Expensive, Ineffective, & Occasionally Counterproductive

Clean Peak Standards Simulation Results for New England.

B.W.Griffiths[i] | 3-24-2020

Abstract

Clean Peak Standards ("CPS") have been proposed as a method to better align renewable generation with periods of higher electricity demand and higher emissions, by requiring that a percentage of peak period demand be met with renewables or clean-charged energy storage. Proponents argue that CPS can reduce costs, reduce emissions, and improve market efficiency.

Using a production-cost and capacity-expansion optimization model, we assess how CPS may affect wholesale market outcomes. We parameterize the model to approximate the New England system, and we test combinations of CPS and Renewable Portfolio Standards (RPS) that reflect needs into the 2040s.

In some instances, we find that CPS are ineffective and expensive; in others, we observe that CPS make the grid dirtier and more expensive. CPS offer *de minimis* reductions in production costs (<1%), suggesting efficiency is not improved. Depending on formulation, CPS lead to modest increases in carbon emissions (<2%), or modest reductions. Reductions, when present, come at high cost: RPS can reduce emissions by 5-10 times more, per dollar spent. Despite the paucity of benefits, CPS increase system costs (<5%). These results suggest that regulators can achieve similar market and environmental outcomes, at lower cost, if they simply do not implement CPS.

Keywords: Policy Effects; Energy Storage; Renewable Electricity; GHG Emissions Reductions; Wholesale Electricity Markets

---

[i] griffiths@bwgriffiths.com. *This article represents the opinions and conclusions of its author and not necessarily those of the Office of the Attorney General.*

1. Introduction

As states continue to push for larger quantities of renewable resources, policymakers have started to look for new tools to ensure that the capacity they procure will maximize value to consumers and to the grid. Historically, states have relied on Renewable Portfolio Standards ("RPS") – which require that a specified percentage of annual electricity sales come from renewable resources – to "green" the grid. To date, more than half of states have established binding RPS or non-binding renewable energy goals and approximately half of all growth in US renewables is associated with RPS requirements.[1] As the quantity of wind and solar on the grid increases, some have questioned whether RPS alone will lead to efficient capacity buildout. In states like California, the infamous "duck curve" is putting more strain on the grid by creating shorter-but-steeper ramping events. Higher renewable penetrations may cause similar needs in other jurisdictions. Over the long run, quantity maximizing policies may create periods of renewable oversupply in lower load seasons, "spilling" renewable energy.

Recently, several states have a proposed a relatively new concept: the Clean Peak Standard ("CPS"). A CPS requires that a certain percent of energy delivered to customers during peak load hours must be derived from clean energy sources. Targeting peak load is significant, the theory goes, becaues it tends to be met using dirtier and more expensive generation. Thus, proponents of the CPS argue that the simple MWh-based approach used by RPS might be less beneficial than one that is more coincident with these high-load periods.[2] Proponents argue that a CPS could encourage peak focused renewables buildout which could lessen carbon and/or criteria pollutant emissions during peak hours, lessen the need for fast-ramping ancillary services, and lessen transmission and distribution costs.[3,4] Advocates differ as to whether a CPS should target the peak hours of the *year* (e.g. the top 10% of the year) or the top hours of the *day* (e.g. 2-6 PM). While a CPS is a different planning constraint than an RPS, a single resource could simultaneously contribute to both requirements. In effect, the CPS creates additional preference for generation that occurs during high-load periods and for energy storage. In August 2018, Massachusetts signed the nation's first CPS into law.[5]

While Massachusetts has already developed robust climate policy including binding greenhouse gases ("GHG") reduction targets, an RPS, solar mandates, and the nation's first large-scale off-shore wind procurement, the state argued that a CPS could nevertheless reduce ratepayer costs and lower greenhouse gas emissions.[6] The proposal targets high-demand hours on each work-day, with additional preference for generating during the summer and winter seasons. Wind, solar, and other RPS-eligible resources are eligible to participate in the CPS. Energy storage, either paired with renewables or "virtually" charged from renewables, would also qualify.[7]

Despite the growing interest in CPS, many of the program's fundamental assumptions remain completely untested. Quantitative and qualitative analysis remains scarce. So far as the author can tell, there are only three prospective analyses of CPS in the literature. An analysis focusing on California suggests that CPS are a feasible method to reduce carbon emissions but that the policy may not be cost effective.[8] The Massachusetts Department of Energy Resources ("DOER") commissioned an analysis on its proposed regulations which indicates that the CPS will offer net ratepayer benefits of $710 million and 563,359 metric tons of carbon reduction over 10 years.[9] The Massachusetts analysis provides top-line numbers only, and was opaque as to how the identified price and emission benefits were achieved. Finally, a prospective study of the Massachusetts draft CPS regulations focusing on storage operation, shows that the policy is "largely ineffective" at achieving emissions reduction goals, and that other climate policies such as carbon taxes are better suited to this task.[10]

While Clean Peak Standards have been subject to only limited analysis there are, however, robust literatures focusing on various intended objectives of CPS including pathways for deep decarbonization[11,12], using storage to enable more cost effective renewables buildouts[13], methods for mitigating the duck curve[14], and benefits of reducing peak demands.[15,16,17] To the extent that a CPS can internalize some of these benefits, then it could prove to be a useful policy tool. But, there is no *a priori* reason to assume from the literature that the CPS can provide the salve it claims, or to suggest that it will be cost-effective policy.

Given that one state has adopted a CPS and several others are considering them, it is worth understanding how CPS interact with other state climate policies and whether CPS meet their objectives. Moreover, it is important to assess whether CPS are a cost-effective way to meet climate goals, relative to other policies, such as an accelerated RPS or a carbon tax.

In this analysis, we develop a combined economic dispatch and capacity expansion model, simulating the New England grid, which efficiently schedules existing power plants and builds new renewable or storage assets to comply with CPS and RPS requirements. We investigate the equilibrium build-out of wind, solar, and storage resources required to meet various CPS and RPS requirements (ranging from 0% to 50%) and then assess the impact of these policies on system efficiency (i.e. total cost of production), GHG emissions, and costs. We focus on the ISO New England ("ISO-NE") grid because it is the first market that will be affected by a CPS and because there are plans to add a substantial amount of wind, solar, and storage to the system in the years to come.[18] Note that the model does not report *when* a new CPS-eligible resource would be built, only that it would be built as part of an optimal system.

The purpose of this analysis is to provide directional results on the effects of adding CPS to existing climate policy and to explore how CPS interact with wholesale markets. Our results should be treated as indicative rather than definitive. We are not attempting to offer specific predictions of costs or benefits, and this analysis should not be treated as a forecast of renewables development in the region or of future market prices. Further, we are not attempting to model any *specific* CPS proposal in detail.

For a speculative analysis of this sort, it is critical to note that the analysis is reliant on a number of assumptions, most notably overnight capital costs of various compliance technologies, storage operation, and a simplified thermal supply stack. The model may not capture all CPS-related value or all CPS compliance strategies. For example, the model omits certain costs and benefits such as transmission or distribution upgrades require to integrate renewables, or the value of avoiding these upgrades through strategic placement of new resources. Separately, the model makes no distinction between behind-the-meter ("BTM") or utility-scale resources. From an energy standpoint, there is no difference between solar directly serving a residential customer and utility solar flowing to that same home (the model does not capture T&D losses). There may be important distinctions, however, in pricing regimes that could affect new resource decisions. On the wholesale side, for example, capacity markets have biases that encourage the development of some kinds of resources rather than others because of the way these markets are structured.[19] On the retail side, distributed and behind-the-meter resources are often subject to flat or time-of-use energy tariffs which provide less granular and less precise price signals than those found in the wholesale market, which makes it less likely that these BTM resources will accurately internalize and respond to system needs in real-time. In general, however, we think that it is unlikely that adding BTM resources will reduce the total cost of operating the system in a market context.[ii]

[ii] The addition behind-the-meter policy resources will change the allocation of costs between energy, capacity, and subsidies but should not affect total costs. First, assume that all resources are in front of the meter, then the cost of the capacity market is $Capacity\ Cost_{all\ FTM} = P \times Q$, where P is the clearing price of the market and Q is the quantity of capacity required. Now, let's shift a fraction of that quantity, ΔQ, behind-the-meter. So long as the behind-the-meter supply is not marginal then, in equilibrium, the peak contribution of ΔQ should shift both the supply curve and the demand curve to the left by ΔQ. Because change in supply equals change in demand, the change in price, ΔP, is zero. In effect, consumers avoid paying the inframarginal capacity rents to ΔQ. Overall capacity costs are now:

2. Methods

2.1 Optimization Model

Our model integrates elements of an hourly production cost model ("PCM") and of a capacity expansion model ("CEM") into a single-level linear program. Specifically, the model function seeks to minimize the combined costs of (a) new resources required to satisfy RPS and CPS requirements, (b) the system's annualized cost of producing energy, and (c) the carbon costs (nil by default). The model simulates a single bus system without transmission constraints.

The CEM portion of the model endogenously selects the least-cost portfolio of existing thermal generators, on-shore wind, off-shore wind ("OSW"), solar, and storage resources needed to satisfy load as well as exogenous RPS and CPS requirements. Each model run starts from a blank-slate of resources. Existing resources which are not built within a model are implicitly "retired." The model does not include a full representation of the wholesale capacity market. Unlike the ISO New England ("ISO-NE") Forward Capacity Market ("FCM"), the model only accounts for the *cost* of procuring sufficient generation capacity – and not the rents associated with being an inframarginal capacity resource. This formulation still captures the ability of new renewables or storage obviating the need for expensive "peaking" resources that run infrequently.

The PCM component of our model develops efficient hourly schedules for a set of power plants to meet load while minimizing the system's operating costs (i.e., total cost of production – "TCP"). It returns operational schedules for each resource on the system as well as the cost to run the system and the price paid by load for electricity. If we set a price on carbon emissions, these costs also affect the total system costs and generator dispatch. Within the PCM, storage is dispatched to both maximize energy revenues and help comply with the CPS. When storage is used to meet the CPS, we require it to be charged by clean resources: solar, wind, and offshore wind (as

---

$$Capacity\ Cost_{partial\ BTM} = [(P - \Delta P) \times (Q - \Delta Q)] + [\Delta Q \times C]$$

With the first bracketed term reflecting the capacity market costs and the second reflecting the capacity cost of the behind-the-meter resources. If the fixed costs of ΔQ are less than the capacity market clearing price, then overall costs are reduced. But, this does not capture the full story for resources supported for policy reasons – the BTM resources at issue. These resources require net payments such that:

$$Cost\ of\ New\ Renewables\ \leq Energy\ Revs + Capacity\ Revs + Subsidies$$

To the extent that a new behind-the-meter policy resource is not paid infra-marginal rents from the capacity market, the amount of subsidy must be increased dollar-for-dollar. So, in a giant game of whack-a-mole, society pays less in capacity costs but more in subsidies, leading to no change in the total costs. Taking money from your left pocket and putting it into your right pocket doesn't make you any richer.

modeled, storage charging demand cannot exceed instantaneous renewable output). When storage is used for energy arbitrage, it is indifferent to energy source. Storage operation also affects market prices. While storage does not directly set the market's price, its operation affects the dispatch of other resources and, consequently, market prices set by resources with non-zero SRMCs.[iii] The PCM also includes ramp rates for thermal units to capture duck-curve related inefficiencies but omits all other operational or intertemporal constraints.[iv]

Our model was formulated specifically for this analysis. (A complete formulation of the linear program is provided in Supplementary Information §1) . The linear program was developed using Python 2.7 and the Pyomo optimization programming library.[20] It was solved using the GNU Linear Programming Kit (GLPK).[21]

2.2 Parameterization

Our analysis compares the same basic system subject to various exogenous conditions. We run the model over 13 weeks of hourly data which, in aggregate, are representative of patterns in electricity demand, natural gas prices, and wind and solar output in the New England over 2017 and 2018 (for details, see Supplementary Information §3). We do not modify the underlying load data because ISO-NE forecasts little change in peak demand and annual energy consumption out through 2028 (the last year forecasted).[22] ISO-NE forecasts that summer peak demand, net of energy efficiency, will decline by 2.2% over the next decade, while energy demand will increase by 0.8%. Hourly generation profiles for on-shore wind, solar, and imports are also developed using ISO-NE market data[23] and matched with the load data.[24] The off-shore wind profile is developed using historic meteorological data from the MassCEC[25], paired with a GE Halide 150-6 wind-turbine power curve – the same kind of turbine used in the nation's first off-shore wind farm.[26]

We approximate ISO-NE's existing thermal supply stack using 17 composite units, for reasons of computation tractability. (For details, see Supplementary Information §3.) These composite units are generated using a k-means clustering algorithm and unit-specific data on fixed costs, variable O&M, and heat-rate from S&P Market Intelligence.[27] The supply stack includes nuclear, gas and oil units but omits cogeneration facilities, biomass, and coal units. Nuclear units are steam turbines, while the oil and gas units are a mixture of combined cycles, combustion turbines, and steam turbines. The model can build new gas combined cycles and combustion

[iii] Storage operation can also be thought of as a price-responsive demand-side resource dynamically shifting loads to minimize costs.
[iv] E.g., minimum up-time requirements, minimum down-time requirements, minimum generation thresholds.

turbines, but these resources are never selected in practice. A summary of thermal resources is provided in Table 1 and full treatment is provided in the Supplementary Information.

Table 1: Summary of Existing Thermal Resources

Fuel	Technology	Number of Units	Total MW	Average Going Forward Cost ($/kW-Yr)	Average Heat Rate (Btu/kWh)	Average Non-Fuel Variable O&M ($/MWh)
Natural Gas	Combined Cycle	6	12,777	16.79	8,324	3.94
	Combustion Turbine	2	906	4.4	11,007	15.38
	Steam Turbine	2	1,294	13.76	16,682	31.16
Petroleum (DFO)	Combined Cycle	2	390	19.44	10,311	47.92
	Combustion Turbine	2	180	5.79	15,040	117.92
	Steam Turbine	2	3,339	5.66	11,699	53.32
Uranium	Steam Turbine	1	3,336	111.01	10,400	5.3

The model can also build solar, wind, off-shore wind ("OSW"), and energy storage systems ("ESS"). These resources can be used for RPS and CPS compliance. Forward-looking costs for these resources is sourced from the 2019 NREL Annual Technology Baseline for the year 2025.[28] Table 2 depicts key data about each technology type and highlights tradeoffs between different resources. On an annualized basis, solar is less expensive to build than wind, but has a significantly lower capacity factor. OSW is more expensive than terrestrial, but has a higher annual output and higher capacity potential.

Table 2: Parameters for New Builds

Type	Offer ($/MWh)	Annualized Cost of New Builds ($/kW)	Capacity (MW)		Max. Capacity Factor (%)
	All	2025	Initial	Max	
Solar	0	215	1,100	Inf.	16%
Wind	1	593	1,400	9,000	36%
OSW	2	215	1600	155	55%
Hydro	15	445	3,000	3000	75%
Storage	--	127	0	Inf.	N/A

Notes: Cost data from the 2019 NREL Annual Technology Baseline. Capacity Factors based on ISO-NE (Wind, Solar) and Massachusetts CEC (OSW) generation output profiles. We rely on C&I solar cost estimate – a middle ground between lower-cost utility-scale solar and higher-cost residential solar. Offers are low but non-zero for wind and OSW to enable economic curtailment during periods of overgeneration. Overnight costs are annualized assuming a 10% discount rate and a 30-year lifespan. The model will tend to build as much wind as possible, so we add a cap at 9,000 MW – which was ISO-NE's assessment of the full set of "best onshore" resource; or a doubling of all proposed on-shore wind in New England [29,30] OSW has a maximum capacity of 155 GW, well above buildout required in this model.[31] Solar and storage can be built in any quantity.

Storage is modeled as single homogenous product having 85% round-trip efficiency and a four-hour duration, in line with current estimates of lithium-ion battery technology.[32]

2.3 Experimental Design

The experiments in this study explore how changes to CPS and RPS requirements affect overall costs, hourly production costs, and carbon emissions. For each run, we rely on the same underlying single-zone system, with RPS ranging from 0% to 50% of annual energy and CPS ranging from 0% to 50% of peak period energy. RPS and CPS are assessed in 5% increments.

For a given CPS and RPS requirement level, we also assess the impact of CPS formulation. We test two different possible CPS types: a *peak hours of the day* formulation (*daily* CPS) and a *peak hours of the year* formulation (*annual* CPS). In the former, we set predefined compliance windows for the four hours in each season when the system tends to peak, based on the input load data. In the latter, we use the top 10% of the year with the highest system load as our set of compliance hours (876 hours per year; 218 hours in our 13-week sample). In both cases, we assume that market participants know the set of CPS hours with certainty. The two CPS variations are not directly comparable due to the difference in compliance hour specification, but do provide complementary views into Clean Peak Standards. In each of the central cases we assess 94 discrete combinations of RPS, CPS, and CPS type.

As a final reminder, we are modeling a hypothetical CPS and a hypothetical RPS for the New England system, and it does not actually match any existing RPS (or portfolio of state RPS) in effect today. Nevertheless, it is representative of RPS and CPS generally. Note also, that the model reflects how new resources are built and operated in an end-state, but not the year-over-year progression of capacity expansion required to get to that end. It is certainly possible that higher CPS or RPS requirements may lead to non-monotonic changes in capacity across the various resource types.

3 Results for Central Case

3.1 Ability of CPS or RPS to affect outcomes

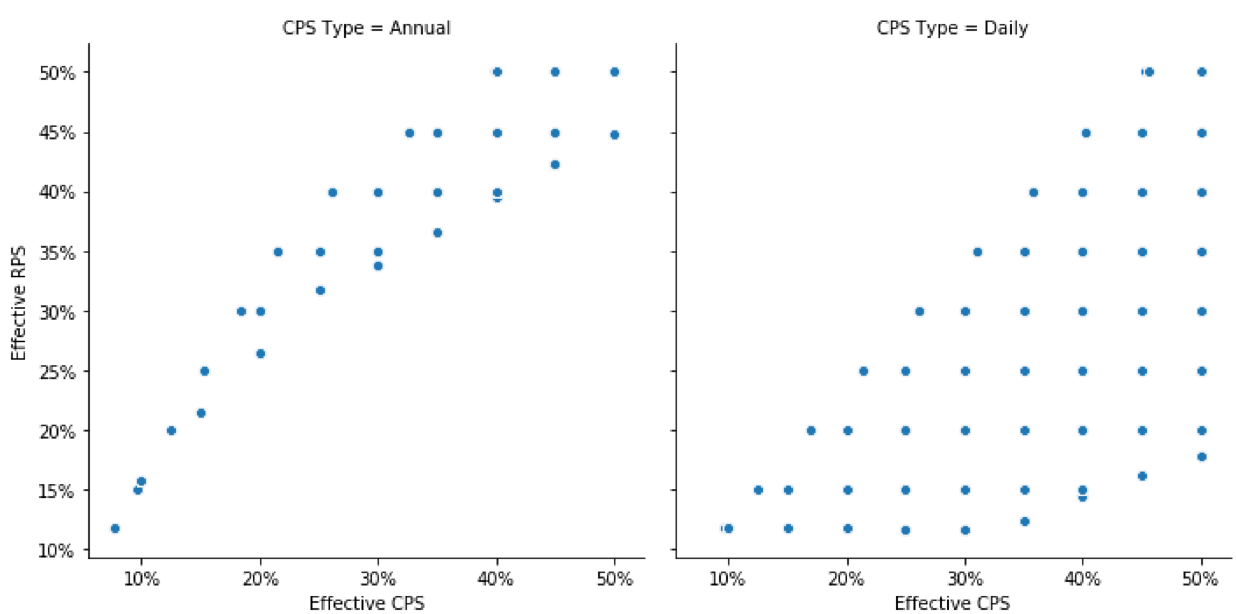
Although we run scenarios based on a 5% by 5% grid of nominal CPS/RPS combinations, we find that one policy or the other is non-binding in many instances. By non-binding, we mean that one-policy or the other does not change behavior or affect optimal capacity expansion. This is for two different, but related, reasons.

When a CPS requirement is "too low" for a given statutory RPS level, the CPS doesn't matter because the resources built to satisfy the RPS also generate electricity during the peak periods when the CPS is in effect. For example, if the RPS requires that 35% of annual energy comes from renewable resources, it is unlikely that none of this will occur during the peak hours. Indeed, we find that for that 35% RPS will also lead to 20% to 25% of peak period energy will be sourced from renewables – without any formal CPS requirement at all.

Similarly, when a CPS requirement is "too high" for a given statutory RPS level, we observe higher *effective* RPS than may be nominally required. As peak hours are a subset of all hours, so resources tailored to generate during the former will also happen to generate during the latter by definition. For example, a 50% CPS paired with a zero percent RPS requirement will nevertheless induce a positive effective RPS. The level of effective RPS is a function of the resources developed to comply with the CPS: more renewables will spur a higher effective RPS while more storage will induce a lower.

For the remainder we report results based on *effective* CPS and *effective* RPS, rather than nominal. The set of unique scenarios that have different effective CPS and effective RPS requirements is our feasible region – the domain over which CPS and RPS policies both matter. Figure 1 depicts the set of feasible RPS/CPS policy requirements. The empty area in the lower-right of each subplot reflects the area where CPS requirements are "too high" leading to effective RPS outcomes in excess of nominal requirements. Similarly, the empty area in the upper-left reflects the area where the CPS requirements are "too low", leading to effective CPS outcomes in excess of the nominal requirements.

Figure 1: Central Case Scenarios



Note in Figure 1 that high *annual* CPS tends to induce higher effective RPS rates than those observed under a high *daily* CPS. This suggests that the compliance strategies used to meet the two CPS formulations are different – with the *annual* CPS building more renewable generation. In this regard, a high annual CPS requirement approximates higher RPS requirement.

3.2 Effect of CPS on Resource Mix

Adding a CPS or RPS requirement changes what resources are built on the system. Figure 2 depicts how capacity (MW) and energy (GWh) change in response to an increasing RPS. Increasing the RPS, absent a CPS, will primarily spur the development of wind and solar assets. The system builds additional onshore wind up to its 9 GW exogenous cap, then starts building incremental OSW and solar assets. OSW is more expensive than solar but generates more energy on an annual basis. As the RPS increases past 25% of annual energy, the system also increases storage from nil to 1.6 GW. These storage deployments are economic: increased renewable generation leads to price differentials which are sufficient to encourage the build out of storage to store surplus generation and shift it to higher-priced periods. This storage deployment also reduces curtailment of renewable generation by storing surplus generation and using it to serve load at a later period. As the RPS grows, the share of fossil fuel generation falls – squeezed by near-invariant output from nuclear and hydro on one hand, and by increasing amounts of renewables on the other.

Adding a CPS changes how the system is developed, separate from underlying capacity additions required to comply with Renewable Portfolio Standards, Different CPS formulations lead to radically different compliance strategies: a *daily* CPS formulation leads to a resource-shifting compliance strategy while an *annual* CPS formulation leads to a *new generation* compliance technique. In the former case, the system almost exclusively builds new energy storage. In the latter, a mixture of renewables and storage is developed.

Figure 3 explores how adding a daily CPS affects the optimal resource mix, holding the RPS constant at 20% of annual energy – in effect, this is a horizontal transect through the points on Figure 1. The figure allows us to compare how buildout changes as the effective CPS rises (e.g. RPS = 20%; CPS = 20% vs. RPS = 20%; CPS = 50%). Note that the left most bar on Figure 3 plots is equivalent to the 20% RPS bar in Figure 2. (This left-most bar is labeled as having a 17% effective CPS because the 20% RPS generates this amount of clean energy during peak periods.) We selected the 20% RPS transect to most clearly depict the effect of adding or increasing CPS. Other transects at other RPS levels show similar trends – indicating that the presented results are indicative of broader trends.

Figure 2: Capacity (MW) and Energy (GWh) by RPS – <u>No CPS</u>

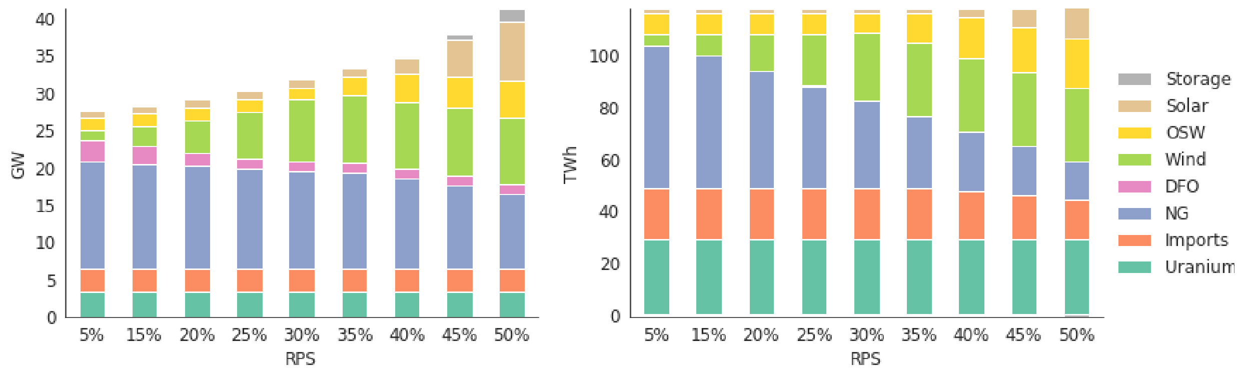


Figure 3: Capacity (MW) and Energy (GWh) by Effective <u>Daily CPS</u> – 20% RPS Transect

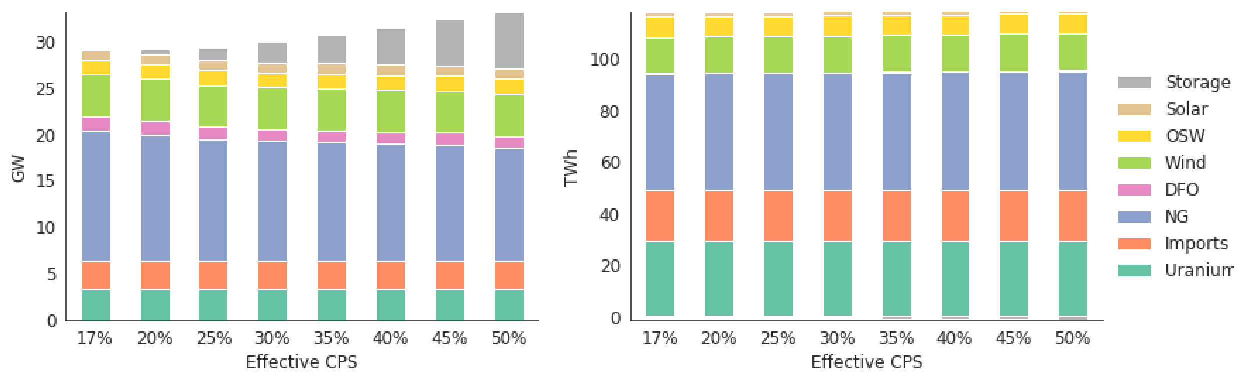
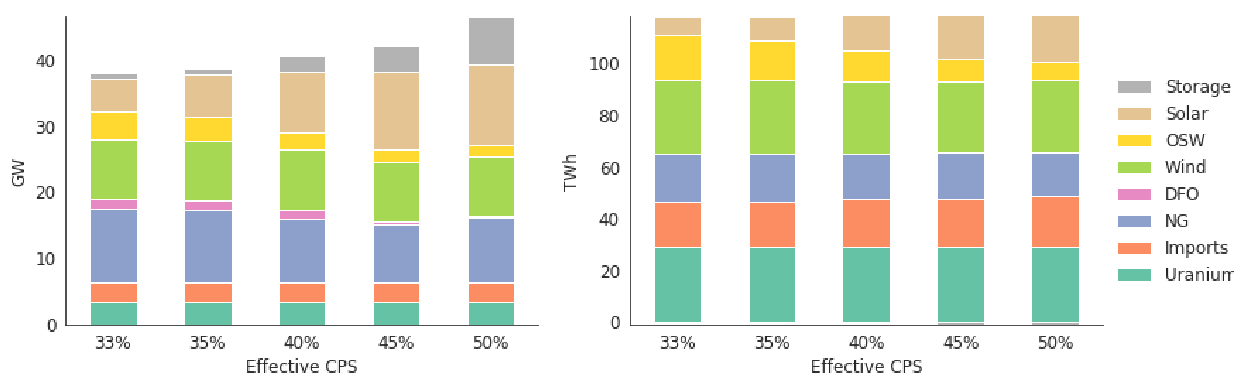


Figure 4: Capacity (MW) and Energy (GWh) by Effective <u>Annual CPS</u> – 45% RPS Transect



For a constant 20% RPS, Figure 3 indicates that increasing the CPS will increase the amount of energy storage on the system. When the nominal CPS is zero, the optimal resource mix includes no storage. But, when the CPS rises to 30% the system builds 2.2 GW of storage, and 6 GW when the CPS rises to 50%. The daily CPS formulation is particularly conducive for building storage. With 365 opportunities a year to cycle, even relatively small amounts of energy storage can shift enough energy to comply with CPS requirements. The same trends exist at other transects.

On an energy basis, increasing the CPS decreases the amount of petroleum burned. When the required CPS is nil, the system generates about 0.15% of energy from distillate fuel oil ("DFO") but when the CPS rises to 50%, DFO production falls by a third to 0.1%. The amount of energy produced from natural gas rises slightly. Note that the energy subplots reflect primary energy and does not include storage dispatch.

Figure 4 shows that implementing an *annual* CPS spurs the development of new renewables and storage. As the peak hours of the year are grouped into a smaller number of days, meeting the annual CPS with storage would require significantly more storage capacity than needed for a daily CPS. Instead of moving a modest amount of renewable energy to peak periods each day, it would need to move a large amount of energy on a relatively small number of days. This sort of storage-only compliance approach is less efficient, however, than building a significant amount of new renewable resources and a smaller amount of energy storage. Compared to the RPS-only resource mixes, an annual CPS spurs more new resource capacity overall, with relatively more solar and storage but no new OSW. As the effective CPS increases from 40% to 50%, the amount of solar increases from 8 GW of solar to 12.6 GW while the amount of OSW falls from 4.9 GW to 3.2. The bias towards solar and away from OSW is due to solar generation's higher coincidence with peak demand hours. The new renewable generation built to meet the annual CPS also generates electricity in other periods – increasing the effective RPS. This is why the feasible region for the annual CPS in Figure 1 is so thin – the least cost method of complying with the CPS is approximately the same as simply having higher RPS.

3.3 Effect of CPS on System Dispatch

CPS succeeds at changing how the system is dispatched. It increases the amount of clean energy used during peak periods and reduces reliance on more costly and polluting fossil power plants. In the figures to follow, we present hourly generation for the week with highest peak demand. Each scenario has the same 45% RPS, but different CPS requirements. Figure 5 depicts a 45% RPS and no CPS, Figure 6 a 45% RPS paired with a 50% *daily* CPS, and Figure 7 a 45% RPS paired with a 50% *annual* CPS. While these scenarios are extreme, they clearly demonstrate how the system responds to the adoption of CPS requirements.

Figure 5: Weekly Dispatch under 45% RPS and No CPS

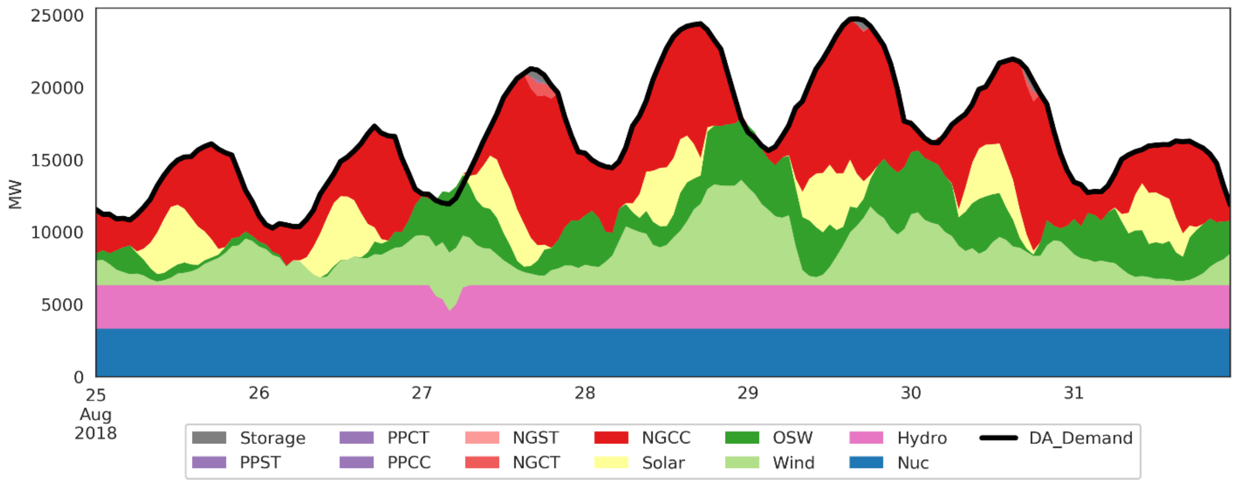


Figure 6: Weekly Dispatch under a 45% RPS and a 50% Daily CPS

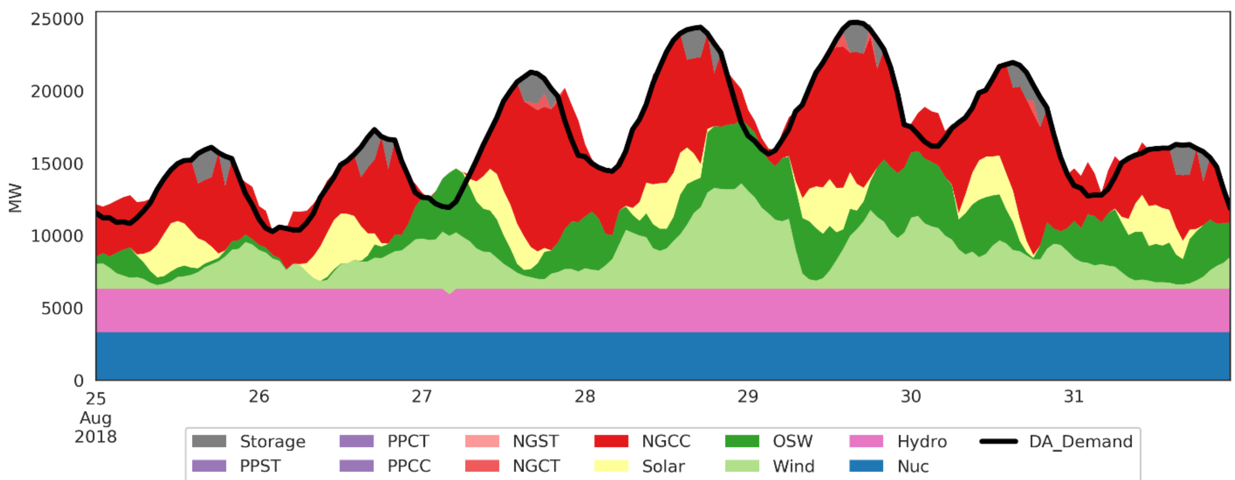
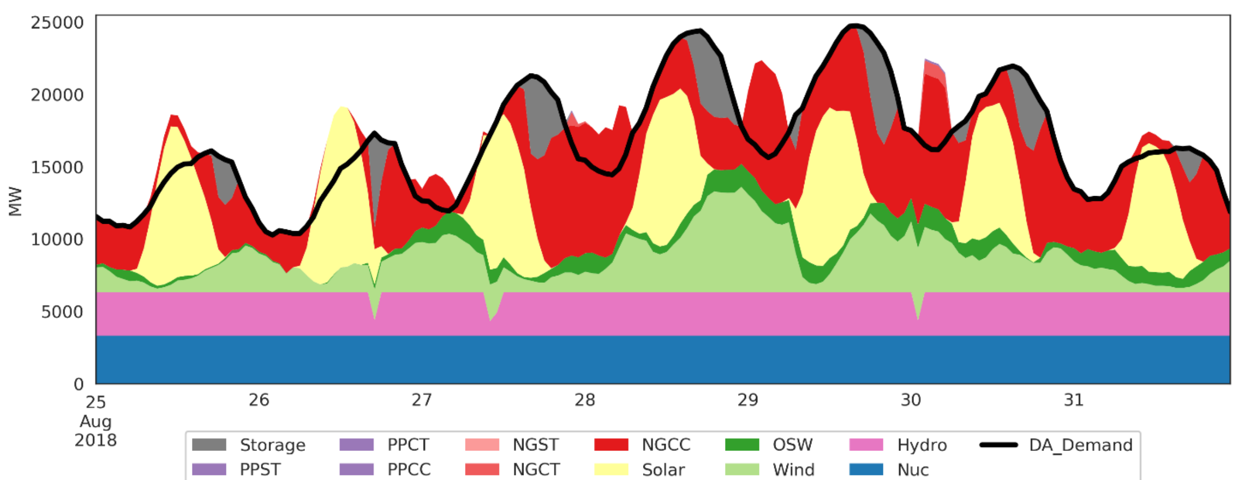


***Figure 7*: Weekly Dispatch under a 45% RPS and a 50% Annual CPS**



In the RPS-only scenario, Figure 5, we observe significant reliance on solar, wind, and off-shore wind resources. Energy storage is discharged during a small number of peak hours when lower efficiency gas combustion turbines are on the margin. Storage charges in the low-demand periods (where supply exceeds the black net demand line). On two nights, we observe that renewables, hydro, and nuclear generation serves all of demand for several hours.

Adding a 50% daily CPS to the system, as depicted in Figure 6,leads to a significant reliance on energy storage but only modest effects to the underlying renewable resources. We observe daily cycling of the battery charging in overnight and morning hours and discharging during the afternoon clean-peak periods (Hours 15, 16, 17, 19). Here, the CPS reduces fossil generation during peak periods by increasing reliance on energy storage. It does not completely obviate the need for the lower efficiency natural gas combustion turbines ("NGCTs") during peak hours, however. As before, storage charging tends to occur during the low-load overnight period. While harder to see, note too that even though the storage itself is charging from clean resources, the system as a whole must generate more total energy due to storage losses, and that incremental energy generally comes from fossil fuels.

Adding a 50% *annual* CPS, as depicted in Figure 7, leads to newfound reliance on solar. Compared to the wind-heavy systems in the prior figures, solar generates more energy during peak load hours and better aligns with annual CPS needs. Storage is used to reduce fossil generation during high-load evening hours. That storage charges from surplus early-morning solar or overnight wind. Note that on some days, the storage is mostly charged from solar that would otherwise be curtailed, but on other days fossil units are more heavily used.

3.4 Energy Revenues by Resource Type

The preceding sections demonstrate that adding a CPS to the market changes what resources are built and how they are operated. Unsurprisingly, this affects energy market revenues for CPS and RPS compliance technologies. We find that solar, wind, and OSW recover between 15% an 60% of their fixed costs through the energy market. For both kinds of wind resources, revenues decline as the RPS rises – due to the insertion of zero-marginal cost resources suppressing market prices. For a given RPS, however, revenues are largely unchanged as the CPS increases. By contrast, an increasing CPS requirement generally erodes the value proposition of solar resources. As the CPS increases, more energy is delivered to peak periods from renewables and storage – lessening the need for expensive peaking units which, in turn, reduces daytime energy prices and solar revenues.

Unlike the renewable generators, storage quickly erodes its value proposition. When storage is first added to the system, it can recover 7-17% of its costs through the energy market. As CPS requirements increase – and as more storage is added to meet the CPS – storage revenues fall towards zero. Worryingly, at very high CPS levels, storage operates at a loss in the energy market. In many high CPS scenarios, we find that the least-cost compliance CPS strategy is to build batteries, co-optimize their dispatch for CPS compliance and energy profit maximization, run them at a loss in the energy market, and then (implicitly) make them whole through side payments (e.g. Clean Peak Credits or cash subsidies from the State).

While these side payments are not formally calculated in the model, it suggests that meeting the CPS – in some cases – would require subsidy payments in excess of 100% of the annualized capital costs of the storage asset. This counterproductive storage dispatch does not manifest itself in the RPS-only markets: while storage may not be particularly profitable in RPS-only markets, storage will never run at a loss.

3.5 Effect of CPS on System Emissions, Market Efficiency, and Costs

Adding a CPS to power markets changes how the power system is built and operated. In this section, we focus on four base system metrics and two composite metrics:

- Carbon Emissions: The total quantity of power system CO_2 emissions (megatonnes/year)
- Cost of Production: The cost of running the power-system on an hour-to-hour basis; a metric of system efficiency ($ billion/year)
- Fixed Cost of Capacity: The fixed costs power-plants used to generate electricity in the region ($ billion/year)
- Marginal Price of Energy: The load-weighted marginal price of energy, which we set equal to system's highest offer price in a given hour ($/MWh)
- Total System Cost: the sum of fixed and hourly production costs, which reflects system costs in a rate-regulated jurisdiction ($ billion/year).
- Total Market Cost: the sum of fixed capacity costs and the price of the energy market (marginal price of electricity times total MWh sold). This metric approximates the price of wholesale markets in competitive regions, like ISO-NE ($ billion/year)

Figure 8 (and following) plot how increasing CPS requirements affect each of these metrics. Each figure is composed of a set of RPS isoquants and depicts how CPS affects a metric, while holding the RPS constant (e.g RPS = 20% or RPS = 40%). Each curve can be thought of as a distinct horizontal transect of runs depicted in Figure 1. Variations on these figures, showing percentage effects of adding the CPS, relative to an RPS-only baseline, compared to the RPS only, are provided in Supplementary Information §4 (These variations offer finer detail on the "shape" of each iso-quant curve.)

Figure 8 depicts how system emissions vary by CPS, for a constant RPS. First, observe that as we jump between RPS isoquants, the amount of system emissions changes materially – a 5% increase in RPS reduces emissions by about 2 megatonnes per year. Second, we can observe that increasing the CPS – for a given RPS level– also changes emissions. (This can be seen by following each isoquant curve from left to right.) For a given RPS requirement, adding a daily CPS will consistently increase system emissions – albeit by a small but meaningful amount. For example, adding a 50% daily CPS to a 20% RPS will yield an increase in system carbon emissions of 2.4% (17.75 megatonnes with no CPS; 18.17 megatonnes with the 50% CPS). Annual CPS are less consistent in their emissions impact: when paired with an RPS less than 35% the CPS will slightly increase emissions, but at higher RPS levels, the CPS reduce emissions. With both CPS specifications, the change in system emissions small.

Figure 9, depicting total cost of production, suggests that the daily CPS has no effect on market efficacy. While total cost of production ("TCP") – our metric of system efficiency – changes with RPS (indicating the introduction of new zero-marginal cost renewables resources reducing system fuel costs), it is practically invariant with CPS. This suggests that the CPS does not reduce ramping constraints. Slight reductions in TCP associated with high annual CPS suggest that solar energy – coincident with periods of peak demand – are limiting the use of expensive Peaker units and reducing short-run costs (cf. Figure 6 and Figure 7).

Figure 10 shows that both CPS specifications consistently reduce the marginal price of electricity. For example, in a market with a 30% RPS – increasing the daily CPS from 20% to 50% decreases prices from $34.95/MWh to $33.62/MWh (an 4% reduction). This suggests that the CPS does affect how the power system is operated on the margin – as implied by Figure 6 and Figure 7. Solar and storage, in particular, are able to reduce the use of expensive fossil-fuel peaking resources which, in turn, reduces prices. Reduced energy prices benefit consumers.

Figure 8: Total CO_2 Emissions by RPS (megatonnes / year)

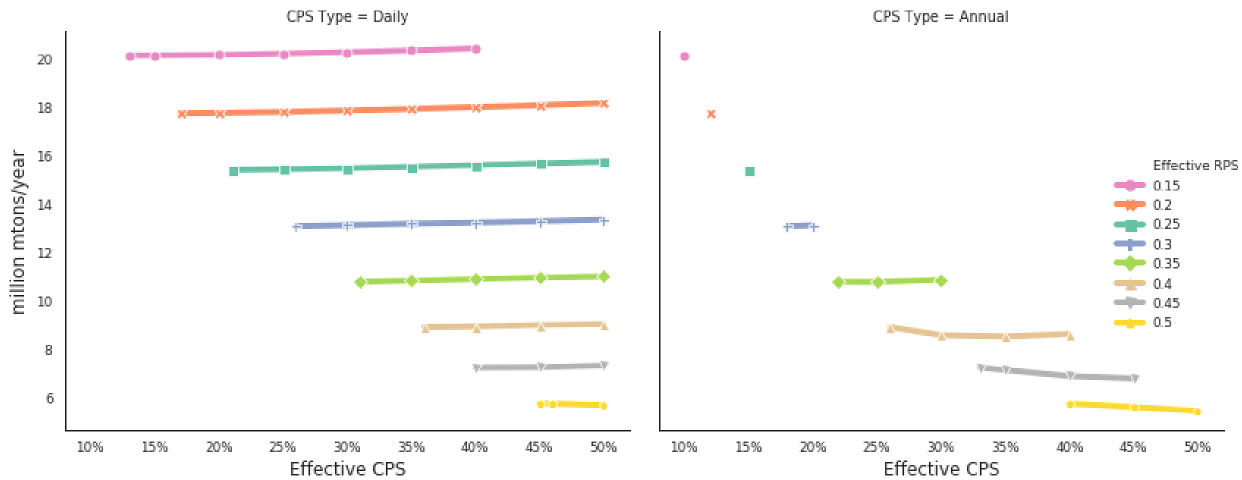


Figure 9: Total Cost of Production by RPS ($bn / year)

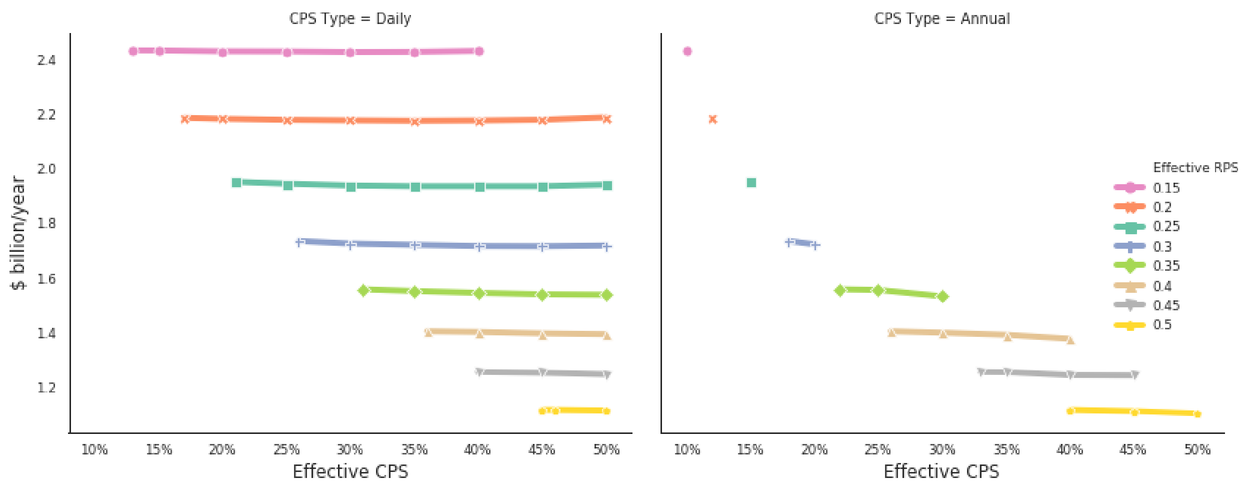


Figure 10: Marginal Price of Electricity by RPS ($/MWh)

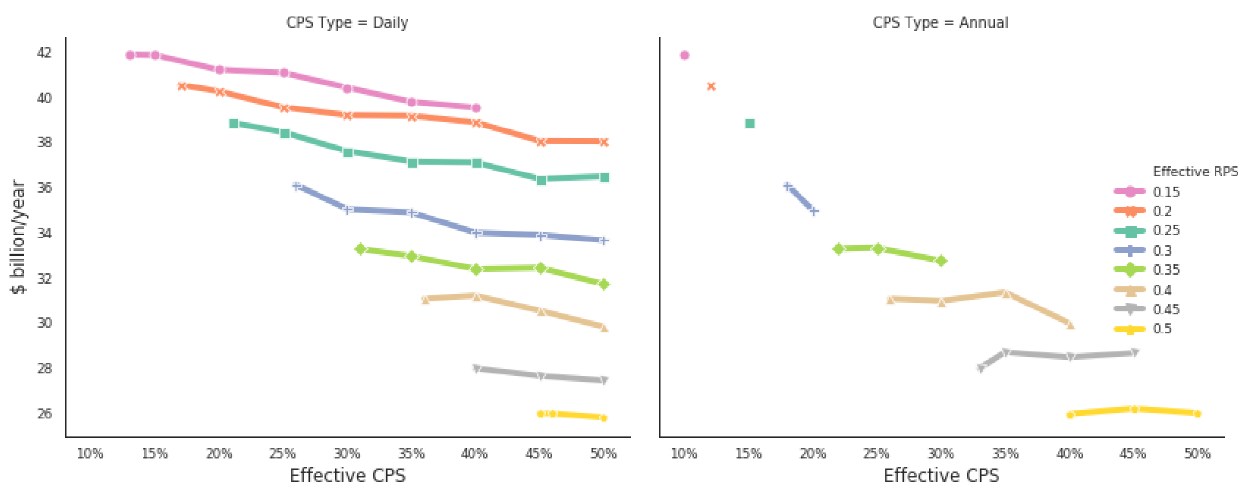


Figure 11: Total Fixed Costs ($bn / year)

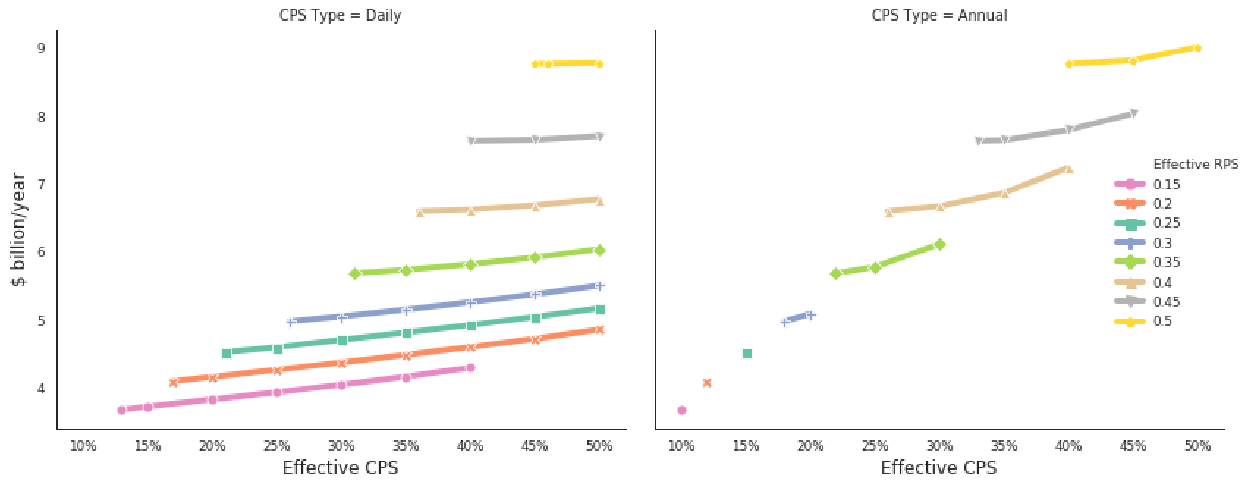


Figure 12: Total System Cost ($bn / year)

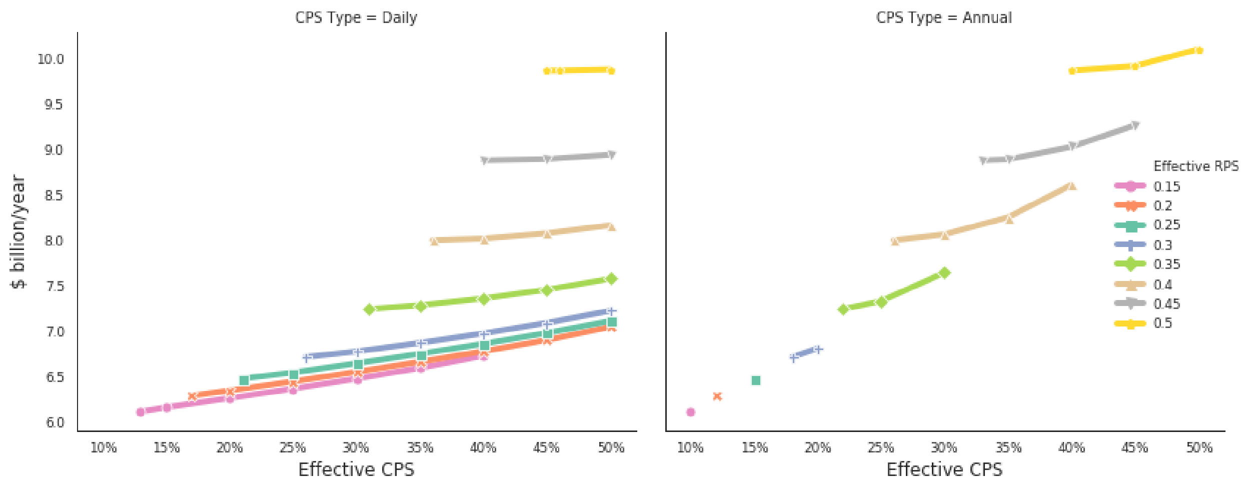


Figure 13: Total Market Cost ($bn / year)

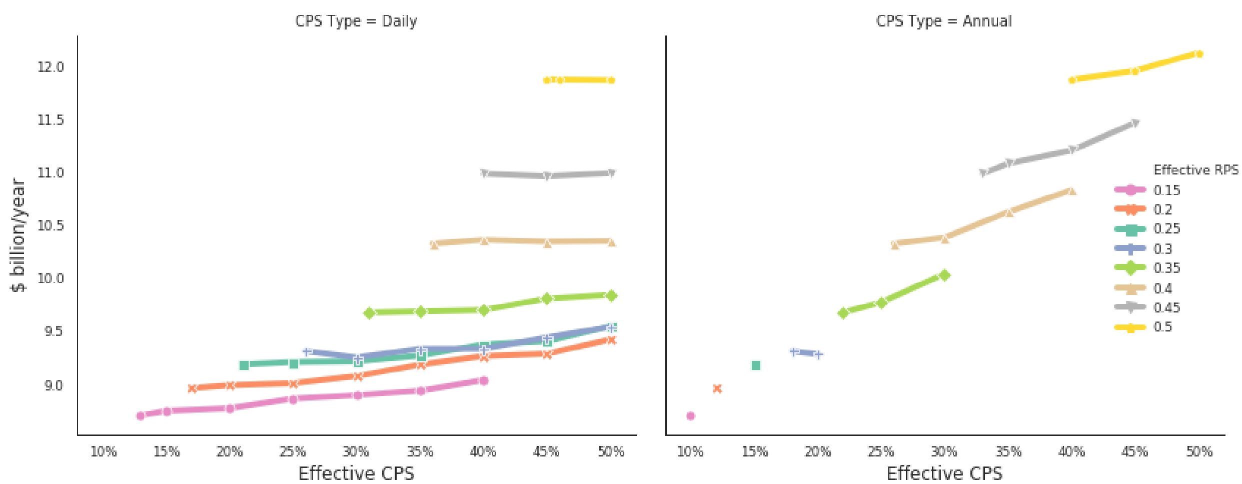


Figure 11 depicts the fixed costs of capacity. Here, we observe that as the RPS increases, so do prices. For example, the cost of a market with a 35% RPS and no CPS is $7.2bn. The same market with a 40% RPS, however costs $8bn. This reflects the fact that renewables are expensive, compared to the cost of already installed capacity (with modest going-forward costs). Increasing the CPS – for a given RPS – increases costs still more. For example, the $7.2bn market cost associated with a 35% RPS increases to $7.6bn as the effective annual CPS rises from 22% to 30%. If a daily CPS were implemented, then the market cost would rise from $7.2bn to $7.3bn (CPS=35%), to $7.6bn (CPS = 50%). Under both CPS specifications, the higher the CPS, the faster the increase in costs. Increasing the CPS from 30% to 35% increases costs by $40 million, while increasing the CPS from 45% to 50% increases costs by $120 million.

The total cost of the running the system depends on whether the power system is rate-regulated or subject to market prices. In the former, the system's cost is the sum of production and fixed costs. Under rate regulation, adding a CPS consistently increases costs – irrespective of CPS specification or RPS requirement. These escalating costs are depicted in Figure 12.

Under cost- or price-based system, these results indicate that a "too high" CPS requirement can lead to inefficient deployment of capital. For a given RPS requirement, with a generically high CPS requirement, there is almost always a lower CPS option that provides the same benefits at lower cost, or a higher RPS/ lower CPS option that provides more benefits for the same cost. We can attribute the increase in total costs to the adoption of more expensive renewable resources (e.g. solar instead of wind) and of storage which is not cost-effective, but-for implied CPS incentive payments.

3.6 CPS Benefit Attribution

Using our simulated results, we now turn to empirically assessing the incremental benefits of adding a Clean Peak Standard. In this section, we formulate a basic linear regression model which allows us to suss out the incremental value of CPS.

In the preceding figures, we observe that as the RPS rises, the minimum effective CPS rises too. This means that our effective CPS contains two different trends – the underlying escalation in minimum effective CPS, and the relative increase in CPS from that minimum. We control for this effect by regressing against relative CPS (*effective* CPS for a given *effective* RPS, less minimum *effective* CPS). In effect, this shifts each iso-quant to the left, until each starts at zero.

Separately, we observed that increasing the RPS (jumping between RPS iso-quant curves) often has a bigger effect than increasing the CPS (moving along a given curve). As we are primarily interested in how CPS affect the system (irrespective of RPS level), we control for RPS-related benefits by shifting each curve down until its left-post point is set to zero. This results in a curve which depicts the change in a given metric, *relative* to the RPS-only starting-point.

The combination of these two transformations functionally results in us dragging each isoquant from the Figure 8 through Figure 13 down and to the left, until the left-most point of each curve is at the origin (0,0). Supplementary Information §4 presents transformations of Figure 8 through Figure 13, which control for these factors. Thus, our regression model is of the following form:

$$Relative\ Metric = \ 0 + \ \beta_1(Relative\ CPS)$$

We present results for four system metrics for both CPS formulations in Table 3. The same process is used to assess impact of expanding the RPS, all else equal.

Table 3: Impact of CPS & RPS on Market Outputs

Metric	CO_2 Emissions (kilotonnes/year)		Operating Cost / Mkt Efficiency ($mm/year)		Energy Mkt Price ($/MWh)		Fixed Cost ($mm/year)		Total Market Costs ($mm/year)	
CPS Type	Annual	Daily	Annual	Daily	Annual	Daily	Annual	Daily	Annual	Daily
*Results for a 1% Change in **CPS***										
R^2	0.791	0.889	0.818	0.559	0.135	0.954	0.927	0.980	--	--
Value	-31.27	9.92	-1.42	-0.51	-0.03	-0.09	38.22	21.17	34.81	10.47
Value / $mm	-0.898	0.948	-0.041	-0.049	-0.001	-0.009	1.098	2.023		
*Results for a 1% Change in **RPS***										
R^2	0.929	-0.997	0.971	0.989	0.727	0.974	0.949	0.943	--	--
Value	-328.6	-453.1	-26.30	-41.80	-0.22	-0.35	115.60	92.82	88.74	50.45
Value / $mm	-3.703	-8.982	-0.296	-0.829	-0.003	-0.007	1.303	1.840		
CPS / RPS Ratio	24%	-11%	14%	6%	32%	122%	84%	110%		

Notes:

- Value / $mm reflects the change in a parameter per change in Energy + Fixed Costs. It is a metric of relative value.
- CPS / RPS Ratio reflects the relative value of spending $1 on an expanded CPS compared to spending that on RPS.
- All Parameters are significant at P<0.05 level.

Considering emissions first: a 1% increase in *annual* CPS requirement leads to a 31 kilotonne decrease in annual system emissions – all else equal – while a 1% increase in daily CPS increases carbon emissions by 9 kilotonnes. Turning to system efficiency, we find that increasing a *daily* CPS by 1% leads to reductions in operating costs of $0.51 million/year, while a 1% increase in *annual* CPS leads to a reduction in costs of $1.42 million/year. As operating costs range from $1.1 to $2.4 billion/year – the efficiency benefits of the CPS are *de minimis.* At the same time, however, fixed costs increase markedly. A 1% increase in annual CPS increases fixed costs by $38.22 million/year while a daily CPS increases fixed costs by $21.17 million.

In a market setting, we observe that CPS increases costs by $10-35 million per 1% increase in requirements. Thus, a 20% increase in daily CPS requirements leads to total costs rising by about $210 million per year. Under a rate-regulated setting, the effect is more dramatic, because the price-supressive benefits of the CPS are much less unimportant. Under these circumstances, a 1% increase in CPS increases costs by $21 to $37 million per year.

Increasing an RPS also increases costs but provides more material benefits. Increasing the RPS increases fixed costs because new renewables replace existing fossil resources with more modest going forward costs (e.g. are partially depreciated). At the same time, however, these new renewables drive down emissions and operating costs (because of increased reliance on zero-marginal cost resources).

Separately, we observe that increasing an RPS by 1% reduces system emissions by 329 to 453 kilotonnes per year at a net cost of $50 to 89 million. While increasing the RPS increases fixed costs, it also drives down operating costs. By taking the ratio of emissions rates to cost, we see that an additional dollar spent expanding the RPS will reduce system emissions by 5 to 10 times more than a dollar spent on an expanded CPS.

This analysis indicates that the annual CPS offers modest carbon reductions at reasonably high cost, while the daily CPS consistently increases both costs and emissions. Both CPS formulations offer less value to the system – and to customers – than simply expanding the RPS.

4 Sensitivities:

4.1 Effects of Storage-Focused CPS

While our analysis indicates that energy storage is already an essential component of technology-neutral CPS compliance, some policymakers have developed CPS regulations that provide preferential treatment for storage resource. Massachusetts, for example, biases its program towards energy storage by derating the value of renewable generation for purposes CPS. With derating in place, the State expects that storage will meet 59% of CPS compliance requirement – compared to just 5% if without the renewables derating.[33]

This sensitivity analysis looks at the general effect of derating renewables for CPS compliance, and modifies the base model by derating the value of renewable generation by 75% when used for CPS compliance (i.e. 1MWh of renewable output during peak hours yields 0.25 MWh of CPS compliance). Storage is not derated.

Derating renewables for CPS compliance increases the share of energy storage on the system. Figure 14 is analogous to the capacity portions of Figure 3 and Figure 4, but depicts capacity buildout assuming that renewable output is derated by 75% when used for CPS compliance. Compared to our central case, we observe that derates lead to an increase storage capacity by one-third for a *daily* CPS and by more than 50% for an *annual* CPS.

As before, changing the resource mix changes compliance cost, system operation, and net emissions. Compared to the central case, we find that this storage heavy system costs more than the central case, and offers fewer benefits. Table 4 mimics Table 3. We observe that total costs rise markedly for the annual CPS ($63 million/year per 1% increase in CPS vs. $35 million) and modestly for the *daily* CPS ($12 million per 1% increase in CPS vs. $10 million). Efficiency benefits, already modest in the central case, are further reduced. Worse, the emissions rise are 40% higher for the *daily* CPS (13.8 kilotonnes per 1% increase in CPS vs. 9.9 kilotonnes); and that emission reductions in the *annual* CPS cases are 72% lower. Overall, we find that attempts to tilt the CPS in favor of storage leads to higher costs and worse emissions outcomes than a technology-neutral CPS.

Figure 14: Capacity (MW) by Effective CPS (Renewables derated 75% for CPS)

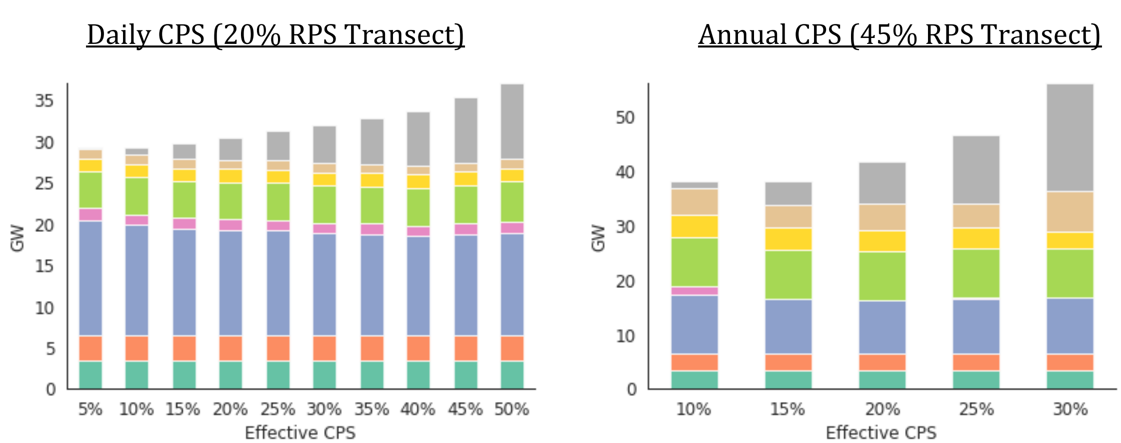


Table 4: Impact of CPS & RPS on Market Outputs (Renewables derated 75% for CPS)

Metric	CO_2 Emissions (kilotonnes/year)		Operating Cost / Mkt Efficiency ($mm/year)		Energy Mkt Price ($/MWh)		Fixed Cost ($mm/year)		Energy + Fixed Costs ($mm/year)	
CPS Type	Annual	Daily	Annual	Daily	Annual	Daily	Annual	Daily	Annual	Daily
*Results for a 1% Change in **CPS***										
R^2	0.300	0.920	0.112	0.286	0.736	0.955	0.920	0.967	--	--
Value	-8.91	13.790	-0.570	-0.250	-0.156	-0.091	82.050	23.090	63.306	12.134
Value / $mm	-0.141	1.136	-0.009	-0.021	-0.002	-0.008	1.296	1.903		
*Results for a 1% Change in **RPS***										
R^2	0.989	0.997	0.970	0.992	0.962	0.979	0.962	0.975	--	--
Value	-428.0	-446.0	-37.92	-42.19	-0.409	-0.413	100.5	111.7	51.432	62.104
Value / $mm	-8.322	-7.182	-0.737	-0.679	-0.008	-0.007	1.954	1.799		
CPS / RPS Ratio	2%	-16%	1%	3%	31%	113%	66%	106%		

4.2 CPS under Carbon Tax

Carbon taxes are frequently touted as an efficient method to reduce carbon emissions in the electric sector. Many states, including Massachusetts and California, have incorporated carbon pricing into their electricity markets. In this sensitivity, we explore how CPS would interact to a system that is subject to both an RPS and a $50/mton carbon tax – in line with estimates of the social cost of carbon.[34]

Adding a carbon tax leads to no directional change in our results (cf. Table 5 and Table 3). As before, we find that adding a daily CPS will increase emissions, decrease operating costs by a *de minimis* quantity, and materially increase total costs. The annual CPS formulation again fares better – modest carbon reductions at high cost. Under a carbon tax, the RPS will continue to drive material reductions in carbon emissions at lower cost than what can be achieved via the CPS.

Table 5: Impact of CPS & RPS on Market Outputs ($50/mton Carbon Tax)

Metric	CO_2 Emissions (kilotonnes/year)		Operating Cost / Mkt Efficiency ($mm/year)		Energy Mkt Price ($/MWh)		Fixed Cost ($mm/year)		Energy + Fixed Costs ($mm/year)	
CPS Type	**Annual**	**Daily**	**Annual**	**Daily**	**Annual**	**Daily**	**Annual**	**Daily**	**Annual**	**Daily**
*Results for a 1% Change in **CPS***										
R^2	0.740	0.557	0.693	0.705	0.493	0.847	0.912	0.931	--	--
Value	-29.65	9.210	-1.87	-1.02	-0.041	-0.094	40.41	18.30	35.514	7.044
Value / $mm	-0.835	1.307	-0.053	-0.145	-0.001	-0.013	1.138	2.598		
*Results for a 1% Change in **RPS***										
R^2	0.963	0.997	0.996	0.996	0.899	0.986	0.970	0.979	--	--
Value	-337.5	-429.6	-25.30	-32.65	-0.330	-0.428	128.43	137.40	88.818	86.016
Value / $mm	-3.800	-4.994	-0.285	-0.380	-0.004	-0.005	1.446	1.597		
CPS / RPS Ratio	22%	-26%	18%	38%	31%	267%	79%	163%		

5 Discussion

In some instances, we find that CPS are ineffective and expensive; in others, we observe that CPS make the grid dirtier and more expensive. The adoption of a *daily* CPS consistently increases costs to consumers and increases emissions, compared to a system without a CPS. Adding an *annual* CPS can make the system slighter cleaner at very high cost, by substituting higher-cost solar for wind. Neither formulation materially changes system efficiency; both materially increase cost. Our findings do not suggest that CPS will yield better results with time: even as CPS spur peak-aligned renewables and the retirement of dirty peaking resources – emissions do not materially improve.

The underlying problems we identify with CPS exist in both the daily and annual formulations. These trends are observed across a wide range of RPS, CPS requirement levels indicating that the problem is structural, rather than the result of specific circumstances. Our results align with the results from California and Massachusetts which indicate that an annual CPS leads to better outcomes than a daily CPS.[35,36] But, after controlling for other factors, we find both variations of CPS ineffective. Compared to an expanded RPS, both CPS formulations offer poor value for money: abatement of carbon emissions costs 5 to 10 times more when achieved using CPS instead of Renewable Portfolio Standards. While certainly possible, it seems unlikely that any tweaks to CPS will solve the structural problems.

CPS portrays itself as a technology neutral method to spur the adoption of technologies with generation profiles coincident with periods of peak MW demand. In Figure 4, we observe just this:

CPS shifts the resource mix away from higher capacity factor wind and towards solar and storage. This results in a more balanced, fuel-diverse resource mix. In this context, CPS acts as *de facto* subsidy for these resources, and the cost of this subsidy can be observed in both Figure 11 and Table 3.

When policymakers offer some sort of side-payment or make-whole arrangement, it should be because the market is not capturing all the value society bestows on the underlying product. For RPS, rationales include increasing fuel security, improving cost certainty, and reducing system emissions. In a market without a meaningful carbon price, that lack of emissions is not formally compensated in the market, so a side-payment via Renewable Energy Credits ("RECs") can align private and societal interests.

The problem with the CPS isn't incentive payments, *per se*. The problem is that while a REC adequately captures a set of actual – but unpriced – societal interests, Clean Peak Energy Credits do not. The supposed benefits of CPS – reducing costs, reducing emissions, and relieving ramping constraints – are mostly priced into our power markets already. The region already prices carbon through the Regional Greenhouse Gas Initiative, renewable attributes through RECs, and the value of energy through wholesale prices which vary over time and space. To the extent that renewables create new ramping constraints, these are priced via wholesale market reserves or uplift payments. New England does not have a serious problem with renewables integration, with ramping, or with excessively high peak-period emissions that could be resolved through the CPS. Thus, the CPS is driving down theoretical problems which do not actually manifest themselves.

Reducing an inconsequential problem with excess zeal introduces new problems. As observed in Section 3.d, when the CPS is ratcheted up, the least-cost compliance CPS strategy is to build batteries, co-optimize their dispatch for CPS compliance and energy profit maximization, run them at a loss in the energy market, and then make them whole through side payments. Table 3 implies that the CPS can make society worse off because society is offering side-payments to induce batteries to operate in a way that society doesn't actually want, only to end up where we started. This perverse outcome does not occur in the absence of a CPS.

To the extent that is the underlying goal of CPS is to provide subsidies to energy storage, then our research suggests that that regulators should look elsewhere. While a CPS only offers a single value stream for storage (bulk energy time shifting), other incentive programs can target specific system needs or simply buy-down the cost of storage in advance of a high-renewables future. Instead of focusing on an attribute-based program, it may be more efficient to simply provide a fixed $/kW subsidy (e.g. California's Self Generation Incentive Program) or a tax credit to reduce capital costs (e.g. the Federal Investment Tax Credit). These structures would allow storage developers to pursue higher value projects and might allow for more storage development per incentive dollar spent.

If a regulator's goal for the CPS is to reduce emissions or help with renewables integration, then they would be better off simply expanding or accelerating the procurement of renewables via an RPS or carbon tax. These are proven methods to reduce emissions at reasonable cost.[37] If a region is grappling with specific problems (e.g. limited ramping capability), then more targeted programs may be more effective than the CPS's kitchen-sink approach.

6 Conclusion

Regulators and policymakers should be cognizant of the way that new policy measures interact with existing tools. While accretive policymaking can provide incremental value, unexpected and undesirable outcomes are possible, especially when substantive due diligence occurs *after* a policy is codified. While its heart is in the right place, our results indicate that CPS are, at best, inefficient and, at worst, counterproductive.

Our analysis indicates adding a CPS *changes* the resource mix (more solar and storage) but offers few incremental benefits that could not also be achieved at lower cost through an expanded RPS. For a given level of RPS, a *daily* CPS offers no incremental cost/emissions/efficiency benefits. For a given level of RPS, an *annual* CPS offers emissions benefits, albeit at higher cost than those same benefits achieved by expanding the RPS.

More bluntly, our findings suggest that regulators can achieve the same market and environmental outcomes at lower cost if they simply do not implement Clean Peak Standards. Or, for the same level of ratepayer spending, regulators could achieve better outcomes by simply accelerating their RPS. While these results are deeply pessimistic about the value of Clean Peak Standards, it is worth reiterating that CPS is nascent policy and that this work is preliminary. It is certainly possible that CPS may work *better* in other regions or if it is narrowly tailored to a specific set of circumstances. Before regulators propose CPS in new jurisdictions, we encourage them to carefully examine their intentions and to thoughtfully assess how the adoption of a CPS will affect their region.

[1] Barbose, Galen L. (2018). U.S. Renewables Portfolio Standards: 2018 Annual Status Report. 2018. Lawrence Berkeley National Laboratory, p3. Available at: http://eta-

publications.lbl.gov/sites/default/files/2018_annual_rps_summary_report.pdf

[2] Huber, L. and Burgess, E. (2016). Evolving the RPS: A Clean Peak Standard for a Smarter Renewable Future, p3-5. Available at https://www.strategen.com/new-blog/2016/12/1/evolving-the-rps-a-clean-peak-standard-for-a-smarter-renewable-future.

[3] Huber, L. and Burgess, E. (2016), p3-5.

[4] Massachusetts Department of Energy Resources (DOER) (2019). The Clean Peak Energy Standard: Draft Regulation Summary, p3. Available at: https://www.mass.gov/files/documents/2019/08/07/Draft%20CPS%20Reg%20Summary%20Presentation%208.6.pdf

[5] An Act to Advance Clean Energy, August 9, 2018. MA Laws 227. Available at: https://malegislature.gov/Laws/SessionLaws/Acts/2018/Chapter227

[6] Massachusetts Department of Energy Resources (DOER) (2019), p38-39.

[7] Massachusetts Department of Energy Resources (DOER) (2019), p13.

[8] Chaurey, A., Huang, Z., Khan, L., & Pratson, L. (2018). Energy Storage Pathways to Meet California's 2030 Greenhouse Gas Goals. Duke University Master's Project. Available at: https://dukespace.lib.duke.edu/dspace/bitstream/handle/10161/16552/Energy%20Storage%20Pathways%20to%20Meet%20California%20s%202030%20Greenhouse%20Gas%20Goals-Chaurey,%20Huang,%20Khan%20(High%20Resolution).pdf?sequence=5

[9] Massachusetts Department of Energy Resources (DOER) (2019), p39.

[10] Shrader, J. Lewis, C., McCormick, G., Rabideau, I., and Uncel, B. *"(Not So) Clean Peak Energy Standards"* December 10, 2019. https://ssrn.com/abstract=3502271.

[11] Davis, S. J., Lewis, N. S., Shaner, M., Aggarwal, S., Arent, D., Azevedo, I. L., ... & Clack, C. (2018). Net-zero emissions energy systems. *Science*, *360*(NREL/JA-5D00-70804). Available at: DOI: 10.1126/science.aas9793

[12] De Sisternes, F., Jenkins, J. & Botterud, A. (2016). The vale of energy storage in decarbonizing the grid. Applied Energy 175, 368-379. Available at: https://doi.org/10.1016/j.apenergy.2016.05.014.

[13] Arbabzadeh, M., Sioshansi, R., Johnson, J. X., & Keoleian, G. A. (2019). The role of energy storage in deep decarbonization of electricity production. Nature communications, 10(1), 3413. Available at: https://www.nature.com/articles/s41467-019-11161-5

Braff, W. A., Mueller, J. M., & Trancik, J. E. (2016). Value of storage technologies for wind and solar energy. *Nature Climate Change*, *6*(10), 964. Available at: https://www.nature.com/articles/nclimate3045

[14] Denholm, P., O'Connell, M., Brinkman, G., & Jorgenson, J. (2015). *Overgeneration from solar energy in California. A field guide to the duck chart* (No. NREL/TP-6A20-65023). National Renewable Energy Lab.(NREL), Golden, CO (United States).Available at: https://www.nrel.gov/docs/fy16osti/65023.pdf.

[15] Strbac, G. (2008). Demand side management: Benefits and challenges. *Energy policy*, *36*(12), 4419-4426. Available at: https://www.sciencedirect.com/science/article/pii/S0301421508004606

Feldman, B., Tanner, M., & Rose, C.,(2015). Navigant Consulting for Advanced Energy Economy. Available at: https://info.aee.net/peak-demand-reduction-report

[16] Fares, R. L., & King, C. W. (2017). Trends in transmission, distribution, and administration costs for US investor-owned electric utilities. *Energy Policy*, *105*, 354-362. Available at: doi.org/10.1016/j.enpol.2017.02.036

[17] Ralph, M., Ellis, A., Bomeo, D., Corey, G., Baldwin, S., (2011). Transmission and Distribution Deferment using PV and Energy Storage. Sandia National Laboratories. SAND2011-4171C. Available at: https://www.osti.gov/servlets/purl/1120304.

[18] ISO New England (2018). Generator Interconnection Queue (As of 9/5/2019). Available at: https://iso-ne.com/system-planning/transmission-planning/interconnection-request-queue

[19] Mays, J., Morton, D.P. & O'Neill, R.P. Asymmetric risk and fuel neutrality in electricity capacity markets. *Nat Energy* **4,** 948–956 (2019). https://doi.org/10.1038/s41560-019-0476-1

[20] Hart, W., Laird, C. Watson, J., Woodruff, D., Hackebeil, G, Nicholson, B., Siirola, J. (2017). Pyomo – Optimization Modeling in Python, Second Edition. Springer.
Cf. Hart, W E., Watson, J. Woodruff, D. (2011) Pyomo: modeling and solving mathematical programs in Python. Math. Prog. Comput 3 (3), 219–260.

[21] GNU Linear Programming Kit (GLPK), https://www.gnu.org/software/glpk/glpk.htm

[22] ISO New England (2019). 2019 CELT Report. Available at: https://www.iso-ne.com/system-planning/system-plans-studies/celt/.

[23] [dataset] ISO New England Daily (2016-2018) Generation by Fuel Type. Retrieved from https://www.iso-ne.com/isoexpress/web/reports/operations/-/tree/daily-gen-fuel-type.

[24] [dataset] ISO-NE, (2016-2018). * SMD Hourly Data for node MassHub (ISO-NE reference point). Retrieved from: https://www.iso-ne.com/isoexpress/web/reports/load-and-demand/-/tree/zone-info (Accessed September 2019).

[25] [dataset] Massachusetts Clean Energy Center (2019). MassCEC Metocean Data Initiative. Available at: https://www.masscec.com/masscec-metocean-data-initiative

[26] Alstrom (2015). Haliade150 – 6MW Type Certificate Validation. Available at: http://www.ewea.org/offshore2015/conference/allposters/PO019.pdf

[27] S&P Global Market Intelligence, ISO-NE Supply Curve, Summer 2021.

[28] Vimmerstedt, L. J., Akar, S., Augustine, C. R., Beiter, P. C., Cole, W. J., Feldman, D. J., ... & Turchi, C. S. (2019). *2019 Annual Technology Baseline* (No. NREL/PR-6A20-74273). National Renewable Energy Lab.(NREL), Golden, CO (United States). Available at: https://atb.nrel.gov/

[29] Henderson, Bill. "New England Wind Integration Study: Abbreviated Results", MIT Wind Club Wind Integration Workshop, Jan 21, 2011http://web.mit.edu/windenergy/windweek/Presentations/Henson-NEWIS%20MIT%20wind%20club.pdf p7.

[30] Van Welie, G. *ISO-NE State of the Grid: 2019.* Feb 20, 2019. https://www.iso-ne.com/static-assets/documents/2019/02/20190220_pr_state-of-the-grid_presentation_final.pdf p17.

[31] Beiter P., Musial, W., Kilcher, L., Maness, M., and Smith, A (2017). *An Assessment of the Economic Potential of Offshore Wind in the United States from 2015 to 2030* (NREL/TP-6A20-67675). National Renewable Energy Lab.(NREL), Golden, CO (United States). Available at: https://www.nrel.gov/docs/fy17osti/67675.pdf

[32] Lazard (2018). Lazard's Levelized Cost of Storage Analysis – Version 4.0. Slide 28. Available at: https://www.lazard.com/media/450774/lazards-levelized-cost-of-storage-version-40-vfinal.pdf.

[33] Massachusetts Department of Energy Resources (DOER) (2019). The Clean Peak Energy Standard: Draft Regulation Summary, p28.

[34] US Environmental Protection Agency (2017). The Social Cost of Carbon: Estimating the Benefits of Reducing Greenhouse Gas Emissions. Available at: https://19january2017snapshot.epa.gov/climatechange/social-cost-carbon_.html.

[35] Cf. Chaurey, A., Huang, Z., Khan, L., & Pratson, L. (2018).

[36] Shrader et al (2019).

[37] Mai, T., Wiser, R., Barbose, G., Bird, L., Heeter, J., Keyser, D., ... & Millstein, D. (2016). *A prospective analysis of the costs, benefits, and impacts of US renewable portfolio standards* (No. NREL/TP-6A20-67455). National Renewable Energy Lab.(NREL), Golden, CO (United States). page xi. Available at: http://eta-publications.lbl.gov/sites/default/files/lbnl-1006962.pdf.

Supplementary Information

Expensive, Ineffective, & Occasionally Counterproductive

Clean Peak Standards Simulation Results for New England.

B.W.Griffiths[1] | 3-24-2020

1. Model Summary

1.1. INTRODUCTION

Our model integrates elements of an hourly economic dispatch model ("EDM") and of a capacity expansion model ("CEM") into a single linear program. The economic dispatch component of this model efficiency schedules a set of power plants to meet load while minimizing the system's total cost of production. It returns operational schedules for each resource on the system as well as the cost to run the system and the price paid by load for electricity. Storage is dispatched endogenously to both maximize energy revenues and help comply with the Clean Peak Standard ("CPS"). Importantly, storage dispatch affects the dispatch of other resources and, consequently, market prices. The capacity expansion portion of the model endogenously builds the least-cost portfolio of resources needed to generate electricity to serve demand and to satisfy environmental requirements (e.g RPS or carbon tax). The model reflects the system as a single bus and ignores all transmission constraints.

Because the model integrates both dispatch modeling and capacity expansion, it explicitly considers the feedback loops between adding new resources or retiring existing resources, and hourly market prices. For example, as more renewables are built to meet Renewable Portfolio Standard ("RPS") or CPS requirements, energy prices fall and some existing resources exit the market. There are trade-offs between renewables too: as more of one kind of renewable resource is built, its $/MWh market revenues will decrease due to price suppression effects which, in turn, might make a different kind of resource more cost-effective to build thereafter.

In the context of capacity expansion, the cost-minimizing framework is equivalent to a profit-maximizing framework because the new resources being built are price-takers. For the renewable

[1] griffiths@bwgriffiths.com. *This article represents the opinions and conclusions of its author and not necessarily those of the Office of the Attorney General.*

generators this is clearly true, and for storage it is true in as much as its value is dependent on other resources in the thermal generating stack. Note that the model does not include payments for "missing money" that might be required to make the new assets profitable, such as capacity or REC payments. Incorporating these payments would change overall cost but would not change optimal build or optimal dispatch.

The linear program was developed using Python 2.7 and the Pyomo optimization programming library.[i] It was solved using the GNU Linear Programming Kit (GLPK).[ii]

1.2. NOMENCLATURE

Sets by Resource Type

VALUE	UNITS	DESCRIPTION
T	Set	Set of timesteps measured in hours
DISPATCHABLE	Set	Set of dispatchable generators (e.g. NGCC, nuclear)
VARIABLE	Set	Set of variable generators (e.g., solar, wind, offshore wind)
STORAGE	Set	Set of storage resources (e.g. batteries, pumped hydro)
PDR	Set	Set of price responsive demand and load shedding
GENS	Set	Union of Dispatchable, Variable, PDR Sets
RESOURCES	Set	Union of Gens and Storage Sets

Variables (Generator Related)

VALUE	UNITS	DESCRIPTION
E	MWh	Energy in each hour by each resource
P	MW	Maximum Power / Nameplate Capacity of each resource
C	\$/MWh	Short-run Marginal Cost of generating 1 MWh of energy
CAPEX	\$/MW-year	Annualized Cost of a MW of each resource
RU, RD	%	Ramp up / Ramp-down rates (measured as an hourly share of P)
ER	kg/MWh	CO2 Emissions Rate for each resource in **G**
CF	%	*Capacity Factor of Resource*
PROFILE	%	Renewable Resource Generation Profile (0-1), for each hour ***t***
$\boldsymbol{\eta}$	%	One-way efficiency of energy storage
HOURS	Hours	Number of hours in T

1.3. MODEL FORMULATION

Objective

Our model's objective function seeks to minimize the combined costs of (a) new capacity to satisfy load and environmental requirements, (b) the system's annualized total cost of production, and (c) carbon costs. Equation 1 summarizes this function, while Equations 2-4 define the three cost components. Equation 2 calculates the total, annualized capital costs of generating resources. Equation 3, reflecting the total cost of production, calculates the total cost of running the system hour-to-hour. Because capacity costs are annual values ($/MW-year), but we only calculate system dispatch for a subset of weeks, we annualize the summed hourly production costs. Equation 4, mirrored on Equation 3, calculates the total cost of carbon emissions (by default, this cost is nil).

$$Objective\colon \min[Fixed\ Capacity\ Cost + Production\ Cost + Carbon\ Cost] \tag{1}$$

$$Fixed\ Capacity\ Costs = \sum_{r=1}^{Resources} CAPEX_r \times P_r \tag{2}$$

$$Production\ Cost = \frac{8760}{Hours} \sum_{t=1}^{T} \left(\sum_{g=1}^{Gens} C_{g,t} \times E_{g,t} \right) \tag{3}$$

$$Carbon\ Cost = \frac{8760}{Hours} \sum_{t=1}^{T} \left(\sum_{g=1}^{Gens} ER_{g,t} \times E_{g,t} \right) \times Cost\ of\ Carbon \tag{4}$$

Capacity Expansion

In addition to going-forward costs of capacity resources included in Equation 2, each resource class is defined by two related terms. Each resource may be constrained by minimum and/or maximum installed capacity (Equations 5-6). Some resources, such as hydropower, may also be constrained by minimum or maximum amount of annual energy production (Equations 7-8). Instead of a MWh metric, we impose this constraint using a capacity factors, which reflect the amount of generation as unit produces over the year, as a function of capacity (endogenous variable P).

$$P_{r.min} \leq P_r, \forall\, r \in Resources \tag{5}$$

$$P_r \leq P_{r.max}, \forall\, r \in Resources \tag{6}$$

$$\left(P_r \times CF_{r,min} \times Hours\right) \leq \sum_{t=1}^{T} E_r\,, \forall\, r \in Resources \tag{7}$$

$$\sum_{t=1}^{T} E_r \leq \left(P_r \times CF_{r,min} \times Hours\right), \forall\, r \in Resources \tag{8}$$

Economic Dispatch Model

The EDM portion of our model establishes optimal schedules for each resource on the system while ensuring all that generator, system, policy constraints are satisfied. The EDM represents a single region-wide market, absent transmission constraints. The model requires data on system load, wind and solar generation profiles, power plant characteristics, fuel prices, and environmental policy. For all generators, we assume that renewable and thermal resources formulate their supply offers based on their short run marginal costs (“SRMC”), where SRMC ($/MWh) equals fuel cost ($/MMBtu) times heat rate (MMBtu/MWh) plus variable O&M ($/MWh).[2]

The EDM portion of the objective function is subject to seven constraints. Equation 9 requires that demand in each hour must be met by some combination of thermal generation, renewable generation, storage, imports, and load shedding. Equations 10-11 require that output from each dispatchable generator, in each hour, ranges from nil to its nameplate capacity. (N.b., storage resources skip the constraint in Equation 10, and can have negative output – i.e., charging.) Equations 12 and 13, when paired, allow for renewable curtailment during low-load periods. Equation 12 sets generation from each variable output resource in each period as less than or equal to its capacity multiplied by its output profile (0-1 normalized). Equation 13 limits total renewables output to a value less than or equal to storage adjusted demand. Equations 14 and 15 constrain ramp-rate constraints for dispatchable generators which specify that generation in the current period must be within the ramp-up and ramp-down range of the prior period’s generation. Ramp rates are defined as a percentage change in nameplate-capacity in one hour.

$$D_t = \sum_{r=1}^{Resources} E_{r,t} \tag{9}$$

$$0 \leq E_{g,t}, \forall\, g \in Gens \tag{10}$$

$$E_{d,t} \leq P_d, \forall\, d \in Dispatchable\ Resources \tag{11}$$

$$E_{v,t} \leq P_v \times Profile_{v,t}, \forall\, v\ \in Variable\ Resources \tag{12}$$

$$\sum_{v}^{Variable} E_{v,t} \leq\ D_t + \sum_{s}^{Storage} \left(I_{s,t} \times \eta_{s,t}\right) \tag{13}$$

$$E_{g,t-1} - \left(P_g \times RD_g\right) \leq E_{g,t}, \forall g\ \in Gens \tag{14}$$

$$E_{g,t-1} + \left(P_g \times RU_g\right) \geq E_{g,t}, \forall g\ \in Gens \tag{15}$$

Storage Operation & Dispatch

We model storage as a stand-alone, grid-connected device which can be dispatched to (a) maximize energy-market revenues and (b) comply with the Clean Peak Standard. When used for energy arbitrage (“EA”), storage buys electricity from the grid when prices are low and sells to the grid when prices are

[2] We rely on historic daily natural gas prices from Algonquin Citygate (the New England reference price for interstate pipeline gas) but hold annual fuel prices constant for other technologies (using New England region fuel forecasts, for the year 2025, from the 2020 EIA AEO).

high. Revenue maximizing storage dispatch is implicit in the model's objective function and the constraints outlined below. If a storage resource can make money by charging when prices are low and discharging when prices are high, it must also reduce the system's total cost of production. As modeled, storage does not have any operating costs *per-se*, but its charging costs are embedded in the model by way of the affected dispatch of other generators, and in turn, changed total cost of production. From the change in production costs, we can calculate ESS operating costs *post-hoc.*

Technically, we model the ESS as four discrete elements that are combined into a single storage device: a charging device for energy arbitrage, a discharging device for energy arbitrage, a charging device for "clean" charging, and a discharging device for the same. This four-part representation allows the ESS capacity to be used for purely economic activity like energy arbitrage, while also ensuring that the ESS is charged from clean sources when used for meeting the certain environmental programs. Note that as represented here, the Clean Peak Standard can be satisfied using storage charged from clean resources, but not storage charged from the general system power.

The device subparts are them combined into a single resource, using Equations 16-19. Equation 16 states that the system's overall charge rate in period t, measured in MWh, is the sum of charging for energy arbitrage and charging for CPS compliance, while Equation 17 is the discharge equivalent. Equation 18 states that the storage device's overall state of charge, measuring how "full" a battery is at a given point in time, equals the state of charge of both sub-functions. Equations 16-18 are measured at the storage device. Equation 19 calculates the net effect of energy storage on the grid equals loss-adjusted discharging less loss-adjusted charging, and where η is the one-way efficiency of the storage device.

Storage dispatch is constrained by maximum charge and discharge rates (Eqs 20-21). In a given period, storage can be charged or discharged for one or both functions. Storage dispatch is also constrained by its state-of-charge. Overall SOC, measured in MWh, ranges from zero to the capacity of the ESS (MW) multiplied by its duration (Eq 20). For both storage subfunctions, SOC in period t must equal the SOC in the prior period plus injections less withdrawals (Eq 21).

$$ESS\ Charge_{s,t}^{Total} = ESS\ Charge_{s,t}^{EA} + ESS\ Charge_{s,t}^{CPS}, \forall\ s \in Storage \tag{16}$$

$$ESS\ Discharge_{s,t}^{Total} = ESS\ Discharge_{s,t}^{EA} + ESS\ Discharge_{s,t}^{CPS}, \forall\ s \in Storage \tag{17}$$

$$ESS\ SOC_{s,t}^{Total} = ESS\ SOC_{s,t}^{EA} + ESS\ SOC_{s,t}^{CPS}, \forall\ s \in Storage \tag{18}$$

$$E_{s,t} = \left(\eta_{s,t} \times ESS\ Discharge_{s,t}^{Total}\right) - \frac{ESS\ Charge_{s,t}^{Total}}{\eta_{s,t}}, \forall\ s \in Storage \quad 19$$

$$0 \leq ESS\ Charge_{s,t}^{Total} \leq P_s\ \ , \forall\ s \in Storage \quad 20$$

$$0 \leq ESS\ Discharge_{s,t}^{Total} \leq P_s\ \ , \forall\ s \in Storage \quad 21$$

$$0 \leq ESS\ SOC_{s,t} \leq ESS\ SOC_{s,max}, \forall\ s \in Storage \quad 20$$

$$ESS\ SOC_{s,t} = ESS\ SOC_{s,t-1} + ESS\ Charge_{s,t} - ESS\ Discharge_{s,t}, \forall\ s \in Storage \quad 21$$

1.3 Environmental Mandates

The model incorporates four different environmental mandates, each of which can be toggled separately:

- **Carbon Tax**: a $/mton tax on all carbon emissions within the system.
- **Carbon Cap**: a maximum amount of emissions from the power system, expressed as the system's average emissions rate (mtons/MWh).
- **Renewable Portfolio Standard** ("RPS") or Clean Energy Standard ("CES"): a share of annual generation coming from a specific set of resources. An RPS specifies that a certain share of generation comes from renewables (such as wind and solar), while a CPS specifies that a share comes from non-emitting resources, (such as wind, solar, and nuclear).
- **Clean Peak Standard**: a CPS requires that a certain percent of energy delivered to customers during peak load hours must be derived from clean energy sources. In effect, the CPS creates additional preference for generation that occurs during high-load periods and for energy storage. CPS can target either the peak hours of the *year* ("annual CPS") or the top hours of the *day* ("daily CPS"). While a CPS is a different planning constraint than an RPS, a single resource could simultaneously contribute to both requirements.

The carbon tax is computed in Equation 4 and assumes that carbon costs are not internalized in generator bids. Equation 22 requires that total CO_2 must be less than or equal to the required CO_2 rate multiplied by total demand.

Equation 23 states that output from renewables must equal or exceed the RPS compliance quantity, where the compliance quantity is measured as an annual percentage of system load (including increased load due to storage operation).

Equation 24 is the primary CPS constraint. It states that output from renewables and clean-charged storage in peak time-periods ("Peak T") must equal or exceeding the annual CPS target, which is measured as a percentage of annual demand. Equation 25 specifies that loss-adjusted charging used for CPS compliance must be less than or equal to total renewables output in each period. This constraint ensures that storage used to meet the CPS is charged from clean resources.

$$Total\ CO_2 \leq Max\ CO_2\ Rate\ \times \sum_{t=1}^{T} D_t \tag{22}$$

$$\sum_{t=1}^{T}\left(\sum_{rps=1}^{RPS\ Elig.} E_{rps}\right) \leq RPS\ Rate\ \times \sum_{t=1}^{T}\left(D_t + \sum_{s=1}^{S} E_s\right) \tag{23}$$

$$\sum_{t=1}^{Peak\ T}\left(\sum_{cps=1}^{CPS\ Elig.} E_{cps}\right) \leq\ CPS\ Rate\ \times \sum_{t=1}^{Peak\ T}\left(D_t + \sum_{s=1}^{Storage} E_s\right) \tag{24}$$

$$\sum_{s}^{Storage} \frac{ESS\ Charge_{s,t}^{CPS}}{\eta_{s,t}} \leq \left(\sum_{cps=1}^{CPS\ Elig.} E_{cps}\right) \tag{25}$$

2 Resource Parameterization

Thermal Resources

We approximate ISO-NE's existing thermal supply stack using 19 composite units, for reasons of computation tractability. These composite units are generated using a k-means clustering algorithm and unit-specific data on fixed costs, variable O&M, and heat-rate from S&P Market Intelligence. The stack includes nuclear, gas and oil units but omits cogeneration facilities, biomass, and coal units. Nuclear units are all operate steam turbines, while the oil and gas units are a mixture of combined cycles, combustion turbines, and steam turbines.

For generators, the model includes ramping rates by technology type but no other intertemporal constraints. We assume gas and oil steam units have a ramp rate of 15% of their capacity in each hour, combined cycles have a ramp rate of 30% of their capacity, and gas turbines / combustion turbines can reach 100% of their nameplate capacity within one hour.[iii] Nuclear units cannot change output within a given sample week, but can change output levels between non-sequential sample weeks.

For all generators, we assume that renewable and thermal resources formulate their supply offers based on their short run marginal costs ("SRMC"), where SRMC ($/MWh) equals fuel cost ($/MMBtu) times heat rate (MMBtu/MWh) plus variable O&M ($/MWh). We rely on historic daily natural gas prices from Algonquin Citygate (the New England reference price for interstate pipeline gas) but use EIA AEO 2020 forecasts for uranium and distillate fuel oil (DFO).

Renewables

Capital cost data for solar, wind and off-shore wind are sourced from the 2019 NREL Annual Technology Baseline. We annualize NREL's cost estimates assuming a 10% discount rate and a 30-year resource lifespan.[iv] We assign a very low operating cost for each class of renewables equal to their assumed curtailment costs.

Hourly generation profiles for on-shore wind, solar, and imports are also developed using ISO-NE market data and matched with the load data. The off-shore wind profile is developed using historic meteorological data from the MassCEC[v], paired with a GE Halide 150-6 wind-turbine power curve – the same kind of turbine used in the nation's first off-shore wind farm.[vi] Renewable resources have no ramping constraints and are treated as "must-take" unless curtailment is required.

Local and imported hydro is scheduled economically, up to regions maximum import capacity in each period (3 GW), and up to the annual imported energy (75% capacity factor). The annual energy metric is based on average historical imports from HydroQuebec and estimates of incremental energy from forthcoming hydropower. For hydro resources, we assume a low SRMC of $15/MWh and a no ramping constraints.

Storage

Like the renewables, we source storage cost data from the 2019 NREL Annual Technology Baseline and annualize costs in the same manner. Three parameters define the ESS: power (**P**) measured in MW, the storage duration (**D**) measured in hours, and the one-way efficiency (**η**). P is endogenously assessed, Duration is set to 4-hours, and round-trip efficiency is set at 85%. We also assume that losses from charging and discharging are assumed equal, so $\eta = \eta_{roundtrip}^{0.5} = 0.924$. This configuration approximates the characteristics of lithium-ion batteries such as Tesla Powerpack. Although there are a variety of battery chemistries that could be used for energy storage, lithium-ion remains dominant and accounted for more than 94% of all deployed capacity in 2015 and 2016.[vii]

Data on each resource type is provided in **Table 1**, below.

Table 1: Resource Parameters

Unit Parameters						Unit Costs			Unit Emissions		
Unit Name	Fuel	Type	Max Cap (MW)	Heat Rate (Btu/kWh)	Ramp Rate	Fixed O&M ($/kW-Yr)	Non-Fuel Variable O&M($/MWh)	Avg. SRMC ($/MWh)	CO2 (kg/MWh)	SO2 (kg/MWh)	NOX (kg/MWh)
Nuc_1	Uranium	ST	3,336	10,400	1.3%	111.01	5.30	13.70	0	0	0
NGCC_1	NG	CC	2,812	7,157	33.3%	11.76	1.25	29.81	385	0.003	0.060
NGCC_2	NG	CC	805	6,684	33.3%	14.18	1.03	30.11	359	0.003	0.061
NGCC_3	NG	CC	7,123	7,522	33.3%	11.80	2.35	34.23	404	0.003	0.063
NGCC_4	NG	CC	1,495	7,959	23.6%	14.06	3.61	38.71	428	0.004	0.059
Coal_1	Coal	ST	821	11,745	33.3%	27.50	10.31	40.10	1105	2.401	1.053
NGCC_5	NG	CC	480	8,997	33.3%	19.44	6.22	46.56	483	0.004	0.082
NGCT_1	NG	CT	199	9,528	100.0%	3.84	5.87	46.80	516	0.009	0.255
NGCT_2	NG	CT	633	11,204	100.0%	5.33	4.12	52.73	607	0.010	0.300
NGCC_6	NG	CC	62	11,626	33.3%	29.54	9.21	58.79	625	0.005	0.105
NGST_1	NG	ST	847	11,987	23.6%	13.47	19.31	70.87	655	0.158	0.832
NGCT_3	NG	CT	74	12,291	100.0%	4.04	36.14	89.52	665	0.011	0.329
PPST_1	DFO	ST	2,177	13,196	23.6%	8.01	31.53	133.14	944	0.928	0.796
NGST_2	NG	ST	447	21,378	23.6%	14.06	43.02	135.85	1168	0.281	1.484
PPCC_1	DFO	CC	87	11,065	33.3%	29.54	9.21	154.65	813	2.510	6.025
PPST_2	DFO	ST	1,162	10,203	23.6%	3.30	75.10	176.71	730	0.718	0.616
PPCT_1	DFO	CT	130	12,600	100.0%	4.65	37.35	202.96	927	0.429	1.721
PPCC_2	DFO	CC	303	9,557	33.3%	9.33	86.62	212.24	702	2.168	5.203
PPCT_2	DFO	CT	50	17,480	100.0%	6.94	198.48	428.24	1281	2.157	4.116
Wind	Wind	–	9,000	–	100.0%	232	1.00	1.00	–	–	–
OSW	OSW	–	20,000	–	100.0%	593	2.00	2.00	–	–	–
Solar	Solar	–	50,000	–	100.0%	215	0.00	0.00	–	–	–
Hydro	Hydro	–	3,000	–	100.0%	445	15.00	15.00	–	–	–
Storage	–	–	50,000	–	100%	127	0	0	–	–	–

Notes

Unit Types: Steam Turbine (ST), Combined Cycle (CC), Combustion Turbine (CT).

Fuel Types: Uranium, Natural Gas (NG), Petroleum Products / Distillate Fuel Oil (DFO).

3 Selection of Representative Weeks

Our model requires a set of hourly data which is representative of trends in the New England Region. The computation power required to run a joint CEM/EDM over two representative years (17,520 hours) is both substantial and infeasible. So, instead of relying on a full year of hourly data, we instead select a subset of weeks which are representative of the complete two-year dataset.

Methods

There are many techniques for load sampling but we relied on a variation on the curve-fitting technique described in de Sisternes & Webster (2013).[viii] This approach selects a set of sample weeks, linearly scales that sample to match the number of hours in the full dataset, sorts both sets into duration curves, then compares that scaled sample it to the full dataset using an error metric. The set of weeks used for capacity expansion are those which minimize the error metric. This approach creates a set of sample weeks which capture:

1) The overall distribution of the complete dataset.
2) Week-scale continuous timeframes, which is essential for scheduling energy storage.

This approach does not ensure, however, that parameters that covary with one-another on seasonal timescales are accurately represented. Given the storage-centric issues at play in our analysis, it is preferable to other sampling techniques which identify "typical" weeks or "typical" days, but may not capture the full range in seasonal variability, or techniques which rely on sets of single-day samples do not allow for capturing how storage may charge or discharge over a multi-day timeframe (e.g. charge on the first day, hold charge on second, and discharge on a third day).

We extend the de Sisternes & Webster approach to allow for the selection of weeks which minimizes the error across a range of different parameters, not just hourly load. The extension is simple enough. Instead of minimizing error between full and sample datasets using the root mean squared error (RMSE) metric, we instead minimize parameter-weighted normalized RMSEs (NRMSE). The lower the (N)RMSE, the better the sample approximates the full set.

Formally, for a given vector parameter P with a complete dataset C_p and a randomly drawn sample S_p, and a weight of W_p, the error metric is:

$$Weighted, Normalized\ Error = \frac{\sum_p \left(W_p \times {}^{RMSE_p}\!/_{\overline{C_p}} \right)}{\sum_p W_p}$$

$$Where, \quad RMSE_p = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(C_{p,i} - S_{p,i}\right)^2}$$

For this analysis, we relied on the weights presented in Table 2. These weights were determined experimentally. We identified the best-fitting set of weeks by applying our error metric to 10,000 randomly selected sets of 13 weeks from the complete two-year (104 week) dataset, comprising all hours of 2017 and 2018. This two-year period represents the full set of years where each of the variables is fully available. We rely on an iterative random sampling approach instead of a brute-force assessment of all possible combinations, because the number of possible combinations is too large to be assessed analytically.

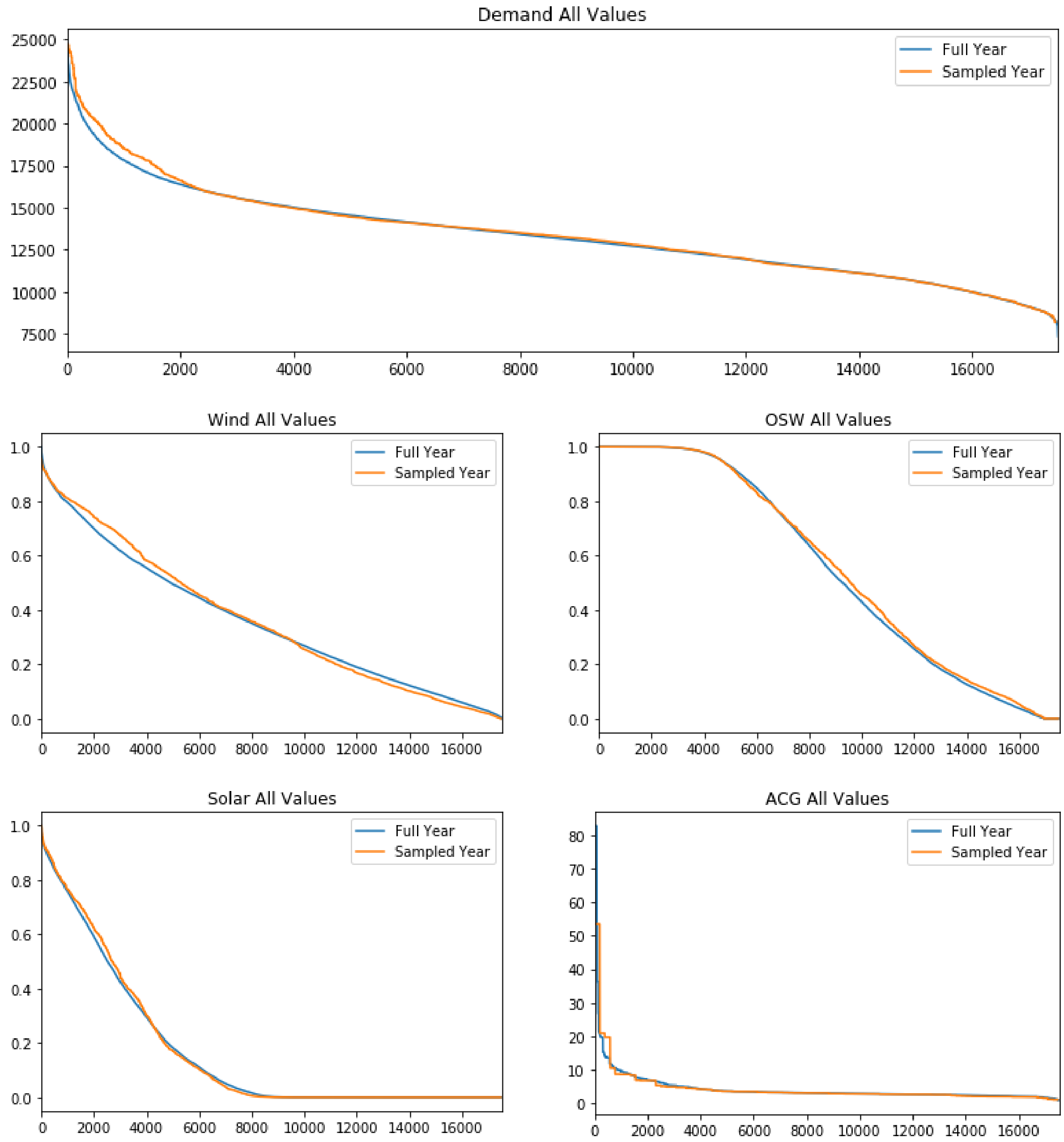
Fit

Table 2 provides data on the weights of each parameter as well as RMSEs for the best-fitting set of weeks. The sample has a peak demand of 24,754 MW – in line with ISO-NE peak demand forecasts for the 2020s. In general, parameters have NRMSEs within a few percent of perfect. Natural gas prices fit is the least-good, in large part due to very high prices on a few winter days. The goodness-of-fit across each assessed parameter can also be visually assessed in duration curve subplots, Figure 1 below.

Table 2: Sample Fit

Parameter	Units	Weight	RMSE	NRMSE
Hourly Load	MWh	50%	265	0.0199
Natural Gas Price	$/MMBtu	25%	2.904	0.6494
Solar Profile	%	8.33%	0.0125	0.0760
Wind Profile	%	8.33%	0.0238	0.0668
Off-Shore Wind Profile	%	8.33%	0.0160	0.0292

Figure 1: Duration Curves by Parameter



4 a) Supplemental Figures (RPS isoquants with Relative CPS)

In the Figures 8-13 of the primary report, we observe that as the RPS rises, the minimum effective CPS rises too. This means that our effective CPS contains two different trends – the underlying escalation in minimum effective CPS, and the relative increase in CPS from that minimum. To better depict CPS-specific changes, we control for RPS related effects by making two transformations.

First, we control for the escalation in minimum effective CPS by creating a *relative* CPS metric (*effective* CPS for a given *effective* RPS, less minimum *effective* CPS). This In effect, this shifts each iso-quant to the left, until each starts at zero.

Second, we observed that increasing the RPS (jumping between RPS iso-quant curves) often has a bigger effect than increasing the CPS (moving along a given curve). As we are primarily interested in how CPS affect the system (irrespective of RPS level), we control for RPS-related benefits by shifting each curve down until its left-post point is set to zero. This results in a curve which depicts the change in a given metric, *relative* to the RPS-only starting-point. The combination of these two transformations functionally results in us dragging each isoquant from the Figure 8 through Figure 13 down and to the left, until the left-most point of each curve is at the origin (0,0).

Separately, we present a variation on these figures by computing the percentage change in a metric (e.g. total cost) from the RPS-only value. These figures allow for added clarity on the magnitude of the observed effects.

Figure 1: Total CO2 Emissions by RPS (megatonnes / year)

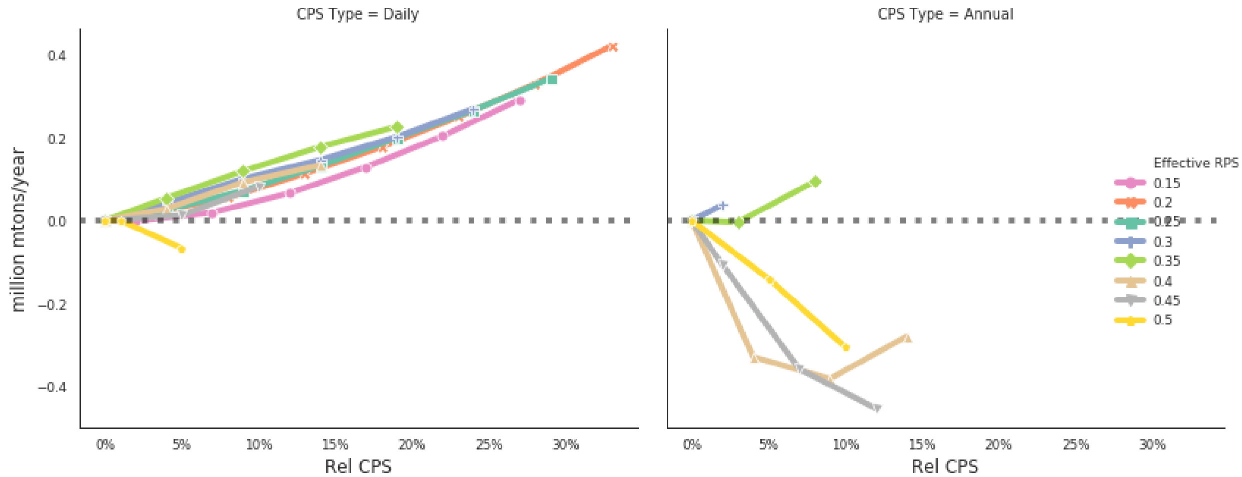


Figure 2: Total Cost of Production by RPS ($bn / year)

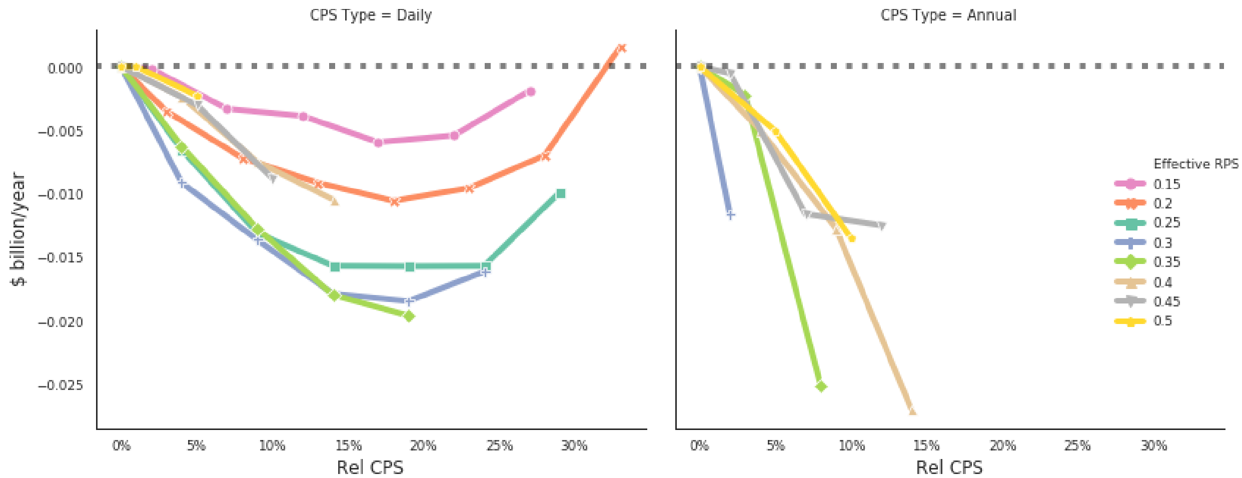


Figure 3: Marginal Price of Electricity by RPS ($/MWh)

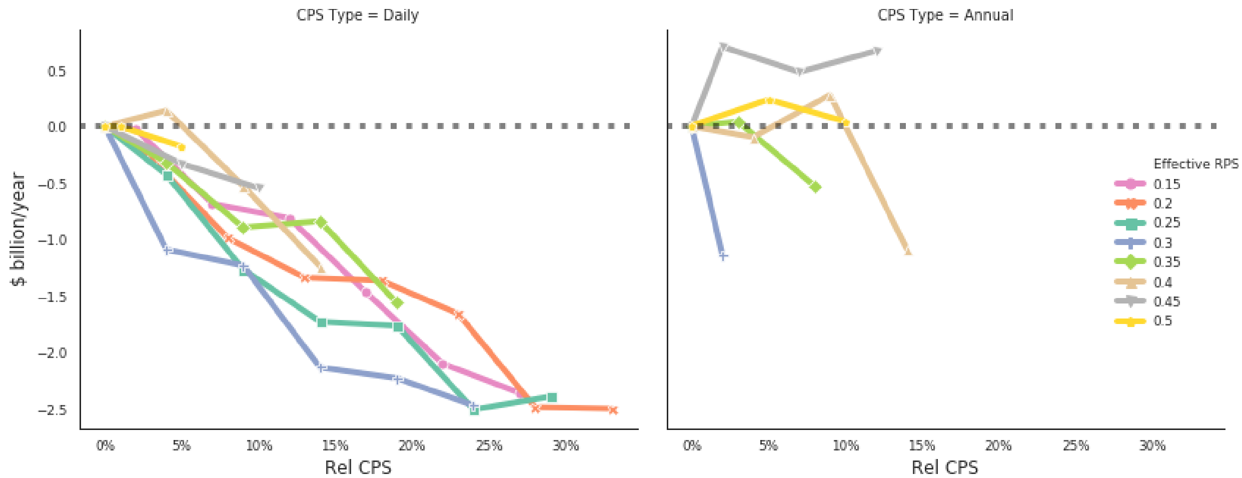


Figure 4: Total Fixed Costs ($bn / year)

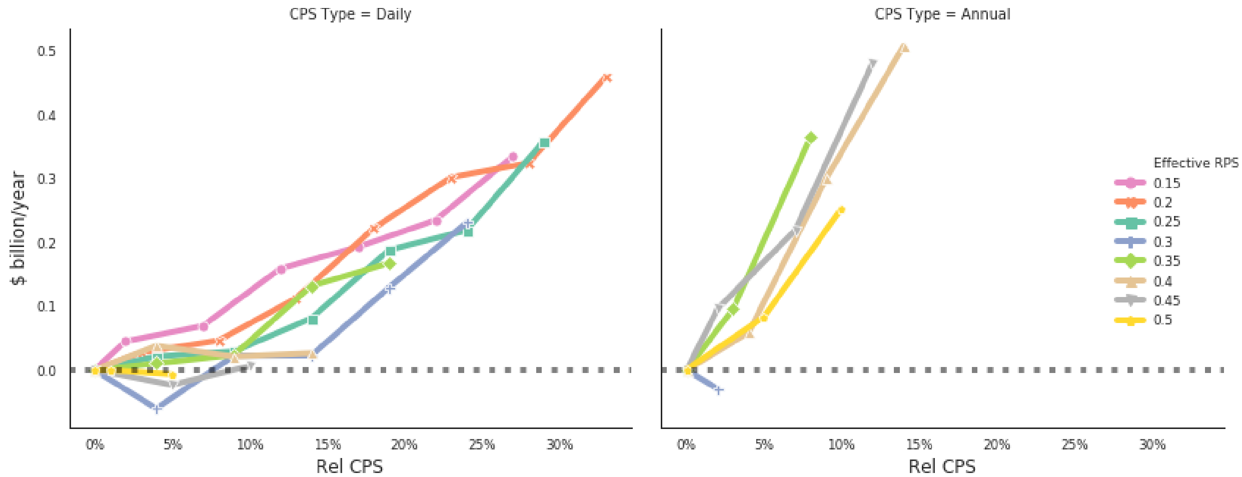


Figure 5: Total System Cost ($bn / year)

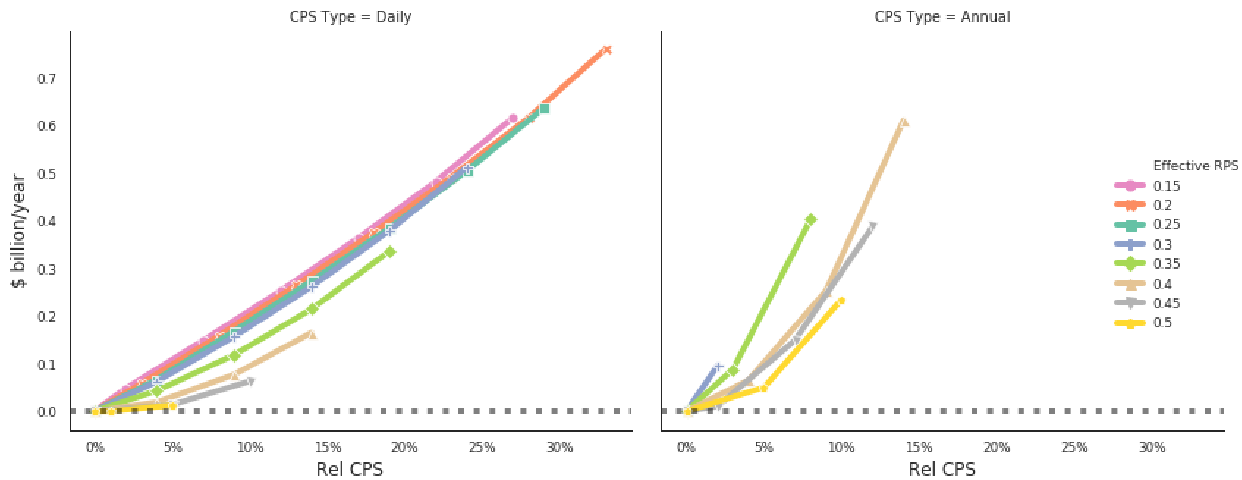
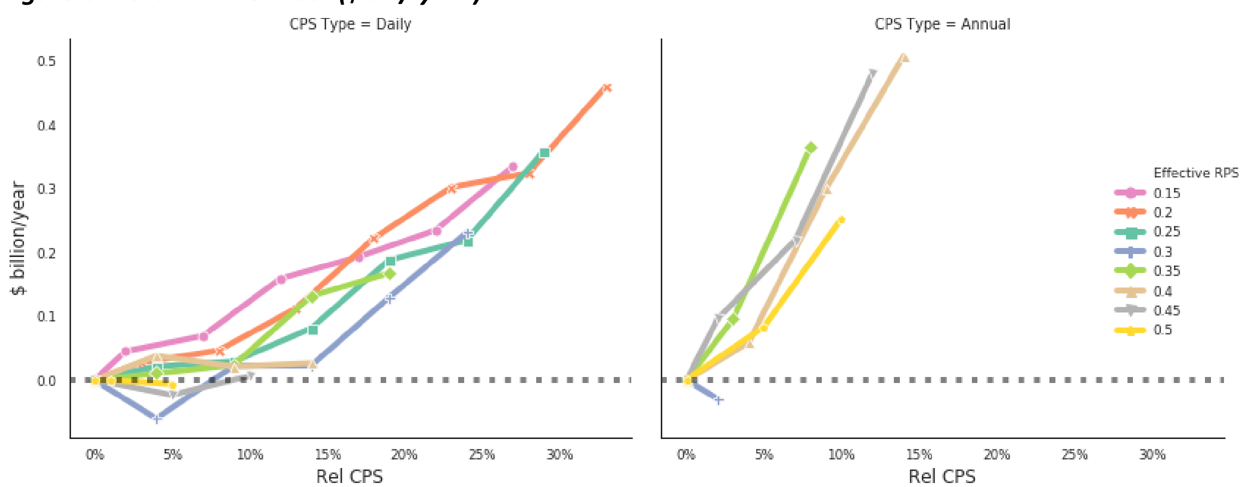


Figure 6: Total Market Cost ($bn / year)



b) Supplemental Figures (RPS isoquants with Proportional Effects)

Figure 1: Percentage Change in Emissions from RPS-Only, due to CPS Adoption

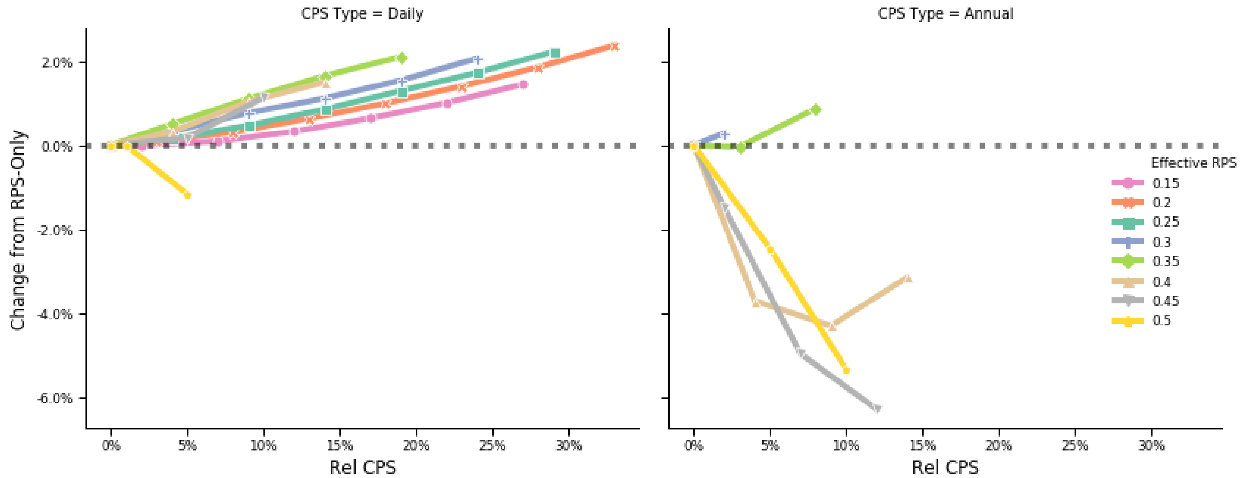


Figure 2: Percentage Change in Total Cost of Production from RPS-Only, due to CPS Adoption

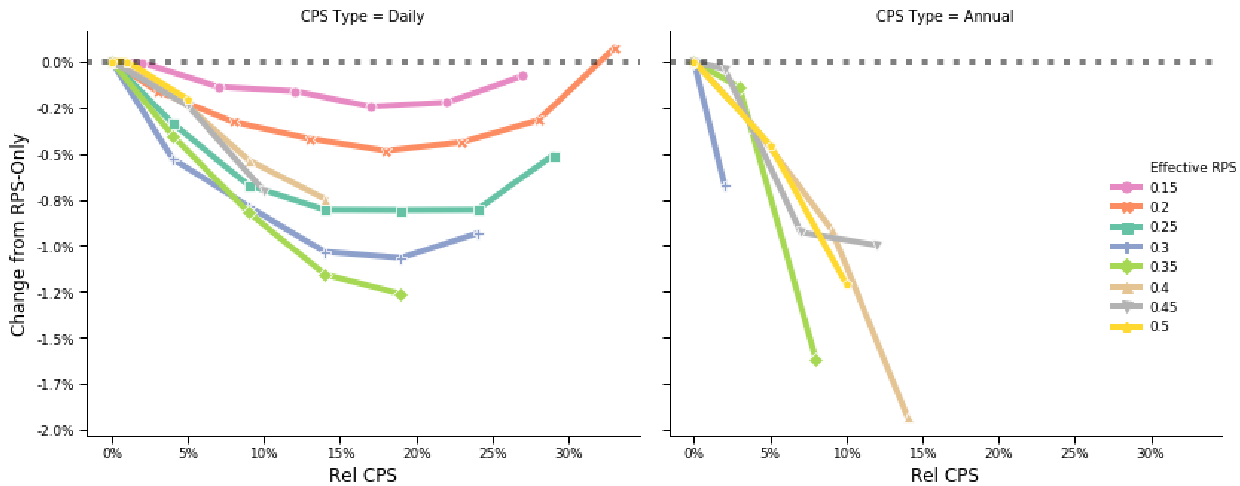


Figure 3: Percentage Change in Marginal Price of Electricity from RPS-Only, due to CPS Adoption

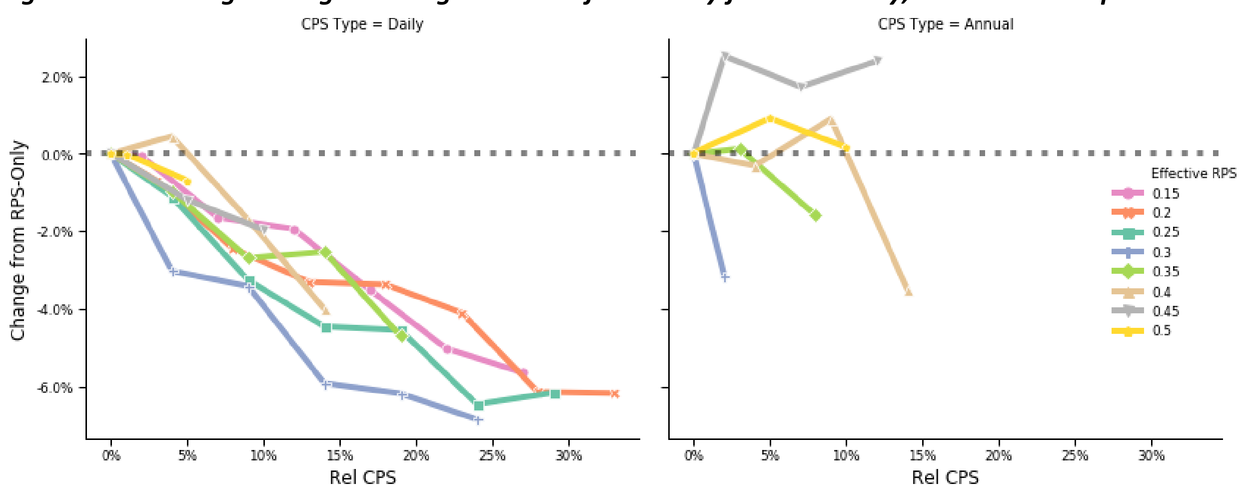


Figure 4: Percentage Change in Total Fixed Costs from RPS-Only, due to CPS Adoption

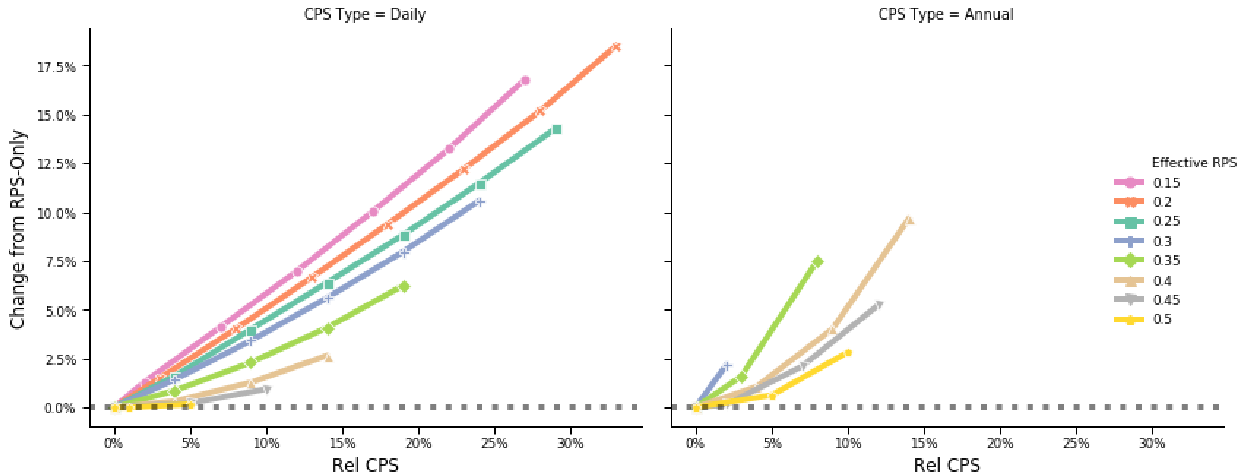


Figure 5: Percentage Change in Total System Cost from RPS-Only, due to CPS Adoption

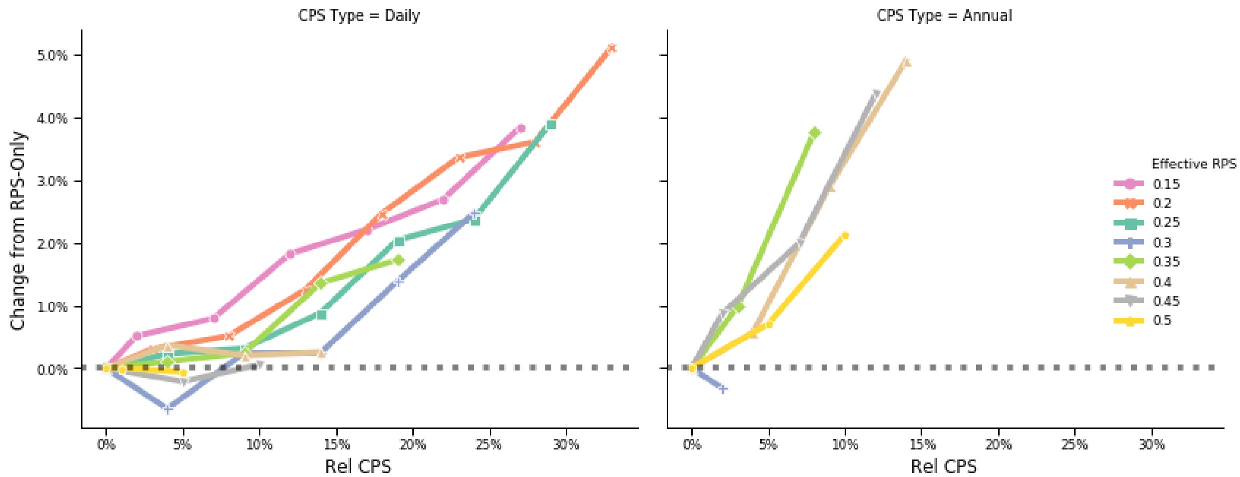
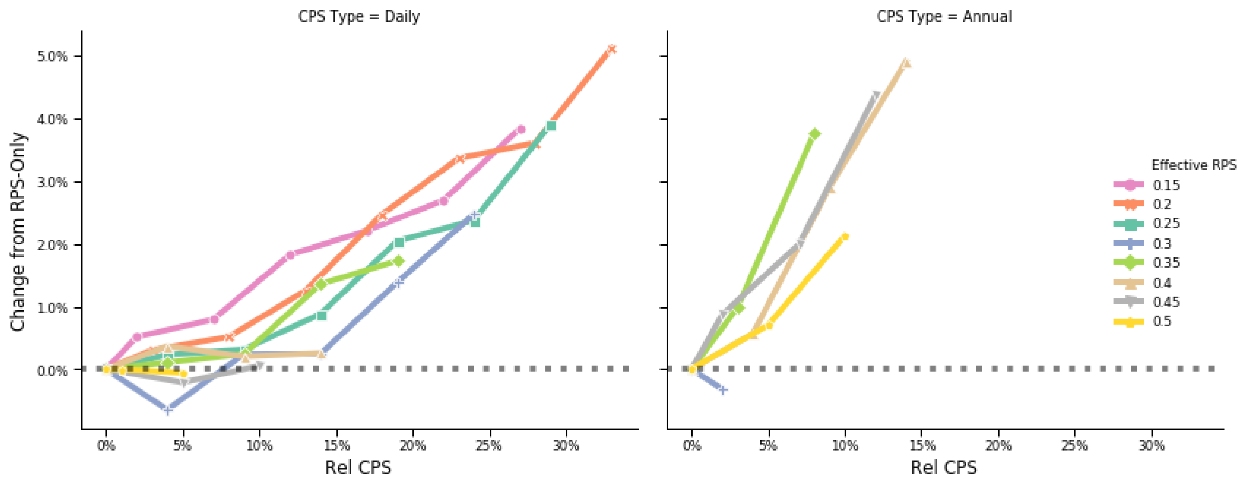


Figure 6: Percentage Change in Total Market Cost from RPS-Only, due to CPS Adoption



[i] Hart, W., Laird, C. Watson, J., Woodruff, D., Hackebeil, G, Nicholson, B., Siirola, J. (2017).

[ii] GNU Linear Programming Kit (GLPK). Available at: https://www.gnu.org/software/glpk/glpk.htm.

[iii] Gonzalez-Salazar, M. A., Kirsten, T., & Prchlik, L. (2018). Review of the operational flexibility and emissions of gas- and coal-fired power plants in a future with growing renewables. *Renewable and Sustainable Energy Reviews*, *82*, 1497-1513. Tables 6,9,11. Available at: https://doi.org/10.1016/j.rser.2017.05.278.

[iv] Vimmerstedt, L. J., Akar, S., Augustine, C. R., Beiter, P. C., Cole, W. J., Feldman, D. J., ... & Turchi, C. S. (2019).

[v] [dataset] Massachusetts Clean Energy Center (2019). MassCEC Metocean Data Initiative. Available at: https://www.masscec.com/masscec-metocean-data-initiative

[vi] Alstrom (2015). Haliade150 – 6MW Type Certificate Validation. Available at: http://www.ewea.org/offshore2015/conference/allposters/PO019.pdf

[vii] GTM Research, (2017). U.S. Energy Storage Monitor: Q3 2017 Executive Summary. GTM Research, 6 ⟨https://www.woodmac.com/research/products/power-andrenewables/us-energy-storage-monitor/⟩ (Accessed February 2019).

[viii] Fernando De Sisternes & Mort Webster. *Optimal Selection of Sample Weeks for Approximating Net Load in Generation Planning Problems.* ESD Working Paper Series. January 2013. https://dspace.mit.edu/handle/1721.1/102959.