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# (Not so) Clean Peak Energy Standards<sup>☆</sup>

Jeffrey G. Shrader <sup>a, \*</sup>, Christy Lewis <sup>c</sup>, Gavin McCormick <sup>c</sup>, Isabelle Rabideau <sup>c</sup>, Burcin Unel <sup>b, \*\*</sup>

<sup>a</sup> School of International and Public Affairs, Columbia University, 420 W 118th St., New York, NY, 10027, United States

<sup>b</sup> Institute for Policy Integrity, New York University, New York, United States

<sup>c</sup> WattTime, Oakland, CA, United States

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#### ABSTRACT

The emissions impact of operating an energy storage system depends on the system's efficiency and the generation mix of the grid. Growth in energy storage, therefore, has the potential to increase emissions. Concerns about this outcome are currently prompting many policies to address the issue. We study a particularly popular policy proposal called the "Clean Peak Standard" that incentivizes storage to discharge during periods of high electricity demand. The stated goal of the policy is to shift storage discharge so that it offsets production from peak generators with high emissions. We show that the policy is largely ineffective at achieving this emissions reduction goal. The policy reinforces existing incentives faced by storage operators, so it does not have a strong effect on discharging behavior. It is also unable to capture high-frequency changes in marginal operating emissions rates. Alternative policies, such as a carbon tax, are more effective at reducing the emissions increase caused by storage operations. Policymakers considering Clean Peak-style policies should instead consider these alternative policies.

#### 1. Introduction

Energy storage has received substantial attention for its potential to ease the transition to clean energy sources by mitigating the variability of renewable energy sources such as solar and wind, and, in turn, help achieve climate policy goals. A series of recent papers, however, have shown that if bulk energy storage operates in a purely profit-maximizing way based on current incentives, then it may lead to perverse outcomes. In particular, because charging and discharging lead to changes in grid operations and generator dispatch, energy storage operations based on arbitrage might cause increases in emissions from the power sector.<sup>1</sup>

In response to concerns about storage-related emissions and the fast growth of bulk energy storage,<sup>2</sup> grid operators and regulators have begun proposing and adopting new rules with the goal of improving the emissions effects of storage. A particularly popular, new policy to address these concerns is the so-called "Clean Peak Standard." This policy incentivizes energy storage operators to discharge energy during periods of the day when demand is typically high. As a result, some policymakers claim, energy storage can shift the use of renewable generation to displace higher emitting generation during peak periods and reduce emissions [5]. We analyze this policy and show, contrary to policymaker claims, that it is largely ineffective at reducing emissions, both in absolute terms and in comparison to alternative policies like carbon taxes.

The claim that a Clean Peak Standard will reduce emissions rests on the idea that a given energy storage system lowers emissions if it is being charged during periods when renewable generation is abundant and discharged during periods with a high percentage of



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<sup>\*</sup> Corresponding author.

<sup>\*\*</sup> Corresponding author.

*E-mail* addresses: jgs2103@columbia.edu (J.G. Shrader), christy@watttime.org (C. Lewis), gavin@watttime.org (G. McCormick), isabelle@watttime.org (I. Rabideau), burcin.unel@nyu.edu (B. Unel).

<sup>&</sup>lt;sup>1</sup> [1] provides an overview of the incentives owners of storage face and explains in detail the underlying mechanisms for how energy storage systems could increase emissions given various policy, regulatory, and technology settings [2] show bulk storage arbitrage increases CO<sub>2</sub> emissions in the Texas energy market, potentially leading to net social welfare losses [3] conduct a similar analysis across the entire U.S., showing that bulk storage leads to emissions increases everywhere, though the magnitude of the increase in a given region depends on the differences between the emission rates of marginal generators during on- and off-peak periods.

 $<sup>^{2}</sup>$  For recent reporting on the rate of growth of energy storage, see for instance Ref. [4].

emitting generation. In other words, these policies rely on the assumption that the *average* emission intensity of the grid—how much CO<sub>2</sub> is emitted per megawatt-hour of electricity generated on average—should be used when calculating the emission impacts of adding another unit of energy storage system to the grid.

However, this argument disregards how the electric grid operates. Grid operators rely on least-cost economic dispatch algorithms to balance the electricity demand and supply in real time. As a result, increasing (or decreasing) demand at a given time affects the operation of only the marginal units in the dispatch order, and not the infra-marginal units.<sup>3</sup> Therefore, emission implications of energy storage depend on *marginal* operating emission rates—how much  $CO_2$  is emitted per megawatt-hour of electricity generated by the *marginal* units [6,7].<sup>4</sup> And relying on average emission intensity of the grid to calculate the emission impacts of energy storage would lead to incorrect results.

Based on marginal operating emission rates, storage can increase emissions for two reasons. First, a profit-maximizing storage operator will store energy when wholesale electricity prices are low and discharge that energy when prices are high. For many electricity grids, low wholesale prices routinely correspond with high marginal operating emission rates and high prices correspond with low marginal operating emission rates. For example, this pattern will hold in locations where base-load power is generated by coal-fired units while peak load is met is met by natural gas-fired units. In such cases, storage would increase the generation from higher-emitting resources and reduce the generation from loweremitting resources, essentially leading higher emitting generation to be substituted for lower emitting generation, and increasing total emissions from the power sector. Second, storage operates with less than 100% efficiency. Charging and discharging result in a loss of some electricity, necessitating more generation from power plants to achieve the same level of final electricity consumption. If the storage is being charged from an emitting source—as is the case in most locations around the world where fossil-fuel sources are the marginal generator most of the time—then the losses due to inefficiency can also increase emissions.

Currently, Clean Peak Standard discussions are taking place in multiple jurisdictions in the U.S. Massachusetts is finalizing their rule, and debates and proposals around this idea are underway in Arizona, North Carolina, New York, and New Jersey.<sup>5</sup> While the exact design of the policy might end up differing between different states, the core idea of the policy—incentivizing storage operations to discharge during peak demand hours to reduce emissions—is the same among all states. In this paper, we examine the performance of the proposed Clean Peak Standard in Massachusetts.

We focus on the case of Massachusetts because policymakers there are the furthest along in the policy making process. They have also released details about their proposed policy, allowing us to accurately model the effects of the policy. With Clean Peak Standards, energy storage operators earn certificates if they discharge electricity during certain times of day, which we call "Clean Peak windows." These certificates can then be sold to retail electricity suppliers, which are obligated to buy enough certificates to correspond to a certain percentage of the load they serve in a given year, providing an incentive for storage operators to discharge during the Clean Peak windows. In the proposed policy, the Clean Peak windows are 4 h long and are set seasonally. In the spring, fall, and winter the windows are from 4 to 8 p.m. In the summer, the window is 1 h earlier, from 3 to 7 p.m.

We analyze the Clean Peak Standard by using a revenue maximizing linear optimization model where a front-of-the-meter battery operator can create revenue through both wholesale energy arbitrage and by generating Clean Peak Certificates (CPCs).<sup>6</sup> In order to do this, we adapt and combine two models: the front-ofthe-meter revenue maximizing model of Arciniegas and Hittinger [16] and the behind-the-meter cost *minimizing* Open Source Energy Storage Model [17]. We use the resulting model in two ways: to find the optimal operational schedules of a battery as a function of carbon dioxide emissions and wholesale prices, and to find the optimal operational schedules of a battery as a function of wholesale price and CPCs. Running the model both ways results in a dispatch program that allows us to determine when a storage operator will charge and discharge under a no-policy baseline, under the Clean Peak Standard, and when subject to a carbon tax. Knowing the charging and discharging periods as well as which electricity generating units are affected by that charging behavior allow us to calculate the emissions consequences of increased bulk storage in the three scenarios.

We show, first, that the addition of new energy storage increases emissions. This result replicates previous findings by Hittinger and Azevedo [3]; Arciniegas and Hittinger [16] and others. Second, we show the effect of the Clean Peak Standard is minimal relative to a baseline without this policy. Overall, Clean Peak is ineffective at achieving its environmental goals. Clean Peak only achieves about a 5% reduction in emissions relative to our no-policy baseline in most seasons of the year.

We find that Clean Peak does not lead to large emission reductions compared to the no-policy baseline for two main reasons. First, because marginal operating emission rates for the relevant zones in Massachusetts (ISO-NE) are relatively flat over the day, there is not much potential for energy storage to reduce emissions by shifting when charging and discharging occur during the day. Shifting the timing of discharge is the main effect of the Clean Peak Standard, so there is consequently little difference in marginal operating emissions rates between when the policy causes storage to discharge versus when it charges. On the contrary, as overall electricity generation needs to increase to account for storage efficiency losses, emissions increase. Second, because the policy design only reinforces the inherent incentive of a storage unit to discharge during high-demand, high-price hours, the policy does not induce much change in behavior. With or without the policy, storage units are most likely to discharge during periods of high demand and charging during periods of low demand.

This stands in sharp contrast to other policies available to policymakers. For example, a carbon tax levied on the electricity sector would raise the price of electricity from higher-emitting resources, making charging from lower-emitting resources more desirable. Another alternative, and the tactic adopted by California's Self Generation Incentive Program (SGIP), is simply a cap on storage emissions supported by a real-time emissions signal. Both of these

<sup>&</sup>lt;sup>3</sup> The marginal units will be determined by the size of the change in demand. Energy traders sometimes refer to the price-setting power plant as "the" marginal unit. In our analysis and use of the term, there can be several units that change their behavior in response, i.e. are marginal. Only one of them will be the unit that precisely determines wholesale prices. But empirical models can measure the change in emissions of all the marginal units regardless of whether the end up being the price setter.

<sup>&</sup>lt;sup>4</sup> Note that the same logic applies to any other incremental demand- or supplyside resource that leads to load-shifting [8-10].

<sup>&</sup>lt;sup>5</sup> See, for example, proposals in New Jersey, New York, and Arizona [11–13] as well as discussions by industry analysts and proponents [14,15].

<sup>&</sup>lt;sup>6</sup> Given the increasing popularity of batteries, we have chosen to model a battery in this paper. However, our results can be generalized to any storage technology that relies on revenue maximization. While the magnitudes of the results for other technologies would be different because of differences in the magnitude of efficiency losses, the qualitative results would remain the same.



**Fig. 1.** Marginal Operating Emission Rates Over Time. *Notes*: The figure shows marginal operating emissions rates (MOERs) in tons of CO<sub>2</sub> per MWh, over time. Red and orange values indicate that the marginal power generator is relatively polluting while green or blue colors indicate that the marginal generator produces relatively low emissions. The white area in the upper left is due to daylight saving time. Table 1 provides more formal definitions of terms used in the figure. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

policies directly internalize the social cost of emissions. The policies create an incentive for storage providers to displace emissions whenever marginal operating emission rates are high. This timevarying incentive is much more effective at reducing the emissions caused by the introduction of more storage. Even a \$1 carbon tax is roughly as effective at reducing emissions over the year as the Clean Peak policy. A more substantial but still modest carbon tax of \$50-equal to the external damage estimates calculated by the Interagency Working Group on the Social Cost of Carbon [18]would result in emission reductions of 65% relative to the no-policy baseline.<sup>7</sup> Even in this case, though, the addition of storage would lead to an increase in emissions. This is simply because the current grid mix in ISO-NE means that a storage operator is almost always charging from a natural gas-based generator and discharging to displace a natural gas-based generator, but with energy losses in between due to imperfect round-trip efficiency of storage systems.

We then look at whether simple modifications could improve the effectiveness of the Clean Peak Standard. We modify the proposed Clean Peak windows to better align with the periods with the highest marginal operating emission rates. If the goal of the policy is to displace high-emitting generation, then the Clean Peak windows should be based on the periods with high marginal operating emission rates rather than high demand. Unfortunately, the modification would not substantially improve the policy. This result is due to the fact that the proposed Clean Peak Windows were already closely aligned with periods of peak marginal emissions in Massachusetts. In other words, the proposed policy is quite close to the best possible case for this type of policy, and merely shifting the windows during the day could not result in large changes in policy effectiveness. Other modifications such as expanding the windows could capture more periods with high emissions, but comparison to the behavior of a storage operator facing a carbon tax shows that any fixed window policy will be unlikely to yield large emissions reductions. The ineffectiveness of this style of policy is due to the lack of any incentives for responding to the dynamic changes in marginal operating emission rates that occur over time.

Our results have policy implications beyond our empirical setting of Massachusetts. As more policymakers and power providers are thinking about ways to accelerate energy storage deployments, it is important to pay attention to the grid mix, and more specifically marginal operating emission rates. Clean Peakstyle policies, in which there is a fixed discharging time period, could achieve the goal of reducing emissions under some circumstances. For example, if marginal operating emission rates are highly and positively correlated with high demand, and if there is high enough variation between the marginal operating emission rates of high demand and low demand periods to offset the emission increases due to energy losses, then the policy can reduce emissions. However, in areas where high demand and marginal operating emissions are negatively correlated, Clean Peak standards would lead to further increases in emissions over and above those caused by the introduction of more storage.

Also, it is important to note that marginal operating emission rates are highly dynamic, and intra-day patterns of marginal operating emission rates depend on how the grid mix evolves over time. As the percentage of generation from renewable sources—particularly wind and hydro—increases, it will become more

<sup>&</sup>lt;sup>7</sup> Which means that the introduction of storage would still result in an increase in emissions. To reduce emissions from the introduction of storage to zero in the setting we study, the carbon tax would need to be greater than \$100.

likely that those resources will be on the margin. Having marginal generation from renewable sources increases the possibility that a Clean Peak-style policy will reduce emissions. Therefore, if adopted, their specific design should not be a one-time decision but should instead be updated frequently. and (2), and is a combination of Arciniegas and Hittinger [16] wholesale objective function and the retail objective function from OSESMO [17]. The objective function is a yearly sum of all revenue from selling electricity less costs of buying electricity, including efficiency losses and cycling costs.

$$V(P_e, \text{MOER}) = \max_{E_{out}, E_{in}} \sum_{t=1}^{N} [(P_e(t) + (P_c \text{MOER}(t))E_{out}(t)) - (P_e(t) + (P_c \text{MOER}(t))E_{in}(t)) - \left(\frac{c_{cycle}}{2S_{max}\sqrt{\eta_{rt}}}\right) E_{out}(t) - \left(\frac{\sqrt{\eta_{rt}}c_{cycle}}{2S_{max}}\right) E_{in}(t)]$$

$$(1)$$

Finally, it is well established that energy storage can play multiple different, valuable roles on the electric grid, even if it does not reduce emissions (Hittinger et al. [19]; Fitzgerald et al. [20]; Condon et al. [21]; Revesz and Unel [1]). Further, storage will undoubtedly play an important role as many states and countries move toward 100% clean energy goals. Therefore, whether its operation increases or decreases emissions is not the sole factor in determining policy. In the near-term, however, policymakers should be careful when adopting policies aimed at improving the environmental performance of energy storage.

The rest of the paper is organized as follows: Section 2 provides background on the Clean Peak Standard in Massachusetts, describes the model of electricity generation, and provides details on the data. Section 3 shows the results from analyzing the policy. Section 4 discusses the results. Finally, Section 5 concludes.

#### 2. Methods, data, and background

#### 2.1. Baseline storage optimization model

To understand the effects of Clean Peak policy, we first model the baseline behavior of a front-of-the-meter storage operator in the 2018–2019 Massachusetts energy sector. We model the operations of a front-of-the-meter storage system using models by Arciniegas and Hittinger [16] and the Open Source Energy Storage Model [17], which were used by a group of experts in California's SGIP [22]. The resulting model uses perfect-information linear programming to simulate a front-of-the meter energy storage operator, and calculates the optimal dispatch program over a specified time period based on wholesale energy market prices. We chose to simulate a battery with a capacity of 6.7 MWh and a discharge rate of 20 MW, operating at a round-trip efficiency of 85% to reflect current storage characteristics [23]. We ran the model in two ways: (1) as a function of wholesale price and emissions, using a carbon price to add value to emissions, and (2) as a function of wholesale price and Clean Peak certificates. We take as given all policies that were in place during our analysis period. For example, the state is a member of the Regional Greenhouse Gas Initiative (RGGI), which gives a modest carbon price signal-currently around \$5/ton of CO<sub>2</sub>—to the market [24].<sup>8</sup>

The objective function remains almost identical in both cases (1)

where  $P_e$  is the wholesale price of electricity in dollars per MWh,  $P_c$  is the carbon price in dollars per ton of carbon, *MOER* is the marginal operating emissions rate in tons of  $CO_2$  per MWh,  $E_{in}$  is the power used to charge the battery in MW,  $E_{out}$  is power discharged from the batter in MW,  $\eta_{rt}$  is round trip efficiency of the battery,  $c_{cycle}$  is the degradation cost per battery charge/discharge cycle in dollars per cycle, and  $S_{max}$  is the nameplate energy capacity of the battery in MWh.

Charging and discharging efficiencies of batteries vary based on several factors including, but not limited to, ambient temperature, auxiliary power consumption, and charge/discharge rate [25,26]. It is expected that as charge and discharge rates increase, the power loss increases as well. Sarker et al. [27] measured the impact of the charge and discharge rates on the power loss of a battery, and found similar loss patterns for both charging and discharging. Because of the variation in the numerous factors that could potentially influence efficiency, we use an average round trip efficiency of 85%. In Tables A.2 A.3, we show emissions for scenarios where the charge and discharge efficiencies are not equal. We find similar results to our baseline, symmetric, specification.

#### 2.1.1. Constraints

The difference in the energy level of the battery, as represented by *S*, is equal to the power in minus power out, with an efficiency penalty on both sides.

$$S(t+1) = S(t) + \left[\sqrt{\eta_{rt}} E_{in}(t) - \frac{1}{\sqrt{\eta_{rt}}} E_{out}(t)\right]$$
(2)

The state of the charge of the battery is constrained between zero and the maximum nameplate capacity of the battery ( $S_{max}$ ).

$$0 \le S(t) \le S_{max} \tag{3}$$

The battery cannot charge or discharge at a rate higher than the maximum charge/discharge rate of the battery ( $R_{max}$ ).

$$-R_{max} \le E(t) \le R_{max} \tag{4}$$

The state of charge of the battery begins and ends at half capacity.

$$S(0) = \frac{S_{max}}{2} \tag{5}$$

$$S(-1) = \frac{S_{max}}{2} \tag{6}$$

<sup>&</sup>lt;sup>8</sup> We further assume that RGGI and RGGI participants will not respond in a way that affects our results. In principle, because emissions in Massachusetts are capped by RGGI, increases or decreases in emissions caused by Clean Peak or alternative policies might not lead to changes in overall emissions for the state. A full analysis would depend on whether the marginal generator(s) affected by the policy are subject to the RGGI cap.

#### 2.2. Modeling the Clean Peak standard

#### 2.2.1. Background on the Massachusetts Clean Peak standard

With the passing of "An Act to Advance Clean Energy," Massachusetts established the "Clean Peak Energy Standard." As part of this policy, any eligible resource that can discharge to the electric grid during certain windows would generate Clean Peak Energy Certificates. New renewable energy resources, older renewable energy resources co-located with new energy storage resources,

#### 2.2.2. Clean Peak model

With Clean Peak Standards, energy storage operators earn certificates if they discharge electricity during certain times of day, so we modify the baseline model to allow for this potential new revenue. To incorporate the Clean Peak Standard, we adapt the model for the scenario in which a storage operator would like to cooptimize for the revenue that can be earned by wholesale price arbitrage and selling Clean Peak credits. In order to simulate this cooptimization, we alter the objective function to be

$$V(P_{e}, \text{MOER}, \lambda) = \max_{E_{out}, E_{in}} \sum_{t=1}^{N} [(P_{e}(t) + (P_{CPC}\lambda(t))E_{out}(t)) - (P_{e}(t) + (P_{CPC}\lambda(t))E_{in}(t)) - \left(\frac{c_{cycle}}{2S_{max}\sqrt{\eta_{rt}}}\right)E_{out}(t) - \left(\frac{\sqrt{\eta_{rt}}c_{cycle}}{2S_{max}}\right)E_{in}(t)]$$

$$(7)$$

demand response resources, or energy storage resources that follow a certain pattern of charging and discharging would be eligible to generate these certificates. Retail electricity suppliers in the state would then be obligated to buy a certain amount of these certificates, based on a minimum percentage of their annual sales, starting at 1.5% in 2020 and increasing to 48% in 2051. The revenues that can be earned by selling credits, therefore, act as an incentive for storage operators to supply electricity during the Clean Peak windows.

The policy establishes peak periods for each of the four seasons based on the historical peak electricity demand in the state:

Spring: 4 p.m. to 8 p.m. Summer: 3 p.m.–7 p.m. Fall: 4 p.m.–8 p.m. Winter: 4 p.m.–8 p.m.

In each hour during these windows, a resource can generate Clean Peak Energy Certificates based on its average performance (MW) multiplied by any applicable multipliers during that period. A resource can also generate certificates during the actual monthly system peak based on the same formula. Additional certificates are awarded during certain times of year. Generation during the Clean Peak window generates 1 certificate per MW during spring and fall but 3 certificates during winter and summer. The policy also provides additional certificates during the so-called "Actual Monthly System Peak," which has a multiplier of 15. These multipliers are meant to reflect the higher demand experienced during summer and winter as well as within specific months each season and increase the incentivizes discharging during those periods. Finally, there is a Resilience Multiplier (1.5) for resources that have the additional ability to provide electricity during outages, and an Existing Resource Multiplier (0.1) for existing resources.

Retail electricity suppliers can comply with the policy in multiple ways. They can buy enough certificates to meet the percentage threshold for a given calendar year, they can use any banked certificates from previous years, or they can make an Alternative Compliance Payment. The Alternative Compliance Payment starts at \$30 in 2020, remains at \$30 until 2030, and falls linearly to \$0 in 2051. where  $P_{CPC}$  is the price of a Clean Peak Certificate in dollars per CPC, and  $\lambda$  is the multiplier for CPC generation, as defined by the CPC rules.

We now add a term that is the Clean Peak multiplier times varying credit prices. Thus, the single objective function continues to be maximizing profit for the generator, but the profit associated with discharging energy during Clean Peak hours is increased due to the potential to generate credits during that time. The losses associated with cycling costs and efficiency losses remain unchanged in this new model. In order to preserve linearity while ensuring the model does not behave unrealistically, we weight charging and discharging equally. The policy as written does not disincentivize charging during Clean Peak hours, which is counterintuitive to the purpose of the policy. Consequently, this model is working under the assumption that despite the lack of explicit instruction for charging, the battery operators will not be allowed to charge excessively during Clean Peak periods. As the rule is written, it could be highly profitable for a battery to cycle excessively during the Clean Peak period, a perverse outcome which we believe should be addressed by policymakers.

#### 2.3. Data

We use marginal operating emission rates (MOERs) calculated by WattTime, based on a proprietary model that extends the basic methodology used by both Siler-Evans et al. [7] and Callaway et al. [6] but adapted for real-time use. WattTime calculates these marginal operating emission rates in real-time, every 5 min using a combination of grid data from the respective ISO and 5 years of historical Continuous Emissions Monitoring System data [28]. In order to model the effects of the Clean Peak policy in Massachusetts, we use 5-min MOERs for the Independent System Operator (ISO) New England Southeastern Massachusetts sub region (ISO-NE SEMA), which is one of the relevant balancing authority for the state. There are two other ISO-NE sub regions in Massachusetts, Western Central and Northeastern. The variations between the three are minimal, and we chose SEMA as a representative of the entire state.

The MOERs for the study period are shown in Fig. 1. The figure

Table 1 List of nomenclature.

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Variable	Notation	Reference Unit	s Short description
Marginal operating emission rate	MOER(t)	Eq. (1) t/MV	Vh Tons of $CO_2$ released per MWh of generation of marginal powerplant.
Storage (fraction of capacity)	$S(t)/S_{max}$	Eq. (3) unit	ess Current stored energy (MWh) divided by nameplate storage capacity (MWh).
Discharge	$E_{solved}(t)$	Eq. (8) MW	Net amount of power released from storage each time period.
Emissions	$- E_{solved}(t) \times MOER(t)$	Eq. (8) t	Total emission of $CO_2$ per period. Negative if storage is discharging on net.
Relative emissions		unit	ess Emissions with policy in place (Clean Peak or carbon tax) divided by emission with storage but no policy.
Clean Peak incentive	P <sub>CPC</sub>	Eq. (7) \$/M	Nh Price paid by Clean Peak policy per Clean Peak Certificate (typically \$30).
Locational marginal price	$P_e(t)$	Eq. (1) \$/M	Nh Wholesale electricity price.

*Notes:* The table provides a glossary of terms used in the figures and display of results below. The column "Notation" gives the formal notation (if applicable) used in the model described in Section 2, and the column "Reference" indicates the model equation where the variable is first used.

shows MOERs for every 5 min during the course of each day from March 2018 through March 2019. From the figure, one can see that MOERs change considerably both within a day and over the year. The afternoon tends to exhibit higher marginal emissions than the morning. The marginal producers in both the summer and winter tend to be higher emitting than the spring or fall. These regular patterns are one motivation behind the Clean Peak policy. The policy is intended to shift discharge of stored energy to the times of day that routinely exhibit high emissions. The figure also shows, however, that there is considerable heterogeneity in the timing of high marginal emission periods each day. The policy will have a difficult time capturing these dynamics, as we discuss in Section 3.4.

Pricing data for the model comes from ISO-NEs Application Programming Interface (API). Like the MOERs, we use prices for every 5-min period from March 2018 to March 2019. The prices are real-time locational marginal prices (LMPs) for ISO-NE SEMA pricing node. Figure A2 shows the LMP data used in the study for each 5-min period from March 2018 through March 2019. Figure A1 shows that LMPs and MOERs are positively correlated in ISO-NE.

The Clean Peak multiplier data are an array of 5-min multipliers based on the guidelines established in the Clean Peak policy proposal. As discussed in Section 2.2.1, the proposed policy provides a baseline incentive for discharge during an afternoon "Clean Peak window." The policy calls for a higher incentive during the summer and winter as well as additional incentive to discharge during the hour of the day each month when peak load occurs. We determined the actual monthly system peak load hour based on the system load information from ISO-NE for the study period. Figure A3 shows these multiplier values for each 5-min interval over the year.

The values shown in figures throughout the rest of the paper are defined in Table 1. The table gives formal and informal descriptions of each variable and indicates where more information on the variable can be found in the paper.

#### 2.4. Analysis

The model returns vectors containing the optimal values for  $E_{out}$  and  $E_{in}$  for every 5-min interval in the year. Subtracting these two values for each timestamp results in a useable variable,  $E_{solved}$ .  $E_{solved}$  is negative when the battery is charging and positive when the battery is discharging.

$$E_{\text{solved}}(t) = E_{\text{out}}(t) - E_{\text{in}}(t) \tag{8}$$

Revenue for each 5-min period was calculated for both scenarios by multiplying  $E_{solved}$  by the real time wholesale energy price in dollars per MW-5min. Emissions were similarly calculated by multiplying  $-E_{solved}$  by the corresponding MOER for each 5-min period, in units of tons of CO2 per MW-5min.

#### 3. Results

#### 3.1. Baseline storage and emissions rates

We first report baseline results from adding bulk storage to the grid but without any change in policy. As in Hittinger and Azevedo [3]; Arciniegas and Hittinger [16] and related work, an increase in bulk storage increases emissions compared to the baseline scenario. Without additional policies, bulk storage of the size and efficiency considered in this paper would be expected to increase emissions by about 3 tons of CO<sub>2</sub> per day (see Table A.1 for a breakdown of the emission increase by season). This increase occurs despite relatively low average emissions by Massachusetts electricity generators.

Fig. 1 shows the marginal emissions rate in over the course of the day and year during the sample period. The marginal emissions rate is often close to 0.5 tons of  $CO_2$  per MWh. In the spring and fall, the emissions profile over the course of typical day is also relatively flat, meaning that there is not much potential for storage to shift emissions between two points during the day. In such a case, emissions will increase with the introduction of bulk storage in large part due to round trip efficiency losses as the storage charges (usually with natural gas as the marginal fuel) and discharges (again usually offsetting natural gas as the marginal fuel).

Fig. 2 shows typical storage behavior at baseline. For most of the year, the storage provider builds up stored energy during the night from about 3 a.m. until 8 a.m. This stored energy is then discharged during the morning as a local peak in demand occurs. Storage is recharged in the middle of the day in preparation for discharge in the late afternoon as another peak in demand occurs. Behavior during the summer is slightly different because demand remains high throughout the day, causing the storage operator to charge during the night and typically only discharge during the peak demand period in the afternoon.

#### 3.2. Clean Peak policy and emissions rates

Fig. 3 shows how emissions change under the Clean Peak policy. In this figure, baseline emissions are indexed to 1, and the figure shows emissions relative to this baseline for different levels of incentives coming from Clean Peak credits. Table A.1 shows the level of emissions in each of the cases discussed below.

The policy as written calls for a \$30 credit price. For every season aside from winter, the Clean Peak incentive does very little to reduce emissions. Even paying \$30 per MWh leads to only a 5% reduction in emissions compared to the emissions under the baseline—roughly equivalent in effectiveness to a \$1 carbon tax. The emissions improvement is smallest in spring due to the very flat intra-day emissions profile during that season. For almost all



Fig. 2. Storage Level For Baseline. Notes: The figures show the average level of storage (as a fraction of battery capacity) for each hour of the day for the four Clean Peak seasons. The storage is for the baseline scenario with no carbon tax and no Clean Peak incentives. Table 1 provides more formal definitions of terms used in the figure.



**Fig. 3.** Emissions Under Clean Peak Standard Relative to Baseline. *Notes:* The figure shows emissions from storage under different policy scenarios relative to baseline for each season of the year. The solid lines show how emissions change as the incentive to discharge during the Clean Peak window increases. The dashed, black line shows the emissions reduction from a \$1 carbon tax for comparison. Table 1 provides more formal definitions of terms used in the figure.

hours of the day in spring, the marginal generator is a gas power plant with an emissions rate just below 0.5 tons/MWh. Energy storage cannot deliver substantial emissions reductions during these seasons because it is not possible to shift supply between high- and low-emitting times of day.

Relative emissions fall more strongly in the winter. Recall from Fig. 1 that winter exhibits the strongest and most coherent peak in marginal emissions. In winter, some high-polluting fuels are on the margin in the afternoon. The Clean Peak policy causes storage operators to discharge more during this period, resulting in a

reduction in emissions of about 15%. This effect is still small relative to what is achieved by a moderate carbon tax. A carbon tax of \$50/ ton—roughly the current value of the Interagency Working Group's Social Cost of Carbon—would result in a 65% reduction in emissions relative to the no-policy baseline [18]. To reduce emissions from the introduction of storage down to zero or below, the carbon tax would need to be greater than \$100/ton.

Table A.3 shows the effects of a \$30 Clean Peak credit price and \$30 carbon tax under alternative assumptions about the relative charge and discharge efficiency of the storage. In the baseline model, charge and discharge efficiency were assumed to be the same (see Equations (2) and (7)). In the table, we consider two cases where the round-trip efficiency is the same as in the baseline but where either the charging or the discharging is relatively more efficient. In all cases, you can see that relaxing this assumption has small overall effects on the performance of either policy. The Clean Peak credits lead to a roughly 12% reduction in emissions on average, and the carbon tax leads to a roughly 50% reduction on average. For Clean Peak, relatively efficient charging is slightly more effective than the baseline model because the storage operator needs to draw slightly less power from emitting resources to fill the storage unit in this case.

#### 3.3. Clean peak reinforces pre-existing storage incentives

Clean Peak does not cause substantial reduction in emissions because it largely reinforces pre-existing incentives faced by the storage provider. Fig. 2 shows that at baseline, storage was already being used to meet peak demand because peak demand periods are also likely to be periods with high prices. Small reductions in emissions occur in the Massachusetts case because periods with



Fig. 4. Storage Behaviors in Response to Clean Peak and Carbon Tax Relative to No Policy. *Notes*: The figures show average charging and discharging behavior by a storage operator in response to either the Clean Peak policy (left column) or a carbon tax of \$30 (right column) relative to the no-policy baseline. Positive values indicate that the policy is causing additional energy to be discharged relative to the baseline, and negative number indicate relatively more charging. The grey shaded bars show Clean Peak windows. Table 1 provides more formal definitions of terms used in the figure.



Fig. 5. When Do Peak Emissions Occur? Notes: The figures show the probability of a day's peak emissions occurring within any given hour of the day in the baseline scenario. Each panel shows a different Clean Peak season. The grey bars are the Clean Peak windows based on average peak demand. Table 1 provides more formal definitions of terms used in the figure.

high demand also happen to be periods with high marginal emissions rates. Figure A1 shows that locational marginal prices are positively correlated with marginal emissions rates. This correlation need not be positive, and in cases where the correlation is negative, a Clean Peak policy will likely lead to *further increases* in emissions over and above what is already caused by the introduction of bulk energy storage.

Fig. 4 shows how storage providers respond to a \$30 Clean Peak incentive and a \$30 carbon tax relative to baseline (we use \$30 carbon tax for comparability, but a \$50 carbon tax, closer to the current Social Cost of Carbon, would only make the differences even more stark). One can see that in all seasons, Clean Peak causes storage providers to shift discharge to correspond with the Clean Peak window. This shift is on top of the high levels of discharge that are already occurring during this time window at baseline, as shown in Fig. 2. This extra discharge comes from increased charging just before and after the Clean Peak window. Charging just before or after the Clean Peak window further dampens any potential environmental gains from the policy because the storage is charging from resources that are almost as dirty as the resources displaced during the Clean Peak window.<sup>9</sup>

A carbon tax induces substantially different behavior. Fig. 4 shows that under a carbon tax, storage charge and discharge will

occur throughout the day as the storage provider works to offset high emission resources. As we discuss below, these resources routinely come online outside of the late afternoon period covered by the Clean Peak window. The behavior under the carbon tax also shows that in the Massachusetts case, pre-existing incentives coming from wholesale prices are already doing a good job of directing storage to offset late afternoon generation and emissions. If anything, the Clean Peak incentive is causing "too much" afternoon discharging by storage resources.

# 3.4. Peak emissions routinely occur outside of the Clean Peak windows

Aside from reinforcing pre-existing incentives, the Clean Peak policy is also ineffective because it is a static policy in a highly dynamic environment. Fig. 5 shows the baseline frequency that a day's peak emissions occur within a given hour of the day. The figures show empirical probability densities for each season, so each area under the curve integrates to 1. From the figure, it is clear that peak emissions often occur outside the Clean Peak periods. The winter peak is the most coherent and best captured by the policy, but in all other seasons, the policy does a poor job capturing hours with peak emissions.

The most likely single hour for peak emissions is captured by the window in each season. But in two out of four seasons, the window does not even capture the three highest emitting hours of the day. In three out of four seasons, the window also captures substantially less than 50% of peak emissions periods. In spring and summer, peak emissions occur during the Clean Peak window about one-quarter of the time. In other words, the policy misses peak

<sup>&</sup>lt;sup>9</sup> To receive Clean Peak credits under the Massachusetts policy, a storage operator must qualify by meeting one or more criteria. One way to qualify is by charging during solar and wind power generation periods at night and in the morning [29]; Section 21.05). Clean Peak causes increased charging outside of these qualifying windows, but the overall shift is small enough that generators would still qualify based on their unchanged nighttime charging behavior (see Fig. 2).

emissions periods 75% of the time during those seasons. The policy does slightly better in the fall, with peak emissions occurring during the Clean Peak window 40% of the time. The only season where the policy captures peak emissions more than half the time is winter, when peak emissions occur during the Clean Peak window 69% of the time.

#### 3.5. Alternative policies

We also examine a series of alternative policies that keep the basic feature of the Clean Peak policy—fixed windows where discharge is incentivized—but try to improve the policy's effectiveness. The most basic improvement would be to align the 4-h Clean Peak windows with periods of peak marginal emissions rates rather than peak demand. As Figure A1 shows, in Massachusetts peak demand corresponds closely with periods of peak marginal emissions, so this would entail a small shift in the windows. The spring window would shift 1 h later, the summer window would shift 2 h later, and the fall and winter windows would be unchanged.

Figure A4 shows that in spring and summer, aligning the windows with periods of peak emissions would reduce  $CO_2$  emissions by one percentage point more than the state's proposed Clean Peak windows. This is a large difference relative to the modest improvements in emissions that the state's policy achieves. But the overall effectiveness is still low.

Given the relatively coherent periods of peak marginal emissions shown in Fig. 1, another alternative would be to expand the size of the Clean Peak windows. To capture 50% of the peak emission periods, the windows in each season aside from winter would need to be expanded. The spring window would need to include the 6 h from 6 to 8 a.m., 6–9 p.m., and 11 p.m. The summer window would need to be 7 h long and cover the period from 5 p.m. until midnight. The fall window would need to be 6 h long and include 6-8 a.m. and 4-8 p.m. Even with these extended windows, the policy would just reach half of the peak emission hours during our sample period in each season. Figure A5 shows the emission reductions relatively to baseline for a version of the policy that expands the Clean Peak windows. One can see that the change makes the policy substantially more effective in summer, leading to emission reductions roughly as large as those seen in winter. The change has small effects in spring and fall.

Seasonal Clean Peak policies could potentially be more effective than an annual policy. Fig. 3 shows that the policy as written leads to substantially greater reduction in emissions in winter than in the other seasons. If the policy is being discussed in locations where Clean Peak causes increases in emissions in some seasons and decreases in other seasons, the policy could be limited to the most effective seasons to enhance its outcomes.

The results show, however, that a carbon tax achieves much greater relative emission reductions from storage. For energy storage systems to be deployed in a manner that can reduce emissions, their operating incentives based on revenue opportunities must align with the opportunities to reduce emissions based on marginal emission rates. A carbon tax, by increasing the energy market prices at times when higher-emitting generators are on the margin, automatically aligns energy arbitrage incentives with the emission reduction potential based on marginal operating emission rates.

#### 4. Discussion

Driven by the goal of reducing emissions from the power sector, policymakers are discussing and implementing rules to govern the behavior of energy storage providers. The results in this paper show that care must be taken to ensure that these policies actually achieve their environmental goals. The Clean Peak Standard provides weak incentives for pollution abatement. The Clean Peak policy in Massachusetts is roughly as effective as a \$1 carbon tax.

The case we analyze is also likely to be one of the best-case scenarios for a Clean Peak policy. Massachusetts has a relatively low-emission grid. And in most seasons, there are clear and consistent periods during the day when marginal operating emission rates are high (Figs. 1 and 5). These periods of peak marginal operating emission rates are also periods of peak demand (Figure A1). In areas that have different generation mixes or different daily emissions profiles, the effect of the policy can be worse. In particular, in power grids where low cost power is being provided by coal while peak demand is being met by natural gas, then a Clean Peak-style policy will incentivize storage operators to increase demand for coal power while offsetting generation by gas power. This would lead the policy to increase emissions profiles, a Clean Peak policy will capture fewer hours of actual peak emissions.

The policy can be improved in a few ways. The simplest improvement would be to align the Clean Peak window with periods of peak marginal emissions rather than peak demand. Differences in emissions due to even small changes in the Clean Peak windows highlight the importance of updating those windows over time as the grid mix changes and marginal emissions rates potentially move to other hours of the day. At the same time, a change to align the window with marginal emissions rates does not alter the overall conclusions about this policy.

Reducing emissions from storage operations further would require policy that better handles real-time changes in marginal emissions. As discussed in Section 3.2, a carbon tax is substantially more effective at reducing emissions in this setting. The carbon tax is effective, in part, because it incentivizes the storage operator to discharge whenever a high-emitting resource is on the margin. Other policies that link revenue opportunities directly to behavior based on marginal operating emission rates can also achieve these types of improvements. For example, California's SGIP provides real-time marginal operating emission rate signals for storage operators to internalize pollution externalities—just like a carbon tax does. The incentive payments energy storage can get are directly linked to them successfully reducing emissions based on these signals. In other words, to get the incentive payments, energy storage has to operate similarly to how it would operate under a carbon tax [22], but without needing to pay the tax.

Clean Peak Standards do have a potential advantage in terms of simplicity and predictability. Storage operators might prefer a Clean Peak-style policy to a carbon tax because capturing the gains from a carbon tax relies on the storage operator effectively forecasting when a high emitting resource will be on the margin. A Clean Peakstyle policy provides more certainty to the storage operator because the periods of time when Clean Peak certificates can be generated is fixed and known in advance. Regulators will need to assess whether this increased certainty is worth the loss in environmental performance. As the electricity sector continues to decarbonize, renewable energy resources will be on the margin more often. Storage technology will be useful for matching supply and demand in these cases. Many projections of electricity generation in a world with high renewable penetration emphasize the importance of having large amounts of bulk energy storage [30]. Policymakers could, therefore, want a Clean Peak-style policy to spur construction of bulk storage. The policy does provide a strong incentive for construction of storage, because storage providers will be paid extra for generation during periods when they are already receiving high prices. If the policymaker believes that storage construction will be a slow process, then encouraging more or faster investment might be worthwhile. At the same time, in the short-run, more storage will lead to even higher emissions.

Here, we have analyzed a single storage operator. Adding more storage would have two effects. On the margin, additional storage would lead to the same emissions increases we have discussed above. For non-marginal increases in storage, different results could occur. If enough stored energy is released during a period of peak demand, for instance, then the baseline marginal generator could be entirely displaced. The effect on emissions would then be determined by marginal and non-marginal generating units. These units might have different emissions profiles, and careful attention to the size of storage needs to be paid to fully capture emissions effects in this case.

#### 5. Conclusion

As electricity production transitions toward intermittent renewables, grid operators and policymakers are looking for way to incorporate more energy storage. Recent work has shown that, absent effective policy, energy storage can lead to substantial increases in emissions. A policy that encourages storage to charge during periods of low marginal emissions and discharge during periods of high marginal emissions would help mitigate this increase. Unfortunately, currently popular policies to address this issue do not incentivize this type of behavior. This paper has shown that a particularly popular "Clean Peak" policy that incentivizes storage to discharge during periods of high demand is largely ineffective at reducing emissions. In areas where electricity production is higher emitting during periods of time with low demand, this policy could even lead to increases in emissions. The analysis highlights the importance of crafting effective policies to address the emissions caused by grid storage. Fortunately, examples already exist of policies which are effective in this regard. Both a conventional carbon tax, and the Self-Generation Incentive Program's emissions cap, successfully internalize the externality of emissions and are more effective at reducing emissions. States considering "Clean Peak" policies should either consider these alternative policies or decide whether successfully reducing emissions is in fact a policy priority in their energy storage regulations.

#### **Declaration of competing interest**

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

#### Appendix. for online publication



**Fig. A1.** Price and Marginal Emissions Are Positively Correlated. *Notes*: The figure shows the relationship between locational marginal price (LMP) and marginal emissions rate. The values are averages for each hour of the day in the sample period. Table 1 provides more formal definitions of terms used in the figure.



 $\ast$  all times of LMP > \$300 are captured by the maximum end of the color scale.

**Fig. A2.** Wholesale Electricity Prices (LMPs) Over Time. *Notes*: The figure shows the LMP at the ISO-NE SEMA pricing node during the study area. Color indicates the level of the price, with orange and red colors indicating higher prices while green and blue colors indicate lower prices. The white area on the upper left is due to daylight saving time. Table 1 provides more formal definitions of terms used in the figure.



**Fig. A3.** Clean Peak Credit Multiplier Over Time. *Notes:* The figure shows Clean Peak Credit multiplier over the time period of the study. The multiplier scales the incentive earned by storage operators for discharging during Clean Peak windows. The color indicates the level of the credit, with red, orange, or yellow indicating higher multipliers while blue indicates lower multipliers. The white area on the upper left is due to daylight saving time. Table 1 provides more formal definitions of terms used in the figure.



**Fig. A4.** Emissions Under "Marginal Clean Peak" Windows. *Notes*: The figure shows emissions from storage under different policy scenarios relative to baseline for each season of the year for a modification of the Clean Peak policy that shifts the discharge incentive windows to correspond exactly with the 4 h of peak marginal emissions. The solid lines show how emissions change as the incentive to discharge during the "Marginal Clean Peak" window increases. The dashed, colored lines show how emissions change under the Clean Peak Standard as written. These lines are the same as in Fig. 3. The dashed, black line shows the emissions reduction from a \$1 carbon tax for comparison. Table 1 provides more formal definitions of terms used in the figure.



**Fig. A5.** Emissions Under "Expanded Clean Peak" Windows. *Notes*: The figure shows emissions from storage under different policy scenarios relative to baseline for each season of the year for a modification of the Clean Peak policy that expands the Clean Peak windows so that they cover 50% of the peak emission hours during the day. The solid lines show how emissions change as the incentive to discharge increases. The dashed, colored lines show how emissions change under the Clean Peak Standard as written. These lines are the same as in Fig. 3. The dashed, black line shows the emissions reduction from a \$1 carbon tax for comparison. Table 1 provides more

## Table A 1: Level of Emission Increase Under Policy Alternatives

	Baseline	Clean Peak Standard			Carbor	n Tax	
Season		\$10	\$20	\$30	\$1	\$30	\$50
Spring	2.69	2.65	2.61	2.6	2.53	1.68	1.25
Summer	3.25	3.15	3.12	3.08	2.85	0.93	0.17
Fall	3.41	3.32	3.29	3.25	3.3	2.22	1.64
Winter	3.2	2.84	2.78	2.75	2.97	1.7	1.24

*Notes*: The table shows the daily average increase in emissions (tons of CO<sub>2</sub>) from the introduction of a single storage unit in each season. The baseline makes no change in policy over the status quo. The Clean Peak Standard columns use three levels of Clean Peak credit incentives. The Carbon Tax columns use three levels of carbon tax. Table 1 provides more formal definitions of terms used in the figure.

#### Table A

2.	Emissions	Using	Different	Charge	and	Discharge	Efficiency	Values
۷.	LIIII33I0II3	Obling	Different	Charge	and	Discharge	Lincichcy	varues

Carbon tax:	\$0	\$1	\$30	\$100
Baseline	3.16	2.98	1.61	0.28
Relatively efficient charging	3.12	2.93	1.59	0.29
Relatively efficient discharging	3.20	3.02	1.63	0.28

*Notes*: The table shows average daily emissions (tons of  $CO_2$ ) from the introduction of a single storage unit in 4 different carbon tax scenarios and 3 different charging efficiency scenarios. All charging scenarios have the same round trip efficiency. The relatively efficient charging scenario has a charging efficiency of 0.95 and a discharging efficiency of 0.8947 (for a round-trip efficiency of 0.85, as in the baseline). The relatively efficient discharging scenario uses the reverse values. Table 1 provides more formal definitions of terms used in the figure.

#### Table A. 3

Fraction of Emissions Relative to No-policy Scenario for Three Different Charging Efficiency Assumptions

	Symmetric	Relatively	Relatively	
	efficiency	efficient	efficient	
	(baseline)	charging	discharging	
\$30 Clean Peak credit	0.8830	0.8821	0.8831	
\$30 Carbon tax	0.5100	0.5117	0.5090	

*Notes:* The table shows the emissions reduction relative to the no-policy case from the introduction of a single storage unit in 2 different policy scenarios and 3 different charging efficiency scenarios. All charging scenarios have the same round trip efficiency. The relatively efficient charging scenario has a charging efficiency of 0.95 and a discharging efficiency of 0.8947 (for a round-trip efficiency of 0.85, as in the baseline). The relatively efficient discharging scenario uses the reverse values. Table 1 provides more formal definitions of terms used in the figure.

formal definitions of terms used in the figure.

#### References

 Revesz RL, Unel B. Managing the future of the electricity grid: energy storage and greenhouse gas emissions. Harv Environ Law Rev 2018;42:139–96.

#### J.G. Shrader, C. Lewis, G. McCormick et al.

- [2] Carson RT, Novan K. The private and social economics of bulk electricity storage. J Environ Econ Manag 2013;66(3):404–23.
- [3] Hittinger ES, Azevedo IML. Bulk energy storage increases United States electricity system emissions. Environ Sci Technol 2015;49(5):3203–10.
- [4] Bade G. Us energy storage market expected to more than double in 2019, report says. 2019. Accessed: 2019-12-09, https://www.utilitydive.com/news/ us-energy-storage-market-expected-to-more-than-double-in-2019-reportsays/549890/.
- [5] DDER. The clean peak energy standard draft regulation summary. 2019. Accessed: 2019-12-09, https://www.mass.gov/doc/drafts-cps-reg-summarypresentation/download.
- [6] Callaway DS, Fowlie M, McCormick G. Location, location, location: the variable value of renewable energy and demand-side efficiency resources. J Assoc Environ Resour Econ 2018;5(1):39–75.
- [7] Siler-Evans K, Azevedo IL, Morgan MG, Apt J. Regional variations in the health, environmental, and climate benefits of wind and solar generation. Proc Natl Acad Sci Unit States Am 2013;110(29):11768–73.
- [8] Holladay JS, Price MK, Wanamaker M. The perverse impact of calling for energy conservation. J Econ Behav Organ 2015;110:1–18.
- [9] Graff Zivin JS, Kotchen MJ, Mansur ET. Spatial and temporal heterogeneity of marginal emissions: implications for electric cars and other electricity-shifting policies. J Econ Behav Organ 2014;107:248–68.
- [10] Shrader JG, Unel B, Zevin A. Valuing pollution reductions. Technical report, institute for policy integrity. 2018. Accessed: 2019-12-09.
- [11] New Jersey Board of Public Utilities. Draft 2019 New Jersey energy master plan policy vision to 2050. 2019. Accessed: 2019-12-09, https://nj.gov/emp/ pdf/Draft%202019%20EMP%20Final.pdf.
- [12] New York Department of Public Service. New York state energy storage roadmap and department of public service/New York state energy research and development authority staff recommendations. Accessed: 2019-12-09, http://documents.dps.ny.gov/public/Common/ViewDoc.aspx?DocRefId=% 7b2A1BFBC9-85B4-4DAE-BCAE-164B21BDDC3D%7d; 2018.
- [13] Spector J. Arizona regulator proposes biggest storage and clean energy target yet. Accessed: 2019-12-09, https://www.greentechmedia.com/articles/read/ arizona-regulator-proposes-sweeping-clean-energy-plan; 2018.
- [14] Van Atten C, Hill S. Clean peak standards. 2018. Accessed: 2019-12-09, https:// mjbradley.com/sites/default/files/MJBA\_Clean%20Peak%20Standard\_2018-10-17.pdf.
- [15] DiFelice R. Deploying more renewables now through an energy storagecentric clean peak standard. 2019. Accessed: 2019-12-09, https://www. utilitydive.com/news/deploying-more-renewables-now-through-an-energy-

storage-centric-clean-peak/549787/.

- [16] Arciniegas LM, Hittinger E. Tradeoffs between revenue and emissions in energy storage operation. Energy 2018;143:1-11.
- [17] OSESMO. Osesmo optimization algorithm outline. Tech Rep 2018.
- [18] IWG. Technical update of the social cost of carbon for regulatory impact analysis under executive order 12866. Tech Rep Interagency Work Group Soc Cost Greenh Gases 2016.
- [19] Hittinger E, Whitacre J, Apt J. What properties of grid energy storage are most valuable? J Power Sources 2012;206:436–49.
- [20] Fitzgerald G, Mandel J, Morris J, Touati H. The economics of battery energy storage: how multi-use, customer-sited batteries deliver the most services and value to customers and the grid. Tech Rep Rocky Mountain Instit 2015. Accessed: 2019-12-09.
- [21] Condon M, Revesz RL, Unel B. Managing the future of energy storage: implications for greenhouse gas emissions. Tech Rep 2018. Institute for Policy Integrity. Accessed: 2019-12-09.
- [22] GHG Signal Working Group. Sgip greenhouse gas signal working group. Tech Rep 2018.
- [23] Environmental and Energy Study Institute. Fact sheet: energy storage. Tech Rep 2019. Accessed: 2019-12-09.
- [24] RGGI. Auction results. 2019. Accessed: 2019-10-24, https://www.rggi.org/ auctions/auction-results.
- [25] Schimpe M, Naumann M, Truong N, Hesse HC, Santhanagopalan S, Saxon A, Jossen A. Energy efficiency evaluation of a stationary lithium-ion battery container storage system via electro-thermal modeling and detailed component analysis. Appl Energy 2018;210:211–29.
- [26] Feehally T, Forsyth A, Todd R, Liu S, Noyanbayev N. Efficiency analysis of a high power grid-connected battery energy storage system. Presented at the IET international conference on power electronics, machines and drives (PEMD). 2018.
- [27] Sarker MR, Murbach MD, Schwartz DT, Ortega-Vazquez MA. Optimal operation of a battery energy storage system: trade-off between grid economics and storage health. Elec Power Syst Res 2017;152:342–9.
- [28] EPA. Air markets program data. 2019.
- [29] Massachusetts Department of Energy Resources. 225 cmr 21.00 clean peak standard regulation. https://www.mass.gov/doc/225-cmr-21-clean-peakstandard-regulation; 2019.
- [30] Williams JH, DeBenedictis A, Ghanadan R, Mahone A, Moore J, Morrow WR, Price S, Torn MS. The technology path to deep greenhouse gas emissions cuts by 2050: the pivotal role of electricity. Science 2012;335(6064):53–9.