regions in the summer period that consumed more natural gas based flexible resources. CAISO region has higher NGCT and NGCC to address the fast ramping requirement for late evening peak which coinside reduced solar PV generation*

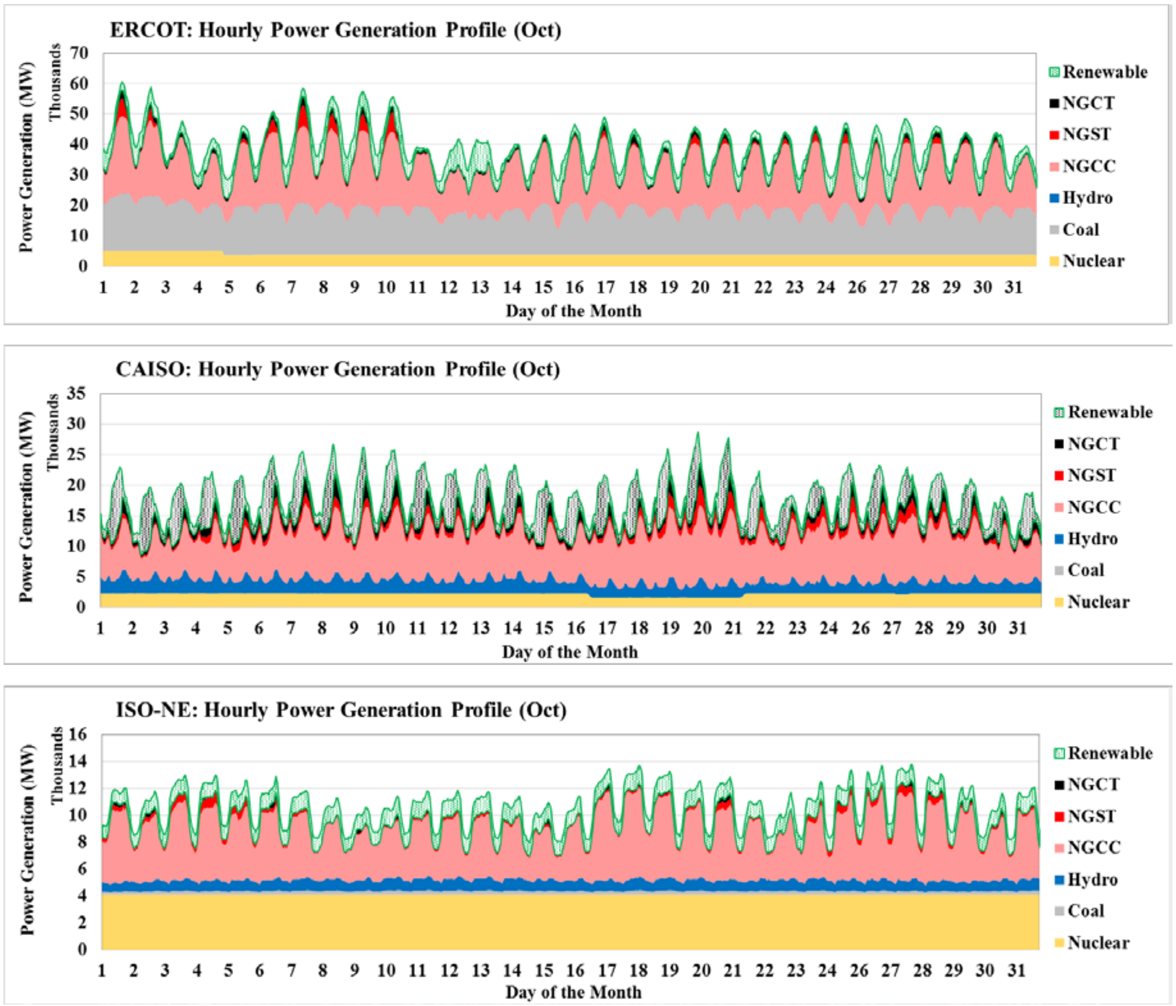


***Figure 10**: Hourly resource mix stack from the economic dispatch model for the month of october in three grid regions. Winter month has lower daily peak load compared to june month. ISO-NE region observed higher share coal resources on the grid compared to other months.*

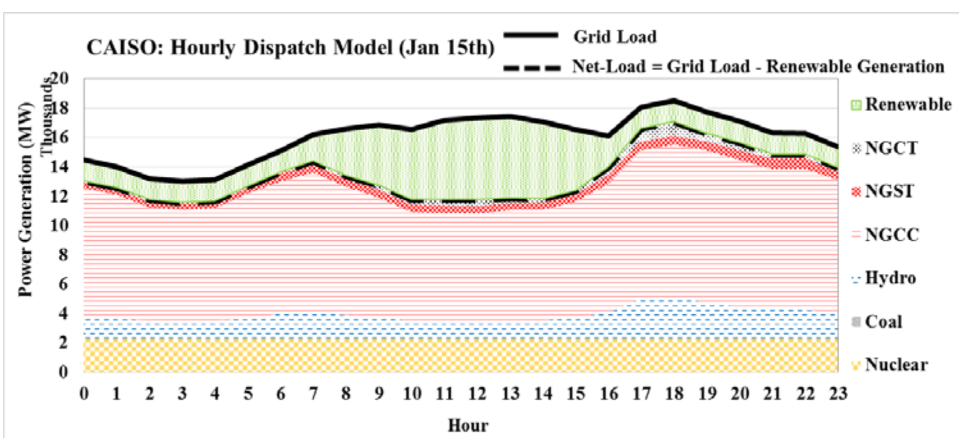


***Figure 11**: Daily economic dispatch model results for the given hourly net-load where resources are stacked based on cost of generation to meet the net-load with lest marginal cost*

Appendix B: Model Validation

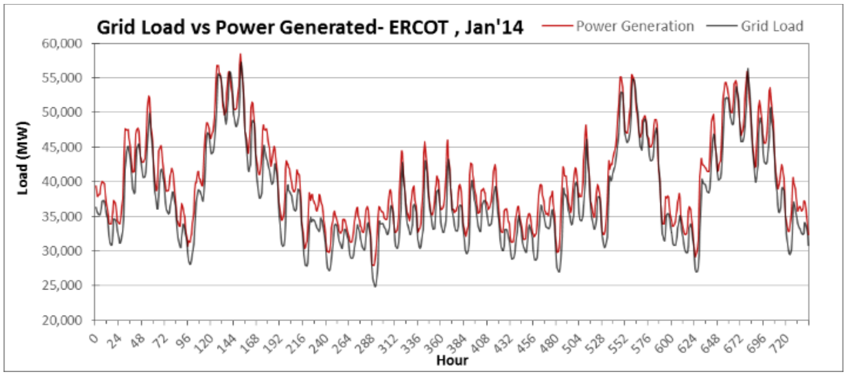


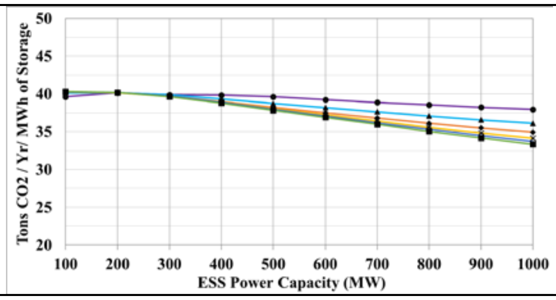
Figure 12: *Baseline dispatch model validation using generated load vs historical grid load*

Appendix C: Emissions reduction and EAOI for other ESS technologies

ERCOT

	Avoided CO_2 emissions from fuel combustion	Emissions avoided over emissions invested (EAOI)

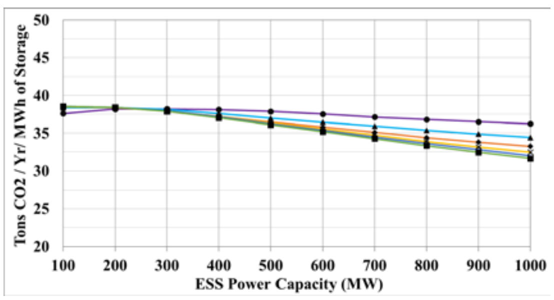
VRFB



Power Rating (MW)

Energy Capacity (hr)	100	200	300	400	500	600	700	800	900	1000
1	1.9	1.9	1.9	1.9	1.9	1.9	1.8	1.8	1.8	1.8
2	2.7	2.7	2.7	2.7	2.6	2.6	2.6	2.5	2.5	2.5
3	3.2	3.2	3.2	3.1	3.0	3.0	2.9	2.9	2.8	2.8
4	3.5	3.5	3.5	3.4	3.3	3.2	3.2	3.1	3.0	3.0
5	3.7	3.7	3.7	3.6	3.5	3.4	3.3	3.3	3.2	3.1
6	3.9	3.9	3.8	3.7	3.6	3.5	3.5	3.4	3.3	3.2

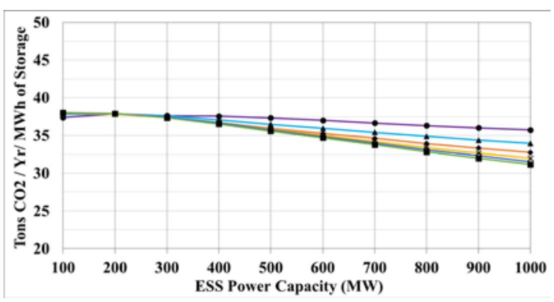
NaS



Power Rating (MW)

Energy Capacity (hr)	100	200	300	400	500	600	700	800	900	1000
1	2.1	2.1	2.1	2.1	2.1	2.1	2.0	2.0	2.0	2.0
2	3.3	3.3	3.2	3.2	3.1	3.1	3.1	3.0	3.0	2.9
3	4.0	4.0	3.9	3.9	3.8	3.7	3.6	3.6	3.5	3.4
4	4.5	4.5	4.4	4.3	4.2	4.1	4.0	4.0	3.9	3.8
5	4.9	4.8	4.8	4.7	4.6	4.5	4.3	4.2	4.1	4.0
6	5.1	5.1	5.0	4.9	4.8	4.7	4.6	4.4	4.3	4.2

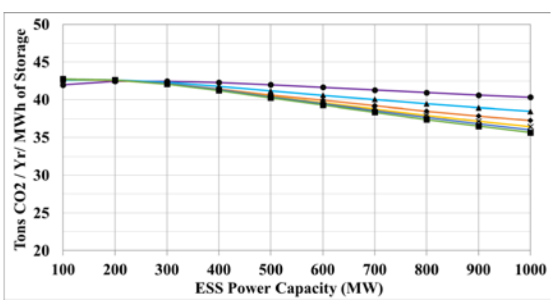
PbA



Power Rating (MW)

Energy Capacity (hr)	100	200	300	400	500	600	700	800	900	1000
1	1.5	1.6	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5
2	2.2	2.2	2.2	2.2	2.1	2.1	2.1	2.0	2.0	2.0
3	2.6	2.5	2.5	2.5	2.4	2.4	2.3	2.3	2.2	2.2
4	2.8	2.8	2.7	2.7	2.6	2.6	2.5	2.4	2.4	2.3
5	2.9	2.9	2.9	2.8	2.8	2.7	2.6	2.5	2.5	2.4
6	3.0	3.0	3.0	2.9	2.8	2.8	2.7	2.6	2.6	2.5

Li - ion



Power Rating (MW)

Energy Capacity (hr)	100	200	300	400	500	600	700	800	900	1000
1	3.5	3.5	3.5	3.5	3.5	3.5	3.4	3.4	3.4	3.4
2	6.0	6.0	6.0	5.9	5.8	5.7	5.7	5.6	5.5	5.4
3	7.8	7.8	7.7	7.6	7.5	7.3	7.2	7.1	6.9	6.8
4	9.2	9.2	9.1	8.9	8.7	8.5	8.4	8.2	8.0	7.9
5	10.3	10.3	10.2	10.0	9.7	9.5	9.3	9.1	8.9	8.7
6	11.2	11.2	11.0	10.8	10.5	10.3	10.0	9.8	9.6	9.3

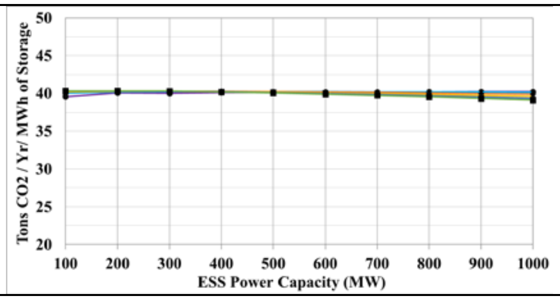
1 Hr, 2 Hr, 3 Hr, 4 Hr, 5 Hr, 6 Hr

EAOI	1.0	2.0	3.0	4.0	5.0	6.0	7.0	8.0	9.0	10.0	11.0	12.0

CAISO

	Avoided CO_2 emissions from fuel combustion	Emissions avoided over emissions invested (EAOI)

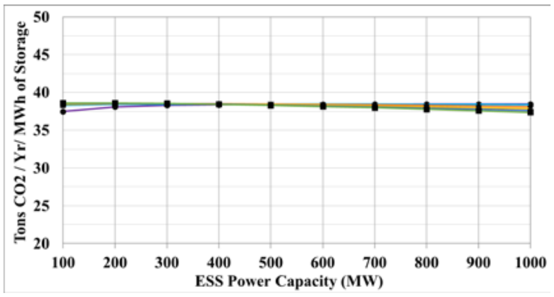
VRFB



Power Rating (MW)

Energy Capacity (hr)	100	200	300	400	500	600	700	800	900	1000
1	1.5	1.6	1.6	1.6	1.6	1.6	1.6	1.6	1.6	1.6
2	2.2	2.2	2.2	2.2	2.2	2.2	2.2	2.2	2.2	2.2
3	2.5	2.6	2.6	2.6	2.6	2.5	2.5	2.5	2.5	2.5
4	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.7	2.7	2.7
5	2.9	2.9	2.9	2.9	2.9	2.9	2.9	2.9	2.9	2.9
6	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0	2.9

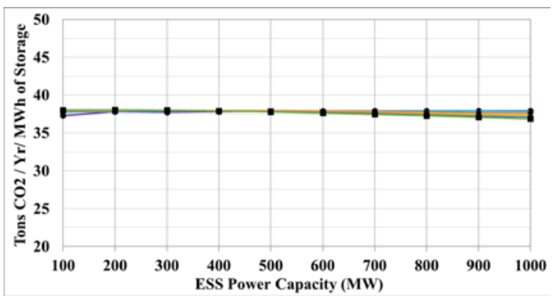
NaS



Power Rating (MW)

Energy Capacity (hr)	100	200	300	400	500	600	700	800	900	1000
1	2.1	2.1	2.1	2.1	2.1	2.1	2.1	2.1	2.1	2.1
2	3.3	3.3	3.3	3.3	3.3	3.3	3.3	3.3	3.3	3.3
3	4.0	4.0	4.0	4.0	4.0	4.0	4.0	4.0	4.0	4.0
4	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.4	4.4	4.4
5	4.9	4.9	4.9	4.8	4.8	4.8	4.8	4.8	4.8	4.7
6	5.1	5.1	5.1	5.1	5.1	5.1	5.1	5.0	5.0	5.0

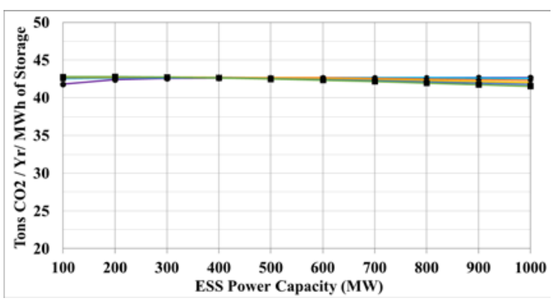
PbA



Power Rating (MW)

Energy Capacity (hr)	100	200	300	400	500	600	700	800	900	1000
1	1.9	1.9	1.9	1.9	1.9	1.9	1.9	1.9	1.9	1.9
2	2.7	2.7	2.7	2.7	2.7	2.7	2.7	2.7	2.7	2.7
3	3.2	3.2	3.2	3.2	3.2	3.2	3.2	3.2	3.2	3.2
4	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.4
5	3.7	3.7	3.7	3.7	3.7	3.7	3.7	3.7	3.6	3.6
6	3.9	3.9	3.9	3.9	3.8	3.8	3.8	3.8	3.8	3.7

Li - ion



Power Rating (MW)

Energy Capacity (hr)	100	200	300	400	500	600	700	800	900	1000
1	3.5	3.5	3.6	3.6	3.6	3.6	3.6	3.6	3.6	3.6
2	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0
3	7.8	7.8	7.8	7.8	7.8	7.8	7.8	7.8	7.8	7.8
4	9.2	9.2	9.2	9.2	9.2	9.2	9.2	9.1	9.1	9.1
5	10.3	10.3	10.3	10.3	10.3	10.2	10.2	10.2	10.1	10.1
6	11.2	11.2	11.2	11.2	11.1	11.1	11.0	11.0	10.9	10.9

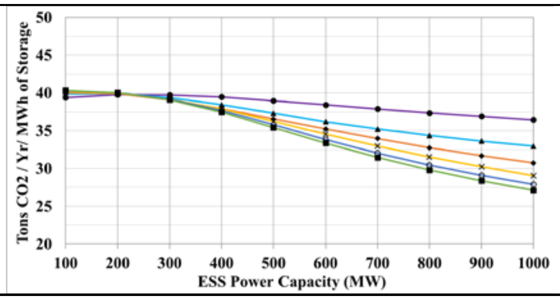
1 Hr, 2 Hr, 3 Hr, 4 Hr, 5 Hr, 6 Hr

EAOI: 1.0, 2.0, 3.0, 4.0, 5.0, 6.0, 7.0, 8.0, 9.0, 10.0, 11.0, 12.0

ISO-NE

Avoided CO_2 emissions from fuel combustion | **Emissions avoided over emissions invested (EAOI)**

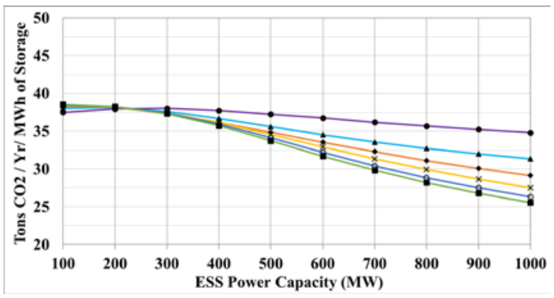
VRFB



Power Rating (MW)

Energy Capacity (hr)	100	200	300	400	500	600	700	800	900	1000
1	1.9	1.9	1.9	1.9	1.9	1.8	1.8	1.8	1.8	1.7
2	2.7	2.7	2.7	2.6	2.5	2.5	2.4	2.3	2.3	2.2
3	3.2	3.2	3.1	3.0	2.9	2.8	2.7	2.6	2.5	2.4
4	3.5	3.5	3.4	3.3	3.2	3.0	2.9	2.7	2.6	2.5
5	3.7	3.7	3.6	3.5	3.3	3.1	3.0	2.8	2.7	2.6
6	3.9	3.8	3.7	3.6	3.4	3.2	3.0	2.9	2.7	2.6

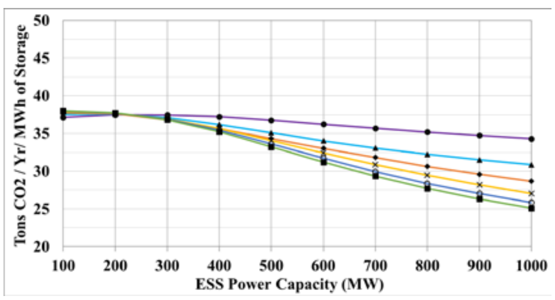
NaS



Power Rating (MW)

Energy Capacity (hr)	100	200	300	400	500	600	700	800	900	1000
1	2.1	2.1	2.1	2.1	2.1	2.0	2.0	2.0	1.9	1.9
2	3.2	3.2	3.2	3.1	3.0	2.9	2.9	2.8	2.7	2.7
3	4.0	4.0	3.9	3.8	3.6	3.5	3.4	3.2	3.1	3.0
4	4.5	4.5	4.4	4.2	4.0	3.8	3.7	3.5	3.3	3.2
5	4.8	4.8	4.7	4.5	4.3	4.1	3.8	3.6	3.5	3.3
6	5.1	5.1	5.0	4.8	4.5	4.2	4.0	3.8	3.6	3.4

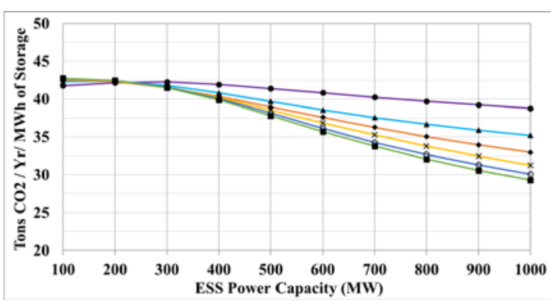
PbA



Power Rating (MW)

Energy Capacity (hr)	100	200	300	400	500	600	700	800	900	1000
1	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.4	1.4	1.4
2	2.2	2.2	2.2	2.1	2.0	2.0	1.9	1.9	1.8	1.8
3	2.5	2.5	2.5	2.4	2.3	2.2	2.1	2.1	2.0	1.9
4	2.8	2.8	2.7	2.6	2.5	2.4	2.3	2.2	2.1	2.0
5	2.9	2.9	2.8	2.7	2.6	2.4	2.3	2.2	2.1	2.0
6	3.0	3.0	2.9	2.8	2.7	2.5	2.3	2.2	2.1	2.0

Li - ion



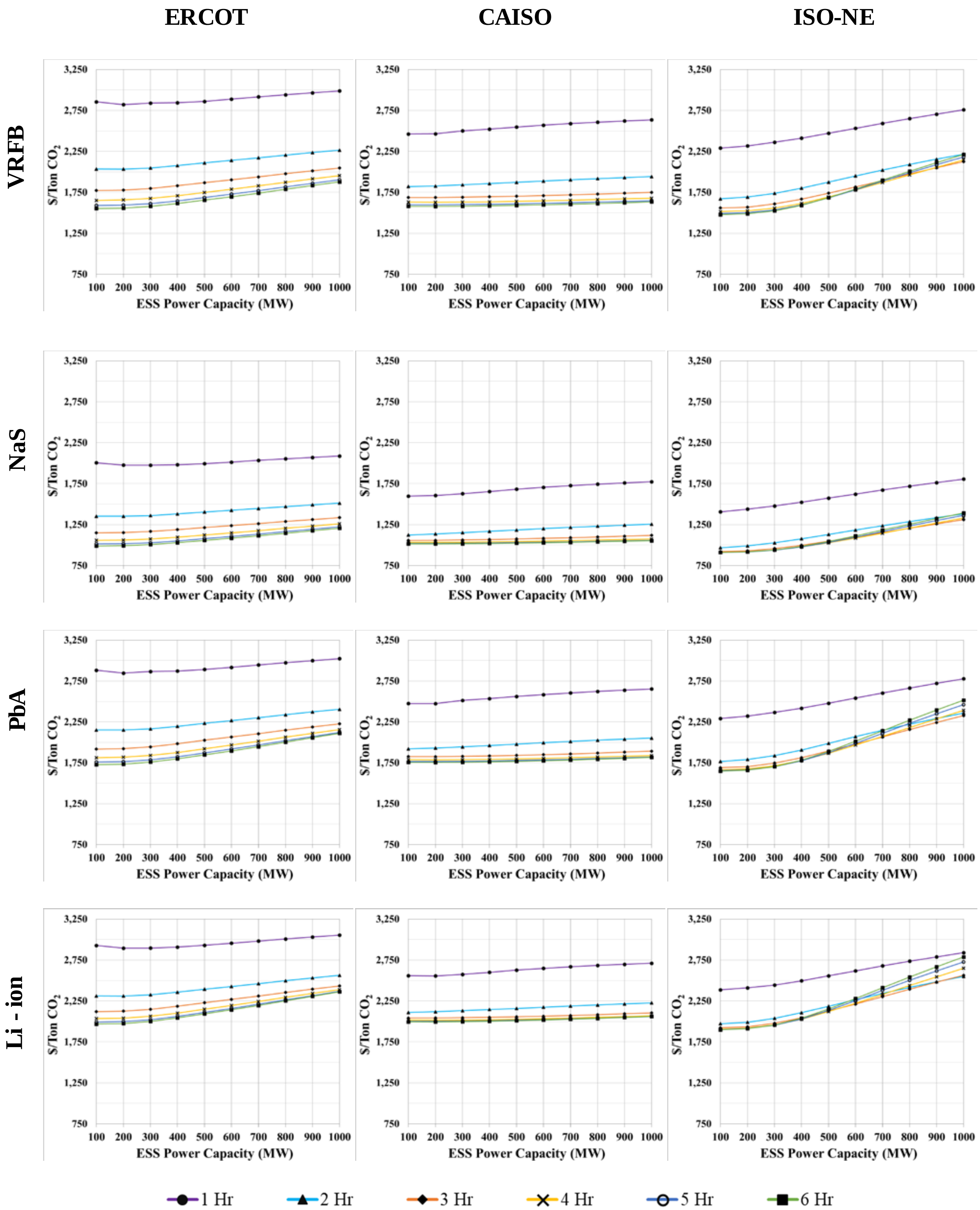
Power Rating (MW)

Energy Capacity (hr)	100	200	300	400	500	600	700	800	900	1000
1	3.5	3.5	3.5	3.5	3.5	3.4	3.4	3.3	3.3	3.2
2	6.0	6.0	5.9	5.8	5.6	5.4	5.3	5.2	5.1	5.0
3	7.8	7.8	7.6	7.4	7.1	6.9	6.7	6.4	6.2	6.0
4	9.2	9.1	9.0	8.7	8.3	8.0	7.6	7.3	7.0	6.7
5	10.3	10.2	10.0	9.7	9.2	8.7	8.3	7.9	7.5	7.3
6	11.2	11.1	10.9	10.4	9.9	9.3	8.8	8.4	8.0	7.7

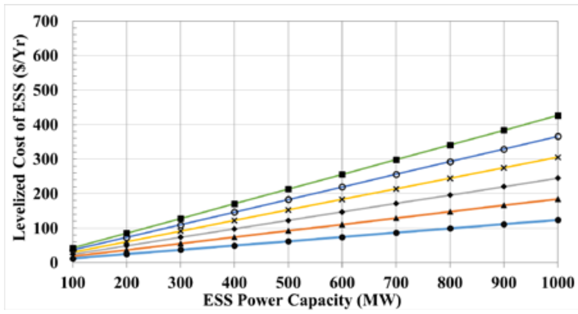
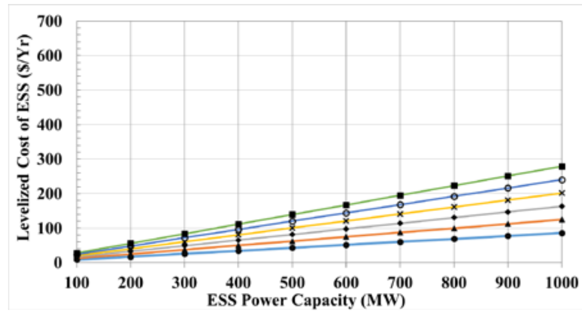
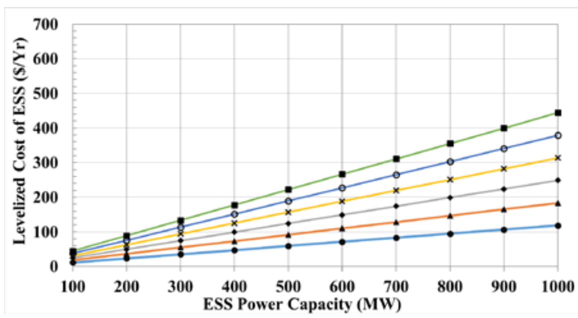
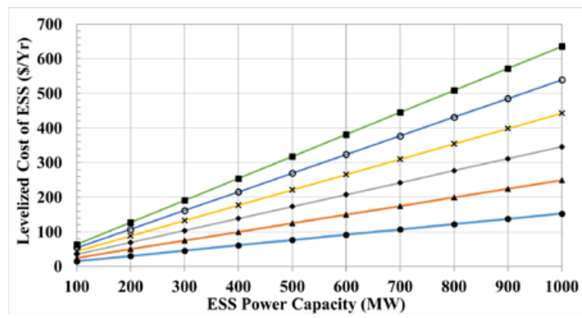
1 Hr 2 Hr 3 Hr 4 Hr 5 Hr 6 Hr

EAOI 1.0 2.0 3.0 4.0 5.0 6.0 7.0 8.0 9.0 10.0 11.0 12.0

Appendix D: Cost of Emissions Abatement with Energy Storage Systems



Appendix E: Levelized cost of Energy Storage Systems

Vanadium redox batteries (VRFB)	Sodium Sulfur (NaS)
	
Lead-Acid (PbA)	**Lithium ion (Li-ion)**
	

1 Hr 2 Hr 3 Hr 4 Hr 5 Hr 6 Hr

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