Tradeoffs between revenue and emissions in energy storage operation

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Abstract

Grid-level energy storage is an emerging technology that provides operational flexibility for managing electricity demand, integrating renewable energy, and improving system reliability. However, it has been established that revenue-maximizing grid-level energy storage tends to increase system emissions in current US electricity grids. In this work, we consider storage operational strategies that value both revenue and CO_2 emissions to understand the tradeoffs between these two criteria. We use actual electricity prices and marginal emissions factors in a linear programming model that optimizes operation between annual revenue and CO_2 emissions to find the Pareto Frontier for 22 eGRID sub-regions. We find that, in many US regions, marginal storage-induced CO_2 emissions can be decreased significantly (25-50%) with little effect on revenue (1-5%). Electricity grids with larger flexibility in daily electricity prices and in marginal emissions factors have more potential to reduce annual storage CO_2 emissions at low cost to storage operators. These results show that negative environmental effects of storage operation can be reduced or eliminated at low cost through voluntary or regulatory shifts in operational patterns.

Key words: energy storage, marginal emissions, electricity system, CO_2

Highlights:

-Existing literature agrees that revenue- or value-maximizing energy storage increases electricity system emissions

-We use a linear programming model of storage operation that values both revenue and CO_2 emissions

-Marginal storage-induced emissions can be drastically reduced (~50%) with little loss of revenue

-Increasing the round-trip efficiency of storage provides more capability to reduce storage-related emissions at low cost

Introduction:

Energy storage refers to various technologies, such as pumped hydro, compressed air energy storage (CAES), and batteries, used to store electrical energy. Grid-level energy storage can provide a variety of benefits to electricity systems, from renewable energy integration to frequency regulation, but can generally be considered a tool for increasing operational flexibility of the grid [1], [2]. While still an emerging technology, grid-level energy storage is a promising solution for modernizing the electricity grid and integrating cleaner energy sources such as wind and solar power.

Governments globally and in the US are considering support for energy storage as an important element of grid decarbonization. In the US, state governments have passed laws with the goal of boosting renewable energy integration through bulk energy storage, often defining an adoption target for storage in terms of either power (MW) or energy (MWh) capacities [3], [4], [5], [6]. In 2010, California passed AB 2514 requesting the California Public Utilities Commission (CPUC) to determine an advantageous amount of grid energy storage. In 2013, they arranged a mandate of 1.325 GW of energy storage by 2020 [7]. Likewise, in 2015, Oregon passed HB 2193, mandating 5 MWh of energy storage by 2020 [8]. Massachusetts also approved an energy storage mandate in the 2016 Act Relative to Energy Diversity, demanding 100 MWh of energy storage by 2020 [9]. Nevada passed a renewable portfolio standard which allows up to 10% of energy to come through energy storage [10]. Maryland passed a tax incentive to help stimulate the distributed energy storage industry [11]. These government policies complement the growing private sector market, and their collaboration is expected to lead to rapid growth of the industry over the next decade. In 2015 and 2016 alone, approximately 400 MW of energy storage was deployed onto the US electricity grid [12]. As more states and utilities attempt to innovate creative ways to utilize energy storage on the electricity grid, we will learn much more about the costs and benefits of the technology and about which policy strategy is the most effective.

Energy storage offers many benefits to electricity systems, often providing several services at once [13]. Storage can reduce the need for peaker plants, optimize congested transmission, provide frequency regulation service, and manage electricity demand. In the case of a natural disaster, distributed energy storage can provide power while system operations are restored. Finally, and perhaps most prominent in the popular imagination, a broad literature describes the ability of bulk energy storage to integrate renewable energy into any grid [14]–[20]. An often-overlooked advantage of storage is that it provides a "no regrets" complement to almost any energy future, whether that be massive renewable deployment, smart grid development, nuclear power, or continuation of the status quo.

With its many advantages, energy storage is attracting the attention of policy-makers and flourishing within the energy market. However, recent research warns that assimilation of energy storage could result in an unintentional increase of grid emissions. In 2015, Hittinger and Azevedo [21] found that bulk energy storage would consistently increase electricity system emissions if operated to maximize revenue. Due to inefficiency losses in the energy storage (due to round-trip efficiency less than 100%), the generation from less expensive fuels would increase to displace a small amount of energy during peak demand, thereby increasing baseload emissions. A study done on the PJM interconnect, developed by Lueken and Apt, found that integrating 20 GW of storage would have broad welfare benefits, such as lowering the cost of residential electricity in the market by 2.5 billion dollars annually [22]. However, when they analyzed the life cycle emissions of storage options for the electricity grid, the authors found that adding storage modestly increased greenhouse gas emissions. Similarly, in 2013 Carson and Novan [23] found, when they were modeling the social benefits of storage technology in Texas, that arbitrage will increase unregulated emissions, since renewables were not marginal sources of energy. These effects hold because the emissions rates of peak generators are not sufficiently higher than the emissions rates of generators used during off-peak periods in the Texas energy market. Arbabzadeh et al. intensively investigated feasible storage characteristics to make predictions about the storage factors which induce CO_2 emissions [24]. The authors found that round-trip efficiency, heat rate of the charging technology, and heat rate of the displaced technology had the strongest influence on CO_2 emissions from highly utilized energy storage devices. In another recent study, Fares and Webber found that sending solar energy back into the grid is more environmentally beneficial than storing the energy in household storage devices [25]. The study concluded that managing distributed storage under either the common interest or under the interests the household owner would lead to increased grid emissions, mainly due to inefficiency losses.

The three main factors that affect storage-related emissions are: the marginal emissions of the generator that charged the device, the marginal emissions of the displaced generator when storage discharges, and the roundtrip efficiency of the storage. Round-trip efficiency refers to the ratio of energy into storage to the energy retrieved from storage, which is always less than 100% due to internal resistance, friction, or other processes depending on the technology. In many eGRID sub-regions, due to costs and emissions of actual generators, energy arbitrage results in the displacement of cleaner peak fuels (natural gas) with increasing production from dirty off-peak fuel (coal). Even in regions where combined cycle natural gas provides baseload generation, the inefficiency of storage tends to negate the efficiency advantage of the combined cycle plant. This theory holds unless off-peak generation is sufficiently cleaner than the peak generation, accounting for the energy losses that will occur from charging and discharging the device (e.g. a 75% round-trip efficient storage device needs to charge with off-peak generation that is at least 33% cleaner than peak generation to prevent adding emissions to the grid). With the current US energy infrastructure, storage-induced CO_2 emissions are hard to avoid as long as storage operates to maximize profits or minimize generation costs [21].

Alternative research investigates structures that limit the emissions resulting from the application of storage, but the concept of emissions-free energy storage is very difficult to achieve. Sioshansi [26] built a model to investigate the effects of competing bulk energy storage companies in the Texas electricity grid, and found that storage produces the least amount of emissions if owned by the renewables industry. The partnership of wind energy producers and storage facilities was crucial to limiting the amount of emitted air pollutants. In another wind energy study, Boer et al. [27] found that storage should only be implemented in areas where wind speeds range from medium to high, because storage systems could lose profit and create emissions if the renewable energy in the grid is insufficient. In order to limit the amount of additional emissions from storage systems, Lin et al. [28] developed a stochastic model which sets a coal emissions cap into a grid simulator. The study found that, with the coal emissions cap, storage would be forced to work excessively, increasing emissions from other fuels and from inefficiency losses. Even without the coal emissions cap, storage still had the possibility of increasing emissions due to “reserve capacity” - storage space that is not filled by renewable energy.

Previous research establishes that profit- or value-maximizing storage tends to increase system emissions, at least for current grids in the US. However, changing the operational strategies and patterns of storage operation has not been examined. In this work, we directly address this concept, hypothesizing that the well-established increases in grid emissions associated with new storage could be mitigated by alternative operational strategies that reward emissions reductions. To test this, we use a linear programming model of storage operation that optimizes the trade-offs between storage revenue and increases in system CO_2 emissions, assigning varying weight to the two factors. Using hourly marginal emissions factors and electricity prices as inputs, Pareto-optimal storage schedules are calculated with objectives ranging from maximizing revenue (ignoring emissions effects) to minimizing CO_2 emissions (ignoring revenue).

Data and Methods:

We use a linear programming formulation to simulate an energy storage plant, calculating optimal operating schedules at locations in 22 eGRID sub-regions. The charging and discharging cycles are then used to further calculate annual revenue and the change in system CO_2 emissions resulting from the storage operation. This linear programming (LP) approach, with an objective function to maximize revenue, is a relatively standard storage modeling procedure. Here, we extend the LP model to include an additional objective, namely CO_2 emissions reductions.

In this work, bulk energy storage was modeled using attributes of existing technologies such as pumped hydro, hydro reservoir above a dam, compressed air energy storage (CAES), and battery technologies. The Sandia Laboratory National Energy Storage Database [29] was used to gather technical information about US energy storage devices. A summary of the information can be found in the Supplementary Information (SI). Using technical specifications of commonly integrated bulk energy storage devices, we chose a base-case storage plant with a capacity of 100 MWh, a 4-hour charging rate (hence, 25 MW charge/discharge limit), and a roundtrip efficiency of 75%. Both the storage round-trip efficiency and the charging rate are varied in the sensitivity analysis.

Pricing data for 22 eGRID sub-regions for the year 2014 originates from Horner et al.[29] , [30] which report actual hourly electricity system prices. While energy prices vary by location, we calculate results for a single representative location in each eGRID sub-region. To match state-linked price data to eGRID sub-regions, we use data from the most populous state in the region. A table describing which price data was used for each eGRID sub-region can be found in the SI. Electricity systems in Alaska and Hawaii were omitted from this study, but all other eGRID sub-regions within continental US are analyzed.

Marginal emissions factors (MEFs) used in this work have been derived from the EPA's Continuous Emissions Monitoring System (CEMS) using the same framework as Siler-Evans et al.[32] and are taken from: https://cedm.shinyapps.io/MarginalFactors/. CEMS provides raw mass pollution data for every fossil fuel plant with a capacity of 25 MW or larger within the United States. Hourly emissions for each eGRID sub-region is found using a summation of all of emissions in that hour from every plant that lies within the territory. Then, every hourly mass total is paired with the respective hourly electricity production total and the entire set is linearly regressed. The slope of the regression is the marginal emissions factor (MEF), representing the change in emissions that results from a change in production. MEFs embody the emissions rate from the last (marginal) generator used to meet demand. Siler-Evans et al.[32] calculate MEFs for each hour over a 24-hour cycle in each of three different seasons (summer, winter, intermediate). MEFs represent a valuable tool for accurately assessing the emissions effects of small changes to the grid and are more accurate than average emissions factors [33]. The MEFs methods and data are described in greater detail in the SI, but for a complete accounting the reader should refer to the two Siler-Evans research articles[32], [33].

Storage operation is calculated using a linear programming approach to determine the optimal storage operational schedules as a function of time-varying electricity prices and marginal emissions factors (MEFs). Both of these real-world data sets were integrated into a single objective function by assigning a “carbon value” to storage-induced grid emissions. Storage operation is recalculated using different “carbon values”, ranging from \$0/tonne to \$1M/tonne (effectively infinite) to represent different relative weights between revenue and emissions in the multi-criteria optimization. This approach sketches out a Pareto frontier between the two objectives, giving a set of optimal solutions as the relative weights of revenue and emissions are varied. Each optimal operational schedule is then analyzed and the results represent the maximum annual revenue that the storage device could earn at a given level of CO_2 emissions or, alternately, the minimum CO_2 emissions possible for a given amount of annual revenue. Since the electricity prices and MEFs are taken from actual 2014 data, in markets that have various policy and regulatory constraints but no significant carbon prices, changing the carbon value (CV) does not indicate the outcomes of revenue and emissions effects if a carbon price were actually applied in the market. This is because an actual carbon price would change generator dispatch patterns and alter both price trends and marginal emissions. Rather, the results that we calculate indicate the revenue and emissions effects that result from intentional or regulatory changes to storage operational patterns in current electricity systems. Put simply, the “carbon value” is a tool for the internal decision-making of storage; it is not broadly applied to the market itself.

The main objective function (Equation 1) is to maximize economic value from storage, while CO_2 emissions are integrated with revenue through the "carbon value". The decision variable, $\boldsymbol{E_t}$, is positive if the unit is discharging and selling electricity, and negative if the unit is charging and buying electricity. The system is unable to charge and discharge at the same time. The revenue calculation uses $\boldsymbol{P_t}$, electricity prices, and $\boldsymbol{E_t}$, the displaced energy from bulk energy storage, to find the maximum income. Emissions reduction is included using $\mathbf{MEF}_{\boldsymbol{t}}$, marginal emissions factors in units of tonnes of CO_2 per megawatt-hour, and $\mathbf{V_i}$, the carbon value in units of USD per tonne of CO_2. Together the two objectives form a single objective function:

$$\boldsymbol{max} \sum_{\mathbf{0}}^{\boldsymbol{t}} [[\mathbf{P}_{\boldsymbol{t}} - (\mathbf{MEF}_{\boldsymbol{t}} * \boldsymbol{V_i})] * \mathbf{E}_{\boldsymbol{t}}$$

$$\mathbf{V_i \in 0, 1, 2, 5, 10, 20, 36, 50, 100, 200, 500, 1000, 2000, 5000,}$$

$$\mathbf{10000, 20000, 50000, 100000, 200000, 500000, 1000000.}$$

Objective Function (Equation 1)

For every eGRID sub-region, various optimal solutions are calculated, each using a single carbon value. Collectively, these produce a Patero Frontier. The constraints that bound the feasible region are the same for each iteration, except in sensitivity analysis (discussed below). Equations 2 through 7 describe the capabilities of the storage unit in the form of optimization constraints. The state of charge of the storage unit is initially set to zero and naturally returns there at the end of the year because any residual energy would represent lost revenue/emissions displacement. Equations 2 and 3 track the state of charge of the battery after inefficiency losses, where η_{rt} is the round-trip efficiency set at 75% for the base-case, which is divided between the charge and discharge portions of the cycle. All storage technologies have inefficiency losses, which vary due to the technology and conditions under which they are operated. For storage technologies that can be deployed at large scale (pumped hydro, compressed air, lithium-ion, etc.), round-trip efficiency is normally in the 70-90% range [29], [34].

$$S_t = S_{t-1} - \frac{E_{t-1}}{\sqrt{\eta_{rt}}} \quad \textbf{if } _{-1} \geq 0$$

Efficiency losses during charging (Equation 2)

$$S_t = S_{t-1} - \sqrt{\eta_{rt}} * E_{t-1} \quad \textbf{if } _{-1} < 0$$

Efficiency losses during discharging (Equation 3)

The state of charge is constrained between zero (Equation 4) and the maximum capacity of the device (Equation 5). The base-case storage capacity used was 100 MWh.

$$\forall t, S_t \geq 0$$

Lower Capacity Constraint (Equation 4)

$$\forall t, S_t \leq S_{max}$$

Upper Capacity Constraint (Equation 5)

Lastly, the charging rates of the storage unit are set within the feasible rates of the device (Equations 6 and 7). Maximum allowable charge/discharge rates for the base-case operation are 25 MW (a 4-hour rate). The charge rate is the rate at which energy can be added to or removed from the device, in units of power (MW).

$$\forall \boldsymbol{t}, \boldsymbol{E_t} \leq \boldsymbol{R_{max}}$$

Charging Rate Constraint (Equation 6)

$$\forall \boldsymbol{t}, \boldsymbol{E_t} \geq -\boldsymbol{R_{max}}$$

Discharging Rate Constraint (Equation 7)

Using an array of carbon values, the LP model calculates various optimal charging patterns for every eGRID sub-region. Excluding sensitivity analysis, 462 schedule configurations were found: 21 carbon values for each of the 22 eGRID sub-regions. Each one of these configurations yields different optimum charging schedules, which result in a unique combination of annual revenue and changes in grid CO_2 emissions. After acquiring the optimal operational patterns, calculating annual revenue and storage-induced emissions is straightforward. Annual revenue (Equation 8) is the summation of electricity sold or purchased times the sales price in each hour (during purchases of electricity $\boldsymbol{E_t}$ is negative). It is important to note that the annual revenue calculation assumes that the storage owner is never required to pay for storage-induced emissions, even though the objective function includes a "carbon value". That carbon value is used *only* to determine an optimal storage operation that values emissions reductions, and *is not* actually charged to any entity in the market.

$$\sum_{\mathbf{0}}^{\mathbf{t}} [\mathbf{E_t} \times \mathbf{P_t}]$$

Annual Revenue (Equation 8)

Annual storage-induced CO_2 emissions (Equation 9) were calculated in the same way, using the displaced energy and MEFs for CO_2 for the given hour. The negative sign is needed because selling electricity ($\boldsymbol{E_t}$ is positive) back into the grid reduces marginal emissions (while increasing revenue) and vice versa. Because the electricity prices and marginal emissions factors we use are exogenous to the storage model, the effects of storage operation do not result in changes to either input. Hence, our results apply to a "marginal" addition of energy storage – an amount that is small enough to have a negligible effect on prices and generation dispatch patterns. As storage deployment increases, results could diverge from those we show below.

$$\sum_{0}^{t}[-\mathbf{E_t} \times \mathbf{MEF_t}]$$

Annual Emissions (Equation 9)

As an example of the time-series output, Figure 1 displays four energy storage operational solutions for the eGRID sub-region SPNO (Kansas) from late February to early March. Figure 1 demonstrates the optimal storage schedules for carbon values of \$0, \$36, \$100, and \$1M/tonne of CO_2. As the carbon value is increased, the optimization gives solutions with lower emissions, focusing less on revenue from electricity prices. For example, the observed spike of prices on March 5th becomes less influential in the operations with higher carbon values. Conversely, when the carbon value is high and marginal emissions are relatively flat (February 26-28), storage tends to cease operation unless there are strong changes in energy prices that can produce sufficient revenue. As the carbon value goes from zero to medium values, storage tends to give up cycling that moves a lot of energy but makes little revenue, and shifts charging/discharging into periods that make slightly less revenue but have a larger effect on emissions. As the carbon value becomes very high, storage phases out any operation that does not reduce emissions, eventually operating without regard for revenue.

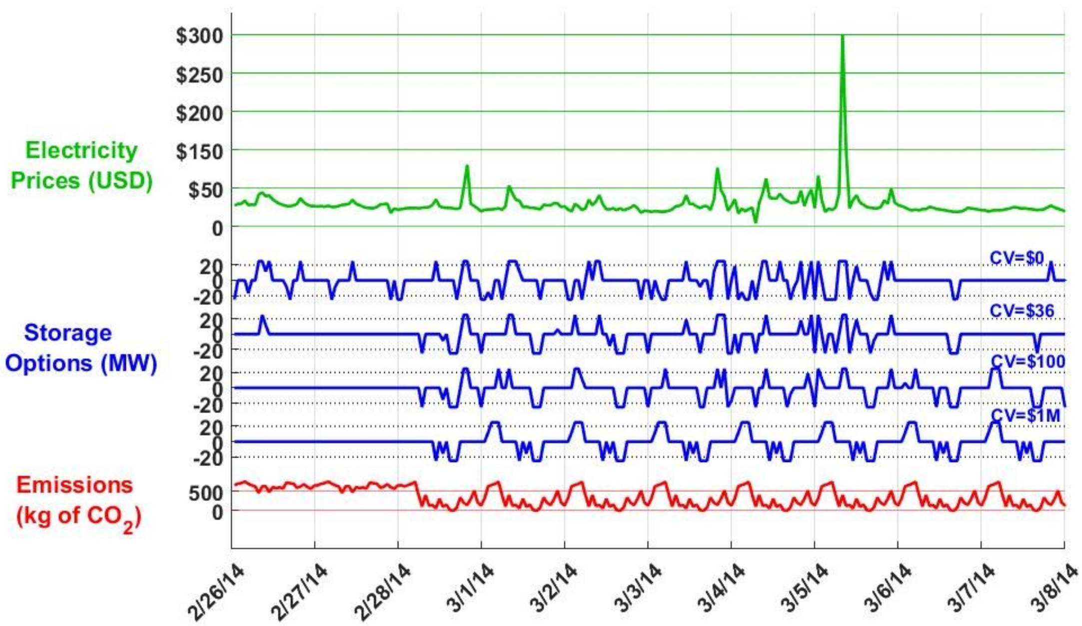

Figure 1. *Four optimal charging and discharging schedules (blue lines in center, positive*

indicates discharge) for bulk energy storage for SPNO (Kansas) during late February and early March in 2014. Prices over the same period are shown on the top green line, while MEFs over the period are on the bottom red line. As the carbon value (CV) increases, storage is less willing to pursue high-cycling, low-value arbitrage opportunities and will shift charging/discharging periods to those that have similar revenue but lower emissions effects. Eventually, at high carbon values, storage becomes primarily focused on reducing emissions and neglects all but the highest arbitrage opportunities.

Results

Figure 2 shows the revenue and emissions results for three different eGRID sub-regions: CAMX (California), NYUP (Upstate New York), and ERCT (Texas). Each point in the figure represents a different carbon value used to calculate the annual revenue and annual CO_2 emissions from a fixed-design storage plant (25MW/100 MWh, 75% round-trip efficiency) in 2014. In particular, carbon values \$0, \$36, \$100, and \$1M per tonne of CO_2 have been highlighted to demonstrate the incremental progression of the Pareto curve, or the representative set of efficient solutions that exist for each eGRID sub-region. As the carbon value is increased, the optimization process prefers schedules that reduce emissions and shifts the charging/discharging operation. But there is a trade-off because these lower-emissions schedules reduce the possible revenue. For each of these regions, using the EPA-derived social cost of carbon of \$36/tonne of CO_2 [35] decreases revenue by a few percent, but it results in a larger reduction of emissions. Theoretically, under these conditions (CV=36), the NYUP eGRID sub-region would have a 56% reduction in storage-induced emissions at a cost to the storage owner of \$30,000/yr, the CAMX eGRID sub-region would have a 70% reduction for \$20,000/yr, and ERCT would have a 30% reduction for \$85,000/yr. For eGRID sub-regions NYUP (Upstate NY) and CAMX (California), where the modeled storage device is expected to make over a million dollars annually, this is a small percent (<3%) of the annual revenue for a large fraction (56-70%) of reduced storage emissions. For ERCT (Texas), it is equivalent to 11% of the annual revenue. However, due to the large range of daily fluctuations in MEFs, more than 2,500 tonnes of CO_2 emissions could be prevented.

When carbon values above \$100/tonne of CO_2 are used, the decrease in emissions slows down, but there is a significant decrease in revenue. It is not surprising that these curves are convex: opportunities for reducing storage-induced emissions can be thought of as a supply curve, with many low-cost, high-benefit shifts that can be initially adopted. Eventually, however, emissions elimination strategies become expensive and storage may instead choose to cease operation entirely. For all three regions, a low to moderate carbon value has a significant, positive effect on emissions with little effect on the economic benefits of the storage unit.

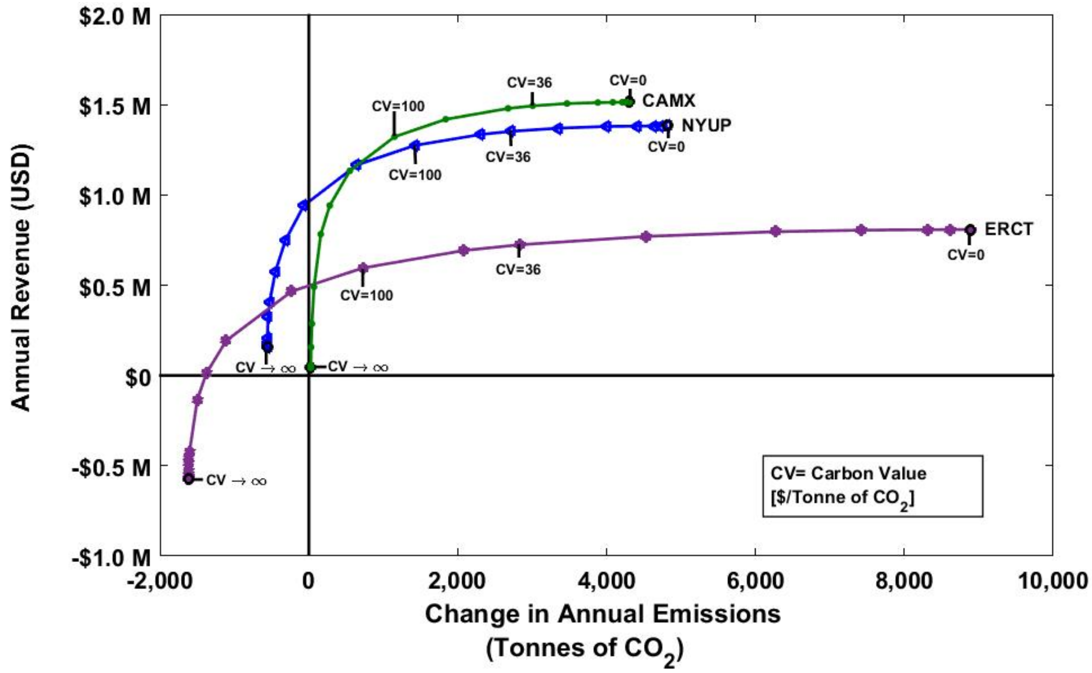

Figure 2. *Bulk energy storage revenue and CO_2 emissions over the year 2014 for three eGRID sub-regions: CAMX (California), NYUP (Upstate New York), and ERCT (Texas). The solid lines represent all the possible Pareto-efficient solutions, as the carbon value is changed, if a 25 MW/100 MWh storage device had been integrated in each eGRID sub-region. The upper right point on each line shows revenue and emissions when storage is operated to maximize revenue, and the lower left point represents a scenario where it operates solely to minimize emissions. In all cases, it is possible to find operational schedules that significantly reduce storage emissions with little effect on revenue.*

The results for all 22 of the examined eGRID sub-regions are shown in Figure 3. The ideal quadrant is in the upper left of the figure, where revenue is high but storage induced emissions are negative. Only a few regions, primarily AZMN (Arizona and New Mexico), have solutions with high revenue and reduced emissions. Nevertheless, there are desirable tradeoffs in many locations: although revenue can never be higher than the case where storage optimizes only for revenue, it is clear that initial emissions reductions can be achieved with little decrease from the maximum revenue. As expected, states with similar electricity prices and energy resources tend to have similar results. For example, NYUP (Upstate New York), NYCW (New York City), NYLI (New York Long Island), NEWE (Massachusetts, New Hampshire, Vermont, Maine, Connecticut, and Rhode Island) and RFCE (Pennsylvania, New Jersey, Maryland, and Delaware) have results that cluster together. Likewise, SPSO (Oklahoma), SPNO (Kansas), SRVC (North Carolina, South Carolina, and Virginia), as well as SRTV (Tennessee and Kentucky), all have lower revenue possibilities but have a large capacity for emissions savings from storage. The results in Figure 3 have been split into several different plots that allow easier investigation of individual eGRID sub-regions; these can be found in the SI. While the nature of the local energy grid plays a huge role in the specific shape and location of the curves, most eGRID sub-regions follow a similar trend. Solutions that reduce storage-induced emissions for a low cost appear in all curves.

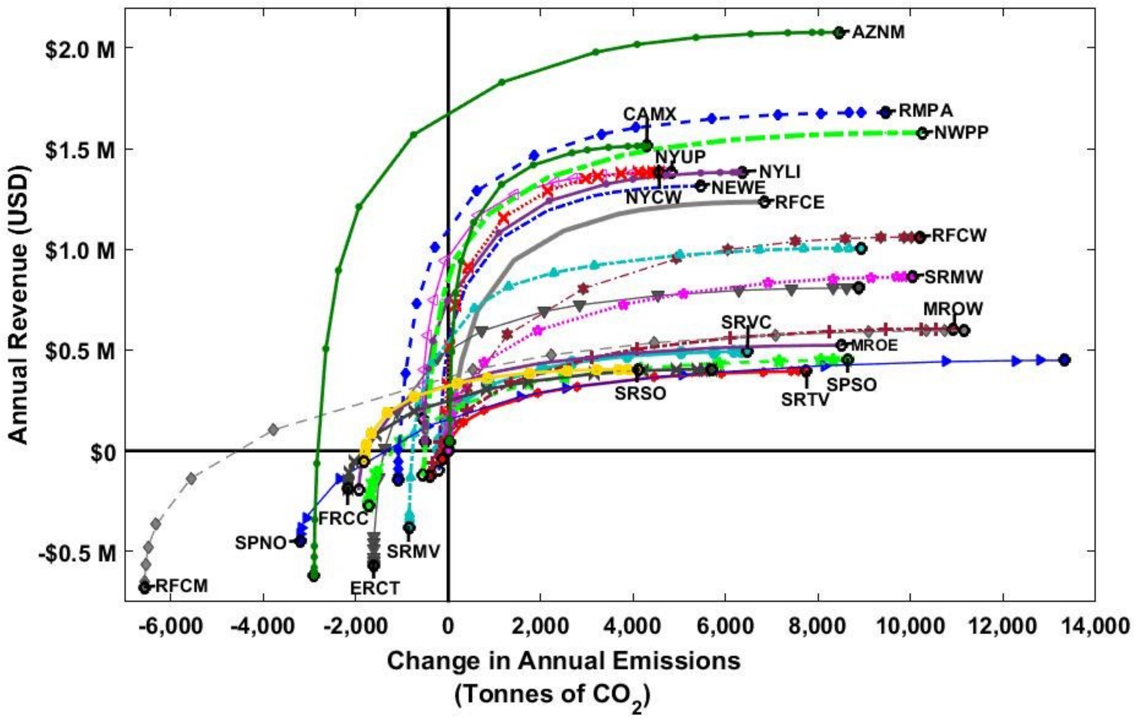

Figure 3. *Bulk energy storage annual revenue and emissions results for 2014 from optimal charging and discharging cycles for 22 eGRID sub-regions. Each line represents a set of possible Pareto solutions within an eGRID sub-region, starting with a carbon value equal to zero (most revenue and highest emissions) and ending with near-infinite carbon value (lowest emissions and least revenue). For all eGRID sub-regions, storage emissions can initially be decreased at very little cost.*

When including CO_2 emissions effects in the optimization of an operational schedule, the response from storage can be reduced to two options: to shift charge/discharge periods or to reduce overall operation (note that a storage device that never operates has zero effect on system emissions). In our results, storage generally prefers the first option: rearranging the scheduling to retain high revenue. This results in a steady decrease of emissions with minimal shift in revenue as seen by the initially flat slopes in eGRID sub-regions like RFCM (Michigan), SPNO (Kansas) and on most curves in Figure 3. Eventually, when the carbon value has too high of a weight, storage finds that reducing operation is the only path to further emissions reductions. Initially this occurs partially within a season, but environmental costs could become so high that the bulk energy storage shuts off completely for a whole season, operating only in periods with high price variability (normally summer). As seen in Figure 3, eGRID sub-regions like CAMX (California), RFCE (Pennsylvania, New Jersey, Maryland, and Delaware), and SRMW (Missouri and Illinois) have a steep drop in potential revenue when the carbon value passes a given amount. Evidently, the cost of increasing pollution becomes too expensive compared to the device's ability to earn revenue. However, this is not the case for all locations: some eGRID sub-regions, like AZMN (Arizona), ERCT (Texas), and RFCM (Michigan), are able to make money while causing a net reduction in CO_2 emissions. Unfortunately, in most cases, bulk energy storage would make little (or negative) revenue by charging with cleaner energy and displacing dirty generation.

Figure 4 shows the same results as Figure 3, except now expressed against emissions rates of energy delivered from storage in kg of CO_2/MWh (rather than total emissions). Similar to Figure 3, Figure 4 shows a steep decrease in pollution rates and a moderate revenue decrease using lower carbon values for most regions. However, there are some eGRID sub-regions that experience large decreases in revenue, like NYCW (New York City), RFCE (Pennsylvania, Maryland, New Jersey, and Delaware), and CAMX (California). As previously explained, this large drop in revenue is driven by the inability of the optimization to shift to "clean" charging schedules. Figure 4 provides a better representation of the total rate of CO_2 emissions for the energy that is being delivered in the units of pollution per MWh by the bulk energy storage.

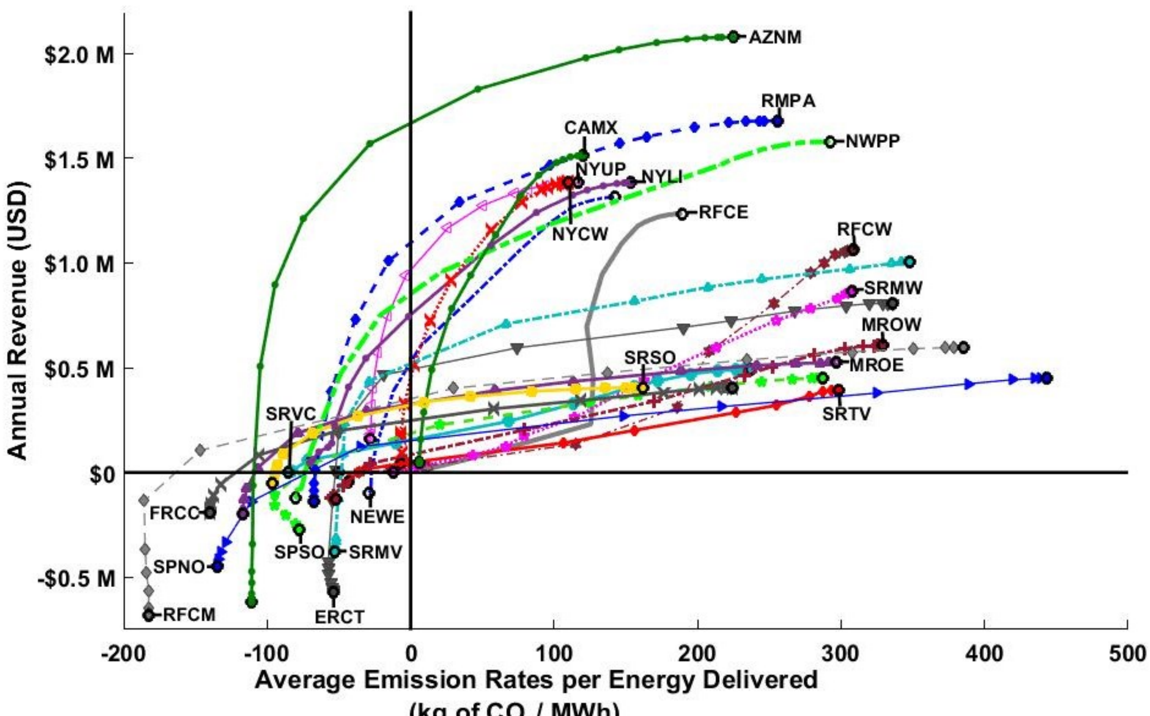

__Figure 4.__ Bulk energy storage annual revenue and normalized emissions results for 2014 from optimal charging and discharging cycles for 22 eGRID sub-regions. Each line represents a set of possible Pareto solutions within an eGRID sub-region, starting with a carbon value equal to zero (most revenue and highest emissions) and ending with near-

infinite carbon value (lowest emissions and least revenue). The number of charging cycles varies across eGRID sub-regions and this figure demonstrates the cleanliness of the energy delivered from bulk energy storage. As carbon values are weighted more strongly within the optimization, regions with larger ranges of MEFs lose revenue gradually while regions with small ranges of MEFs tend to drop rapidly.

Figure 5 displays the same information about CO_2 emissions rates and revenue as Figure 4, but in a different manner, using a map of eGRID sub-regions within the United States. Each eGRID sub-region was independently shaded to represent either the rate of CO_2 emissions per energy delivered (left), or the annual revenue (right). Only four sets of the previous optimal results are shown. The studied carbon values presented in Figure 5 are \$0, \$36, \$100, and \$1M per tonne of CO_2. Although not all of the Pareto solutions are displayed in Figure 5, similar trends appear on the maps. Some eGRID sub-regions, like AZNM (Arizona and New Mexico) and CAMX (California), continue to make significant revenue while simultaneously decreasing their emissions. Other eGRID sub-regions, like SPNO (Kansas), FRCC (Florida), and SRSO (Georgia and Alabama), have low storage revenue but a high ability to reduce grid emissions as carbon values are increased. Contour maps of the eGRID sub-regions within the United States which display similar information for total annual emissions (rather than normalized) can be found in the SI.

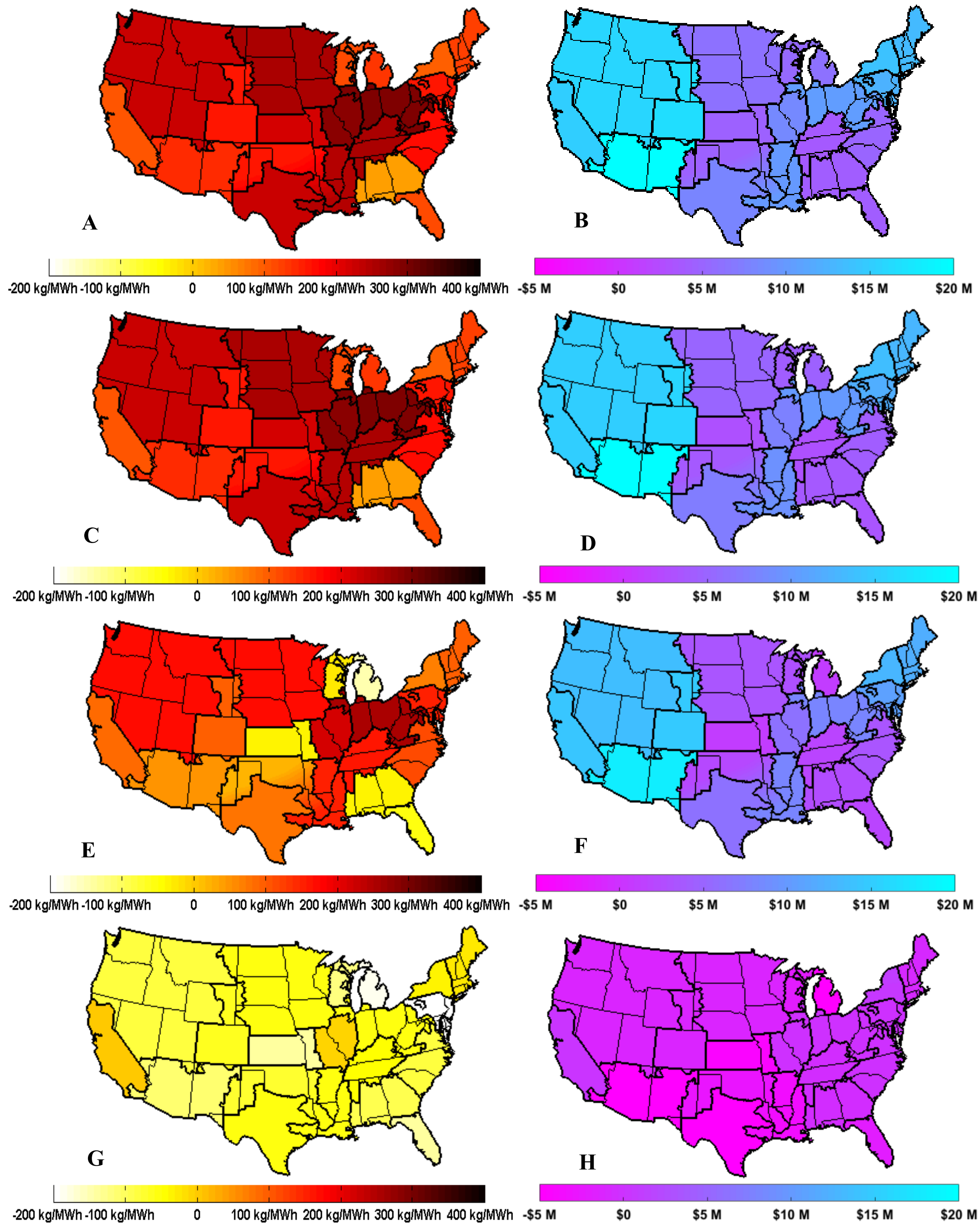

***Figure 5**. US map of emission rates (left) in kilograms of CO_2 per megawatt-hour and annual revenue (right) in USD with increasing carbon values. Maps A & B have a carbon value of \$0 per tonne of CO_2 (maximize revenue). Maps C & D have a carbon value of \$36 per tonne of CO_2. Maps E & F have a carbon value of \$100 per tonne of CO_2. Maps G & H have a carbon value of \$1M per tonne of CO_2 (minimize emissions).*

Bulk energy storage operational decisions originate from two factors: fluctuations in electricity prices and in MEFs. Without changes in prices, storage cannot earn revenue. Likewise, the emissions effect of storage operation is a result of the variability in MEFs. In reality, these factors are complicated by their correlation as well as inefficiency losses, but they represent the primary variables that drive storage revenue and emissions, since inefficiency losses are constant. Both of the inputs used in the objective function (Equation 1) are real-world data sets and therefore generate results that vary by location. But there are useful and logical trends that we observe: the more flexibility a region has in electricity prices or in marginal emissions rates, the more options exist for the bulk energy storage to rearrange schedules in beneficial ways. Figure 6 shows the standard deviation of electricity prices versus the standard deviation of MEFs for the 22 eGRID sub-regions. The graph has been broken up into four quadrants using the mean of each measurement to divide the lower half from the upper half. Roughly speaking, regions that show the greatest capability to reduce storage-induced CO_2 emissions at low cost are located in the upper-right (quadrant I) of the graph, where there is variability in both electricity prices and MEFs. In these locations, the optimization algorithm is able to shift charge/discharge periods to those that have similar revenue but lower emissions. Regions in quadrant III tend to have trouble reducing CO_2 emissions at low cost because there is not much play in either electricity prices or MEFs. In these locations, the algorithm responds to higher carbon values by reducing overall operation, which reduces both revenue and emissions.

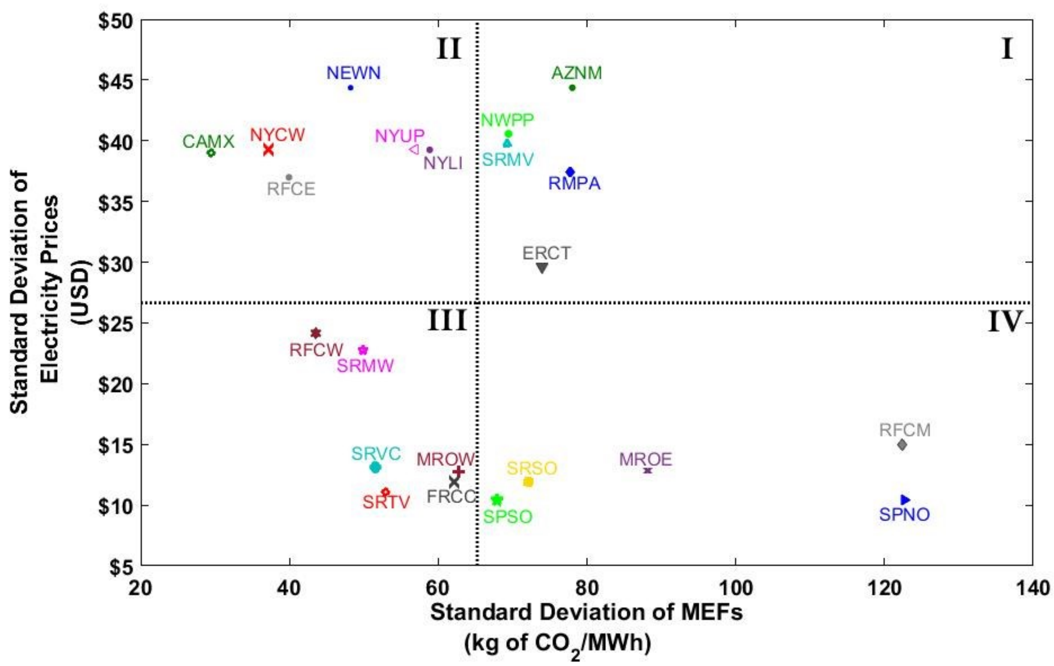

Figure 6. *A scatter plot of the standard deviation of the two inputs used in the optimization objective function: electricity prices and marginal emissions factors for each eGRID sub-region. The quadrants represent the upper and lower halves using the mean of each measurement. The greater the standard deviation in either data*

set, the more flexibility for the storage device to make higher revenue and emit less CO_2 emissions. Locations in quadrant I tend to have the most operational flexibility and can reduce emissions at low cost, while locations in quadrant III have the most difficulty.

We performed sensitivity analysis on both the efficiency and the charging rate of the bulk energy storage. The round-trip efficiency (i.e., the ratio between the input energy and the output energy) was varied between 65% and 85%, relative to the base-case value of 75%. Efficiency has a direct effect on both the ability of the system to cause pollution and earn revenue. Figure 7 shows the sensitivity analysis for bulk energy storage with a 75% efficiency, as well as the cases where the efficiency is low (65%) and high (85%). Operating under a low storage efficiency (65%, red dashed lines) reduces the revenue, but tends to slightly increase emissions when compared to the base-case results. On the other hand, working with a high storage efficiency (85%, blue dotted-dash lines) produces an increase in revenue. However, operating with an efficiency rate of 85% is quite influential in reducing emissions. The reductions in the relative emissions when shifting from 75% to 85% efficiency is more than double than when switching from 65% to 75% efficiency. More importantly, with an 85% round-trip efficiency, the Pareto curves for many eGRID sub-regions include points that are both profitable and emissions-reducing, as shown by the many blue dotted curves that lie in the upper left quadrant. Increasing the efficiency of the system positively impacts revenue but it results in significant CO_2 emissions reductions across every eGRID sub-region.

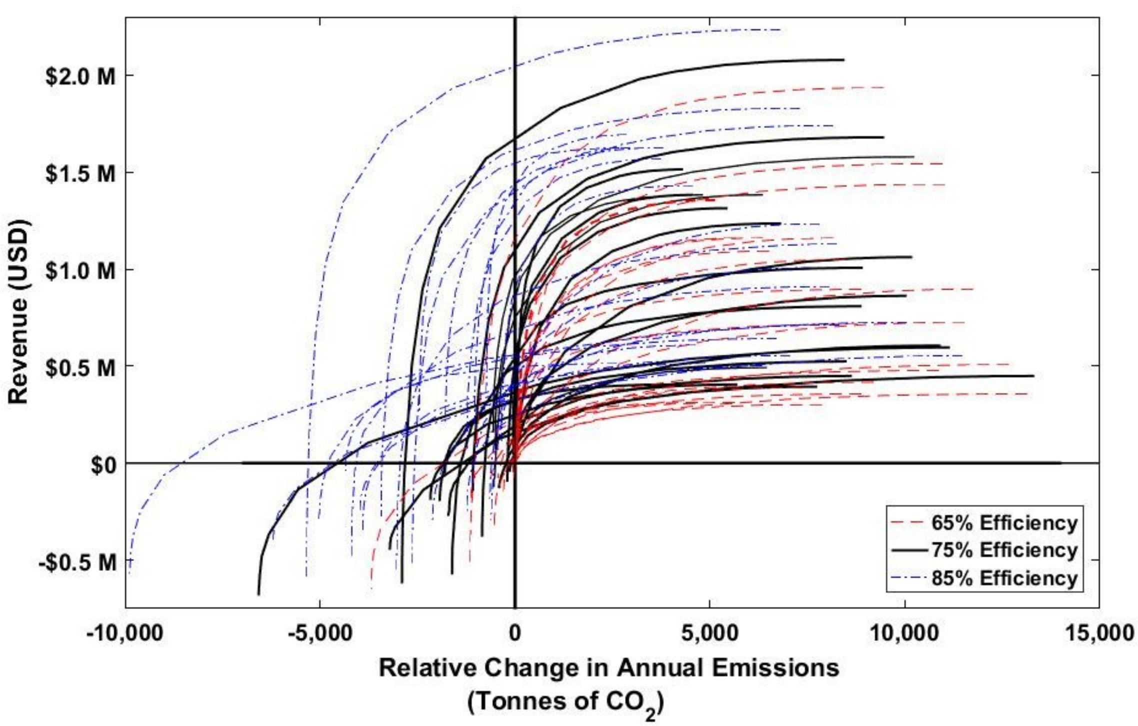

Figure 7. *Sensitivity analysis on the efficiency of the bulk energy storage device. The base-case round-trip efficiency was 75% (solid black lines). A lower efficiency of 65% (red dashed lines), and a high efficiency of 85% (blue dotted lines) are displayed for comparison. Increasing efficiency to 85% increases storage revenue, but shifts the curves significantly to the left, allowing for more solutions that retain revenue while greatly reducing emissions.*

The charge rate for the bulk energy storage device (i.e., the amount of time it takes for the system to charge) is another parameter that varies between storage technologies. A faster charge rate enables the system to act more rapidly during price and emissions fluctuations. This work used an initial 100 MWh storage device and a four hours charge rate as the base-case assumption. Figure 8 shows the sensitivity analysis for charging rates of two hours and eight hours as well as the base-case. When the device operates at a lower charging rate (eight hours, red dashed lines), there is a significant reduction in revenue, and this reduction is accompanied by a reduction in emissions when compared to the base-case. The inability of the slow charging rate to move energy fast enough reduces the total energy processed by the storage device, resulting in lower revenue and emissions. Figure 8 also shows a drastic revenue increase when a device with a fast charging rate (two hours) is used. In this case, the change in emissions tends to exaggerate the existing trend: if emissions were reduced, a faster charging rate reduces them more, and vice versa. The sensible explanation is that a faster charge rate allows storage to simply do more movement of energy under similar patterns, amplifying the current trends in both revenue and emissions.

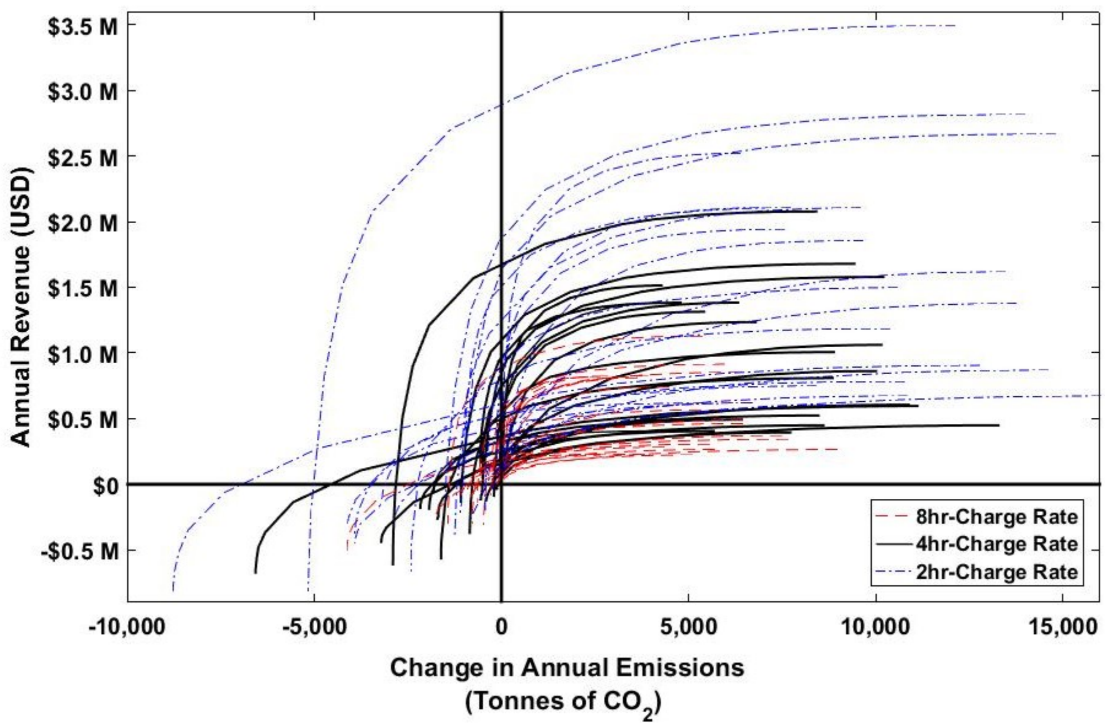

Figure 8. *Sensitivity analysis of the charge rate of energy storage operation optimization. The base-case computation assumes a four-hour rate (solid black lines). This is compared to a slower charge rate of eight hours (red dashed lines), and a faster charge rate of two hours (blue dotted lines). Using a faster charge rate allows storage to move more energy when cycling, tending to amplify existing revenue and emissions results.*

Discussion

Profit-maximizing bulk energy storage systems tend to increase overall electricity grid CO_2 emissions. Currently, real world storage technologies are not subjected to carbon costs, and they are not held accountable for any emissions they generate or induce. Without any intervention, bulk energy storage will continue to cycle large amounts of energy in pursuit of small changes in prices, resulting in increased emissions. In this work, we demonstrate that including a small consideration for CO_2 emissions in the objective function results in storage-related emissions that are greatly reduced at a minimal expense to the owner. And, depending on the social costs of CO_2 pollution, this shift can be a net benefit to society.

Figure 9 uses the change in revenue and storage induced emissions from Figure 3 to calculate an effective cost of CO_2 emissions reductions. The graph shows the cost of CO_2 emissions reductions of storage operation by cumulative percentage intervals for all 22 eGRID sub-regions. The percentages in Figure 9 are relative to a storage device with zero net emissions (ie, 100% emissions reduction refers to the point on the y-axis of

Figure 3). We estimate that reducing the storage-induced emissions by 25% costs less than $10/tonne of CO_2 in all regions; the cost of reducing the storage-induced emissions by 50% is less than $30/tonne of CO_2 in all but one region; the cost of reducing the storage-induced emissions by 75% is less than $30/tonne of CO_2 for sixteen regions; and the cost of reducing the storage-induced emissions by 100% is less than $60/tonne of CO_2 for sixteen regions. In other words, using the EPA-derived social cost of $36/tonne of CO_2 [35] would justify an operational schedule that removes between 30% and 100% of storage-induced emissions, depending upon location.

Only six eGRID sub-regions have 75% carbon mitigation costs that exceed the $36/tonne of CO_2 social cost of carbon: CAMX (California), RFCE (Pennsylvania, New Jersey, Maryland, and Delaware), NYCW (New York City), SRMW (Missouri and Illinois), RFCW (Indiana, Ohio, and West Virginia), and NEWE (Massachusetts, New Hampshire, Vermont, Maine, Connecticut, and Rhode Island). In most of these six locations, this is because the grid is already quite clean and the optimization has trouble further decreasing storage-related emissions. In most of these regions, there is an existing carbon price in a cap and trade system. In California, the cap and trade system has had a carbon price around $12/tonne for several years [36] and the RGGI system (covering New England, New York, and Maryland) prices vary between $2 and $5 per tonne [37]. In these locations, a carbon price is already affecting the dispatch of generation in a direction that reduces the emissions associated with storage operation, which may partly explain the difficulty in those areas to further decrease emissions through changes to storage operational patterns. Overall, for almost half of the eGRID sub-regions, using a carbon value of $36/tonne of CO_2 results in operational patterns in which storage actually reduces a majority of emissions.Figure 9 shows that the costs of reducing emissions through shifting of storage charge/discharge patterns is quite low in most of the US, indicating an opportunity for intervention.

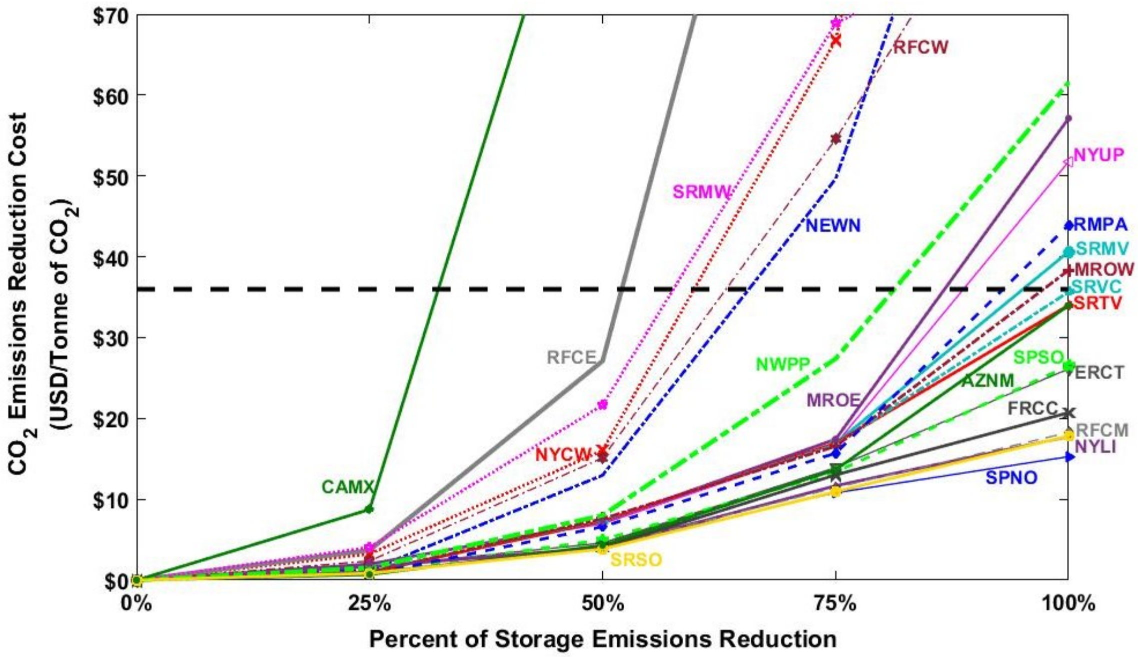

***Figure 9**. CO_2 emissions reduction cost for a marginal energy storage device in 22 eGRID sub-regions. Reducing emissions is initially inexpensive, but costs increase rapidly after 50% reduction. However, even a 100% reduction in emissions (a storage device with net zero emissions) can be achieved at less than $36/tonne in about half of the examined locations.*

While we identify operational strategies that reduce emissions at low cost, it is not obvious how such considerations would be translated into policy or market rules. In a profit-driven industry, it is unlikely that storage would voluntarily operate according to our results because they are not unequivocally free of cost. Conceptually, policy could direct storage operation to reduce emissions, but this type of policy would be quite challenging to write, potentially arbitrary, and overly interventionist. For example, a carbon tax that applies only to storage-induced emissions (and not directly to emissions from generators themselves) would motivate operators to behave according to our results. Likewise, carbon prices on energy storage could be identified individually by region using a percentage of emissions reductions (Figure 9) or a percentage of annual profit. However, such policies are not practical and run contrary to the goal of developing this emerging technology. Additional regulations and auditing may be complex and expensive especially if each region sets its own method for controlling energy storage-induced emissions.

A far more realistic plan would apply a carbon price to power plant emissions, which would change both the distribution and dispatch order of plants in a direction that would inherently make storage operation much cleaner by internalizing the externality. For example, a sufficient carbon price will begin pushing coal generation up the dispatch stack, making it more likely to be displaced by storage operation rather than being used as a charging source for storage. Furthermore, if an emissions fee exists and is set at a level equal to the damages from those emissions, then no alternative operational strategy is needed for storage: because the observed energy prices now include the emissions damages, storage can optimize in a traditional "price-only" strategy. In the absence of a sufficient carbon price, the development of a market rule that encourages or requires a high round-trip efficiency for storage may be a feasible solution. The sensitivity analysis performed in this investigation found that higher efficiencies would greatly reduce emissions in every eGRID sub-region (Figure 7). However, higher efficiencies did not yield significantly higher revenues, implying that companies may hesitate to purchase more efficient technology unless required to do so. This means that the social benefit of higher efficiencies for energy storage may outweigh the private benefit, making an argument in favor of support or regulation for storage efficiency.

Our results represent annual outcomes of introducing a storage device on actual electricity grids in the year 2014. However, as the structure of electricity systems and associated regulations develop, energy storage results will likely vary from the findings of this work. As average emissions rates of electricity generators decrease, storage-induced emissions may be reduced by giving storage devices cleaner fuels from which to charge. This is especially true if coal is phased out. Having vast amounts of renewable power on the grid would also shift the results, as storage would more frequently charge from completely clean energy sources that would otherwise be wasted [38]. Alternately, if electricity price patterns become more favorable for energy storage (by having greater short-term variability), storage is likely to cycle more frequently. The emissions effect of this increased cycling depends on the marginal emissions trends in the region: if operating storage results in significant emissions, then increased cycling will be problematic, but the opposite is true in areas where storage-induced emissions are small or negative. Modernization of the electricity grid will alter the results produced by this mathematical model, but it will remain socially advantageous to select operational strategies which consider storage-induced emissions while maximizing revenue.

Conclusion

This research has highlighted the trade-offs between storage revenue and CO_2 emissions that can be achieved simply through changes in storage operational patterns. We have shown that a multi-attribute objective function that applies a value to emissions can identify operational patterns that reduce CO_2 emissions at low cost. In most locations, storage could reduce CO_2 emissions by 25% for less than \$4 per tonne of CO_2, and half of the locations can eliminate storage-related emissions completely at the EPA-derived social cost of carbon of \$36 per tonne of CO_2 [35]. While the policy implications of these results are complex, they demonstrate that the problematic emissions effects of storage identified in the literature are not an inherent feature of the technology, but rather an outcome of operational strategy and electricity system structure.

Acknowledgements

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