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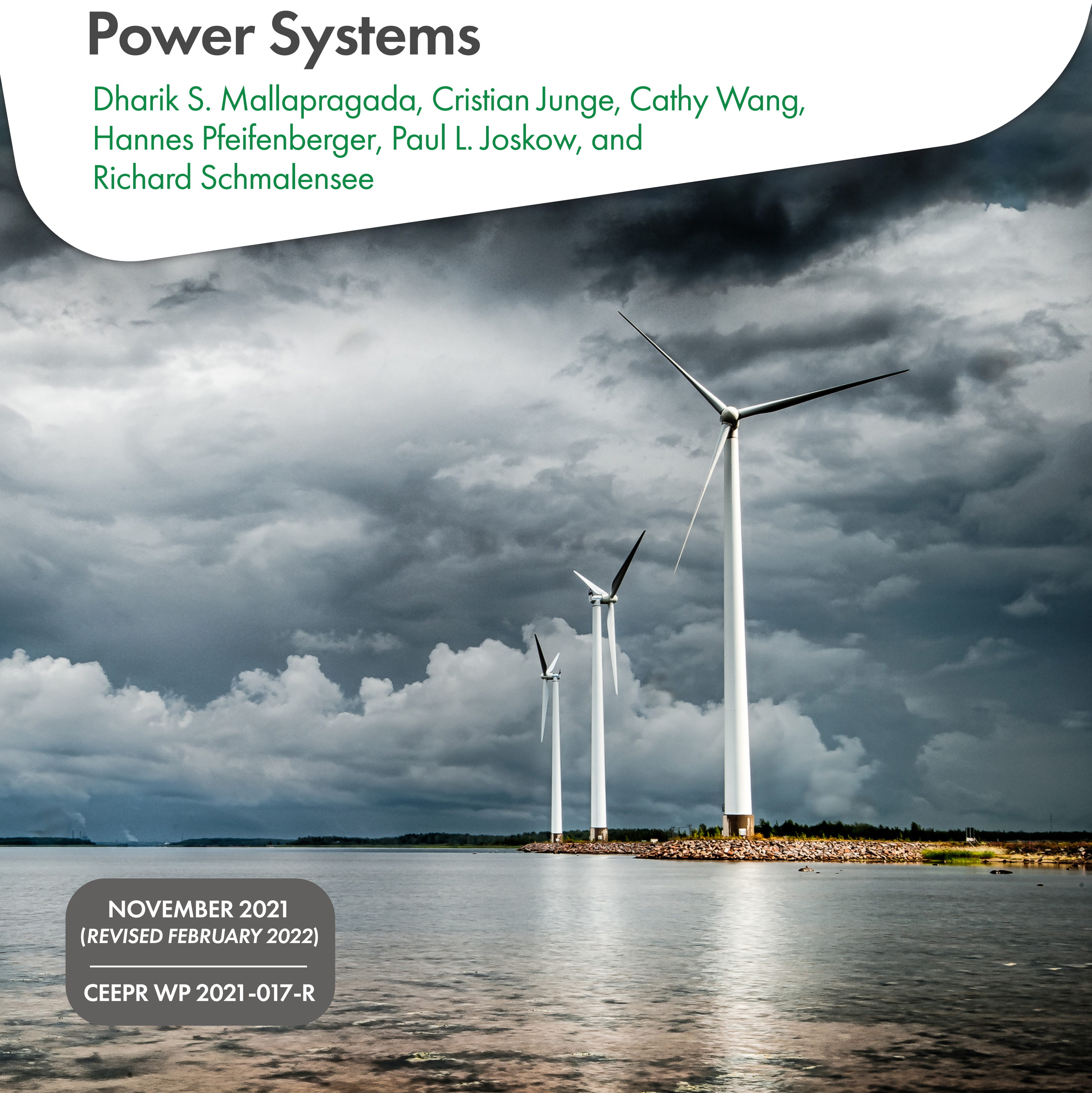

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Electricity Pricing Problems in Future Renewables-Dominant Power Systems

Dharik S. Mallapragada[a*], Cristian Junge[a], Cathy Wang[a], Hannes Pfeifenberger[b], Paul L. Joskow[c], Richard Schmalensee[d]

a. MIT Energy Initiative, Massachusetts Institute of Technology
b. The Brattle Group, Cambridge, MA
c. Department of Economics, Massachusetts Institute of Technology
d. MIT Sloan School of Management and Department of Economics, Massachusetts Institute of Technology

ABSTRACT

Constraints on electric power system carbon emissions will make optimal increased reliance on variable renewable energy (VRE, mainly wind and solar generation), which has near zero marginal operating costs. Using capacity expansion modeling of electric power systems in three US regions in mid-century, we show that under a wide range of plausible demand and supply-side technology assumptions, efficient, deeply decarbonized systems will have many more hours of very low marginal values of electricity (MVEs) and more hours of relatively high MVEs, than today. This result stems from the shift away from systems dominated by thermal generator with well-defined marginal costs to systems dominated by VRE with near zero marginal operating costs as well as energy storage and demand-side resources whose marginal costs vary with time and are often defined by their opportunity costs. While availability of long-duration energy storage resources and demand flexibility reduce instances of near-zero MVE, they do not alter the general pattern of increasing hours of near-zero MVE under tight CO_2 emissions constraints. Such dramatically different MVE distributions also imply that, under an energy-only market design, resources are likely to earn most of their revenues on sales in a handful of hours. To minimize the cost of electricity and to encourage cost-effective economy-wide decarbonization, economic theory prescribes that wholesale and retail prices of electricity should equal MVEs. However, the sharply increased variability of MVEs compared to today means that setting wholesale and retail prices equal to MVEs would likely impose politically intolerable risks at both levels. Potential solutions to this fundamental problem are discussed.

Keywords: decarbonization, storage, pricing, renewables, efficiency, electrification

*Corresponding author

Email addresses: dharik@mit.edu (Mallapragada), Junge@mit.edu (Junge), cathyxw@mit.edu (Wang), Hannes.pfeiffenberger@brattle.com (Pfeiffenberger), pjoskow@mit.edu (Joskow), rschmal@mit.edu (Schmalensee).

1. Introduction

Modeled pathways for energy system decarbonization by mid-century imply an expanded role for electricity in final energy demand, coupled with the decarbonization of electricity supply through dramatically increasing generation from variable renewable energy (VRE) sources, particularly wind and solar[1–3]. For example, in the net-zero by 2050 scenario presented by the International Energy Agency (IEA), electricity as a share of global final energy consumption is projected to increase from 20% in 2020 to 50% by 2050, while wind and solar provide 70% of total electricity generation in 2050 [2]. The dominance of VRE-based power generation in energy system-wide studies is also aligned with more granular power sector assessments [4–12] based on cost-minimizing (or welfare-maximizing) capacity expansion models (CEMs). Both because the electric power sector will grow in relative importance and because electricity prices will affect the vital process of economy-wide decarbonization, the costs of inefficient wholesale and retail electricity pricing will be much greater than at present.

To explore the key features of efficient electricity pricing in future deeply decarbonized power systems, we used the open-source CEM, GenX [13], to simulate efficient, deeply decarbonized electricity systems in three US regions in 2050 under a number of carbon emissions and technological scenarios described in the Methods section. We chose 2050 because many deep decarbonization programs focus on that date and because it is plausible that most existing generation assets will have retired by then, thus permitting a (nearly) greenfield analysis. We imposed system-wide constraints on carbon emissions, which is equivalent to imposing a carbon tax or, under certainty, a competitive cap-and-trade system. The shadow price on the carbon emissions constraint gives the marginal cost of carbon reductions that would be need to be enforced as part of carbon pricing policy approach to achieve the same result [10,14]. Because the modeled marginal cost of going all the way to zero carbon emissions generally exceeded reasonable estimates of the per-ton cost of negative emissions technologies[15], which we do not model, we focus on deep decarbonization scenarios that get close to zero carbon emissions. Our analysis includes a number of advances compared to the existing literature evaluating wholesale electricity price outcomes for VRE-dominant electricity systems[10,14,16–18]. First, we evaluate the impact of various technology options that have previously received only limited attention, including several different energy storage technologies, flexible demand, and the effects of sector-coupling between electricity and other end-use sectors (e.g. industrial process heat). The latter is modeled through the example case of producing hydrogen from electricity and its subsequent use as a low-carbon fuel in the industrial sector. While previous studies have modeled this type of sector-coupling using hydrogen[19,20], the impacts on the wholesale electricity price distribution of such an integration is not discussed. Second, for all technology and emissions scenarios, we discuss the implications for hourly distribution of wholesale electricity prices as well as revenues earned by different technologies if they are paid exclusively through the wholesale market. For example, we illustrate how sector-coupling via H_2 reduces instances of zero-priced hours by setting wholesale electricity prices as per the opportunity of cost of using electricity-derived fuels in other sectors. Third, we elaborate on the implications of the hourly price distributions under carbon-constrained scenarios on economy-wide decarbonization via electrification and retail electricity price reform.

State-of-art CEMs [13,21–24] like GenX evaluate the cost-optimal investment and intra-annual operation of modeled power systems, and thus are in principle able to highlight the implications of temporal variability in electricity demand and in VRE resource availability under alternative assumptions. CEMs are often formulated as linear programs (LPs) with perfect foresight and constant returns to scale; under these and other standard assumptions, CEMs can be used to understand the impact of policy and technology drivers on the hourly frequency distribution of the marginal value of electrical energy (MVE), which is retrieved from the models as the shadow price on the supply/demand constraint at each operating time step. In competitive wholesale electricity markets, absent taxes, subsidies, markets for capacity, and other regulatory/policy interventions, spot prices generally approximate MVEs.[1]

In efficient power systems, governed by the well-documented principle of least-cost economic dispatch [25], at any instant the resource with the highest marginal cost among all operating generators or when generating capacity is fully utilized, a higher price needed to balance supply and demand (scarcity pricing), determines the MVE and the market clearing electricity price. Dispatchable thermal power plants, which dominate the generation portfolio in most power systems today, have positive marginal costs. VRE generators, however, use no fuel inputs and thus have near zero marginal operating costs. In addition, the marginal cost of supply from energy storage systems is generally set by opportunity costs rather physical operating costs and hence can vary substantially over time [10,14]. Thus, a shift from primary reliance on dispatchable thermal generators to primary reliance on VRE generators with a greater role for storage decouples the determination of MVE in efficient systems from marginal generating cost. This transition also seems a priori likely to change the frequency distributions of wholesale electricity prices.

[1] MVEs only approximate spot prices in electricity markets for the following reasons. A) CEMs do not include a detailed representation of the demand elasticity, implying that MVEs during scarcity events do not fully reflect demand's ability to respond to price variations. B) Since capacity is a decision variable in CEMs, MVEs during periods of scarcity could also incorporate the investment cost of new generation, which will not be the case for spot prices in wholesale markets and C) MVE generated using CEMs often incorporates the (linearized) startup cost of generators in certain periods while spot prices generally do not consider these costs. D) the MVE computed here does not reflect the impact of short- and long-term capacity requirements that are often included in organized markets to ensure resource adequacy.

CEMs can be used to understand the impacts on the distribution of MVEs of constraints on carbon emissions in efficient power systems under the condition of full cost recovery[2] for all assets selected by the deterministic LP formulation[3] [10]. Despite the many CEM studies focused on deep decarbonization of electricity systems [4,7,11,26], few studies actually document the implied MVE distributions. Several CEM studies that do discuss MVEs or wholesale electricity prices [10,16–18,27], including the results reported in Section 3, find that wholesale electricity price distributions under low-carbon high-VRE scenarios are likely to have many more hours of very low prices (corresponding to periods of high VRE availability relative to load) than are observed today in wholesale electricity markets (see note S1.3) and more hours of very high prices, approaching the value of lost load (corresponding to periods of high net load i.e. load minus VRE generation). The extent of both these effects is dependent on many factors, notably, a) the stringency and type of policy encouraging low-carbon generation, b) the assumed resource adequacy requirements, if any, c) the temporal resolution of grid operations modeled, which is shown to be important to capture VRE resource and load variations [28,29], d) the cost assumptions and availability of technologies like VRE, storage, low-carbon dispatchable generation and e) the cost and availability of demand response and demand flexibility. The impacts of a number of factors on the distribution of simulated MVEs in future US regional power systems are explored in Section 3.

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[2] Full cost recovery assumes that all binding constraints generate revenues that can be monetized. In case any binding constraint does not yield revenues that could be earned in practice, then full cost recovery is not guaranteed. See [14] for details.

[3] Electricity price outputs are commonly reported by studies simulating grid operations using industry-standard production cost models (PCMs) that closely mimic realistic economic dispatch of the grid over a short-time horizon (typically 24 hours). PCMs are not useful for analyzing electricity prices for deep decarbonization scenarios for two key reasons. First, PCMs don't consider investment costs and so cannot optimize asset portfolios. Second, the prices generated by PCMs do not ensure full cost recovery for all resources, which means the impact of various policies that affect capital cost cannot be compared via these models.

Recently, a few papers have suggested that instances of very low wholesale prices could be infrequent, and prices may never approach the value of lost load, if a large fraction of future energy demand could be met either by electricity or by switching to carbon-free chemical energy carriers (referred here on as “synthetic fuels”). Potential consumers capable of this sort of sector-coupling cited in the literature include district heating systems, plug-in hybrid electric vehicles and dual-fuel boilers in industrial settings [5,30,31]. In deeply decarbonized energy systems, however, the availability and cost of carbon-free synthetic fuels that can substitute for electricity at scale is highly uncertain. Moreover, if electricity is consumed in producing these synthetic fuels, which is likely for H_2-derived synthetic fuels [19], then the cost and availability of synthetic fuel may vary over time, which is inconsistent with the constant cost and availability assumption made by some studies [8,31]. As we show in Section 3, incorporating the investment and operation of the supply chain of synthetic fuels, including production, storage and utilization, within a CEM reduces instances of low and high MVEs (by improving VRE and storage utilization) but does not eliminate them.

As we also show in Section 3, in decarbonized VRE-dominant energy-only wholesale power markets without price caps, in which spot prices approximate MVEs, generators and storage facilities would earn the bulk of their annual energy market revenues in relatively few hours. Financial instruments to hedge price volatility would consequently, be costlier. As Section 4 discusses, it is likely that, as today, many wholesale markets will cap energy prices and will employ capacity remuneration mechanisms to provide adequate investment incentives. Some current mechanisms can be adopted, with difficulty, to handle VRE generation, but storage presents new conceptual challenges, and it is critical to avoid approaches that distort spot prices for the following reason. On the retail side, in order to encourage economy-wide electrification, the marginal retail price of electricity should be low whenever the wholesale MVE is low. But recent grid contingency events (e.g., Texas in Feb 2021) makes clear that requiring retail customers to pay wholesale spot prices on the margin would impose intolerable risks today, and our work shows that those risks would be much higher in future decarbonized systems. With automated control of demand via demand response contracts, Section 4 argues that the risks of price volatility faced by retail customers can be mitigated with appropriate insurance contracts without sacrificing incentives for decarbonization.

The rest of the paper is organized follows. Section 2 describes the methods used, with further details provided in the SI; Section 3 describes the CEM modeling results for three U.S. regions, with a deep dive on the electricity price distribution and revenue distribution outcomes for Texas case study under various technology and carbon emissions scenarios. Section 4 discusses the implications of these findings for wholesale and retail electricity prices. Section 5 summarizes the conclusions and describes areas for future work.

2. Methods

We have constructed detailed models to assess electric power system evolution in three U.S. regions in 2050: the Northeast, the Southeast, and Texas. (See section S1 of supporting information (SI) and the forthcoming MIT Energy Initiative Future of Storage study [32] for more details.) These regions differ on several relevant dimensions, (1) wind speeds and solar irradiation, land availability, and resulting installed costs of wind and solar generation; (2) hydroelectric resources; and (3) industry structure and regulation and associated implications for nuclear power development. As noted above, we assume that the existing stock of fossil generating capacity retires by 2050, so that our analysis examines a "near-greenfield" system developed to meet 2050 demand. Per our (mostly) greenfield modeling assumption, we restrict investment to the following technologies in the base case: utility-scale solar and onshore wind (as well as offshore wind and distributed solar in the Northeast); natural gas-fired plants (open cycle gas turbine (OCGT) and combined cycle gas turbine (CCGT)), with and without amine-based carbon capture and storage (CCS) technology; and hydro resources where they play a major role (Northeast, Southeast). As noted below (see Table 1), we consider impact of alternative demand and supply-side technologies through a scenario-analysis approach. All three regional models use hourly electricity demand projections for 2050 from the high-electrification scenario developed by the National Renewable Energy Laboratory (NREL) for its 2018 Electrification Futures (EFS) study [33]. PV and Wind resource availability were represented using a discretized supply curve approach, described elsewhere (section S2 and [4]), that is developed based on available wind and solar resource databases from NREL. Technology cost assumptions are sourced mostly from the 2020 edition of the NREL annual technology database [34] (further details in section S2 in SI).

The analysis is carried out via GenX [13], a CEM that includes representation of various supply and demand-side resources, including energy storage with independent discharging and charging power capacities and energy storage capacity, demand flexibility (section S4), demand response (section S5), and use of H_2 for non-electric end-uses (described below and in section S6)). Flexible demand resources can temporally shift their energy consumption to some extent, while demand response resources, on the other hand, can forgo consumption entirely when the electricity price is high.

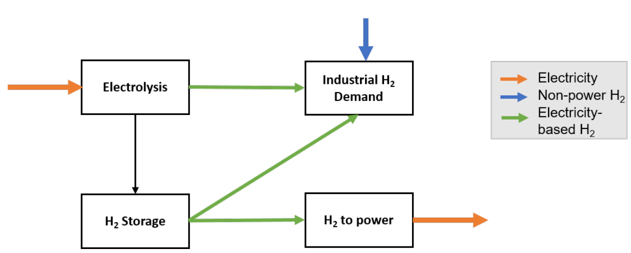

Figure 1. Representation of the power to H_2 to power system within GenX and hydrogen's use for meeting industrial hydrogen demand.

For this study, we include an additional feature in GenX to study the impact of sector-coupling resulting from hydrogen production via electricity and its subsequent use for decarbonizing other difficult-to-electrify sectors like industry[4]. Figure 1 highlights the simplified representation of the modeled electricity-H_2 infrastructure interactions, developed based on our prior work on detailed H_2 infrastructure modeling [19,35], which includes: a) allowing hydrogen technology components to serve both the power sector and external H_2 demand simultaneously and b) use of non-power H_2 supply to meet industrial H_2 demand. The use of electricity to produce H_2 can be flexibly scheduled—because H_2 can be stored at relatively low energy capital cost, even in case we assume above-ground gaseous storage (see Table S 3 in SI)—even though external H_2 demand is modeled to be constant and inflexible across all hours of the year. Moreover, operating H_2 infrastructure this way provides valuable flexibility to the power system without incurring additional capital cost and round-trip efficiency losses associated with regenerating electricity from the stored H_2. Prior comprehensive analysis on electricity- H_2 infrastructure interactions point to limited deployment of H_2 to power assets as compared to electrolyzers when modeling deep decarbonization scenarios using gaseous H_2 storage [19,35]. Therefore, as a simplification, we have ignored the possible use of non-power H_2 sources for power generation here.

Below, we briefly discuss the results for all three regions but focus here primarily on the results for Texas[5]. Texas is represented as a single transmission zone with greenfield conditions reflecting the retirement of the existing fleet of generators by 2050. The model is configured with hourly resolution of grid operations spanning 7 years (61,314 hours) and an approximation of a

[4] This capability is not yet available in cited GitHub repository[13] but will be posted shortly.
[5] Most U.S. wholesale markets have separate energy and capacity prices. The wholesale prices that we simulate here are most comparable to those observed in so-called "energy-only" wholesale markets like ERCOT where a capacity remuneration mechanism (ORDC) includes all energy and capacity payments in the wholesale energy price[61]. Hence, our focus on the model outcomes for the Texas case study.

competitive energy-only wholesale market broadly resembling the market the Electric Reliability Council of Texas (ERCOT) now operates in most of the state. We assume prices can approach the value of lost load (set at $50,000/MWh in our simulations to ensure high reliability outcomes). No other resource adequacy requirements, either at the annual or hourly timescales, are enforced, and generators and storage facilities are fully remunerated through energy market revenues. In the case of the Texas case study, the annual demand data from NREL EFS study [33] was assumed to be same for all seven years of modeled grid operations (see Table S 1 for data for other regions). Further documentation of data inputs and model representation is discussed in Table S 2 - Table S 6 in the SI and in Table 1 below.

Table 1. Scenario groupings evaluated via the GenX model for various CO_2 emissions constraints in this work.

Scenario grouping	**Description**
Base Case	Reference assumptions and conditions; ***Li-ion as the only energy storage*** technology, along with following generation resources: wind, solar PV, natural gas (NG) combined cycle gas turbine (CCGT) with and without carbon capture and sequestration (CCS) and open cycle gas turbine (OCGT). Assumed natural gas fuel price: $4.16/MMBtu – see section S1.
Base + RFB	Inclusion of low-cost energy storage with estimated cost and performance characteristics for ***redox flow battery*** (RFB) systems – see Table S 3
Base + RFB+ Thermal storage	Inclusion of low-cost long-term energy storage with estimated cost and performance estimates for ***thermal energy storage*** systems - see Table S 3
Base + DF	Allowing a pre-specified fraction of ***flexible demand*** from EV charging and buildings to be temporally flexible at no incremental cost, per the assumptions from NREL electrification futures study [33], and summarized in Table S 5.
Base+ DR	Stylized representation of ***demand response***, per the structure described elsewhere [7]. Up to 25% of hourly load can be shed with varying marginal costs for each incremental 5% of load, with the most expensive segment priced at 70% of value of lost load (VoLL, $50,000/MWh) and the least expensive segment priced at 5% of value of lost load (See Table S 6). Further load shedding is possible at the price equal to VoLL.
Base + RNG	Scenario meant to approximate the availability of ***renewable natural gas*** (RNG) ***or hydrogen*** for dispatchable power generation used in other studies [8]. Modeled as carbon-neutral fuel with a cost of $20/MMBtu via an OCGT with heat rate the same as that of conventional NG based OCGT and capital cost that 120% of the NG OCGT capital cost.

Base + RFB + np-H2 @ $2 or 10/kg	Representation of ***exogenous H_2 demand*** outside the power sector (19.7 GW_{H2}) that can be met via a combination of electrolysis, hydrogen storage/ discharging as well as from non-power based H_2 sources with zero process CO_2 emissions with a production cost of $2 or $10/kg – see Figure 1 and section S5 for detailed assumptions. Also includes RFB storage in addition to Li-ion storage in the power sector. Discussed further below.

3 Results

3.1 System outcomes for three regions

Figure 1 (and Figure S 3) summarize the model outcomes for three regions across three alternative emissions constraint scenarios, for the base case technology assumptions. Emissions intensity varies among the regions in the unconstrained ("No Limit") case, reflecting differences in wind and solar resources and in load profiles. Across the three regions, the variability of VRE generation is managed via three mechanisms that are also noted by other CEM studies exploring deep decarbonization of power systems[7,26,36,37]: (1) flexible operation of gas generation to handle long periods of low VRE output, (2) deployment and utilization of energy storage for shorter periods of low VRE output, (3) optimization of the relative capacities of wind and solar generation, and (4) VRE deployment in excess of peak load, which is often called "overbuilding" and leads to curtailment of excess VRE generation at certain times. Thus, for instance, the fact that solar output is lower in the winter than in the summer is managed, not by storing energy for several months, but by building solar capacity that is adequate for the winter and, thus, more than adequate for the peak summer day-time demand. As the carbon constraint is tightened, gas generation is forced to decline, VRE curtailment increases (Figure 2) and contributing to increasing incidence of low MVE periods[10,14]. This is a very robust result under the sort of cost assumptions we have employed. And because all facilities break even at MVE values, just as all real-world facilities need to break even in equilibrium, an increased incidence of low MVE values must be balanced by an increased incidence of high MVE values.

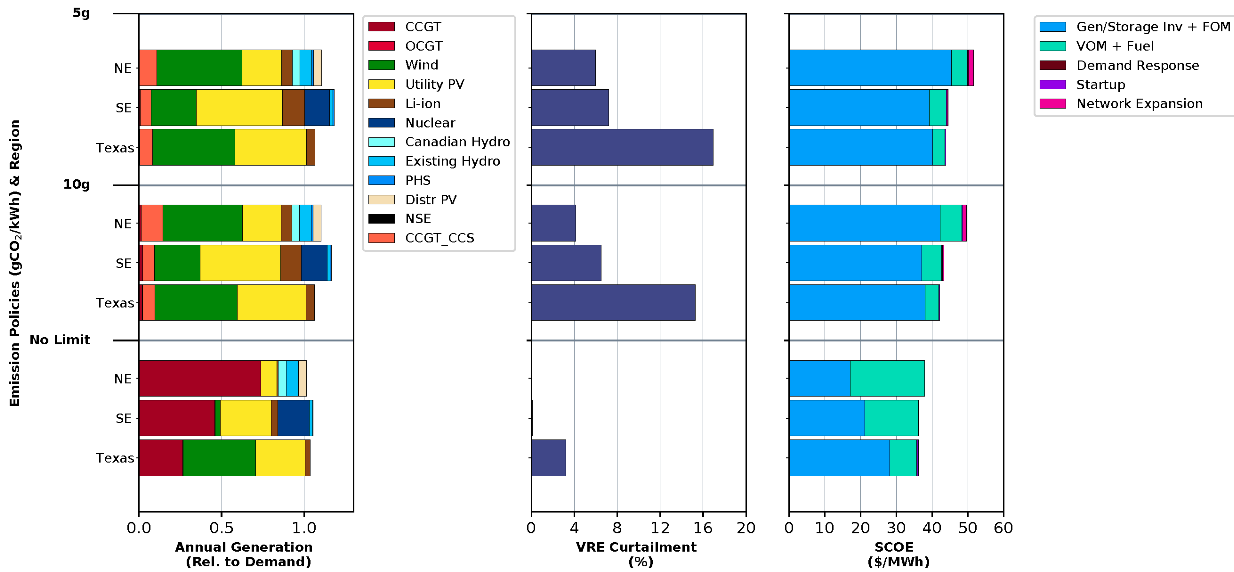

Figure 2. ***Annual generation, VRE curtailment, and system average costs of electricity (SCOE) in the Northeast (NE), Southeast (SE), and Texas (TX) under tightening CO_2 emissions constraints.*** *Modeling results are shown for a scenario with no limit on emissions (bottom row) and for two alternative carbon emissions limits scenario with an emissions intensity limit of 10 (middle row) and 5 gCO2/kWh (top row). SCOE includes total annualized investment, fixed O&M, operational costs of generation, storage, and transmission, and any non-served energy penalty. Emissions intensity under the "No Limit" policy case for each region is as follows: NE: 253 gCO2/kWh, SE: 158 gCO2/kWh, Texas: 92 gCO2/kWh. For the Northeast case, "Wind" represents the sum of onshore and offshore generation. Installed power and energy capacity results for these cases are shown in Figure S 3 in the SI, along with methodological assumptions about the modeling noted in section S1. For comparison purposes, annual generation is normalized to the annual electricity demand in each region.*

3.2 Detailed Results for Texas

Figure 3 highlights key system outcomes under two CO_2 emissions intensity constraints ($5gCO_2/kWh$ and $1gCO_2/kWh$) for Texas for the six out of the eight scenarios defined in Table 1 (demand-side scenario results shown in Figure S 4). Texas emissions in 2018 were 449 gCO_2/kWh, so achieving a grid emissions intensity of 5 gCO_2/kWh or 1 gCO_2/kWh would amount to a 98.9% or 99.8% reduction, respectively. A few main observations should be noted from Figure 1. First, for the same CO_2 emissions constraint, availability of additional flexible resources relative to the base case, either on the supply side via dispatchable renewable generation (RNG) or long-duration energy storage (LDES), or on the demand-side via demand flexibility or demand response (see

Figure S 4), generally reduces VRE curtailment and thus improves VRE capacity utilization[6]. This contributes to reducing the system average cost of electricity (SCOE). Second, increasing stringency of CO_2 emissions limits from 5gCO_2/kWh to 1gCO_2/kWh results in greater VRE curtailment as well as an increase in SCOE across all the scenarios, ranging from 12% (Base + DF – see Figure S 4) to 3% (Base +RFB+ np-H2 @ $2/kg).

Third, the availability of electricity storage technologies with low energy capital cost, represented here by redox flow battery (RFB) technology, thermal storage and hydrogen, increases the value of VRE generation and reduces the role for dispatchable gas generation. As compared to impact of low energy capital cost storage, the system impacts of including demand flexibility or demand response, as characterized in Table 1, are relatively small (Figure S 4). The H_2 scenarios modeled here highlight the potential opportunity to share H_2-related assets, namely the electrolyzer used to produce hydrogen and storage, to serve both the power sector and external H_2 demand simultaneously. This is effectively a special case of demand flexibility, since the use of electricity to produce H_2 via electrolysis can be flexibly scheduled because hydrogen can be stored at relatively low energy capital cost, even though external H_2 demand is modeled to be constant across all hours of the year. For the same CO_2 emissions intensity limit, this type of demand flexibility leads to a greater share of VRE generation (see Figure S 5) but less curtailment and increased energy storage capacity compared to the equivalent case without hydrogen (base + RFB scenario). The impact is greatest when non-power sources of H_2 supply to meet H_2 demand outside the power sector are quite expensive ($10/kg), implying that all of the H_2 demand has to be met by electrolysis.

[6] The exception to this trend is noted in the cases with demand flexibility or demand response and relative high emissions intensity constraint of 50gCO_2/kWh (Figure S 4), where the optimal solution favors using flexible resources to increase gas capacity utilization (OCGT) in favor of utilization of VRE capacity in a way that reduces system cost (partly by reducing need for storage).

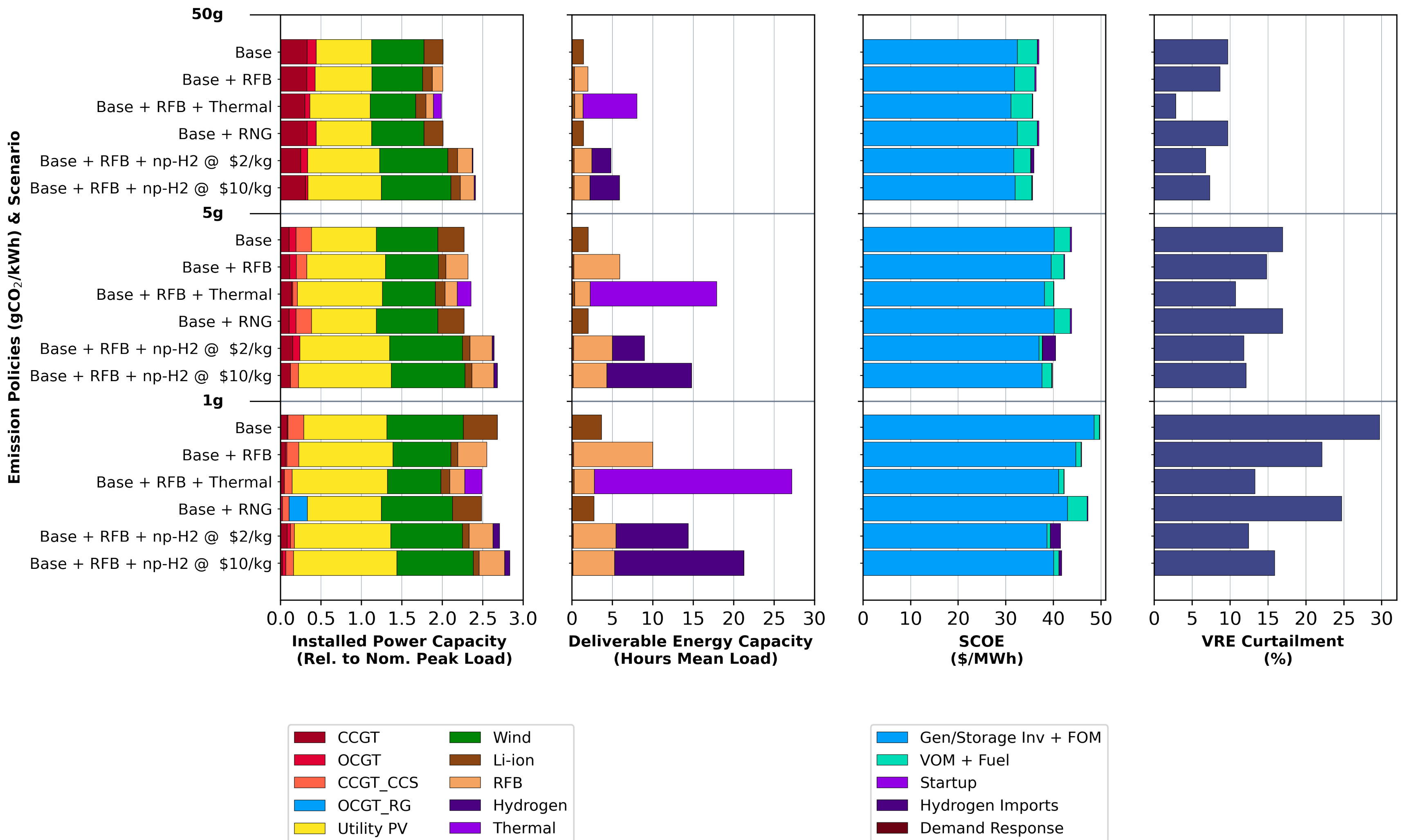

Figure 3. ***Key system outcomes for various CO_2 emissions intensity constraints and technology scenarios for Texas.*** *1st column: installed power capacity by technology type, reported as a fraction of peak load; 2nd column: Deliverable energy storage capacity installed by technology type, reported as a fraction of mean annual demand. Deliverable energy capacity for each storage technology is defined as the installed energy capacity times the discharge efficiency; 3rd column: system average cost of electricity (SCOE), defined as ratio of total system cost by total demand met throughout the year; 4th column: variable renewable energy curtailment, defined as the fraction of available VRE generation that is not dispatched. Note that RNG is not deployed even if made available in the 5gCO_2/kWh and so the results for Base +RNG are identical to Base Case results. Results for cases with demand response (DR) and demand flexibility (DF) as described in Table 1, are shown in Figure S 4 in the SI.*

3.3. Distributions of the Marginal Value of Electricity

Figure 4 provides information on the impact of alternative scenario assumptions on the frequency distribution of MVE for the Texas region[7]. The bands shown in Figure 4 are the following: (1) \$0 to \$5/MWh, characterized mostly by periods of high VRE generation; (2) \$5–\$50/MWh when natural gas is the marginal generator; (3) \$50–\$200/MWh when natural gas capacity needs to be started up and associated (linearized) start-up costs must be recovered; and (4) >\$200/MWh, which corresponds to scarcity events, including times when load-shedding events, if any, are observed. Note that under a CO_2 emissions constraint, the shadow price of carbon emissions is reflected in the wholesale price when natural gas generators are on the margin [10]. Under stringent CO_2 emissions constraints, natural gas marginal costs, therefore, could be much higher than \$50/MWh and might be responsible for high prices, i.e. \$200/MWh or greater. Also, because the marginal cost of supply from storage is based on opportunity cost rather than being physically defined by marginal operating costs, it varies from period to period—consequently, storage charging and discharging can and does occur in multiple price bands (see Figure S 7).

Figure 4 compares the simulated MVE distributions with the actual spot price distributions in ERCOT's energy-only market in Texas in 2018 and 2019. Treating MVEs as approximations of wholesale spot prices, we see that there are many more hours of very low prices in the simulated

[7] The general finding of increasing instances of low prices (<\$5/MWh) with increasing stringency of CO_2 emissions constraints also hold for the SE and NE regions. For example, in the 50gCO_2/kWh vs. 5gCO_2/kWh emissions intensity scenario, prices are \$0-5/MWh for the NE region account for <10% and >20% of hours, respectively. For the SE region, \$0-5/MWh prices represent around 15% and 30% hours for 50gCO2/kWh and 5gCO_2/kWh scenarios, respectively. The reduced incidences near zero prices for the NE and SE regions as compared to the Texas case study for the same emissions intensity constraint can be explained by a combination of factors: a) these regions use lower temporal resolution of modeling grid operations compared to Texas (see Figure S 1) and therefore could miss out on the variability in grid operations (and prices) that is incorporated in the Texas study that models 7 years of grid operations at an hourly resolution, b) SE and NE regions witness lesser VRE curtailment, likely to due to relatively lower quality of VRE resources that makes storage deployment cost-effective (Figure S 3), but also because of availability of non-VRE low-carbon resources like nuclear (in SE) and hydro (in SE and NE).

data, many fewer hours of prices where natural gas generation is on the margin, and more hours of high scarcity prices in the simulated data. Figure 4 shows that as the CO_2 constraint tightens, across all scenarios the number of hours with marginal prices below \$5/MWh increases, and the number of hours in the price band of \$5–\$50/MWh decreases. These trends reflect an increase in the share of VRE generation and a decline in natural gas generation[8].

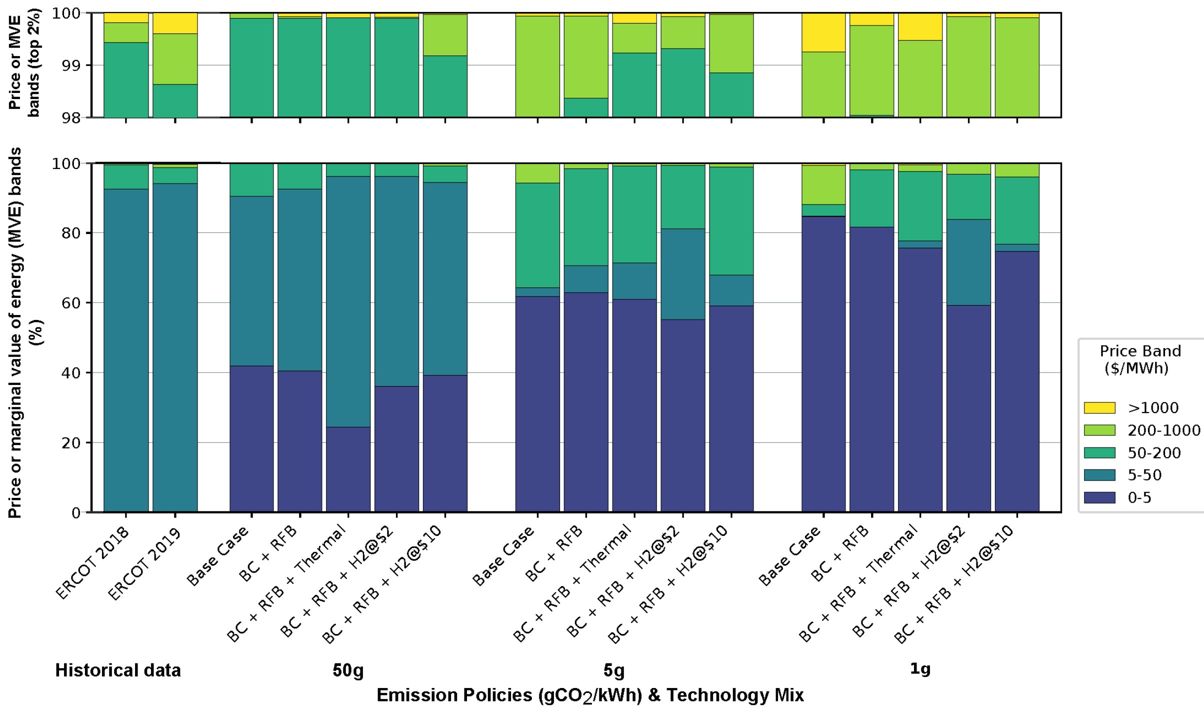

Figure 4. ***Impact of storage technology, external H_2 demand as well as the price of non-power H2 supply on the distribution of Marginal value of Energy (MVE) for various CO2 emissions constraints.*** *For comparison, wholesale energy price distributions from ERCOT in 2018 and 2019 are also shown in the first two columns of the chart* [38]. *Technology scenarios evaluated here are described in Table 1. Labels for scenarios with H2 "Base Case + RFB + np-H2 @ \$2/kg" has been shortened to read as "BC + RFB + H2@\$2" for brevity. Base case corresponds to Li-ion as the sole energy storage technology and no external H_2 demand. BC = Base Case. RFB = Redox Flow Battery.*

[8] It is worth reiterating that these model findings are based on what is effectively a representation of a pure, energy-only electricity market structure, in which all wholesale (and, implicitly, all retail) transactions occur at the spot market price of electricity. Incorporating other resource adequacy mechanisms, such as capacity markets with a required capacity reserve margin, is likely to reduce the magnitude and frequency of scarcity prices but is unlikely to impact the frequency of low prices [16].

3.4. A More Granular View

A more granular view of the modeled MVE distributions for Texas in 2050 can be gained from the price duration curves in Figure 5, in which the scenario-specific curves indicate the percentages of hours for which prices are above the corresponding y-axis values. This view makes it easier to see the impacts of technology interventions on the demand side (demand response (DR) and demand flexibility (DF)) as well as of availability of dispatchable, low-carbon fuel (renewable natural gas (RNG)) than the format of Figure 4. Figure 5 again shows that the frequency of low prices increases as the CO_2 emissions limit is tightened (left vs. right column). For example, in the base case, non-zero prices are observed for approximately 15% of hours in the 1 gCO_2/kWh as compared to nearly 40% in the 5gCO_2/kWh emissions scenario. In the 1gCO_2/kWh, we also see that the adoption of dispatchable low-carbon generation (RNG) reduces instances of near-zero prices that correspond to periods of VRE curtailment (nearly 75% as compared to 85% in the base case) and increases instances of prices covering the marginal cost of various dispatchable generation resources, including RNG ($190-$330/MWh[9]). The impact of demand response and demand flexibility is seen in the very high price portion of the curve (see insets in Figure S 6) where the magnitude and number of instances of high, scarcity prices are reduced compared to the base case. The availability of LDES (RFB, Thermal) compared to the base case, leads to reductions in instances of near-zero prices (due to reduced lower VRE capacity and thus lower VRE curtailment) as well as an increase in the frequency of non-zero prices (e.g.<$100/MWh), when storage charging is effectively setting the wholesale price based on its shadow value of energy.

[9] RNG generation is parameterized with a heat rate of 9.5 MMBtu/MWh, which translates into a variable cost of $190/MWh for the assumed fuel price of $20/MMBtu. We also model the cost of starting up an RNG generator with the possibility of fractional startups, given the linear model formulation. The net impact is that the marginal costs of RNG generator can vary between $190/MWh and near $330/MWh.

However, the availability of LDES alone does not alter the broader trend of increasing hours with near-zero marginal value of energy and increasing peak prices under tightening CO_2 constraints.

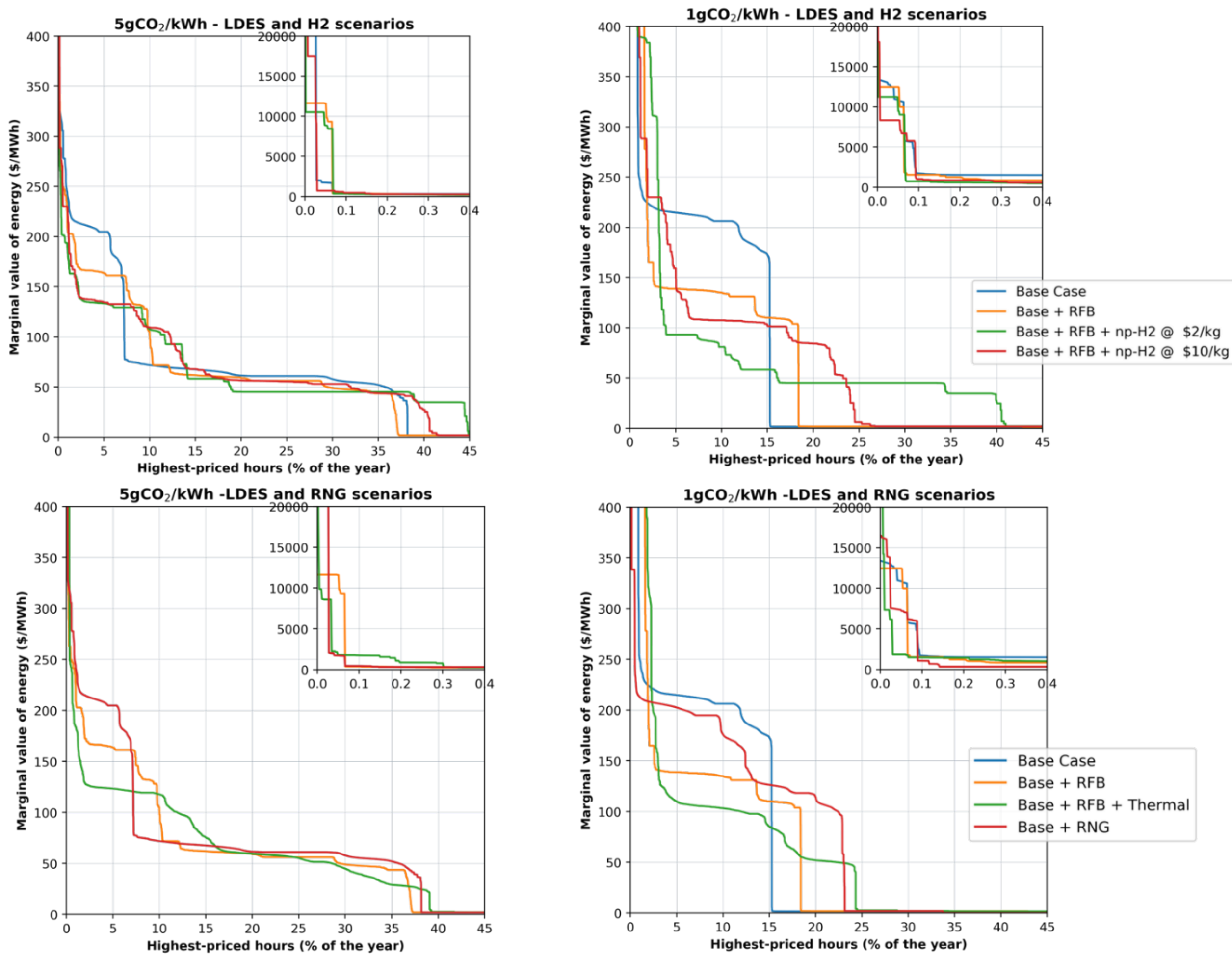

Figure 5. ***Duration curves for 45% of the highest marginal value of energy (MVE) distributions for various technology scenarios and CO_2 emissions constraints.*** *Main plot focuses on the 45% of the hours with prices below $400/MWh. Inset zooms on the small number of hours (<0.5% of hours) when MVEs are approaching the value of lost load ($50,000/MWh). The X-axis of the main plot is only shown for 45% of the total hours to make it easier to see the impacts of various technology availability assumptions and CO_2 emissions constraints on the frequency of high MVEs. In all cases, MVEs are near zero for the hours that are not shown. Note that RNG does not get deployed in the 5gCO2/kWh scenario and thus the duration curve for "Base + RNG" overlaps with "Base".*

3.5. Hydrogen and Sectoral Coupling

The effect of producing H_2 for non-power end-uses on the price distribution is dependent on the cost of non-power H_2 supply. When non-power H_2 supply is cheap, say $2/kg, then the opportunity cost of H_2 production sets the MVE for several hours of the year (see green line in top left panel of Figure 4). Specifically, $2/kg is equivalent to $60/MWh of H_2 based on a lower heating value of H_2 of 120.1 MJ/kg. When accounting for the electrolyzer efficiency of 77% (see Table S 3), this translates into a marginal electricity price of \$46/MWh (flat portion of green line on top right panel in Figure 5). On the other hand, when non-power H_2 supply is expensive, say \$10/kg, then the model places more emphasis on electricity-based hydrogen production, leading to increased VRE deployment and increased frequency of low MVE. The above scenario outputs also yield an estimate of the average H_2 production cost, estimated as the average of the shadow price of the hourly hydrogen balance constraint, which is generally near or below \$1.50/kg for all scenarios assessed here (see Table S 7). The increased deployment of electrolyzer capacity and power generation/storage capacity in the case when non-power H_2 supply is expensive (\$10/kg, see Figure S 5) results in greater average hydrogen production cost as compared to the case when non-power H_2 supply is cheap (\$2/kg).

3.6 Energy Market Revenues

The top panel of Figure 6 shows the fraction of sales each technology makes in each of the MVE bands in Figure 4 in the Base Case under various carbon constraint scenarios, while the bottom panel shows the fraction of revenues received from sales in each band. With more stringent CO_2 constraints, VRE technologies sell more at lower prices but generally rely on a relatively few hours of high prices to earn the revenue required to break even. For example, Figure 4 shows that prices exceed \$200/MWh for just over 5% of hours each year, on average, in the Base Case with a 5 gCO_2/kWh constraint, while Figure 6 reveals that PV earns about 30% of its revenues in those few hours, and Wind and Li-ion earn about 38% and 60%, respectively. In this scenario with a tight emissions constraint, CCGT and OCGT are essentially only run when the price exceeds \$200/MWh, while CCGT_CCS earns about 60% of its revenue in those same hours. In short, under an energy-only wholesale power market design, all resources would be dependent for at least an important fraction of the revenues they need to break even, and in some cases essentially all of those revenues, on sales in a handful of hours. This conclusion is robust to various technology scenarios considered here (see for example Figure S 8 - Figure S 10). Moreover, optimization ensures full cost recovery in the model because the model assumes perfect foresight of load and VRE availability. In reality, it could be difficult to finance investments in generation and storage assets that have to rely for most of their revenues on a handful of operating hours in any given year.

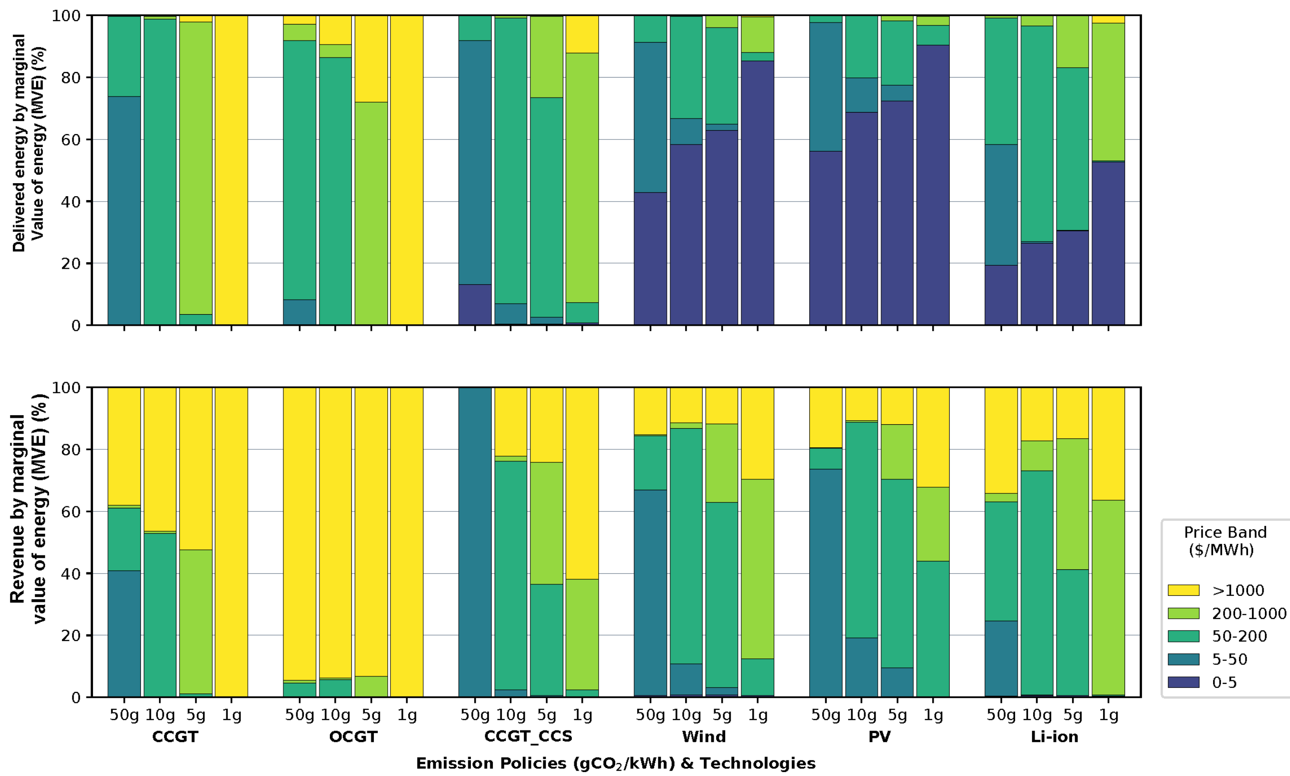

Figure 6. ***Technology operation and revenue by marginal value of energy (MVE) band for various resources under the Base Case defined in Table 1.*** *The upper panel shows the distribution of delivered energy by price band for different technologies and emission constraints. The lower panel shows the revenue distribution by price band.*

4. Pricing Challenges

As noted above, in many respects our model might be considered a stylized version of the energy-only electricity market operated by ERCOT in Texas, updates to reflect estimated 2050 costs. With constraints on carbon emissions, however, our model systems differ from today's

ERCOT in important ways that highlight challenges that will face regulators and market designers in all future decarbonized systems. When carbon emissions constraints are tightened, increased reliance on VRE generation becomes optimal, and the proportion of the time when VRE generation is on the margin increases significantly. Since VRE generation has zero or near zero marginal cost, tightening carbon emissions constraints thus increases the incidence of very MVEs, corresponding to low wholesale prices. High prices are also more common than at present and are necessary to cover the system's higher overall cost. This dramatic change in the frequency distribution of wholesale prices means that in an energy-only market without price caps, generation and storage investments depend for cost recovery on energy market revenues from significantly fewer hours a year than at present. Finally, end consumers in our model systems effectively pay spot wholesale prices for electricity; these prices are much, much more variable than those any real retail customers now face. It is hard to imagine policy makers allowing these outcomes of our modeled systems to emerge in real systems as decarbonization proceeds. How they respond to those challenges will determine the costs of economy-wide decarbonization and perhaps even its feasibility.

4.1 Wholesale Markets

Most organized power markets already have caps on wholesale prices that are below reasonable estimates of the value of lost load, and such caps will almost certainly be present in decarbonizing systems with higher underlying price variability. Price caps reduce energy-market revenues and create the so-called "missing money problem" of sub-optimal incentives for investment in generation [39]. By reducing price variability, such caps will also reduce energy arbitrage opportunities for storage facilities and, thus, reduce incentives to invest in storage below efficient levels.

Market designers have responded to the “missing money problem” by introducing a variety of supplemental capacity remuneration mechanisms [40], and these will be even more important in decarbonized. These mechanisms were originally designed for systems dominated by dispatchable thermal generators, however, which have relatively predictable maximum outputs and marginal costs. These capacity remuneration mechanisms are being adapted to handle VRE generation[41], the outputs of which depend on the weather, which also affects demand. Computing the expected ability of VRE generators to provide both capacity and energy in times of system stress essentially requires an examination of (1) the full probability distribution of supply, both at the bulk power level and from behind-the-meter providers, and (2) the full probability distribution of demand. Analyzing the latter requires properly accounting for correlations between expected production from different types of VRE generators (e.g. output from wind generators in the same area will be much more highly correlated than output from dispatchable generators today) and for correlations between VRE supply and energy demand, both of which will be much more sensitive to variations in weather conditions. A high-VRE system could be stressed in the late evening of a hot day, for example, when demand is below the system peak but there is no solar generation and (potentially) very little wind generation.

Fully adapting these capacity remuneration mechanisms for systems that include significant storage resources will pose new conceptual challenges. Unlike VRE generators, the power that a fully or partially charged storage facility can supply is not likely to vary much over time. However, the length of time over which a storage facility can supply this power (and thus “carry load”) is limited both by the facility’s design duration and, in the short run, by its state of charge. And its state of charge at any time will be determined by prior operating decisions. Since periods of system stress are typically characterized by high energy prices, storage operators will have incentives to have their facilities fully charged just before such periods. System stress, however, cannot be forecast perfectly, and there is essentially no experience with the operating decisions that owners of storage facilities are likely to make when participating in systems with significant VRE and storage resources.

In order for price signals not to distort operating and investment decisions in ways that increase costs, spot prices must track MVEs, even if capacity mechanisms and other interventions move the market away from an energy-only design. This problem is already visible in the U.S.: the production tax credit for wind generators allows then to make a profit even when the market price is slightly negative. They often bid negative prices, which sometimes drives market prices below zero[16].The obvious solution is to make capacity payments or other supplementary payments to generation or storage facilities lump sums, independent of current output.

4.2 Retail Rates

Unlike the retail customers in our modeled systems, only a few customers (almost exclusively large commercial and industrial concerns) pay wholesale spot prices today. Most customers face simple retail tariffs with prices that vary very little over the hours of the year. As wholesale prices become much more variable than they typically are today, it is hard to imagine regulators requiring more customers to pay them. (The February, 2021 energy crisis in Texas, when a few retail customers who had signed up to pay wholesale spot prices received astronomical bills, has provided a strong push in the opposite direction [42].) To encourage economy-wide decarbonization, however, it is essential that all consumers face low prices when wholesale spot prices – and thus the marginal values of electricity – are low.

This immediately implies that the costs of supplemental capacity remuneration mechanisms and other social/regulatory programs should not be recovered by volumetric (per-kwh) charges that vary little over the hours of the year, as they generally are at present. These costs should be covered by customer-specific charges that are fixed in the short run but respond to long-run demand patterns and that vary among customers in a politically acceptable way.

At the other end of the price distribution, efficiency requires that the demand for electricity be reduced when its wholesale price is high, often by shifting demand to other periods or by simply reducing consumption. Efficiency does not require that households and small businesses actually pay high spot wholesale prices, however. We think the most viable solution is for local distribution companies or other intermediaries serving retail customers to contract with small customers to supply electricity at prices that are below some ceiling in exchange for automated, price-responsive control of vehicle charging, HVAC systems, appliances, and other flexible loads and for the payment of a ceiling-specific insurance premium that is independent of current demand.

5. Conclusions

Using capacity expansion modeling of electric power systems in three US regions in mid-century, we show that under a wide range of plausible demand and supply-side technology assumptions, efficient, deeply decarbonized systems will have many more hours of very low marginal values of electricity (MVEs) and more hours of relatively high MVEs, than today. We also highlight that the extent of both these effects is dependent on many factors, including: a) the stringency and type of policy encouraging low-carbon generation, b) the cost assumptions and availability of technologies like VRE, storage, low-carbon dispatchable generation and c) the cost, and availability of demand response and demand flexibility. Other factors that could impact the extent of very low and very high MVE prices estimated from CEMs under carbon-constrained scenarios that are not discussed in detail here include: a) the temporal resolution of grid operations modeled, which is shown to be important to capture VRE resource and load variations and b) prevalence of resource adequacy requirements, beyond the need to meet hourly demand and supply in balance.

This dramatic change in future wholesale market price distributions raises a number of issues for wholesale market design and the structure of retail pricing arrangements. At the wholesale market level, it is not reasonable to expect that optimal investment in generation and storage assets will take place if investors must rely on highly variable and uncertain future wholesale spot prices. VRE-dominant bulk power systems with storage will have relatively high fixed (capital) costs and relatively low marginal operating costs compared to today's bulk power systems, which largely rely on thermal generators. Consequently, the existing supplemental capacity remuneration mechanisms that have been adopted by many systems will likely have to be redesigned both to provide adequate revenues to cover the costs of investing in an efficient portfolio of generating assets and to reflect the attributes of VRE generators and storage technologies. It is not too early to begin to explore and implement alternatives. Advances in financial instruments and contracts to hedge wholesale market price risks are also worthy of more consideration.

At the retail level, except for the largest customers, regulators and other policymakers have been reluctant to implement retail rate designs that allow prices to vary widely with variations in wholesale market prices. This reflects their concerns about the impacts of increased price volatility on the level and variability of retail customer bills and especially their impacts on lower-income consumers. The failure to more closely match the variations in wholesale prices with variations in retail prices already creates inefficiencies given today's wholesale price distributions. The inefficiencies associated with these rate design limitations will increase in the future as wholesale price variability increases and there are many hours of very low prices and a much smaller number of hours of very high prices. For example, it would be desirable for both consumers and the power system if consumers charge their EVs when prices are very low rather than when they are very high [43]. Otherwise, EV utilization of the electric power system will lead to increase in peak capacity requirements and thus increase the cost barrier to grid decarbonization. The reluctance of regulators to place very high levels of wholesale market price and retail bill volatility risks on residential and commercial consumers is understandable from political and equity perspectives. However, hedging and contractual arrangements between retail suppliers and retail customers are potentially available that can effectively give retail customers better incentives to shift and/or reduce demand while reducing the potential bill volatility that would emerge from pure real time retail prices. It is time to expand experiments with retail rate designs with these attributes.

The analysis presented here is not the last word on the attributes of deeply decarbonized electricity systems. There are certainly opportunities to extend the implementation of CEM to study deeply decarbonized electricity systems in a number of ways. First, longer time series and more granular data for electricity demand would help better to capture more extreme demand realizations and their implications for reliability. Second, more robust representations of consumer demand elasticities by alternative types of consumers would allow for a better understanding of the effects of demand response on the optimal portfolio of generation and storage assets as well its effects on wholesale price variations in the context of potential future retail rate design reforms. Third, most of the experience that we have with energy storage in commercial applications has been with Li-ion batteries. While CEM representation of Li-ion storage can also be improved, notably to consider their use-dependent degradation[44], the operational representation of alternative storage technologies can also be improved in CEMs with increasing commercial experience.

Fourth, expanded linkages between CEMs, economic dispatch models, transmission network models, and system reliability criteria would help to expand our understanding of potential additional operational issues associated with systems with high VRE penetration and solutions to them, especially the role of storage for mitigating operational issues associated with transmission limitations and the role of VRE and storage in providing ancillary network support. Finally, developments in low and no carbon dispatchable generating technologies continue to emerge, including modular nuclear power plants, the Allam-Fetvedt cycle[45], gas turbines capable of using hydrogen, etc. Low and no carbon generating technologies can help to reduce the costs of deeply decarbonized electric power systems consistent with meeting emissions constraints and system reliability criteria. Incorporating credible real world information about these technologies into CEMs can provide valuable insights into potential alternative configurations of deeply decarbonized electric power systems.

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Declaration of Interests

Paul Joskow is on the Board of Directors of Exelon Corporation. Exelon had no involvement with this paper or the underlying research.

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Supporting Information

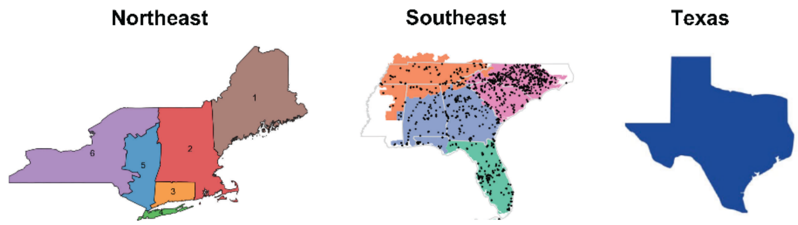
S1. Notes on regional modeling

As part of the forthcoming MIT Energy Initiative Future of Storage Study, we evaluated power system evolution under various carbon emissions and technological scenarios for three U.S. regions in 2050: the Northeast, the Southeast, and Texas. We do not seek to develop detailed trajectories of the evolution of the resource mix in these regions, as this evolution will be affected by a range of factors, including the turnover of the existing generation fleet, market design, state incentives, permitting rules, etc. Instead, the modeling focused on the effects of differences in VRE resource quality and the availability of long-lived, existing low-carbon hydro and nuclear generation assets, and pumped hydro storage assets, assuming cost-efficient investment and operation. We also assume that the existing stock of fossil-fuel generating capacity retires by 2050, so that our analysis basically examines a "greenfield" system developed to meet 2050 demand, utilizing existing transmission assets and some other existing non-fossil assets, with some regional differences (as detailed below). New fossil generating capacity may be selected depending on its costs, utilization rates in an optimal system, and the stringency of the system-wide carbon constraint. Given the central role for electrification in long-term U.S. decarbonization efforts, the model-based finding presented here rely on electricity demand projections from a high-electrification scenario developed by the National Renewable Energy Laboratory (NREL) for its 2018 Electrification Futures (EFS) study[33] (See Table S 1).

Here we briefly describe the unique attributes of the three region's power systems as well as their representation in our modeling, along with listing the major input assumptions used in each case (Figure S 1). Since the majority of the paper focuses on modeling outcomes from the Texas case study, the complete details on the modeling for that region are presented in this section and sections S3-S6 of the SI, while details for other regions can be found in forthcoming MIT Energy Initiative Future of Storage study[32].

Assumptions & Sources

- **After-tax WACC:** 4.5%
- **Load:** NREL Electrification Futures Study (2012 weather year) – high electrification
- **VRE resource:** NREL WIND Toolkit, National Solar Radiation Database (PV) (2007-2013)
- **Generation costs:** NREL Annual Technology Baseline (ATB) 2020
- **Storage costs:** Technical teams + NREL ATB 2020 for Li-ion + other literature sources
- **Gas price:** EIA Annual Energy Outlook 2020 estimate for 2050 - \$4.16/MMBtu (2019: \$2.88/MMBtu)
- **Transmission capacity:** EPA Integrated Planning Model's existing capacity (Northeast, Southeast)
- **Existing generation:** Hydro & pumped hydro (Northeast, Southeast), distributed PV (Northeast), nuclear (Southeast)
- **Hydropower:** Oak Ridge National Laboratory database + EIA 923 + Canada energy board



	Northeast	Southeast	Texas
Variable renewables	Wind: Onshore (50% cost premium) + offshore PV: Utility + distributed	Wind: Onshore PV: Utility	Wind: Onshore PV: Utility
Hydro	Yes (domestic + imports)	Yes (domestic)	No
Spatial resolution	6 zones with existing intra-zonal transmission capacity	4 zones with existing intra-zonal transmission capacity	Single zone
Temporal resolution	35 representative periods of 10 days from 2007-2013 weather years, including "extreme" periods (8,400 hours)	35 representative periods of 10 days from 2007-2013 weather years, including "extreme" periods (8,400 hours)	2007-2013 weather years (61,314 hours)

Figure S 1. Summary of modeling assumptions across the Northeast, Southeast and Texas regions. Complete details about the modeling assumptions are documented in the forthcoming MIT Energy Initiative Future of Storage Study[32]..

S1.1. Northeast region

The modeling of the electricity system of the US Northeast, defined as the region served by Independent System Operator (ISO) New England and New York ISO (Figure S 1), is characterized by the following attributes: a) relatively low-quality solar resource, either as distributed or utility-scale installations, but high-quality onshore and offshore wind (VRE resource characterization described in S3), b) non-trivial amounts of hydropower imports from Canada and as well in-region hydro resources that can help to support VRE integration, c) an expectation that penetration of electric space heating anticipated to meet decarbonization commitments (and included in the NREL high electrification demand scenario), will transform the Northeast into a winter-peaking region, d) an expectation that all existing nuclear units in the region retire by 2050, i.e. they do not renew their current operating license and that new nuclear plants are not deployed by 2050 based on available information about the technology's cost and public acceptance challenges, e) existing hydro and pumped storage resources continue to be operational in 2050 and f) for onshore wind, we applied a 1.5x multiplier to the base cost assumptions (sourced from the 2020 edition of the NREL annual technology baseline[34]) in the Northeast to reflect prevailing difficulties in siting and interconnection.

Table S 1. 2050 electricity demand assumptions for the Northeast, Southeast and Texas region modeling. Data sourced from high-electrification scenario of the NREL electrification futures study[33].

	System peak demand (GW)	Annual Demand (TWh)
Northeast	94	454
Texas	151	715
Southeast	298	1,457

S1.2. Southeast region

The modeling of the Southeast region (Tennessee, Alabama, Georgia, North and South Carolina, and Florida) is characterized by the following unique attributes: a) prevalence of winter-peaking demands for some states within the region as of 2018 that remains in 2050 as per demand projections under a high electrification scenario (see Table S 1), b) an extensive nuclear generation fleet, that contributed 28% of the region's annual power generation in 2018 and is assumed to be available in 2050 with the assumption these plants apply and receive second license renewals. This results in approximately 25 GW of existing nuclear capacity available in our modeled 2050 scenario, c) availability of relatively good-quality solar resources and on-shore wind resources. While offshore wind may be a possibility in this region, we have not modeled its availability due to a lack of reliable data to characterize the resource.

The Texas case study is characterized by the following unique attributes: a) high-quality wind and solar resources, b) summer-peaking demand with a strong component of relatively inflexible air conditioning demand, significant penetration of weather-sensitive electric heating, c) strong industrial energy demand that could spur increased demand for electricity to meet industrial hydrogen demand via electrolysis, and d) assumption that the two existing merchant nuclear plants (four units) in the state retire and are not replaced by 2050, which is consistent with the challenged economics of such plants in organized wholesale market today[46].

S2. Generator and storage cost and performance assumptions

Fossil-powered generation and VRE capital and operational costs are shown in Table S 2. The gas, VRE, and Li-ion costs are taken from the 2020 NREL Annual Technology Baseline 2045 "Mid" cost projections[34]. Capital costs for generation and storage were annualized based on an after-tax weighted average cost of capital of 4.5% and a lifetime of 30 years, unless otherwise noted. We also apply a small, non-zero VOM for wind, hydropower, and storage to distinguish their dispatch as part of the economic dispatch modeled within GenX – they do not meaningfully affect resulting system costs.

For storage, system costs are separated as energy-only components (e.g., battery packs for Li-ion, tanks for LDES), or power-only components (e.g., inverter, interconnection and permitting fees, land acquisition costs). In the case of hydrogen and thermal storage, power-only components can further be parsed into charging or discharging power costs (see Table S 3), which are applied to the respective sizing variables in the model. This separation of function-based costs enables the model to independently vary the energy, discharging power, and charging power capacities of the energy storage systems for optimal sizing. For storage technologies other than Li-ion, cost projections used in the analysis are based on bottom-up analysis by MIT team members engaged in the forthcoming *Future of Storage* study[47]. Operational assumptions for natural gas powered generators are summarized in Table S 4. Natural gas fuel price assumptions are taken from the EIA AEO 2020 Reference (EIA 2021) 2050 case and correspond to \$4.16/MMBtu. For CCGT with CCS, the fuel cost is updated to account for assumed CO2 transport and storage cost of \$20/tonne of capture CO_2 (90% flue gas CO2 capture).

Table S 2. Generator capital cost assumptions for GenX model runs discussed in the main text.

Technology	Capital Cost (\$/kW)	FOM (\$/kW-year)	VOM (\$/MWh)
Onshore Wind	1,085	34.6	0.01
Utility-Scale Solar	725	8.5	0.00
CCGT	936	12.9	2.16
OCGT	854	11.4	4.50
CCGT_CCS	2,080	27.0	5.72

Table S 3.Energy storage cost and operational assumptions. Value for Li-ion storage from NREL annual technology baseline 2020. Values for other technologies based on bottom-up analysis from MIT team members of the upcoming MIT Energy Initiative Future of Storage Study. RFB = Redox Flow Battery. Round-trip efficiency (RTE) expressed as a fraction is the product of Efficiency Up and Efficiency Down similarly expressed. Hourly self-discharge rates for storage technologies are also considered in the modeling, but are very small at: 0.002% for Li-ion and metal-air systems, and 0.02% for thermal systems.

Tech	Discharging Capital Cost (\$/kW)	Charging Capital Cost (\$/kW)	Storage Capital Cost (\$/kWh)	FOM (\$/kW-year)	FOM (\$/kWh-year)	VOM (\$/kWh)	Efficiency Up (%)	Efficiency Down (%)	RTE (%)
Li-ion	110	-	125.8	0.8	2.2	0.0	92%	92%	85%
RFB	396	-	48.0	4.1	0.0	0.0	92%	88%	80%
Hydrogen	1,190	479.3	7.0	11.0	0.1	0.0	77%	65%	50%
Thermal	736	3.3	5.4	3.9	0.0	0.0	100%	50%	50%

Table S 4.Thermal generator operational characteristics for the GenX model runs presented in the main text. Data compiled after surveying a variety of literature sources including NREL Annual Technology Baseline[34] *EIA Annual Energy Outlook 2018*[48], *other sources*[7,49–51] *[13,54,57,59] CCGT = Combined Cycle Gas Turbine. OCGT = Open Cycle Gas Turbine. CCS = CO_2 capture and storage.*

Tech	Capacity Size (MW)	Start Cost (\$)	Start Cost (\$/MW/start)	Start Fuel (MMBTU/start)	Start Fuel (MMBTU/MW/start)	Heat Rate (MMBTU/MWh)
OCGT	237	33,147	140	45	0.19	9.51
CCGT	573	34,982	61	115	0.20	6.40
CCGT + CCS	377	36,419	97	75	0.20	7.12

Tech	Min Stable Output (%)	Ramp Up (%)	Ramp Down (%)	Up Time (Hours)	Down Time (Hours)
OCGT	25	100	100	0	0
CCGT	30	100	100	4	4
CCGT + CCS	50	100	100	4	4

S3. VRE Resource characterization

VRE resources are characterized based on the methodology described in [4]. Hourly PV capacity factors are simulated using 2007-2013 weather data from the NREL National Solar Radiation Database [52] through the PVLIB model framework[53], at a 4km x 4km spatial resolution. Hourly wind capacity factors are simulated using the same temporal and spatial resolution using the NREL Wind Integration National Dataset Toolkit [54] and power curve data for the commercial wind turbine Gamesa:G126/2500[55] at 100-meter height. To reduce the spatial resolution of the VRE capacity factor data, we aggregate sites within a zone on the basis of average levelized cost of electricity (including the cost of interconnecting to the nearest substation). Thus, for each resource and zone, we get a supply curve, with each bin representing increasing resource quality with an associated maximum availability (based on land area), interconnection cost and hourly capacity factor profile. For the Texas case study, we use 4 bins to characterize PV and wind resources in the region. Note that the interconnection cost of each bin is added on to the base capital cost of the technology, noted in Table S 2, to develop a bin-specific installed capital cost.

S4. Demand flexibility scenario definition

The potential value of flexibility in electricity consumption for various end-uses increases with greater deployment of smart meters and related technologies and expanded electrification in sectors such as transportation. For these experiments, we consider a very optimistic version of demand flexibility: the ability to shift electricity consumption from specific demand subsectors, highlighted in Table S 5, over constrained (feasible) time windows at zero cost and with zero energy efficiency losses or inconvenience costs. Our assumptions about demand flexibility are based on the NREL EFS enhanced flexibility scenario, which provides potential hours of delay and advance for specific demand subsectors, along with the share of the load that can be shifted[33]. Since the load from each subsector changes over time, potential demand flexibility also varies from hour to hour. For this reason, Table S 5 notes the maximum load that could be shifted for each subsector at any point in time for the Texas region in 2050 under the high-electrification load scenario. It is important to notice that these subsector peaks do not occur at the same time; the actual maximum potential demand flexibility at any particular hour is 47 GW, which corresponds to 31% of total demand in that hour [33].

Table S 5. Demand flexibility assumptions for Texas under 2050 load conditions. HVAC = heating, ventilation and air Conditioning. Data sourced from NREL Electrification Futures Study

Demand Subsector	Hours Delay	Hours Advance	Share of End-Use That Is Flexible	Maximum Hourly Demand Flexibility [GW]
Commercial HVAC	1	1	25%	8.6
Residential HVAC	1	1	35%	7
Commercial Water Heating	2	2	25%	0.2
Residential Water Heating	2	2	25%	1
Light duty vehicles	5	0	90%	33
Medium duty trucks	5	0	90%	3
Heavy-duty trucks	3	0	90%	5

S5. Demand response scenario definition

The demand response scenario modeled here assumes that certain electricity consumers will be willing to forgo consumption above certain electricity prices. These type of demand response programs exist in some regions and are typically used for peak demand management [56]. To capture the underlying goal of these programs for supply-demand balancing, the stylized demand response scenario modeled here assumes that 25% of hourly load in each can be shed at prices below the value of lost load ($50,000/MWh). Table S 6 summarizes the parametrization of this demand response resource in GenX where demand segments 2-6 have an associated quantity

(5% of hourly demand) and marginal cost,that is measured as a fraction of the value of lost load. Demand segment 1 is the most expensive and is priced at the value of lost load.

Table S 6 Demand response resource characterization. VoLL = Value of Lost Load, set to $50,000/MWh.

Demand segment	Cost of demand curtailment as a fraction of VoLL	Maximum demand curtailment per segment as a fraction of hourly load
1	1	75%
2	0.7	5%
3	0.5	5%
4	0.2	5%
5	0.1	5%
6	0.05	5%

S6. H_2 scenario definition

The configuration of Figure 1 is included in the GenX model, where along with specifying the cost of performance assumptions of the elements as used previously (e.g., electrolyzer, storage tank and gas turbines for H_2 storage as per values in Table S 3), we add a constraint that requires the specified H_2 demand from industry to be met by either the electrolyzer or by discharging H_2 storage. This single constraint then enables the utilization of a traditional power-to-H_2-to-power storage system to be also optimized, in terms of component sizes and utilization, to meet H_2 demand in the industrial sector.

Since we are primarily interested in understanding the impact on the power system from this external H_2 demand, we make the following approximations to simplify the representation of the H_2 supply chain. (1) We simplify the representation of non-power sources of H_2 supply, by making them available at a constant cost, either $2/kg or $10/kg, without any supply limits. As reference, the cost of producing hydrogen from natural gas with carbon capture and storage is estimated to be around $2/kg in the U.S. context[57]. (2) We are not considering any spatial distribution in H_2 production and industrial demand and are thus ignoring H_2 transportation. And, (3) we are not including source-dependent delivery costs for H_2 supply that could be associated with adjusting the state of delivered H_2 from different sources to meet industrial customer requirements. Other studies have included these factors in the H_2 supply chain while also contemplating their impacts on the power system evolution [19,58].

Hydrogen demand is modeled as exogenous and uniform throughout the year. Hydrogen demand was estimated using NREL's 2018 Industrial Data Book as a reference[59,60]. This publication contains a dataset detailing the annual energy consumed by large energy-using facilities[10] in 2016. Here, we focus on hydrogen demand from substituting for the use of natural gas for heating purposes. Total natural gas consumption by Large Energy Users in Texas accounted for 0.93 QBTU in 2016, which represents about 44% of the 2.1 QBTU of natural gas consumed by the industry in Texas, as reported by the EIA (Figure S 2). From that 0.93 QBTU, we considered for the analysis Process Heaters, Furnaces, Boilers and Other Combustion Sources as potential units that use natural gas for heating purposes. Moreover, we excluded units whose unit name suggests natural gas is being used as feedstock. This results in 0.59QBTU of natural gas used for heating. By assuming flat demand, the total of 0.59QBTU/year of natural gas heat is equivalent to 19.7GWt of H_2. For comparison purposes a constant 19.7 GWt load is equivalent to an average power demand of 25.6 GWe assuming 77% charging (electrolyzer) efficiency. 25.6 GWe is equal to approximately 17% of projected 2050 peak electricity demand modeled here.

[10] Defined as those facilities that are required to report greenhouse gas emissions under EPA's Greenhouse Gas Reporting Program.

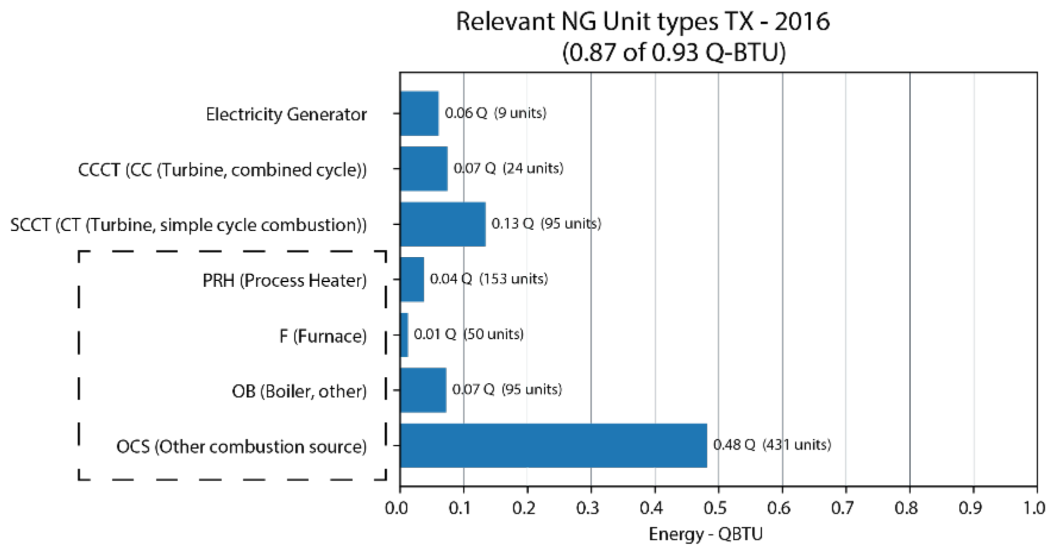


Figure S 2. Natural gas consumption by Large Energy Users in Texas. Demand categories within the dotted box are considered when estimating potential future hydrogen demand for process heating.

S7. Additional Results

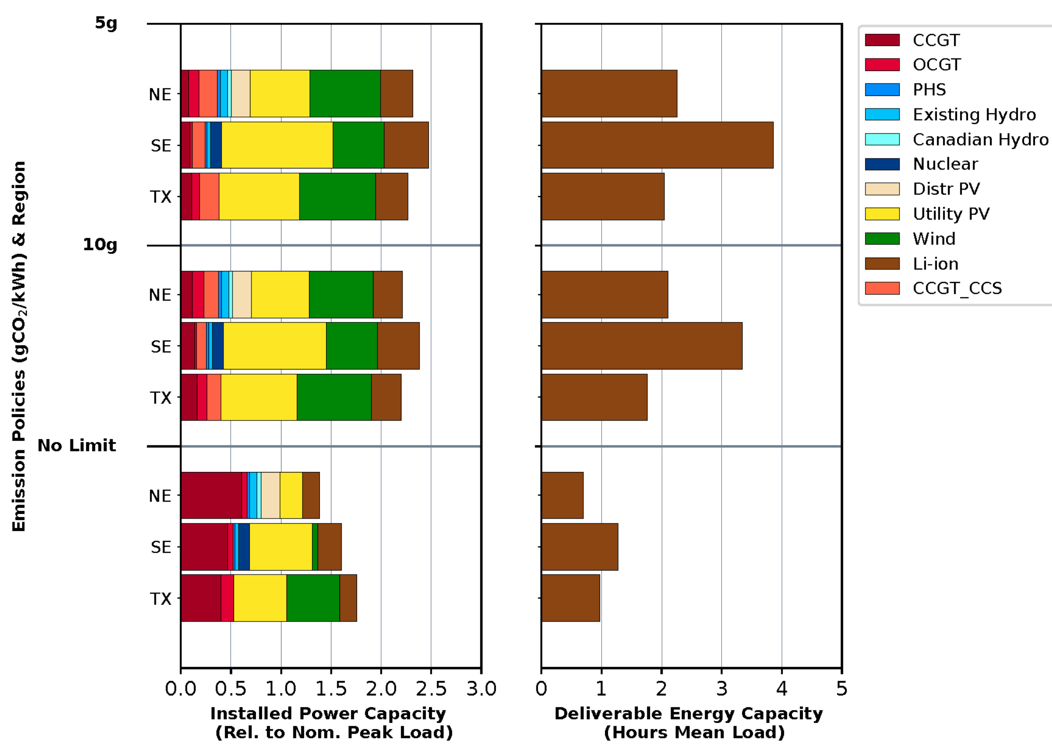


Figure S 3. Installed capacities in the Northeast (NE), Southeast (SE), and Texas (TX) under tightening CO_2 emissions constraints. Left side: installed power capacities (relative to the region's 2050 peak electricity demand); right side: deliverable storage energy capacity to the grid (i.e., product of energy capacity and discharge efficiency, relative to the region's annual *average hourly electricity demand). Capacity factors of CCGTs can be found in Appendix D (Table D-1). For the Northeast, "Wind" represents the sum of onshore and offshore capacity.*

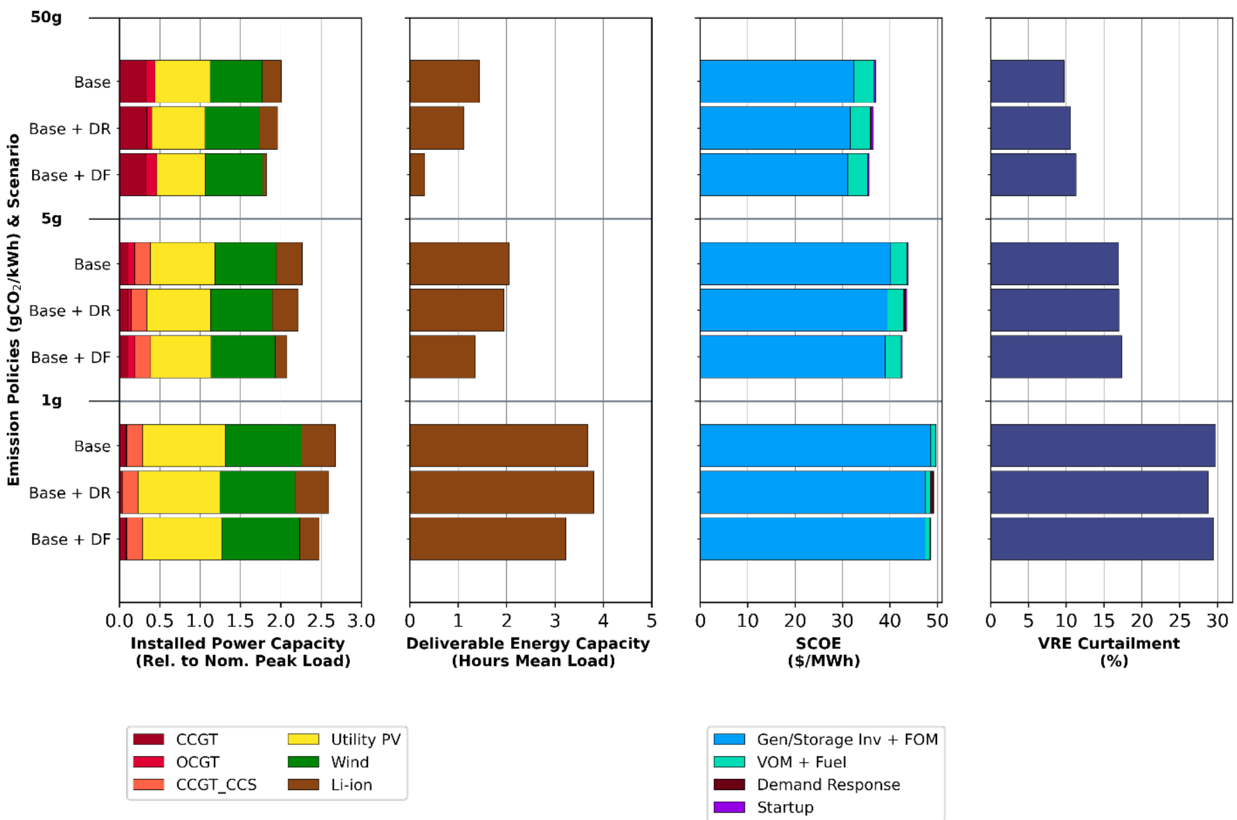


Figure S 4. Key system outcomes for various CO_2 emissions intensity constraints and technology scenarios for Texas. 1st column: installed power capacity by technology type, reported as a fraction of peak load; 2nd column: Deliverable energy storage capacity installed by technology type, reported as a fraction of mean annual demand. Deliverable energy capacity for each storage technology is defined as the installed energy capacity times the discharge efficiency; 3rd column: system average cost of electricity (SCOE), defined as ratio of total system cost by total demand met throughout the year; 4th column: variable renewable energy curtailment, defined as the fraction of available VRE generation that is not dispatched.

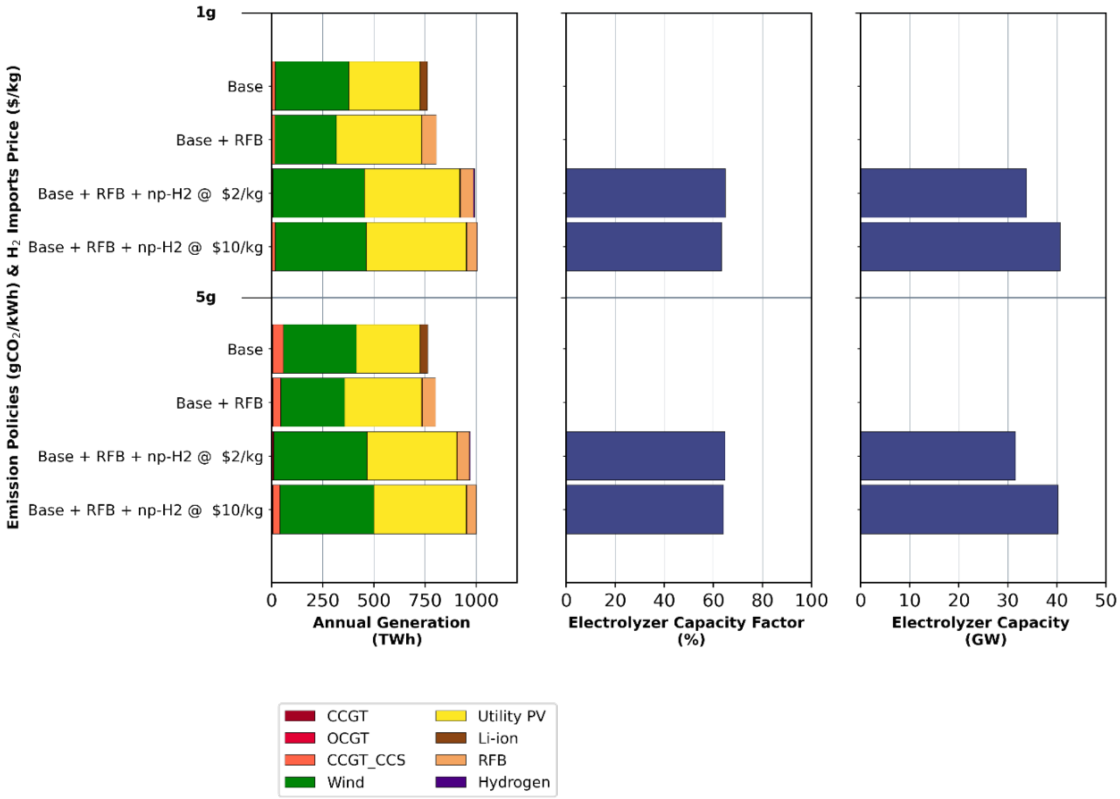


Figure S 5. Key system outcomes for various CO2 emissions intensity constraints and technology scenarios characterized by energy storage availability, existence of non-power H_2 demand and availability of non-power H_2 supply at various prices. 1st column: annual generation mix by resource and storage discharging; 2nd column: annual average power to H_2 (or electrolyzer) capacity utilization; 3rd column: installed power to hydrogen production capacity.

Table S 7 Average hydrogen production cost in $/kg for serving non-power sector hydrogen demand as a function of non-power H2 supply and CO2 emissions intensity constraint. Average hydrogen production cost is computed as the mean of the hourly shadow price associated with hourly H2 supply and demand balance constraint in the model.

	Emissions intensity constraint (gCO_2/kWh)		
	1	5	50
Base + RFB + np-H2 @ $2/kg	1.07	1.15	1.47
Base + RFB + np-H2 @ $10/kg	1.46	1.60	1.57

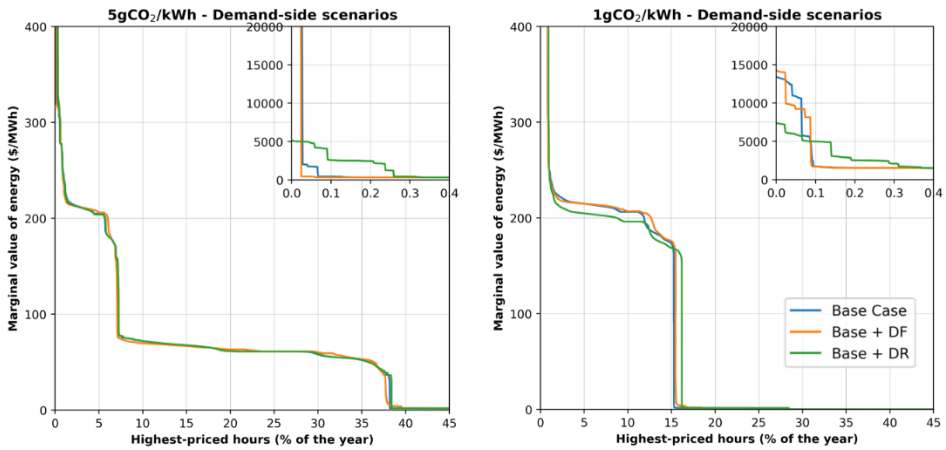


Figure S 6. Duration curves for 45% of the highest marginal value of energy (MVE) distributions for various technology scenarios and CO2 emissions constraints. Main plot focuses on the 45% of the hours with prices below $400/MWh. Inset zooms on the small number of hours (<0.5% of hours) when MVEs are approaching the value of lost load ($50,000/MWh). The X-axis of the main plot is only shown for 45% of the total hours to make it easier to see the impacts of various technology availability assumptions and CO_2 emissions constraints on the frequency of high MVEs. In all cases, MVEs are near zero for the hours that are not shown. Note that RNG does not get deployed in the 5gCO2/kWh scenario and thus the duration curve for "Base + RNG" overlaps with "Base".

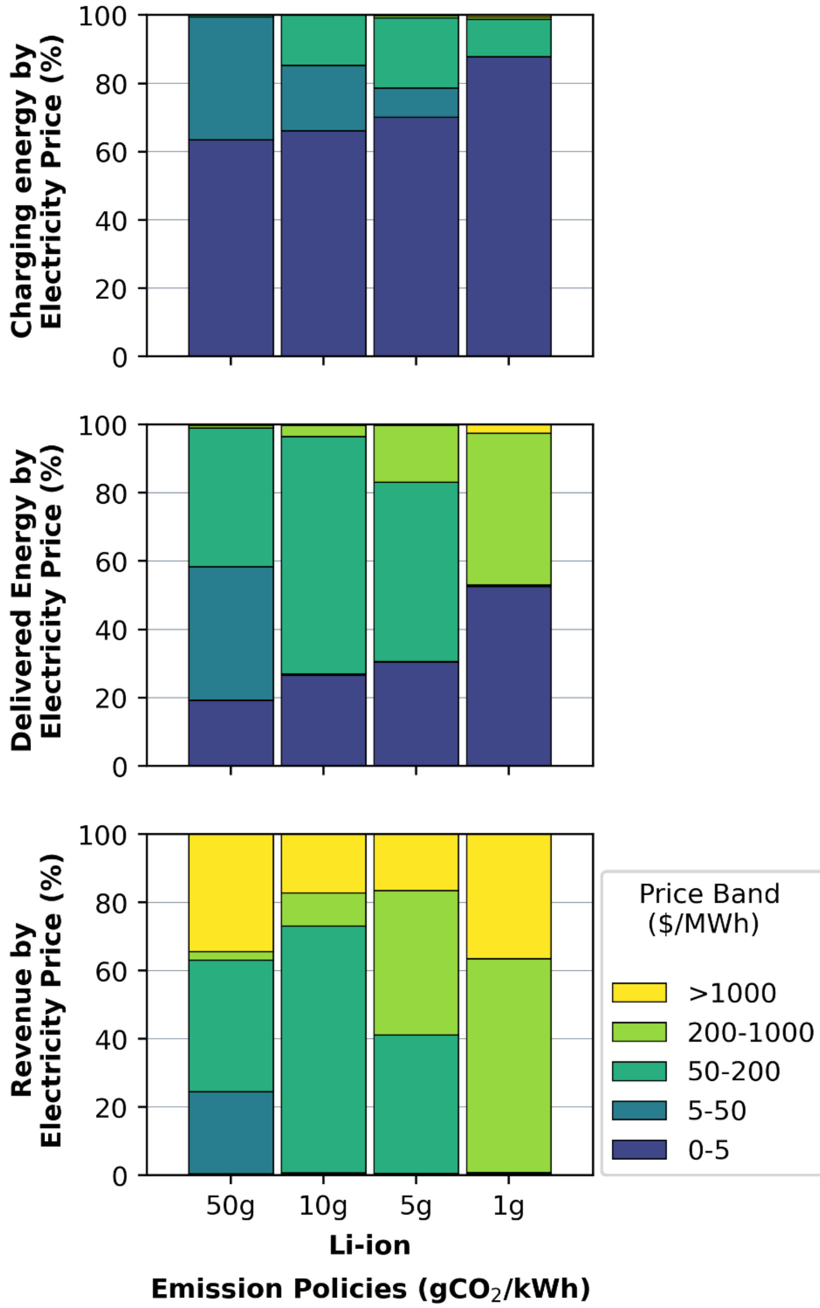


Figure S 7. Distribution of Li-ion storage annual charging (top), discharging energy (middle) and revenue earned (bottom) across the wholesale electricity price bands introduced earlier. Results shown for various CO2 emissions constraints and correspond to "Base" technology scenario described in Table 1. Note that Li-ion charges predominantly, but not exclusively, when prices are in the lowest band.

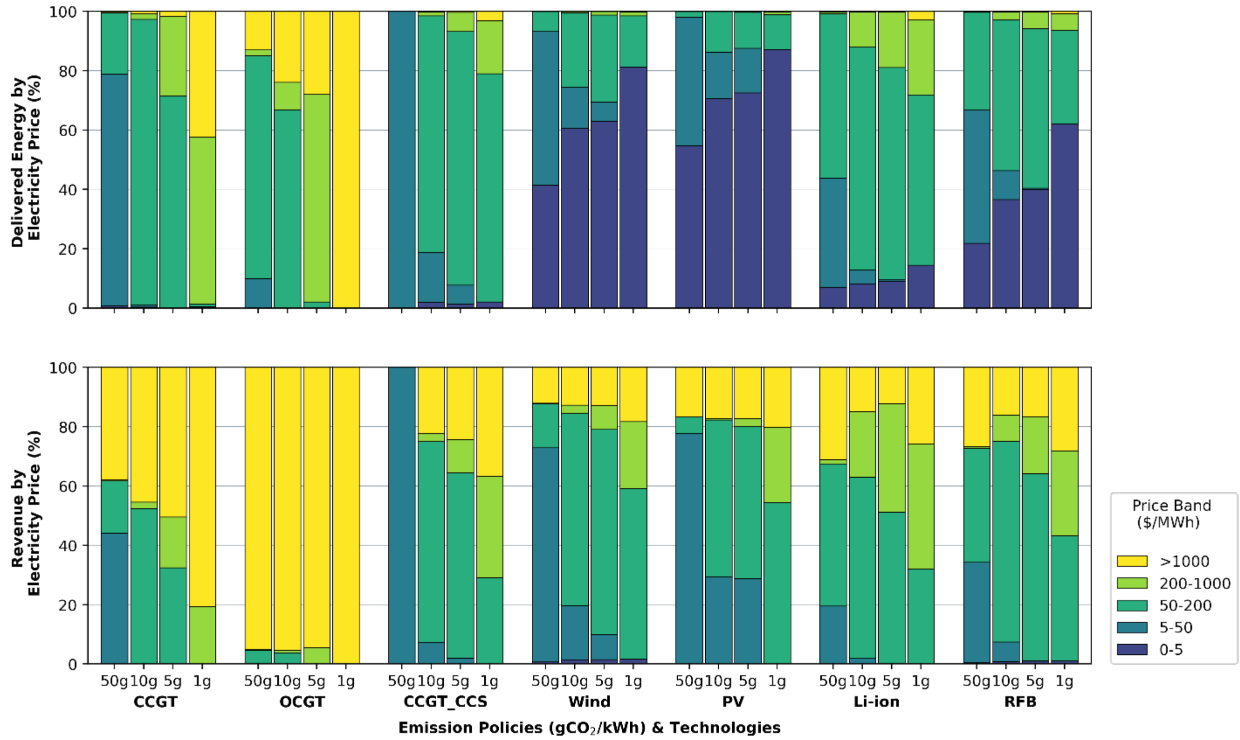


Figure S 8. Technology operation and revenue by price band for various resources under the Base +RFB scenario defined in Table 1. The upper panel shows the distribution of delivered energy by price band for different technologies and emission constraints. The lower panel shows the revenue distribution by price band.

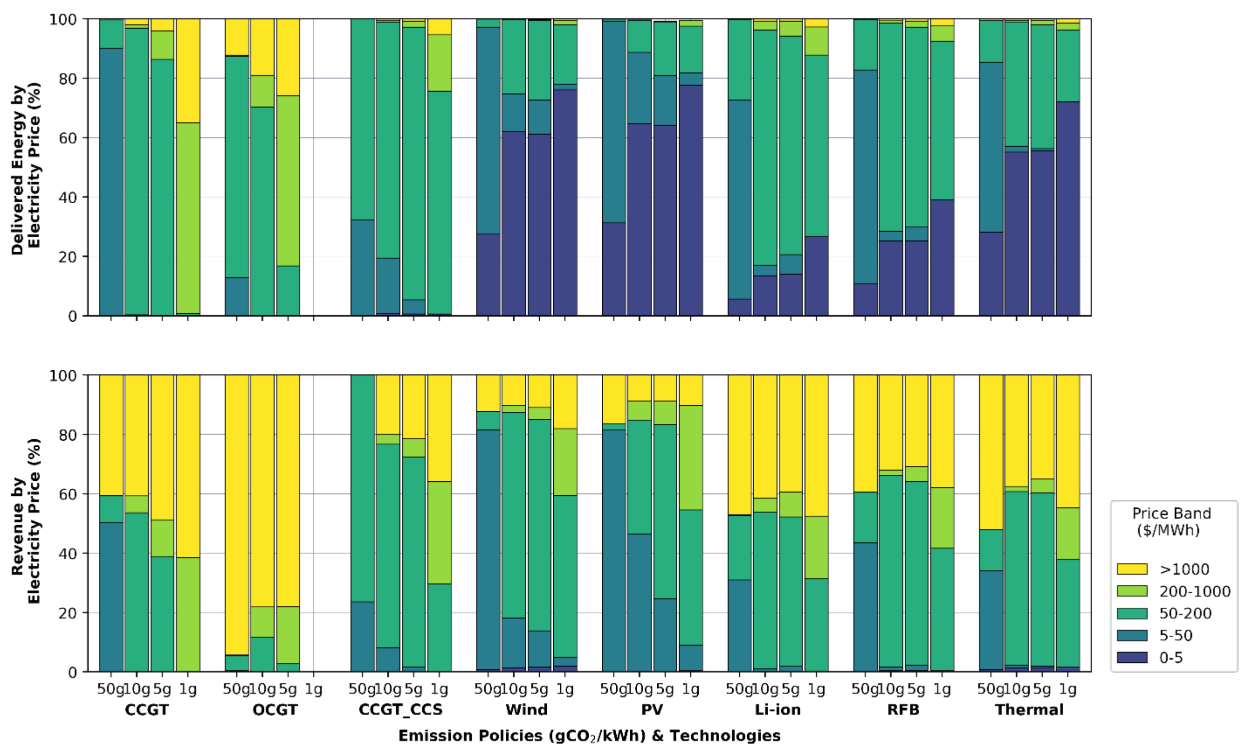


Figure S 9. Technology operation and revenue by price band for various resources under the Base +RFB +Thermal scenario defined in Table 1. The upper panel shows the distribution of delivered energy by price band for different technologies and emission constraints. The lower panel shows the revenue distribution by price band.

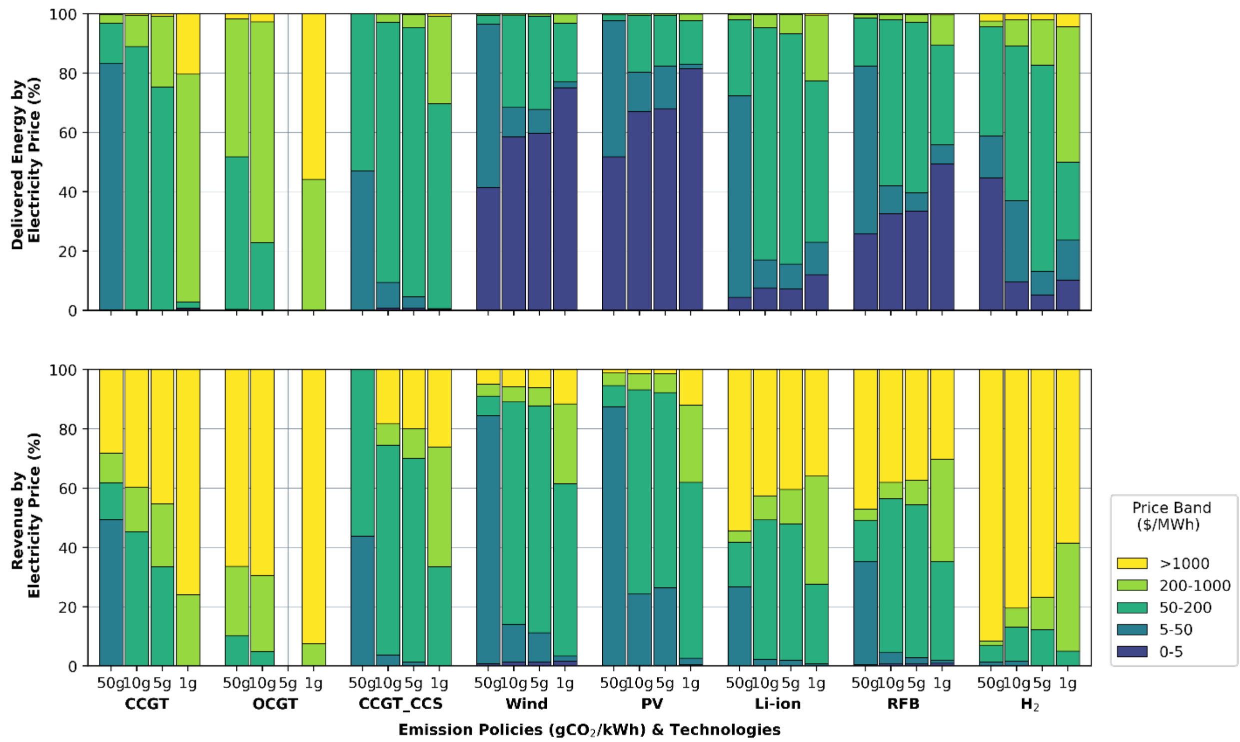


Figure S 10. Technology operation and revenue by price band for various resources under the Base +RFB +np-H2 @$10/kg scenario defined in Table 1. The upper panel shows the distribution of delivered energy by price band for different technologies and emission constraints. The lower panel shows the revenue distribution by price band.

MIT Center for Energy and
Environmental Policy Research

MIT Center for Energy and
Environmental Policy Research
Massachusetts Institute of Technology
77 Massachusetts Avenue, E19-411
Cambridge, MA 02139-4307
USA

ceepr.mit.edu

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