

How does new energy storage affect the operation and revenue of existing generation?

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Abstract

Storage is an important technology for low carbon and sustainable energy systems. As storage is integrated into grids through policies or market forces, it has an effect on the dispatch, economics, and retirement of other generators. While the complementary relationship between storage and renewables is well-known, the effect of storage additions is not necessarily focused only on new renewables. This work models the effects of economic operation of new energy storage on the generation, operating income, and retirement of other electricity generators. We consider system effects at three levels of increasing complexity. First, we evaluate the marginal effects of storage on generation sources based on historical electricity prices and the generation mix for the year 2016. In this case, storage is modeled as a price-taker, and its actions do not affect market prices or change which generators operate at the margin. Second, we use a dispatch model to study bulk storage with capacities up to 15% of average demand in New York Independent System Operator (NYISO), Midcontinent ISO (MISO), and California ISO (CAISO), allowing storage to shift dispatch patterns and affect the operation and income of existing generators. Third, we examine the mid- and long-term effects that storage has on the generation fleet by accounting for the retirement of power plants that lose sufficient annual revenue due to the additional storage. Results suggest that new storage increases coal generation and decreases natural gas generation in the West and Midwest, and increases natural gas generation and decreases coal generation in New England, and California. With bulk storage in the system, the operating income of all other generating units is reduced unless retirement is included. With retirements considered, the least flexible baseload units—coal and nuclear—gain the most operating income with storage in MISO and NYISO. In California, solar gains the most operating income as storage is added. In all cases, power plants operating with gas turbines using natural gas lose the most operating income as they are offset by storage during the discharge phase and retired in the long term.

Keywords: Energy storage, dispatch, renewables, operating income, electricity grid, fuel mix, energy policy, electricity prices, arbitrage

146Introduction and Literature Review

As the costs of grid-scale electricity storage (‘storage’) decline, the technology is increasingly being used for power sector applications. Potential grid services in which storage might provide value include shifting energy generation surplus so as to better align it with demand, improving reliability by providing capacity to meet peak load, or increasing stability and flexibility through ancillary services, among others [1,2]. The flexibility provided by storage is also seen as a pathway for the adoption of higher levels of renewable electricity sources, thus facilitating decarbonization of the power sector [3–5]. Despite these opportunities, in many instances the potential compensation for providing this value to the grid provides insufficient revenue to compensate storage owners or developers [6,7]. As a result, policymakers in the U.S. have sought to encourage the development and deployment of storage, with at least 15 states enacting procurement mandates or financial incentives for storage [8–10].

Whether integrated by mandate or market forces, the system value that storage realizes—through the provision of grid services, investment deferment, emissions reductions, or other mechanisms—is highly dependent on the attributes of the storage, how it is operated, and the context of the system into which it is introduced [1,2,7,11,12]. For example, although storage may help to enable long-term decarbonization strategies, studies have found that adding storage to existing grid mixes can actually increase emissions [13,14]. The sign and magnitude of these effects are determined by the characteristics of the system and can change as the system evolves; for instance, several studies have found that storage increases emissions reductions in current grid mixes but reduces them for future fleet mixes with higher renewable penetrations [15,16]. As a result, it is important for policy makers to evaluate the current or potential future benefits that proposed storage projects or policies would bring.

There are two important dimensions to consider when evaluating the system impact of storage in current or future systems. The first dimension is uncertainty about near-term conditions on the grid, such as near-future electricity prices, the need for ancillary services, or the amount of available wind and solar generation. Storage devices can be modeled with “perfect” knowledge about the entire modeled period so that they can optimally plan operation or with “imperfect” dynamic forecasts (using stochastic optimizations) that are updated as time progresses in the model [17]. The former is easier to program and provides an upper limit to the effects of storage while the latter is more realistic. A second dimension from which to consider storage impacts is related to its effect on market dispatch and prices. One approach is to model storage devices as “marginal” relative to other generating sources, and thus unable to significantly affect market-clearing prices (i.e. storage as a price-taker). Such analysis is typically done when evaluating the profitability of small amounts of storage or assessing its near-term impacts at various locations, often using historical pricing data [13,18,19]. Alternatively, storage operations can be modeled so as to account for their impact on power plant dispatch and market-clearing prices. Throughout this document, we call such storage systems “bulk storage”, which here refers to a modeling approach that allows storage to affect the dispatch of other generators (as well as clearing prices

and income). Because storage benefits from energy arbitrage—buying electricity at low prices and selling at high prices—the economic operation of storage can displace peaking resources. These typically expensive peaking units set the wholesale electricity price in the hours of highest net demand, so the addition of bulk storage reduces peak prices. This price suppression tends to reduce profitability for all generators in the short term and may even force additional plant retirements in the mid- to long-term [20,21]. A reverse effect can occur in off-peak periods as storage charges, though the magnitude of that price effect is usually much smaller.

While economic dispatch models should explicitly capture the various ways storage can affect market operations, they are more difficult to develop, can be computationally intensive, and cannot perfectly reproduce present-day observations. As a result, these studies have often been limited to one region of analysis. In contrast, models where storage effects are marginal fail to capture all of the possible effects of storage but are often based on realistic historical data and are typically easier to calculate for many locations. Hence, comparison between these two approaches, as we provide here, can offer informative triangulation between two imperfect methods.

Since storage typically charges in off-peak hours and reduces ramping, it tends to increase generation from units that are less flexible and have traditionally been operated with little hour-to-hour variation in output [15,22]. A study by Denholm *et al.* showed that adding bulk energy storage increases the generation of base-load marginal power plants such as coal and combined cycle units by 0.6% while decreasing generation from combustion turbines by about 1.5% [7]. Similarly, Zamani *et al.* calculated the effects of storage as a price-maker on the Alberta grid system, concluding that generation from coal and natural gas combined cycle (NGCC) would increase but the revenues of all power plants would decrease due to a steep decrease in wholesale electricity prices [20]. However, these studies do not explore how results might vary across different regions with different grid mixes or compare results from different methods of analysis.

Our work uses both a marginal and a more detailed treatment of large-scale storage (‘bulk storage’) in order to discern the effects of storage on the operating income and generation of renewables and other generating units. We explore these system effects using three models of increasing complexity. First, we assess the marginal effects of storage on the change in generation based on 2016 electricity prices and generation mixes across 22 eGRID regions of the U.S. Here, we capture the dynamics of actual grid operation but not any change in price or profit of the other generators; this approach is appropriate if the additional storage is of a marginally small capacity and the grid mix is similar to the year 2016. Second, in order to evaluate the effect of bulk storage on the operating income of other generators, we employ a simulated dispatch model with bulk storage capacities (up to 15% of the average demand) for three important U.S. electricity grids (CAISO, MISO, NYISO). Here the effect on prevailing prices and dispatch is modeled directly, as storage affects the operational patterns of other generators as well as the market clearing prices. Finally, in order to understand mid- and long-term system impacts, we consider the potential for plant retirements due to eroded operating income from the entrance of

storage, which may in fact benefit plants that remain open. This strategy of increasing complexity in the modeling approaches is useful for comparative purposes but also reflects the shifting effects that storage may have over time as it moves from marginal deployments to a scale that forces retirement of existing peaking generators. To our knowledge, this is the first investigation that compares the impacts of energy storage on the grid at different levels of modeling complexity as well as different grid mixes.

235Methods

In the first part of this work, we estimate the impact of storage on net generation using actual electricity prices and the probability of a particular type (technology) of generator operating as the marginal generator ('marginal generator factors') at a given time from 22 different eGRID regions. A linear programming model is used to optimize the storage operation using the clearing prices in a perfect information model, and the marginal generator factors provide information on the type of generators operating when storage charges and discharges. In the second part, we explore the same question using a different approach; here we employ a capacity expansion/dispatch model to calculate the change in operating income with and without storage (up to 15% of average demand) for three different regions: the Midcontinent Independent System Operator (MISO), the New York Independent System Operator (NYISO), and the California Independent System Operator (CAISO). We simulate bulk storage additions using an iterative optimization of storage within the dispatch model. Finally, in the third part we add retirement of revenue-losing generators after each addition of storage. In this case, the plants that lose the most revenue are retired while retaining the same amount of firm capacity. Each of these models and their assumptions are detailed in sections 3-5 below.

351Effect on generation: price-taker model

152 3.1. Model formulation

In this model, we treat storage as an energy arbitrage device used to move bulk energy from low price/demand periods to high price/demand periods, simulating energy arbitrage or peak demand management. Our treatment of storage applies to operations at utility scale in power networks, though distributed storage may behave in the same way if it is exposed to a rate structure or control scheme that motivates similar behavior. Given that a significant percentage (88%) of storage capacity in the US operates on arbitrage [23], provision of other grid services from storage, e.g. frequency regulation, is outside of the current scope. While storage can never actually have perfect information about future prices, several studies have identified a variety of algorithms that can attain 85% or more of the hypothetically perfect revenue and result in similar operational patterns [6,21,24–27].

Storage systems are described by two primary parameters: round-trip efficiency and charge rate. Round trip efficiency is the ratio of energy output from storage against the quantity of energy required to charge it and is set to 80% as the base-case value for the analysis. Charge rate reflects how rapidly the storage system can charge and discharge energy, measured here in terms of the

minimum time needed for complete charge/discharge; we parameterize this using a value of 4 hours, based on the average charge duration of the current energy storage projects in the U.S. [23]. We mainly discuss storage in power capacity (MW) terms in this work because we compare storage capacity to generation capacity in the third analytical approach, but power capacity of storage can be converted to energy capacity (MWh) by multiplying by charge duration (4 h).

The formulation of storage operation as a price-taker, given perfect information, is a maximization problem as shown in Eq. 1.

Objective function:

$$Revenue = \max(-\sum_{t=1}^{8760} C_t E_t) \quad \text{Eq. 1}$$

Subject to:

$$S_0 = \frac{S_{max}}{4} \quad \text{Eq. 2}$$

$$\forall t, S_t = S_{t-1} + E_t \times \sqrt{\eta}, \text{ if } E_t > 0 \quad \text{Eq. 3}$$

$$\forall t, S_t = S_{t-1} + \frac{E_t}{\sqrt{\eta}}, \text{ if } E_t < 0 \quad \text{Eq. 4}$$

$$\forall t, 0 \leq S_t \leq S_{max} \quad \text{Eq. 5}$$

$$\forall t, -R \leq \frac{E_t}{\text{hour}} \leq +R \quad \text{Eq. 6}$$

Where, C_t – price of electricity in hour t (\$/MWh),

E_t – electricity bought (positive) or sold (negative) by the storage (in MWh),

S_0 – initial state of charge of storage (in MWh)

S_t – state of charge in hour t (in MWh)

S_{max} – maximum state of charge of storage (in MWh)

η – Round-trip efficiency of storage

R – Max Charge/discharge rate (in MWh/h)

t – hour in a year (1 to 8,760)

Note that the revenue does not depend on capital cost, as this does not affect optimal operation. In the model, positive ' E_t ' indicates energy bought (charging) by the storage, and negative ' E_t ' indicates energy sold (discharging). The storage system is arbitrarily assumed to start with a 25% state of charge, given by ' S_0 ' (in MWh) as shown in equation Eq. 2. This is a typical value for state of charge carried over the midnight hour and has little effect on overall operation, which occurs over a full year from this point. S_t (in MWh), the state of charge in each hour, is always less than or equal to the maximum amount of charge attainable by the storage, given by ' S_{max} ' in Eq. 2. The round-trip efficiency, ' η ', is equally divided between charge and discharge cycles in Eq. 3- Eq. 4 [13]. In any hour, energy in/out (' E_t ') ranges between the maximum charge/discharge rate, ' R ' (% of MW/h) as shown in Eq. 6.

3.2. Marginal generator factors and pricing data

We use pricing data from the relevant Independent System Operators (ISOs) across the 22 eGRID regions of our analysis, taken from the relevant ISOs, and averaged out to hourly values in all cases. [28–34]. Additional detail on these data is provided in section 1 of the SI.

To estimate which generators are used to charge (and are displaced by) storage with the price-taker model, we use “Marginal Generator Factors” (MGFs), which represent the likelihood that a specific generation technology type is the marginal generator in a given hour. For example, in MISO, during a typical summer day, a marginal increase in demand of 1 MWh at noon is approximately 60% likely to come from coal, and 40% likely come from a natural gas-based power plant. The likelihood of a generator operating on the margin at a given time depends upon the mix of generators in that region, the price of fuels, and demand at that time. Because the data inputs used to calculate these MGFs come from actual operation of generators, this method reflects the way that generators are actually dispatched rather than how they ought to be dispatched based upon modeled assumptions.

To calculate MGFs for the various subregions in a given hour, we used data from the EPA’s Continuous Emissions Monitoring System (CEMS) from 2016. CEMS provides hourly emissions and generation data from all thermal generating units greater than 25 MW, as well as data on primary fuel input. From the CEMS data, we aggregate to the plant level and build a new dataset tracking the change in generation by power plant between one hour and the next. We then select plants in each hour with more than a 5 MW increase or decrease in generation between any two adjacent hours—these plants are said to be “on the margin” for that given hour. The 5 MW cutoff is chosen because we are searching for the plants that are changing output in response to market or demand changes: we want to filter trivial or incidental shifts in power output. For example, a 400 MW capacity thermal generator might have a measured output of 398 MW in one hour and 399 MW the next hour, but both of these are effectively “maximum capacity” and the shift of 1 MW doesn’t suggest that the plant is responding to market conditions. The 5 MW cutoff was selected to be small relative to the size of power plants (minimum of 25 MW in this dataset) but large enough to filter incidental shifts in output. Using this subset of marginal plants, we then aggregate plants by fuel type to determine the net amount of generation increase/decrease for each fuel as shown in Eq. 7. Because we do not know in advance whether storage will charge (and increase output from marginal generators) or discharge (and decrease generator output), marginal factors of each fuel (f) between one hour and the next (Δt) are calculated from the absolute values of change in generation by fuel (Eq. 8).

$$\text{net marginal generation}_{f,\Delta t} \quad \text{Eq. 7}$$

$$= \sum_p \text{increase}_{p,f,\Delta t} - \sum_p \text{decrease}_{p,f,\Delta t}$$

$$MGF_{f,\Delta t} = \frac{|\text{net generation}_{f,\Delta t}|}{\sum_f |\text{net marginal generation}|} \quad \forall LMP \geq 0, \quad \text{Eq. 8}$$

$$MGF_{f,\Delta t} = 100\% \text{ renewables } \forall LMP < 0$$

Where: f – fuel type

Δt – change in one hour and next hour

p – individual power plant

net marginal generation – net generation on margin (MWh)

increase – Power plants increasing generation (MWh)

decrease – Power plants decreasing generation (MWh)

LMP – Locational Marginal Prices

This aggregation provides us with the total change in generation in each hour (in MW) as well as the percentage of that change coming from coal, natural gas, biomass, and oil in each hour (MGFs).

There are some limitations with this data collection method. First, this data does not capture changes in generation from non-fossil generation, such as nuclear or renewable sources. In order to account for changes from renewables, we assume that they are on margin only when the electricity prices are zero or negative (Eq. 8). In general, renewables are less likely to be on the margin in present-day systems. For example, renewables were on the margin in California for 2% of the total hours in 2016 [31]. While we don't explicitly model operating constraints or physical system limitations, because MGFs are based on observed data of how generators actually change their output in response to changes in demand, they should be a good reflection of real-life operational limitations such as transmission, ramping, or must-run status.

3.3. Estimating net change in generation

Under arbitrage operation, storage charges when the prices are low and discharges when the prices are high. An 8 MW (24 MWh) storage capacity with a round trip efficiency of 80% is assumed for the price-taking model (though scale of storage is not relevant under this price-taker model as long as it is sufficiently small that it doesn't affect the market).

Fuel type used/displaced when the storage charges and discharges is determined from the MGFs of the fuel types at a given hour. Based on the MGFs and the storage operation, we determine the fuel mix of the marginal generators during storage charge and discharge periods, per unit of energy delivered from the storage. Total energy delivered from the storage is the summation of total discharge from the storage (' E ') (Eq. 9). Because of the roundtrip efficiency losses, energy used by the storage is always greater than the energy delivered from the storage. For example,

for a roundtrip efficiency of 80%, storage requires 1.25MWh of energy to deliver 1MWh of energy. Net energy used for each fuel type per unit of energy delivered from the storage (NF_f) is estimated from the sum of fraction of fuel used during the charge phase ($P_x > 1$) and the fraction of fuel used during the discharge phase ($P_x < 1$) per unit of energy delivered from the storage as shown in Eq. 10. This is to account for generation types (coal, for example) that are both used to charge storage and offset by storage during discharge.

$$E = - \sum_t P_t \quad \text{Eq. 9}$$

$$NF_f = \sum \frac{\sum_t MF_{f,\Delta t} * P_t}{E} \quad \text{Eq. 10}$$

Where: f – fuel type

t – hour

P – Energy delivered by storage in a given hour t (MWh/h)

$P > 1$ for storage charge and $P < 1$ for storage discharge

E – Total energy delivered from storage (MWh)

MF – Fraction of fuel type used per MWh delivered energy

NF – Net fraction of fuel type used per MWh delivered energy

4. Net change in short-term operating income

Small capacities of storage are price takers and do not have a significant effect on electricity prices or operating income/operation of the other generators. This no longer holds as larger amounts of storage (bulk storage) are added to a system, so we use a dispatch model to understand the effect of bulk storage capacity additions to the system.

4.1. Economic dispatch model

We combine an economic dispatch model and arbitrage operation of the storage to estimate the operating income to all generators before adding storage up to 15% of mean demand. This level was chosen to represent an ambitious but plausible level of mid-term storage deployment. Additionally, we observed that after approximately 15%, the additional energy needs of storage required additional generation capacity. Scaling storage to mean demand in a system was chosen to make results comparable across electricity systems of different sizes. This results in maximum storage capacities of approximately 3,000MW (12,000MWh) in MISO, 2,500 MW (10,000 MWh) in CAISO, and 2,000 MW (8,000 MWh) in NYISO.

An economic dispatch model determines the lowest-cost operation of generating facilities that can reliably meet a given demand within the generators' ramping constraints [35] and simulates the market clearing prices for electricity. These electricity prices are used in an optimization model to determine the schedule for storage operation, considering the effects of bulk storage on

electricity prices. The model is based on prior work integrating storage into an economic dispatch model [36].

The economic dispatch model is the first block of our framework (Fig. 1) used to generate electricity clearing prices, which are used as an input to model the operation of the storage. We assume an economic dispatch of generators, where generating facilities place bids based on their marginal costs. After placing bids, ISOs dispatch power plants sequentially from lowest to highest bid, within the ramp rate constraints of each generator, until electricity demand is fully met. This enables determination of hourly market clearing prices. The clearing price is the bid price at which the last unit of electricity is supplied to meet the total demand.

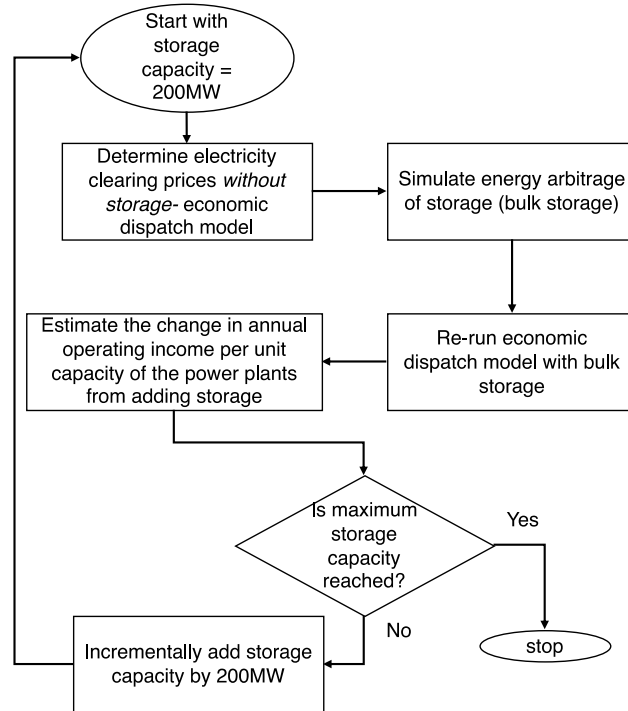


Fig. 1 Flowchart of the framework to evaluate the net operating income per unit capacity of the power plants after adding bulk storage. The model produces a "no-storage" time series of prices, simulates storage operation, then calculates the net operating income per unit capacity (\$/MWh) of the power plants with and without energy storage. For simulating bulk storage operation, we use an iterative dispatch optimization, considering the effect of storage on prices.

The dispatch model includes ramping constraints but does not include transmission constraints. The reference electricity demand is taken from market data available from NYISO, CAISO, and MISO for 2016 [29,32,37]. The fleet of power plants for electricity generation are taken from EPA's eGRID database [38] and the marginal cost (assumed as bid price) of operation for each power plant is calculated based on the power plant's heat rate [38], subsequent fuel costs (Table 1), and variable O&M costs (Table 2) [39].

The Marginal Cost ('MC') given in \$/MWh is the summation of the fuel cost incurred per MWh and the variable O&M costs per MWh as shown in Eq. 11. The Heat Rate ('HR') for each power plant—expressed in Btu/kWh and based on data from eGRID [38]— is used to estimate the fuel

cost incurred to generate one unit of energy in MWh. Variable O&M costs for each power plant are considered based on the generator type and the primary fuel used for the generation of electricity (Table 2). A summary of data sources used in the economic dispatch model are provided in Table S2 of the SI.

$$MC (\$/MWh) = HR * \frac{Price}{1000} + O\&M \quad \text{Eq. 11}$$

Where, *MC* – marginal cost of operation of a power plant (\$/MWh),
HR – heat rate (in Btu/kWh),
Price – national average spot price of fuel (in \$/MMBtu), and
O&M – variable operations and maintenance cost of the power plant (in \$/MWh).

Table 1 and Table 2 show fuels costs and variable O&M costs, respectively, used in the modeling.

Table 1. Average fuel costs used for electricity production during the year 2016. Four major types of fuels used for electricity production are considered. The normalized average price of coal includes the different qualities of coal used for electricity production. The original value of crude oil as per the reference is given in \$/barrel and converted to MMBtu with the conversion: 1barrel = 5.55MMBtu for crude oil. Constant 2016-\$ are used.

Fuel Type	Cost	Units
Natural Gas	2.6 [40]	\$/MMBtu
Coal	2 [40]	\$/MMBtu
Uranium	1.4 [41]	\$/MWh
Crude Oil	7.99 [42]	\$/MMBtu

Table 2. Variable O&M costs of technologies considered in this study [39]. All values are expressed in constant 2016-\$. The variable O&M cost of wind and solar power plants is taken as zero.

Technology	Variable O&M Costs (2016 \$/MWh)
Conventional Hydropower	2.62
Coal power plants with steam turbines	6.96
Combined Cycle power plants (Gas/Oil)	1.96
Conventional Combustion Turbine (Gas/Oil)	3.43
Gas Turbine	3.43
Nuclear	2.26

Using marginal cost as the bid price of power plants, the economic dispatch model is run with an objective of producing electricity at a minimum operating cost using linear optimization (Eq. 12). Marginal cost of operation ('*MC*') of power plants for these scenarios is calculated as

shown in Eq. 11. The generators run with ramping constraints, shown in Eq. 15-Eq. 16, and the constraint that total generation meets total demand (L) (Eq. 14) in each hour (t). The ramping constraints are expressed in percentage of rated power a generator can ramp up (RU) or down (RD) in a given hour (% of MW/h). The dispatch model is run for every hour in a year. Ramping constraints for current hour t depend upon the electricity generated by the power plant in the previous hour $(t-1)$ as shown in equations Eq. 15 - Eq. 16. Ramping rates of different types of turbines are shown in Table 3. Maximum electricity generated by a power plant in an hour t does not exceed the name plate capacity of the power plant (P_p), shown in equation (Eq. 17).

Objective function:

$$\text{minimize } C_t = \sum_p MC_{tp} * e_{tp} = \sum_p (HR * \frac{Price}{1000} + O\&M)_{tp} * e_{tp} \quad \text{Eq. 12}$$

Subject to: Eq. 13

$$\sum_p e_{tp} \geq L_t, \quad \text{Eq. 14}$$

$$e_{tp} \geq e_{(t-1)p} - \frac{RD_p}{100} * P_p, \quad \text{Eq. 15}$$

$$e_{tp} \leq e_{(t-1)p} + \frac{RU_p}{100} * P_p, \quad \text{Eq. 16}$$

$$e_{tp} \leq P_p, \quad \text{Eq. 17}$$

$$e_{tp} > 0 \quad \text{Eq. 18}$$

$$p \leq n \quad \text{Eq. 19}$$

$$t \leq 8760 \quad \text{Eq. 20}$$

Where, Subscript p – Power plant,

Subscript t – Time (in hours),

C_t – cost of electricity generation at hour t (in \$),

MC_{tp} – marginal cost of operation of power plant p at hour t (\$/MWh)

e_{tp} – electricity generated by power plant at hour t (MWh)

L_t – load demand at t^{th} hour (in MWh), and

n – total number of power plants available for dispatch

RD_p – Ramp down rate of power plant p (% of MW/h)

RU_p – Ramp up rate of power plant p (% of MW/h)

P_p – Nameplate capacity of power plant p (MW)

HR – heat rate (in Btu/kWh),

$Price$ – average spot price of fuel (in \$/MMBtu), and

$O\&M$ – variable operations and maintenance cost of the power plant (in \$/MWh).

Table 3. Ramping rates of the electricity generators used in the power plants [43–45]. The units are percentage change of rated capacity achievable between one hour and the next.

Generator Type	Ramping Rate (% of rated capacity achieved/hour)
Gas Turbine/Combustion Turbine (Natural Gas)	100%
Combined Cycle (Primary Fuel- Natural Gas, Secondary Fuel-Coal)	30%
Steam Turbine (Coal)	15%
Nuclear	50%

The model does not consider the imports/exports of electricity from regions outside of CAISO, MISO and NYISO. Hourly variations and the resultant power output (e_p) of wind and solar plants for a given location are taken from Eastern Wind Integration dataset [46], and Eastern Solar Integration Dataset [47] respectively.

The operating income for each power plant is estimated ($O_{f,p}$) based on the clearing price (T) the plant receives from the energy delivered (P_p) at the given time (t), its fixed operating cost (FC), and variable operating cost estimated through marginal cost (MC) of delivering energy (P_p) at the given time. (Eq. 21)

$$O_{f,p} = \sum_t I_t * P_{p,f,t} - FC_{p,f} * P_{p,f} + \sum_t MC_{p,f,t} * P_{p,f,t} \quad \text{Eq. 21}$$

Where: f – fuel type

t – hour

p – power plant

HR – heat rate (Btu/kWh)

$Price$ – average spot price of fuel (\$/MMBtu)

$O\&M$ – variable operations and maintenance cost (\$/MWh)

P – Nominal operating capacity (MW)

I – Clearing price of the electricity (\$/MWh)

O – Operating Income (\$)

4.2. Energy storage operation

Operation of bulk energy storage will influence the market clearing prices and requires a different treatment. We use a self-learning optimization technique, developed in prior work [36], to model the effects of bulk storage. In this approach, the hourly electricity prices from a no-storage optimization are used to calculate how storage would respond to those price signals. Then this storage operation is added to the hourly demand to get an adjusted demand pattern, which is used to produce a new time series of hourly prices, which are themselves used to find a new storage dispatch. This process is continued, and the moving average of the hourly storage charge/discharge at the end of each iteration is tracked until the solution converges. The storage operation converges/remains consistent after about 20 iterations, which we use as the number of

iterations for estimating an optimized solution that maximizes revenue while including the effect that storage has on prices.

4.3. Net change in operating income per unit capacity

To decide which power plants would retire in the third portion of the research, we use a metric for change in operating revenue. The model estimates the net change in operating income at the power plant level before and after adding storage as show in Eq. 22. This is then normalized to the size of the power plant and averaged over all plants of that type in order to calculate the net operating income (ΔO_f) per unit capacity of the given fuel type as shown in Eq. 23.

$$\Delta O_{f,p} = O_{f,p,ns} - O_{f,p,s} \quad \text{Eq. 22}$$

$$N_f = \frac{\sum_p \Delta O_{f,p}}{\sum_{p,f} P_{p,f}} \quad \text{Eq. 23}$$

Where: f – fuel type

O – Operating Income (\$)

ns – no storage

s – after adding storage

$P_{p,f}$ – Nameplate capacity of power plant p of fuel type f (MW)

5. Net change in mid- to long-term operating income including the effect of plant retirements

Bulk storage alters both the dispatch stack and the wholesale electricity prices in the market, changing both the dispatch of other generators and the clearing prices that they earn. A decline in revenues because of decreased capacity factor or decreased electricity prices (or both) could force retirements of existing generating plants [20,21]. The third approach we use includes retirement of plants with large decreases in operating incomes as a result of adding bulk storage.

The algorithm for identifying which capacity to retire is the following: The individual power plants losing the most operating income are retired until total retired capacity is equal to net storage capacity additions in the system. This reflects an assumption that there is a fixed need for reserve capacity in the power plant fleet and that storage capacity directly replaces the equivalent amount of generation. In the real world, any retirement decisions from the power plants are accepted by the ISOs only after ensuring that there is adequate reserve capacity to replace the existing retiring power plants [48,49], and we assume that a 1:1 replacement of storage for thermal capacity would meet that restriction. This process is continued until storage capacity reaches 15% of demand. Retirement of plants is continuous rather than per-plant to prevent “lumpy” changes in overall system capacity. For example, if 30 MW of retirement is called for but the next plant has capacity of 50 MW, the model retires 30 of the 50 MW and leaves 20 MW in operation. The plants that

are retired are those that have the largest losses, in \$/MW of capacity, between the no-storage case and the current quantity of storage. We chose to use change in operating revenues rather than an estimate of overall profitability because many generators, especially the peaker plants that compete with storage, earn a large share of their revenue from capacity markets or other ancillary services that are difficult to accurately calculate. Our method essentially assumes that currently operating plants are similarly profitable and that those which lose the most revenue relative to the status quo are those most likely to retire and that capacity prices will stay the same after 1:1 replacement by storage. One interesting outcome from this set of assumptions is that plants that are currently idle for essentially the entire year (spare capacity) do not lose any revenue after adding storage and are thus not retired. Whether this is realistic depends on which generators storage would replace: it is logical to suggest that storage would replace the least-used generators first, though a counterargument is that currently unused but operational generators are those best suited to provide spare standby capacity to the system and would continue that service even as some storage is introduced.

None of the three approaches in this work allow for new generation capacity to be built. There are three reasons for this. First, we want to understand the effect of storage additions in isolation from other factors, such as an evolving grid mix. Second, the rate at which new generation is introduced is uncertain and heavily policy driven. While it is evident that additions of wind and solar generation should be expected in the future, the rate and total extent are hard to predict. Finally, considering a full capacity expansion model to understand how new renewables and storage may grow in the future is a question that has been studied in the literature, so new insights are not expected if we included that feature.

Results

The results section is organized as follows. First, we present the marginal effects of storage on generating units, to determine which generators are used more/less when marginal storage quantities are added. Second, we describe the effects of storage on the operating income of generating units, assuming no retirements occur. Third, we demonstrate the effects of storage on the operating income of the generating units, assuming there are retirements of power plants with largest loss in revenue due to entry of storage. As described earlier, these three sets of results move from more empirically grounded analysis of small current-day storage additions to more prospective estimates of bulk storage effects in the future.

6.1.1. Impact on generation from storage operating as a price-taker

This section discusses the type of fuels used and displaced when storage capacity is added across the 22 eGRID regions in the U.S. In all cases, the energy used for charging is always greater than the energy displaced because of the round-trip efficiency losses of the storage. Fig. 2 illustrates the fuel types during the charge and discharge phase for a sample eGRID region (CAMX, covering California), and shows the net fuels used for delivering 1 MWh of energy from energy storage.

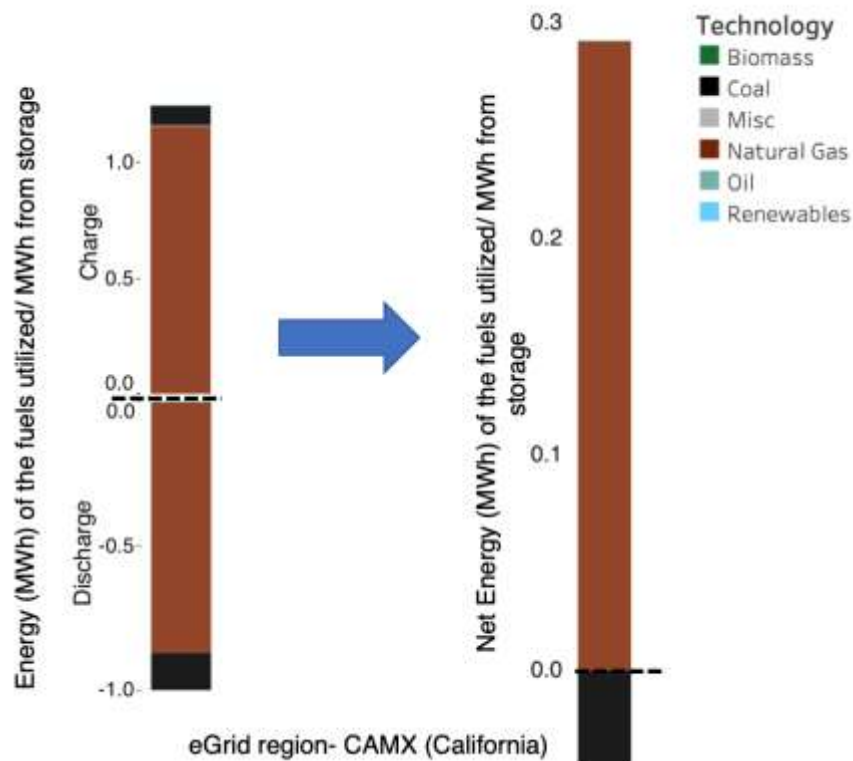


Fig. 2 Energy and net energy of the fuel utilized (MWh) per unit of energy from storage (MWh). Colors of the bars indicate the fuel mix during charge and discharge. The left figure indicates the energy consumed (1.25 MWh, positive side of axis) and displaced (1.0 MWh, negative side of axis) per MWh of energy from storage. The negative y-axis values indicate that storage displaces mostly natural gas and a little coal during discharge. The positive y-axis indicates that the energy mix used to charge storage is similar: natural gas and a little coal. The figure on the right shows the difference between positive and negative values on the left, indicating the net type of fuel used to deliver one MWh from storage (Note the change in y-axis between figures). Overall, a marginal storage unit in CAMX uses 0.28MWh of natural gas generation and displaces 0.04 MWh of coal energy to time-shift 1 MWh of energy.

Comparing across eGRID regions, results can be broadly divided into the West (covering California, Arizona and the other western states), the East (covering most of the eastern coast of the U.S.), and the Midwest, broadly-defined (Fig. 3). Results show that storage operation in most of the West (except California) and in the Midwest consumes both coal-based energy and natural gas during the charge phase and displaces a combination of both during the discharge phase. However, in net, more coal-based energy is used to charge, displacing energy from natural gas generators. In most of the West and the Midwest, storage operation has an average net consumption of 0.3 MWh of coal-based energy and displaces 0.1 MWh of natural gas-based energy per MWh of energy time-shifted by storage. On the other hand, on the east coast, a mix of coal and natural gas-based energy is used during the charge phase and storage displaces a mix of coal, natural gas and oil. While results vary by eGRID region, on average the east coast sees a net consumption of 0.1 MWh of natural gas and 0.02 MWh of coal and 0.0062 MWh of renewables per MWh of energy delivered from storage. Amongst all the regions, California

(CAMX) and New England (NEWE) have a net displacement of coal during the operation of storage. The high availability of renewables, hydro and natural gas during off-peak hours combined with environmental regulation and low natural gas prices pushes the usage of tiny amounts of coal (~10-20MWh) into the evening time in the peak-hours when the storage is most likely to discharge and displace these plants [37].

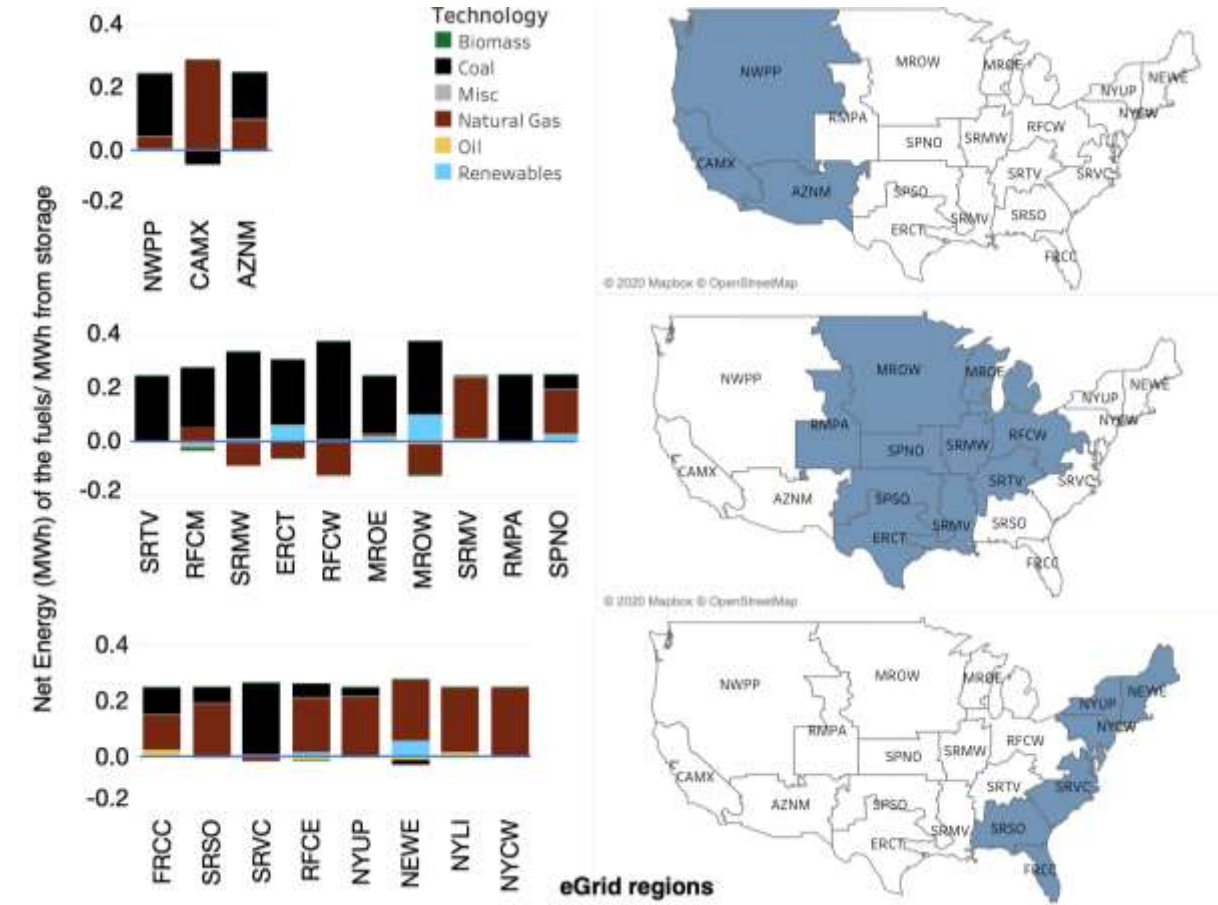


Fig. 3. Fuel type of net energy used (MWh) per MWh of energy transferred by storage for US eGRID regions. The figures in the left column indicate the net energy consumed (positive) and displaced (negative) per MWh of energy from storage. Colors of the bars indicate the fuel type. The right side shows eGRID regions for which the values are plotted. In the center of the US, storage tends to use more coal and sometimes displace natural gas, while results are mixed in the West and East.

6.1.2. Effect of storage operation on operating income of other generators without retirements

The analysis above assumes a quantity of storage that is too small to shift generation dispatch and market prices, but these factors become increasingly relevant as non-marginal amounts of storage are introduced into electricity systems. Fig. 4 illustrates the change in annual operating income per unit of generating capacity when different levels of storage are added to the CAISO, MISO and NYISO regions. These results are based on bulk storage additions without any plant retirements.

In CAISO, as storage is added from 0-2,500 MW (15% of the average load of 10,000 MW), operating income of most generating units decrease. Operating income decreases the most for natural gas combined cycle, geothermal, and nuclear, which are reduced by around \$6,000/MW annually with 2,500 MW storage capacity. At this storage capacity on the grid, gas turbines have an annual loss of \$2,600/MW, followed by hydro at \$1,800/MW, and wind at \$370/MW. Solar sees a small decrease in annual operating income of \$28/MW. While storage is a net consumer of energy, its effects on generator income tends to be negative because new storage brings down peak prices more than it increases off-peak prices. This effect is the same in the other two studied electricity systems.

In NYISO, as storage is added from 0 to 2,000 MW (15% of the average load of 8,000 MW), operating income of all generating units decrease, including for all types of renewables in the grid. Natural gas combined cycle power plants see the largest decrease in annual operating income of \$2,000/MW at 2,000 MW storage capacity. Coal and nuclear follow this closely and lose \$1,700/MW annually. Amongst the renewables, biomass loses by \$660/MW, hydro by \$530/MW, solar \$480/MW, and wind \$320/MW annually. Gas turbines in NYISO lose \$1000/MW, a smaller amount than what is observed in CAISO.

Similar to NYISO, the operating income of all types of generating units decreases in MISO as storage is added from 0 to 3,000 MW (15% of average load of 12,000 MW), without considering retirements. At 3,000 MW of storage capacity on the grid, the largest decrease in annual operating income is for coal at \$150/MW, followed by nuclear at \$140/MW, gas combined cycle at \$95/MW, solar at \$52/MW, hydro at \$41/MW, wind at \$34/MW, and gas turbines at \$14/MW. These price shifts are much smaller in magnitude than in CAISO or NYISO because MISO has a large percentage of coal in the generation mix (>70%), which stabilizes prices with or without storage. The flatter prices in MISO also mean that storage is cycled less, which further reduces effects on other generators: annual charged energy to storage is much lower in MISO (624 GWh), than in CAISO (2,555 GWh), or in NYISO (3,200 GWh). Further notes on the comparison of total storage energy is provided in the SI, Section S3.

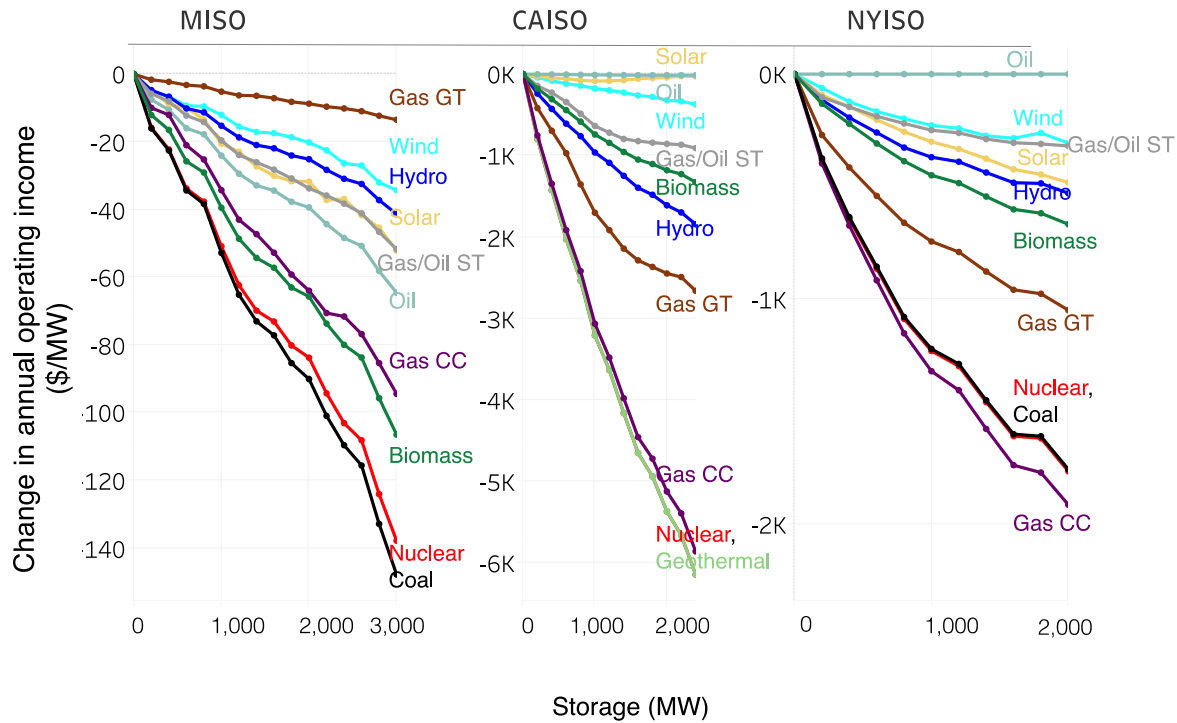


Fig. 4: Change in net annual operating income per unit capacity (\$/MW) before and after adding storage capacity in Midcontinent Independent System Operator (MISO), California ISO, and New York ISO (NYISO) without any retirements. X-axis represents the storage capacity in MW, Y-axis represents the change in operating income per unit capacity in \$/MW after adding storage, and the colors represent generation technologies.

6.1.3. Effect of storage operation on operating revenue of other generators with retirements

In the results above, introducing storage tends to reduce operating income to all types of generation, which is explained by the fact that we are adding resources without removing anything from the system. In reality, this would eventually prompt retirements, which may improve income for the remaining generators. We develop a simple model for this dynamic, where we maintain total generation plus storage capacity and retire the power plants that lose the most operating income as storage is added. Plants are retired until total retired capacity is equal to net storage capacity added into the system to maintain the same total “firm” (thermal + hydro + storage) capacity.

Fig. 5 shows which generators are retired as storage is added. Most of the retired capacity in CAISO are natural gas turbines, followed by combined cycle, and a small percentage of biomass, coal, and oil. In MISO, the retired generators are a mix of gas combined cycle, coal, and a small percentage of biomass plants. In NYISO, the retired capacity is a mix of gas combined cycle, gas-based steam turbines, gas turbines, oil, and biomass. Also, it is interesting to note that most of the retired plants in CAISO were built after 2000 (gas turbines primarily), and in MISO and

NYISO between 1980-2000. The histograms of the built years of the retired power plants in different regions is given the SI, section S4.

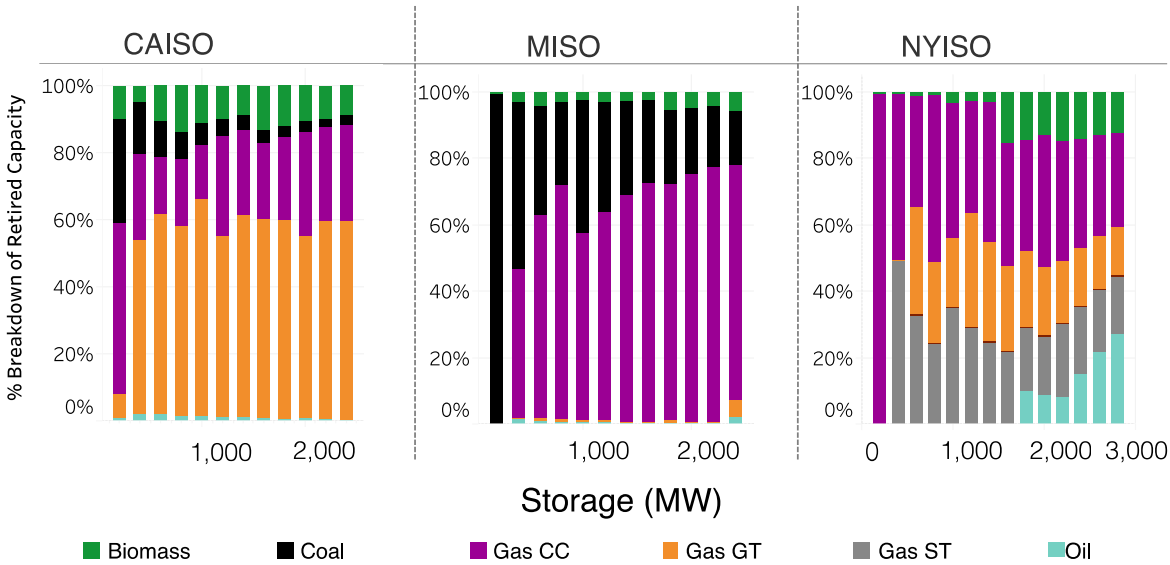


Fig. 5: Generation type of the retired power plants as storage is added. X-axis represents the total added storage capacity in MW and Y-axis represents the percentage of capacity retired at that level of storage deployment (with total retirements equally the amount of storage added). Bar colors represent the fuel/technology type. Each row of plots represents the ISO region: California ISO (CAISO), Midcontinent ISO (MISO), and New York ISO (NYISO).

As with the results without retirement, the change in operating income per unit capacity is estimated before and after adding storage in CAISO, MISO and NYISO regions (Fig. 6). But now, net operating income is additionally affected by economic retirement of the power plants in Figure 5. Retirements improve revenues for the remaining plants but also produce shifts in marginal electricity price and create more noise in the per-capacity operating income as storage levels increase.

In CAISO, as we add storage from 0-2,500 MW (10,000 MWh) and retire revenue-losing plants, the annual operating income of solar increases the most, by \$800/MW at 2,000 MW of storage capacity on the grid. The annual operating income of all other generating technologies decreases or stays approximately flat. The operating income of gas combined cycle units and gas turbines decrease by around \$800/MW, nuclear and geothermal decrease by around \$300/MW, hydro by \$30/MW, and wind by \$123/MW. The operating income of solar increases because of the increase in electricity clearing prices during the charge phase of the storage, which occurs during the mid-day solar peak on some days.

In MISO, as the storage is increased from 0-3,000 MW (12,000 MWh), the largest increase in annual operating income as storage is added is observed for nuclear by \$235/MW, followed by coal at \$180/MW. At 3,000 MW storage capacity, the annual operating income of wind increases by \$82/MW, hydro by \$71/MW, and solar by \$47/MW. The annual operating income of natural gas combined cycle increases by \$13/MW.

Similar to MISO, NYISO sees an increase in annual operating income of coal and nuclear as storage is added from 0-2,000 MW (8,000 MWh) into the grid by \$2,000/MW. This is followed by wind at \$680/MW, hydro at \$580/MW, solar by \$330/MW, gas combined cycle at \$280/MW, and biomass and gas turbine at \$90/MW.

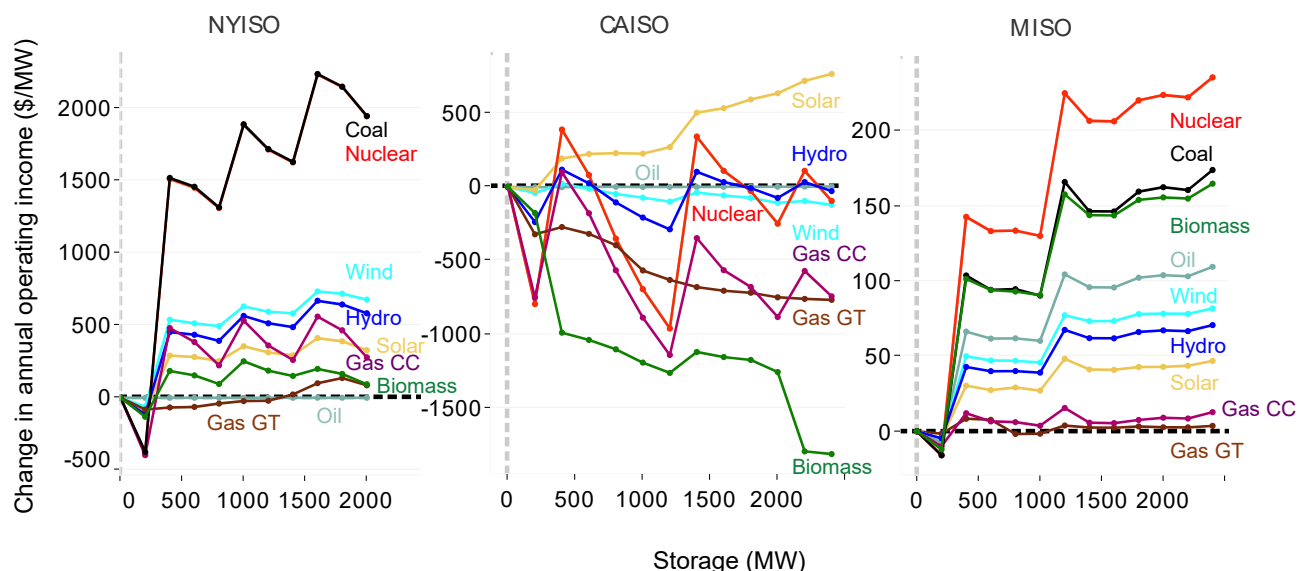


Fig. 6: Change in net annual operating income per unit capacity (\$/MW) before and after adding storage, considering retirement of power plants and bulk storage additions in Midcontinent Independent System Operator (MISO), New York ISO (NYISO), and California ISO (CAISO). X-axis represents the storage capacity in MW, Y-axis represents the net annual operating income after adding storage, and the colors represent generation technologies.

6.1.4. Comparing results across the three modeling approaches

Fig 7 compares the average net generating impacts per MWh of storage discharge for each of the three approaches: price-taker, bulk storage additions without retirements, and bulk storage additions with retirements. The figure demonstrates that, depending on the region, estimates from the price-taker model can bear close resemblance to those generated with a bulk storage affecting prices approach; as an example, the net energy effects of storage in NYISO are consistent in magnitude and fuel mix across three modeling approaches.

Although the estimates of the breakdown of fuels typically used to charge storage are similar across models for CAISO, accounting for retirements yields more generation from natural gas to charge storage and more displacement of coal and biomass. MISO exhibits the most variation across modeling approaches; although coal is used to charge storage in each of the three models, the bulk storage without retirements yields more significant changes to net generation from coal and natural gas. These results illustrate that bulk storage affecting prices generally produces findings similar in direction to those of the marginal storage model, albeit with differences by region. It is notable that the change in generation is linear for both the price-taker model and bulk storage additions without retirements. However, the change in generation of different fuels for

the bulk storage with retirements scenario depends upon the incremental storage additions and retirements at each stage, further illustrated in SI Fig S2.

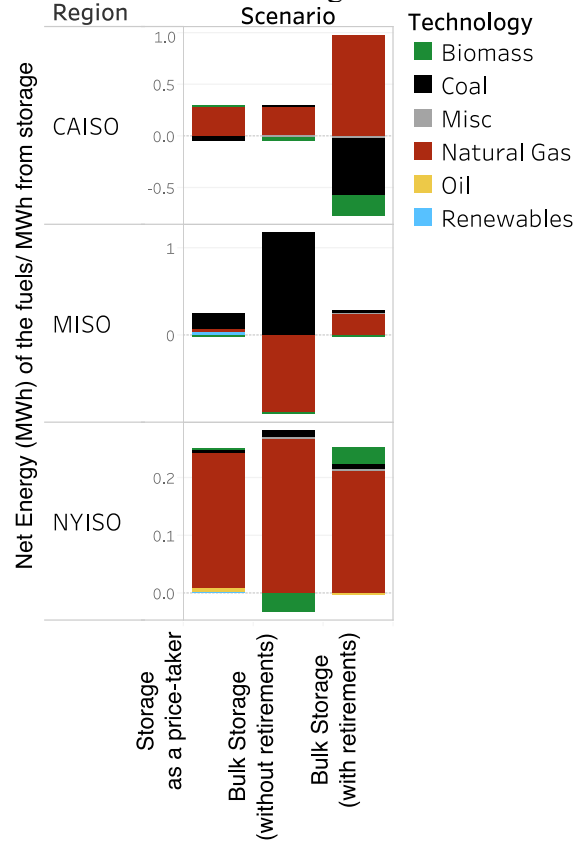


Fig 7: Comparison of estimates of the annual net energy by fuel type per MWh of energy from storage using three modeling approaches: storage as a price-taker, bulk storage without retirements, and bulk storage with retirements. The colors indicate the technology type used/displaced by 1,000 MW of storage.

Discussion

Prior work has established that, depending on the grid mix and the operating strategy of the storage, storage tends to slightly increase prices during off-peak periods and decrease the revenues of most generating units, especially plants that operate during the peak demand hours [20,21,26,50]. The contribution of this work is to quantify the type of generators and the fuels used and displaced by new storage across the U.S. Furthermore, we employ a mix of price-taker and bulk storage modeling approaches in different grids to understand the implications of different modeling strategies on our estimation of the impacts of storage operations. Using this hybrid approach, we are able to characterize marginal impacts on operations for the entire U.S. and more detailed, large-scale impacts on operation and operating income for three grid mixes, which range from coal-heavy to more dependent on renewables.

The results show that the change in generation from energy storage is largely dependent upon the grid mix when the capacities are small and marginal. Although most regions tend to displace natural gas and increase generation from a mix of natural gas and coal, the magnitude of these

shifts vary. Large non-marginal capacities of bulk storage alter the electricity prices, thus affecting not only the plants during the peak demand hours, but also renewables that depend on these prices for profit. Without retirements, the operating income of essentially all units go down (except solar in California, which breaks even) as bulk storage capacities are deployed onto the grid, with natural gas being the most affected.

However, when market balance is considered through retirement of less profitable units from the energy markets, the highest increase in operating income from adding storage is observed for the base-load units supplying energy in the grid when storage charges. Therefore, in NYISO and MISO, less flexible units that have continual output (coal and nuclear) benefit the most from additional storage, followed by wind, solar, and hydro. However, in California, with about 20% generation from solar, solar benefits the most. The operating income of all other fuels is heavily dependent on the fuels that set the market clearing prices. In CAISO's case, the operating income of all the other fuels decreases along with the decrease in operating income of the price-setting natural gas power plants.

The operating income of gas combined cycle units depends upon both the time of the day they are most commonly used and the retirements. In a coal-dominated grid such as MISO, with 15% natural gas combined cycle capacity, storage offsets gas combined cycle during discharge and also retires these plants, driving their operating income down. In gas-dominated grid such as NYISO with 25% combined cycle capacity, NGCC is used both during the charge and discharge phase of the storage. Thus, the net operating income is positive after retirements and storage additions. Overall, storage adds flexibility to the system, benefitting both base-load generators and non-dispatchable generators. In all cases, gas turbines always lose operating income after adding storage. Finally, our comparison of net generating impacts across bulk storage additions and price-taker models suggests that results from these approaches are generally similar in direction, but scale and consistency across the approaches varies by region. Furthermore, in some cases, not accounting for retirements can lead to substantial changes in magnitude of net generation impacts relative to the other approaches.

The results from this study could help regulators to determine whether storage operations are a net social benefit or a net social cost in various regions of the U.S. and to understand the likely effects of broader adoption of storage. The hybrid price-taker and bulk storage approach provides results that are useful both for planners considering small amounts of storage or policy makers considering futures with deeper integration of storage. In addition, the results from the model including retirements provide a clear demonstration of the importance of accounting for market exit when evaluating the mid- to long-term effects on generator profitability for bulk storage.

852Conclusion

653 Because storage is likely to play a pivotal role as an enabling technology in decarbonization of
654 the power sector, there are a number of policy efforts to increase storage on the grid today.
655 Energy storage is often mentioned as a necessary or enabling element for greater shares of wind
656 and solar generation, but this work demonstrates that the effect of storage on other generators is
657 relevant and complex. Wind and solar may benefit from new storage, especially in the presence
658 of retirements, but other technologies may enjoy an even greater economic boost. While the
659 analysis in this work did not add new wind or solar to electricity grids (as is expected in the
660 future), these results should give pause to anyone that believes the benefits of additional storage
661 are enjoyed solely or primarily by renewable energy technologies. Our findings demonstrate that
662 additional storage may help or harm renewables but may also increase generation and
663 profitability from fossil generation given the existing grid mix, thus potentially increasing the
664 challenge of deploying low-carbon sources. This work quantifies some of these effects so that
665 policy makers might account for them when designing storage policies to ensure that they help
666 further renewable energy generation and low-carbon grids of the future.

967Acknowledgements

668 This material is based upon work supported by the Environmental Sustainability program of the
669 National Science Foundation under award number 1706228.

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