Enabling More Solar in Florida: Potential Roles for Power System Flexibility

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Abstract

Although Florida has very little photovoltaic (PV) generation to date, it is reasonable to expect significant deployment in the 2020's under a variety of future policy and cost scenarios. To understand these potential futures, we model Florida Reliability Coordinating Council operations in 2026 over a wide range of PV penetrations with various combinations of battery storage capacity, demand response, and increased operational flexibility. By calculating the value of PV under a wide range of conditions, we find that at least 5%, and more likely 10-24%, PV penetration is cost competitive in Florida within the next decade with baseline flexibility and all but the most pessimistic of assumptions. For high PV penetrations, we demonstrate Florida's electrical net-load variability (duck curve) challenges, the associated reduction of PV's value to the system, and the ability of flexibility options–in particular energy-shifting resources–to preserve value and increase the economic carrying capacity of PV. A high level of demand response boosts the economic carrying capacity of PV by up to 0.5-2 percentage points, which is comparable to the impact of deploying 1 GW of battery storage. Adding 4 GW of battery storage expands the economic carrying capacity of PV by up to 6 percentage points.

Keywords: renewable energy integration, solar photovoltaics, battery energy storage, demand response, operational flexibility

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Acronyms

AEO	Annual Energy Outlook
ATB	Annual Technology Baseline
CC	combined cycle
CT	combustion turbine
DLC	direct load control
DR	demand response
ECC	econmoic carrying capacity
EIA	U.S. Energy Information Administration
EMS	energy management system
ERGIS	Eastern Renewable Generation Integration Study
FRCC	Florida Reliability Coordinating Council
LBNL	Lawrence Berkeley National Laboratory
LCOE	levelized cost of electricity
NREL	National Renewable Energy Laboratory
PV	photovoltaic
SERC	SERC Reliability Corporation
VO&M	variable operating and maintenance

1. Introduction

Much of the detailed analysis of high solar photovoltaic (PV) penetrations has focused on California because of that state's PV market leadership (Margolis et al., 2017). These previous analyses reveal the grid integration challenges due to PV generation starting quickly in the morning and dropping off quickly in the late afternoon, which on low load days creates a net-load pattern that conventional generators must be dispatched around (Figure 5). At high PV penetration these net-load lines vaguely resemble a duck and have thus come to be referred to by the shorthand name "duck curves" (CAISO, 2016). When the duck-curve is severe enough relative to the constraints on conventional generator operations, the result can be a reduction in the value PV provides to the system. On high penetration systems, these issues can occur on enough days of the year to result in significant PV value loss on an annual basis (Denholm et al., 2015; Obi and Bass, 2016). Previous work also shows how increased power-system flexibility could mitigate this loss of value in California (Brinkman et al., 2016; Denholm et al., 2016). Less research,

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however, has focused on the unique characteristics and lessons associated with high future PV penetrations in other potentially important U.S. PV markets.

Florida is one such important but understudied market. It has high solar potential located close to load centers, ranking eighth in the country for rooftop PV potential (Gagnon et al., 2016) and 16th for utility-scale solar potential (Lopez et al., 2012). Yet its solar deployment lags behind other states with similar or worse resource potential. In 2015, solar generation accounted for just 0.1% of Florida's electricity generation, compared with 2.4% in Vermont, 1.4% in Massachusetts, and 1.1% in North Carolina (EIA, 2016b). Steward and Doris (2014) finds that PV market development is highly correlated with state-level policies. The most developed markets in the U.S. are in states with net-metering and best-practice interconnection policies plus at least one other supporting policy. That supporting policy may authorize or allow third-party ownership, or may be a renewable portfolio standard with a solar set-aside. Florida does have a state-wide net metering policy, however, there is no renewable portfolio standard, and third-party ownership is generally disallowed.[1] Thus Florida is both a prime target and a blank slate–the state's PV deployment could rise rapidly if PV costs continue to decline (NREL, 2016; Lazard, 2016) and state-level policies become more supportive. Solar deployment in Florida also depends in large part on the actions of its vertically integrated utilities. Florida is served by two large investor-owned utilities, a number of smaller municipal and co-op utilities, and several coordinating entities. To the extent that these organizations are all very focused on operational reliability, a better understanding of grid integration issues could facilitate this growth or ease potential challenges associated with increasing PV penetration. In addition, Florida is an interesting analytical case because its main power system–the Florida Reliability Coordinating Council (FRCC)–serves almost the entire state and is largely isolated from other systems. This isolation enables direct analysis of flexibility technologies unconfounded by inter-system interactions.

After a brief section on methods (Section 2), we analyze the grid integration challenges associated with high PV deployment in Florida (Section 3.1), and we examine how additional system flexibility from enhanced operational

[1] http://www.dsireusa.org/resources/detailed-summary-maps/

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practices, battery storage capacity, and demand response (DR) might help Florida achieve a cost-effective, high-penetration PV future (Section 3.2). Following Denholm et al. (2016), we evaluate the economic carrying capacity (ECC) of PV in the FRCC power system and how it is impacted by flexibility options (Section 3.3). We also examine the impact of flexibility on system emissions (Section 3.4). One novel aspect of our analysis is our method for simulating flexibility from aggregated DR at new levels of fidelity. In this, we extend a growing body of work examining the value of DR in the bulk grid (Hummon et al., 2013; O'Connell et al., 2015), particularly DR's ability to provide flexibility in power systems with high variable generation penetrations (Denholm et al., 2016; Brinkman et al., 2016; Denholm and Margolis, 2016). We use an updated dataset to model fifteen different demand end-uses providing DR services in various combinations of energy shifting, contingency reserves, and regulation reserves for two different levels of demand response penetration. Our other contributions include examining high-penetration systems under mid and low natural gas prices, and exploring how future PV costs and social cost of carbon assumptions impact the potential deployment of PV in Florida should the economic carrying capacity be realized. In total we analyze 270 high-fidelity production cost simulations. Our high-level findings are summarized in Section 4. Supplemental Information Section 6 provides additional information on methods; Supplemental Information Section 7 presents additional results.

2. Methods

This study is primarily an exercise in production cost modeling of the FRCC power system. The detailed modeling assumptions required to create a realistic model of FRCC in 2026 under a wide range of PV penetrations are documented in Bloom et al. (2016), Denholm et al. (2016), and the Supplemental Information Section 6. Figure 1 depicts the elements we borrow alongside our contributions. In the remainder of this section we describe the methods and data we use to compute the value of PV in FRCC and model flexibility options. We conclude with a description of our scenario framework.

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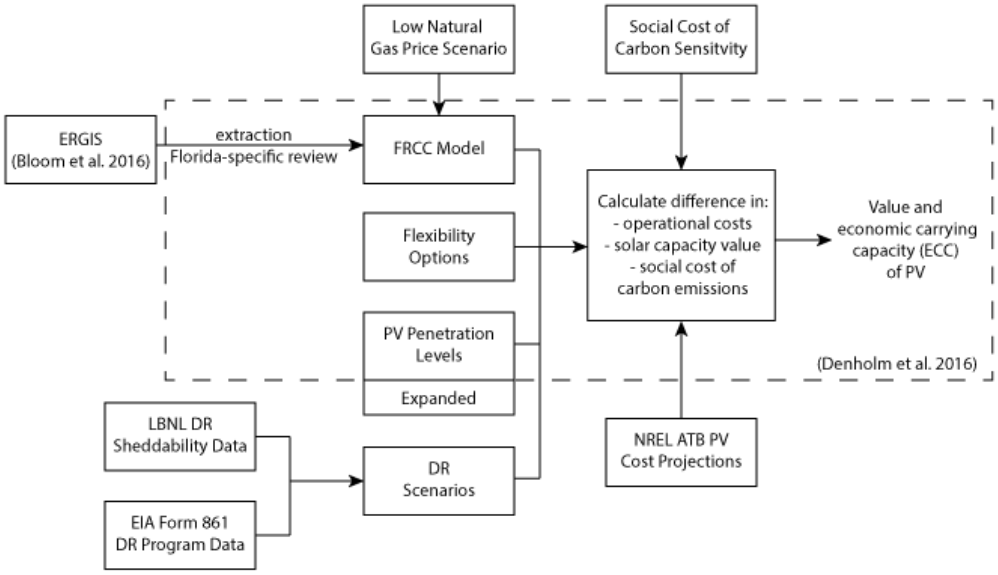

Figure 1: Schematic of methodology and data flow. The inclusion of all items not labeled with a citation into the methodological framework established by Denholm et al. (2016) is a main contribution of this paper. The sources of these data are described and cited in the text below.

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2.1. PV value and economic carrying capacity

We determine the economic carrying capacity of PV in the FRCC power system by equating PV's levelized cost of electricity (LCOE) with the value it provides to the system. The total value changes as more PV is added; we calculate and report the value of the next increment of PV to reflect the value added to the system by new investments. The increments are defined using a sequence of pre-curtailment PV-penetration scenarios, from 5% to 45% of annual load, with each scenario differing by about 5 percentage points. We calculate incremental value by comparing a higher-penetration system to the one just below it, holding everything else about the system constant. Three sources of value are measured: operational value, capacity value, and emissions-reduction value.

We determine operational value using a detailed production cost model of the FRCC system, represented and run in PLEXOS (Energy Exemplar, 2014). This model was developed from the larger Eastern Renewable Generation Integration Study model (Bloom et al., 2016) for Denholm et al. (2016), and it includes an explicit connection to the Georgia portion of the SERC Reliability Corporation[2] (SERC) modeled as a single time series of load, served by a supply curve of generators. The model represents the bulk system expected for FRCC in 2026, including all existing and planned generators, as well as additional PV generation to form the PV penetration scenarios needed for this study. The PV penetration scenarios consist of subsets of the 208 PV generators in FRCC from the ERGIS RTx30 scenario, starting with a sufficient number for the 5% scenario and sequentially adding on to create the scenarios up to 30%.[3] The PV capacity follows a roughly 60:40 split between utility-scale and distributed (residential and commercial rooftop) projects (Denholm et al., 2016). Each modeled PV generator is an aggregation of multiple generation profiles built up from fixed-axis, single-axis tracking, and rooftop settings in the System Advisor Model applied to irradiance profiles from the National Solar Radiation Database gridded dataset (NREL, 2014; Wilcox, 2012). In summary, the model has high geospatial and temporal

[2]Formerly the Southeast Electric Reliability Council (SERC), the SERC Reliability Corporation name was adopted in 2006.

[3]The higher PV penetration scenarios, which were developed primarily to round out our analysis of flexibility impacts at very low (outside the mid-2020s expected range) PV costs, are created by simply scaling the 30% scenario generation profiles.

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(hourly) resolution for power system components, load, and solar generation; capacity by type is shown in Figure 2. The modeled FRCC system has 256 TWh of annual load. In the base case with 5% PV penetration, gas combined cycle (CC) generators provide 62% of generation, coal provides 18%, nuclear 9%, PV 5%, and the remainder of energy is provided by biomass, hydropower, quick-start gas units, and imports from SERC.

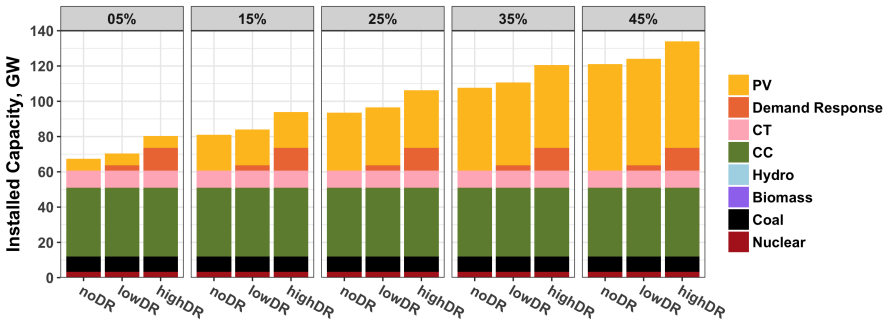

Figure 2: FRCC model installed capacity by solar photovoltaic (PV) penetration and demand response (DR) scenario. The thermal fleet and the PV penetration in SERC are held constant to facilitate comparisons across scenarios. The figure does not depict the battery capacity included in some of our scenarios, which amounts to either 1 GW or 4 GW spread throughout FRCC.

We simulate a year of grid operations at hourly time resolution, with two types of reserves: contingency and regulation. Contingency reserves are additional capacity committed to cover potential generator or transmission line failures. Regulation reserves are additional capacity held to meet normal fluctuations in net-load about its forecasted value. Net-load is the total system demand minus all variable generation. As more variable generation (including PV) is added to the system, somewhat larger net-load fluctuations are expected, and we account for this in the amount of regulation reserves required in each hour, as in Ibanez et al. (2012).

The operational value of the next increment of PV is the amount by which system operational costs fall when the next increment of PV is added. In our annual PLEXOS simulations, these costs include fuel cost, variable operation and maintenance costs, startup and shutdown costs, and the cost of imports. Adding PV to a system almost always reduces fuel costs and variable operation and maintenance costs. The impact of PV on startup and shutdown costs, as well as imports, is more mixed.

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The incremental capacity value of PV is the capacity credit of the next increment of PV, that is, the fraction of new PV capacity that contributes to meeting system peak demand, multiplied by the amount of new PV capacity and the system capacity price. We assume a capacity price of \$75/kW-year, based on the approximate annualized cost of a combustion turbine according to recent Annual Energy Outlook reports (EIA, 2016a), and calculate capacity credit using the system's top 100 net-load hours per Madaeni et al. (2012a). Because our PLEXOS model does not account for capacity expansion, this calculation is done as a post-processing step.

When not otherwise specified, we estimate the value of reduced emissions using a cost of \$50/metric ton CO_2, which is the social cost of carbon listed in Interagency Working Group (2010) for 2030 using a 2.5% discount rate. This emissions cost is not included in the production cost optimization and thus does not impact dispatch decisions; as with the capacity value calculation, it is applied as a post-processing step to determine the emissions-reduction component of incremental PV value. Given the current lack of a fully established carbon price in the United States, as well as the difficulties inherent in assigning costs to low-probability but potentially very severe future impacts, we also present results that use a range of carbon costs from the literature (Tol, 2008; Greenstone et al., 2013; Nordhaus, 2017; Interagency Working Group, 2010; Nordhaus, 2014) both in the main article and in the Supplemental Information. The lowest carbon cost in these reports for the years 2025-2030 is \$8.2/metric ton CO_2, based on the year 2025 and a 5% discount rate (Interagency Working Group, 2010). However, we set a lower bound of \$0/metric ton CO_2 to represent a fully externalized social cost of carbon. The highest reported values are those for the 95th percentile of potential costs attributable to greenhouse gas emissions, which attempt to capture fat tail catastrophic events that would lead to large amounts of harm if they occurred. The highest value used in our analysis is the 95th percentile value for the year 2025 reported in Nordhaus (2017), which is \$284.1/metric ton, although for simplicity we restrict attention in the main paper to the round values of \$0, \$50, and \$100 per metric ton.

2.2. System flexibility options

We investigate the impact of system flexibility on the economic carrying capacity of PV by overlaying a baseline scenario with a number of flexibility

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options. The baseline scenario is defined by a specific gas price and the full range of PV penetrations. In the category of operational flexibility, we group three options described in Denholm et al. (2016) into one Flex System scenario. In this scenario, the minimum generation level of CC units is lowered from 50% to 40%, PV is allowed to provide contingency and regulation reserves, and cooperation between FRCC balancing authorities is enhanced (Table 1). For PV to provide reserves, it must have headroom between its dispatch level and the total energy it is collecting. Thus, this largely occurs when PV is being curtailed. We also adopt the battery energy storage scenarios of 1 GW and 4 GW total capacity, with 6 hours of storage, spread throughout the FRCC territory from Denholm et al. (2016), applying them to the baseline scenario both alone and in combination with the Flex System package.

We construct two DR scenarios using data and methods similar to Olsen et al. (2013) and Hummon et al. (2013). Potential DR resources are modeled by electrical end use, e.g., agricultural water pumping or commercial cooling, and placed throughout the model at the rate of two virtual generators per end use per region. The potential DR available from each end use is constructed by applying time-varying fractional estimates of the degree to which the load can be shed or shifted – based on whether such shedding or shifting is physically possible, technically possible through automatic or manual control, and acceptable to end users – to an overall estimate of that end use's load time series. These estimates vary based on what grid service is being provided. For our operational modeling, we allow DR to provide energy shifting, contingency reserves, and regulation reserves.

We categorize electrical end uses as sheddable, thermal storage, or schedulable DR resources. Sheddable end uses cannot be shifted, and should not be perceptibly shed on a regular basis, but might tolerate short-timescale adjustments to provide regulation reserves or infrequent load sheds to provide contingency reserves. Lighting is a good example of this type of end use. Building heating and cooling are classic thermal storage resources, in which thermal capacitance makes it possible to shift operational timing, and thus provide DR services, with minimal effect on occupant comfort. Like thermal storage resources, schedulable loads enable shifting of energy use, but in a more straightforward manner. Typical schedulable loads include water pumping, and some manufacturing processes. For all end uses, we make particular assumptions about equipment capacity, energy payback, and ac-

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Table 1: Flexibility Packages Applied Alone or In Combination to Produce Flexibility Scenarios

Flexibility Option	Modeling Description	Levels
Demand Response	LBNL + NREL resource data modeled as virtual generators with storage. Two instances are placed per region and end-use combination.	Low DR High DR
Battery Storage	20 batteries of equal size are deployed throughout FRCC. Each battery has 6 hours of storage.	Battery, 1 GW Large Battery, 4 GW
PV Reserve Provider	PV is allowed to provide regulation and contingency reserves.	Flex System, package of all three options
40% CC Min Gen	The minimum generation for all CCs in FRCC is reduced from 50% of maximum capacity to 40%	
Reduced BA Friction	Reserve products (regulation and contingency) in FRCC are merged into a single product rather than individual products for each BA. Hurdle rates to import power are also removed.	

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ceptable event frequencies to create realistic virtual generator models. See the Supplemental Information for details.

The two DR packages are constructed by applying different controllability and acceptability assumptions to the amount of each end use assumed to be physically sheddable. The nature of the assumptions is different depending on whether the end use is considered more likely to be actuated by direct load control (DLC) or an energy management system (EMS). We determine DLC controllability and acceptability based on U.S. Energy Information Administration (EIA) Form 861 data on current proportions of customers enrolled in DLC programs (EIA, 2016c), plus an extra reduction applied to estimate more realistically how much residential cooling might be able to provide regulation reserves. EIA Form 861 data also inform our EMS resource levels through the reported proportions of customers a) with advanced metering infrastructure and b) enrolled in DR programs (EIA, 2016c). In addition, we further restrict the proportion of load in this category that can provide regulation reserves, and we model the acceptability of providing DR from building end uses as inversely proportional to an occupancy proxy; see Olsen et al. (2013) and the Supplemental Information.

Table 2: Potential Peak Load Shed by Sector (GW)

Package/Data Source	Residential	Commercial	Other
Low DR	1.45	1.19	0.02
EIA Form 861, 2015	1.57	1.29	0.34
High DR	3.65	6.90	0.55

We tune the assumptions that define the Low DR and High DR packages so the Low DR resources are similar in magnitude to the amount of DR available in Florida today. Both Florida Power & Light and Duke Energy, the two largest investor-owned utilities serving the state, have large DLC programs. We do not attempt to reflect those programs directly, but we choose our scenario parameters so that adding up the non-coincident contingency reserve peaks in our dataset by sector approximately matches the sum of the non-coincident potential peak load reduction numbers reported per sector and utility in the EIA Form 861 data (EIA, 2016c). The sizes of our DR packages by that measure are given in Table 2. Although we have tried to create DR scenarios of realistic overall magnitude, we are aware that our scenarios in no

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way match the the particulars of current or future DR programs in FRCC. As such, the DR results reported here should be interpreted as illustrative, not as a fully accurate rendering of current or future DR capabilities.

2.3. Scenario framework

The flexibility packages used to construct system flexibility scenarios are listed in Table 1. Individual scenarios are defined by PV penetration, DR option, system flexibility option, and natural gas price (Figure 3). The baseline/mid natural gas prices are from the EIA Annual Energy Outlook (AEO) 2014 Reference scenario for the South Atlantic region (EIA, 2014). Because natural gas prices are currently low, we also perform a low-gas-price sensitivity analysis using the AEO 2016 High Oil and Gas Resource scenario (EIA, 2016a). For the mid gas prices, we ran annual simulations for all combinations of the other options–162 simulations in total. For the low-gas-price sensitivity analysis, we reduce the number of scenarios to 108 by excluding the battery-only flexibility options.[4]

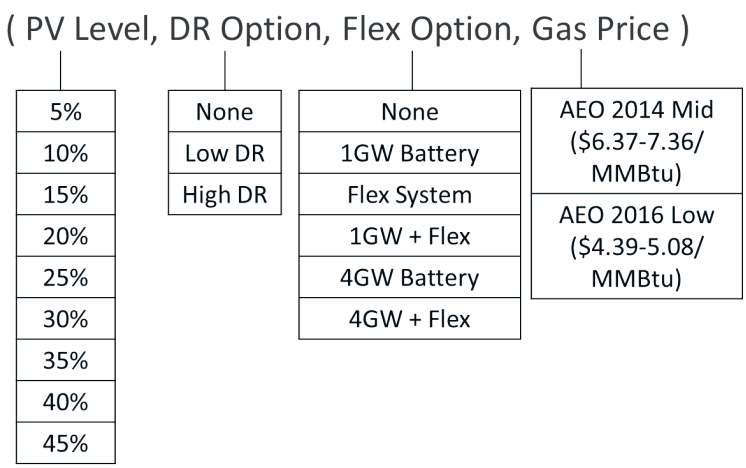

Figure 3: Scenarios are defined by choosing one option from each category. All combinations are simulated for the AEO 2014 mid gas price. The low-gas-price sensitivity analysis excludes the battery-only system flexibility options.

[4]This was done primarily for computational expediency. Each simulation required 15-30 hours of computational time, over 7300 hours for all scenarios included.

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3. Results

Although Florida has very little PV generation to date, it is reasonable to expect significant deployment in the 2020's under a variety of technology cost, fuel price, and policy assumptions (Cole et al., 2016a). For the Eastern Renewable Generation Integration Study (ERGIS) 30% scenarios, FRCC was outfitted with 37 GW and 53 GW of PV in the regional RTx30 and inter-regional ITx30 transmission upgrade scenarios, respectively, which translates to PV penetration levels of 20% and 32%–here and throughout this article, PV penetration is given on an annual energy basis; the penetration scenarios are specified using pre-curtailment annual energy (e.g., 30% PV pre-curtailment means PV could provide 30% of FRCC's annual energy needs if all collected PV energy was used by the system). We find, as detailed below, that flexibility becomes significantly more important for the integration of PV into FRCC starting at penetration levels of 15% to 20%. To fully describe the potential impacts of flexibility under a wide variety of conditions we explore a wide range of PV penetrations, up to 45%. We begin to describe the operational benefits of additional flexibility for systems with high PV penetrations by comparing 5%, 15%, and 30% PV model results.

3.1. Value Losses at High PV Penetrations under Baseline Flexibility Conditions

In both summer and winter, high PV penetrations in Florida would create periodic grid integration challenges owing to steep conventional generation ramping requirements and an inability to absorb all available PV generation. Figure 4 shows the dispatch for two key periods in FRCC. The first column shows a high ramping period in the winter heating season, and the second column shows the peak annual load period.[5] The 5% scenario represents

[5]In this paper we focus on integration issues associated with high PV availability and the subsequent inability of power systems to absorb all available generation. High penetration PV systems also raise reliability questions related to resource uncertainty. On short timescales, this manifests as solar forecasting errors, the desire to reduce them, and the need to adjust reserve requirements accordingly. On longer timescales (i.e., one to ten years) there is the question of what the generation portfolio should look like to ensure that peak demand can be met given the stochastic nature of PV generation. Both of those concerns are outside the scope of this paper, but see, e.g., Ibanez et al. (2012) and Madaeni et al. (2012b).

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baseline operations with minimal PV. For both periods shown, PV generation in the 30% PV scenario drastically impacts the dispatch of other resources. Coal plants turn down to their minimum generation levels in the morning and ramp back up in the evening. Combined-cycle units do the same, or they shut down and then start up again over the same timeframe. Some PV generation is curtailed in the morning when load is still low during the peak period, and more curtailment is seen in the middle of the day during the high ramp period when PV output is the highest. Whatever demand cannot be satisfied by coal and combined-cycle units in the morning and evening is met by quick-start combustion turbines and imports.

At the intermediate stage of 15% PV many of the same patterns are apparent, but they are much less severe; in particular a PV penetration of 15% is not enough to cause significant curtailment. Additionally, the peak load period is not significantly impacted by PV penetration at this point–PV tends to correlate well with load such that its main effect is to reduce peak net-load without creating the high morning ramp rates seen in the 30% PV scenario.

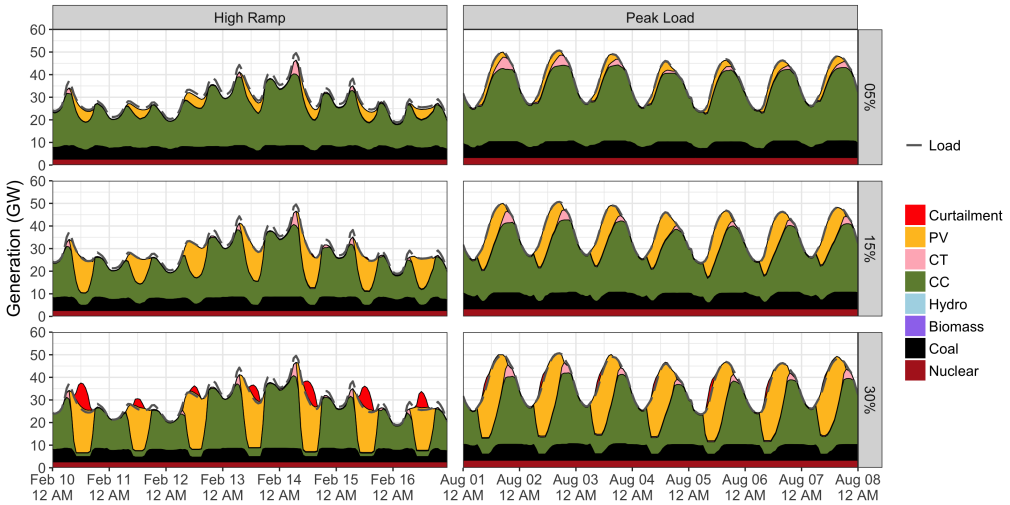

Figure 4: Dispatch of the FRCC system for 5%, 15% and 30% PV penetration during two high-stress periods: high net-load ramping (left) and peak annual load (right). The impacts of PV generation on other generator types can be seen as PV penetrations increase.

The diurnal pattern of PV generation creates daily net-load (load minus generation from variable wind and solar sources) time series with distinct morning and evening peaks that become more dramatic as PV penetration

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increases. (This is in contrast with wind generation patterns, whose variations are not so synchronized with daily cycles.) At high PV penetration these net-load lines vaguely resemble a duck and have thus come to be referred to by the shorthand name "duck curves" (CAISO, 2016). Figure 5 shows the FRCC duck curves for 1 day in the high ramp and peak load periods as PV penetration increases from 5% to 45%. Even before PV is added, the high ramp period has distinct morning and evening load peaks owing to the significant amount of electric heating within the FRCC system; this pattern is accentuated as PV penetration increases, eventually reaching a point where net-load drops below zero for a substantial portion of the day. Increasing PV penetration also creates operational challenges during the peak load period, although high coincident demand significantly delays the appearance of negative net-load intervals.

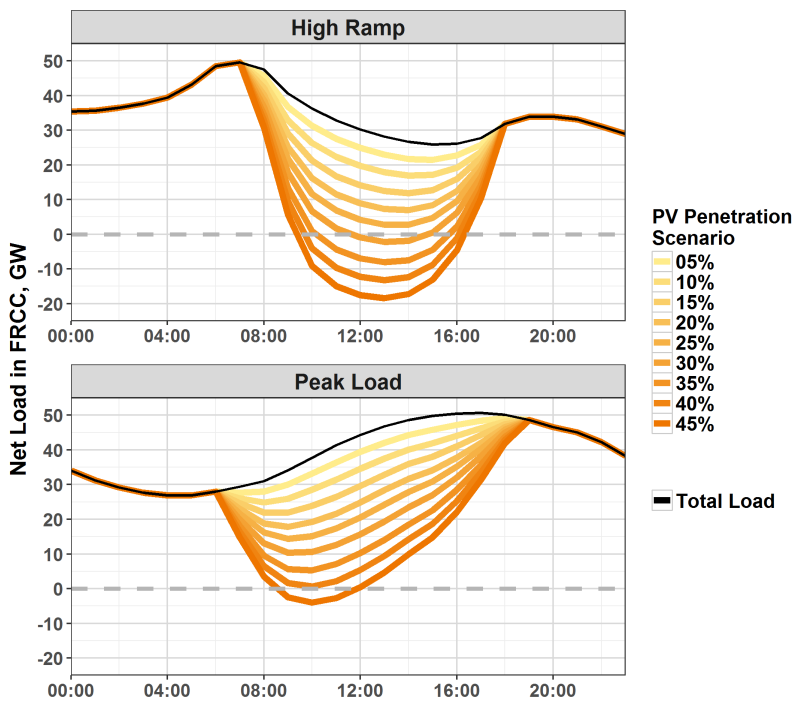

Figure 5: Duck curve in Florida during a day in the high ramp (top) and peak load (bottom) periods

Once high enough penetrations are achieved, such net-load patterns reduce the value of PV to the system and make further PV deployment less eco-

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nomically attractive. Increasing PV energy shifts the net-load peak to later in the day when PV output is lower, such that the next increment of PV contributes proportionally less to satisfying peak net-load, and thus provides significantly less capacity value to the overall system. Conventional generation is forced to start up and shut down more frequently to accommodate PV generation, increasing cycling costs. Negative net-load periods, ramping requirements, and minimum conventional generation levels necessitate increasing PV curtailment. For example, based on the peak load graph in Figure 4 with 30% PV penetration, the system operator reduces output from non-solar resources from 27 GW at 6:00 am to 13 GW at 9:00 am by turning generators down or off, and still must curtail over 6 GWh of PV. Then the operator must be able to ramp back up to the peak net demand of 46 GW at 7:00 pm. Backing down this much generation, or more, is not always feasible and sometimes requires additional PV curtailment, as seen in the high ramp period. As described in the next section, increasing the power system's flexibility can help address these issues and mitigate value losses.

3.2. Preserving Value at High PV Penetration with Flexibility Options

All of the flexibility options described above reduce curtailment in FRCC at high PV penetrations, but how this occurs and what happens at lower PV penetrations varies by scenario. Figure 6 summarizes these impacts as the difference, by technology, in annual generation between each flexibility scenario minus its baseline for mid natural gas prices. Avoided curtailment appears as an increase in solar generation. The columns correspond to different operational flexibility/battery packages, and the rows show different levels of DR. Comparing the Base + High DR scenario with the 1 GW Battery + No DR scenario reveals similar impacts on coal and PV generation, but DR is more likely to preempt combustion turbine use than is battery capacity, whose main effect is to shift generation away from gas combined cycle (CC) units. Comparing the Flex System with the battery-only scenarios shows the batteries consistently shifting generation away from CC units and toward coal, PV, and–at low PV penetrations–additional imports. In contrast, simply operating the system more flexibly consistently reduces imports and increases generation from CCs at low PV penetration.

In all mid-gas-price flexibility scenarios, coal generation increases, particularly at low PV penetrations. Supplementary Figure 17 shows the corre-

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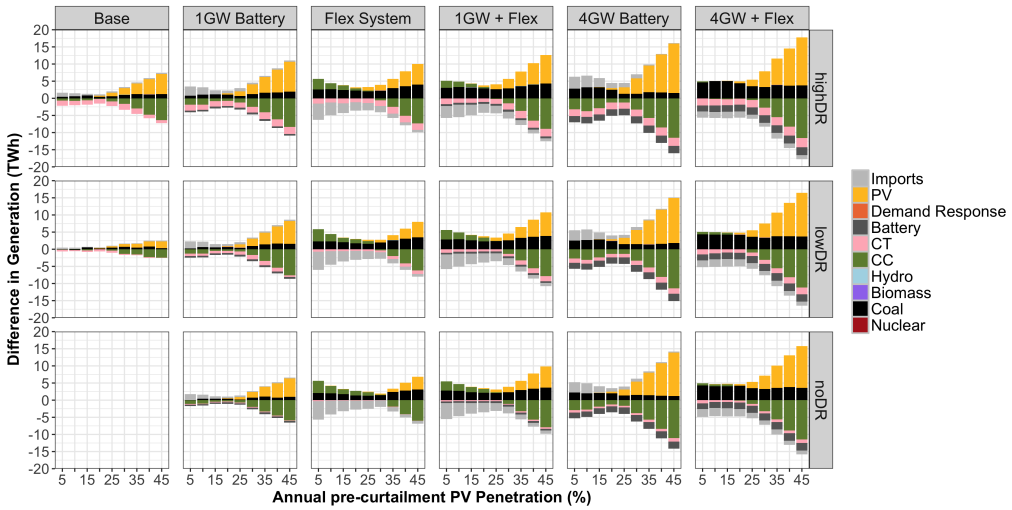

Figure 6: Differences in annual generation from the baseline scenario at each PV penetration, using mid gas prices

sponding changes in generation for the low-gas-price scenarios; in general, these scenarios have higher CC use and lower coal use owing to changes in generator merit order. The Flex System package in particular has a larger impact in the low-gas-price scenarios, because its reduced CC minimum generation levels complement low natural gas prices.

The modeled effects of our flexibility options on generation in FRCC have various impacts on the components of the value PV provides to the system. Figure 7 shows the incremental value of PV, by value component, for each mid-gas-price scenario. In general, PV derives positive value from offsetting fuel, variable operating and maintenance (VO&M), and emissions costs, and from providing capacity. However, PV's tendency to increase the cycling of traditional generators and the associated start and shutdown costs is a consistently negative drag on its value. The value impact of imports on PV is generally small and slightly positive, because PV generation allows FRCC to reduce its imports from SERC. As PV penetration increases, the capacity value of the next increment quickly degrades from its already modest level, and it is unaffected by the addition of flexibility options. The largest value streams for PV – offsetting fuel, VO&M, and emissions costs – also decline as PV penetrations increase, but our flexibility options help preserve some of their value. The effectiveness of flexibility at preserving PV value

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is largely determined by its ability to reduce marginal curtailment rates (see Supplementary Information Section 7.4).

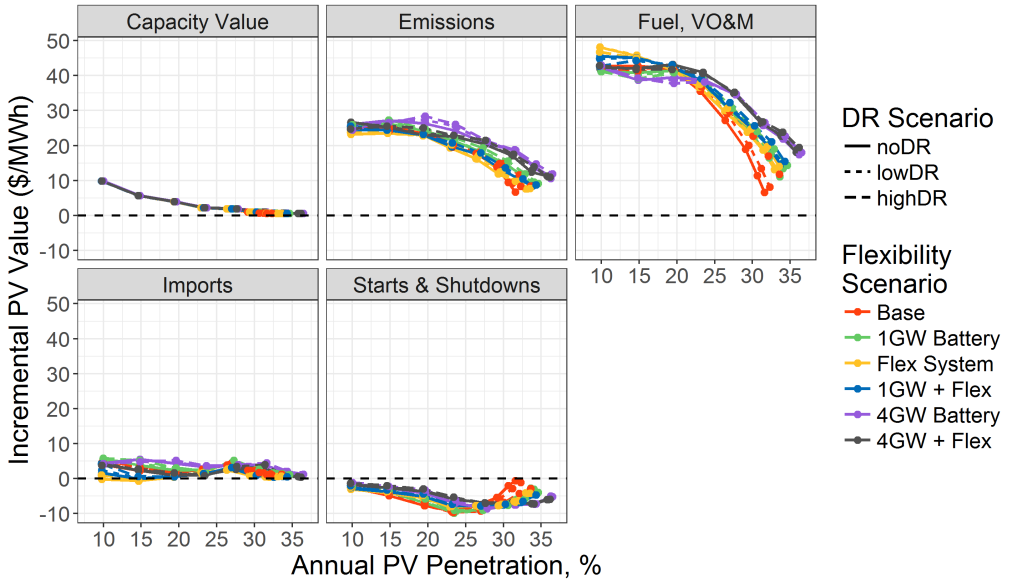

Figure 7: The component-wise incremental value of PV in FRCC under mid natural gas prices. Incremental PV value is measured by comparing each scenario to the one identical to it save for the PV penetration being 5 percentage points less on an annual generation, pre-curtailment basis.

Overall, our flexibility options help preserve PV's value in FRCC at high PV penetrations. Figure 8 shows the total incremental value of PV for all mid- and low-gas-price scenarios. Lower natural gas prices lead to lower average fuel costs and emission rates, thereby eroding the value of the next increment of PV and placing the value curves of the low-gas-price scenarios below the mid-gas-price curves. With low natural gas prices, the flexibility options also tend to shift more generation to CC units, which enhances the trend of lower avoided fuel and emissions values at low PV penetrations. For both the low- and mid-gas-price scenarios, flexibility options add little value at lower PV penetrations. However, the flexibility options–particularly the larger battery capacities available to shift electricity use–reduce curtailment and increase PV value substantially at high PV penetrations.

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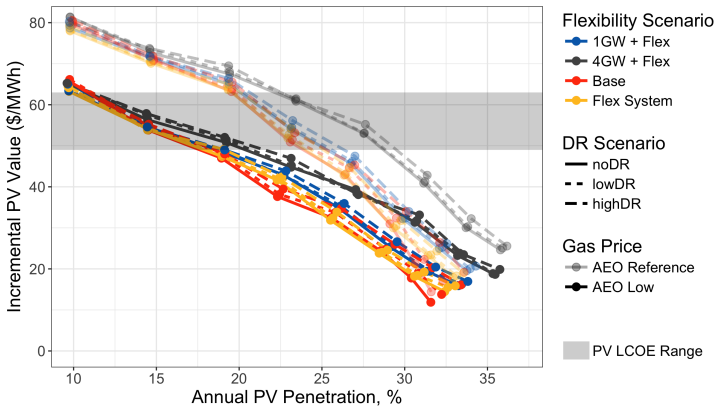

Figure 8: Total incremental value of PV as a function of annual PV penetration for mid- and low-gas-price scenarios and a variety of flexibility packages. The PV LCOE range represents the likely range of PV prices expected in 2026, represented by the ATB mid- to low-PV-price trajectories.

3.3. Flexibility Can Increase the Economic Carrying Capacity of PV

The economic carrying capacity of PV can be elicited from Figure 8 by assuming it is economically efficient to install PV until its incremental value is equal to its cost. For example, at a PV cost of $60/MWh, the baseline economic carrying capacity of PV is about 12% (low gas prices) or 21% (mid gas prices) of annual generation. The impact of different flexibility measures on PV integration can be measured as the percentage-point increase in economic carrying capacity achieved by that flexibility measure as compared with the baseline scenario, for a given PV cost. Figure 9 shows that metric as a function of PV cost for several flexibility options and mid gas prices. The analogous figure for low gas prices is available in Supplementary Information Figure 20.

Our flexibility options generally increase the economic carrying capacity of PV in FRCC. The larger of the two battery capacities (4 GW) has the greatest impact on PV carrying capacity, enabling 4 to 6 percentage points more PV than the base scenario at low PV costs. The Low DR scenario has a minimal impact, less than one additional percentage point, at all PV costs considered here. The High DR scenario performs similarly to a 1-GW battery by this measure; both result in a 1-2 percentage point increase in the economic carrying capacity of PV. The findings with low gas prices are sim-

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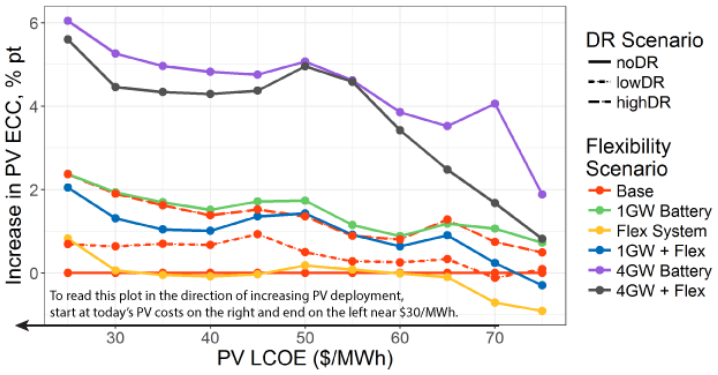

Figure 9: Increase in the economic carrying capacity of PV under mid gas prices for several flexibility scenarios, compared with the base scenario

ilar for low PV costs; however at high PV costs and low gas prices, system flexibility actually reduces the economic carrying capacity of PV by reducing the cost of the generation that PV ultimately replaces. The crossover point varies somewhat by flexibility option, see the Supplementary Information for details.

We extend the above analysis by using the 2016 Annual Technology Baseline (ATB) projections for PV costs in 2026 to translate economic carrying capacity into potential deployment levels in 2026 (NREL, 2016). The costs for a 20% capacity factor utility-scale system are $63/MWh for the mid-PV-price trajectory, and $49/MWh for the low-PV-price trajectory, on a LCOE basis. With the mid PV price, maximum economic deployment of PV in FRCC in 2026 ranges from 10%-24% depending on system gas price and flexibility. Low PV prices increase this estimate to 18%-30%. Those ranges assume a $50/metric ton social cost of carbon. If we instead allow for a range of carbon cost assumptions, we see a wide range of potential penetrations (Figure 10).[6]

[6]Note that while the social cost of carbon attempts very specifically to measure and blend the costs and likelihoods of various potential climate change impacts, additional value assigned to PV generation over and above that derived from reduced production and capacity costs can also be interpreted as a more general preference for cleaner, more local, or more diverse sources of electricity. People generally express very high willingness to pay for such benefits in survey data (Borchers et al., 2007; Longo et al., 2008; Claudy et al., 2011). Lower bounds can be estimated from voluntary green power market participation rates and costs (Heeter et al., 2014).

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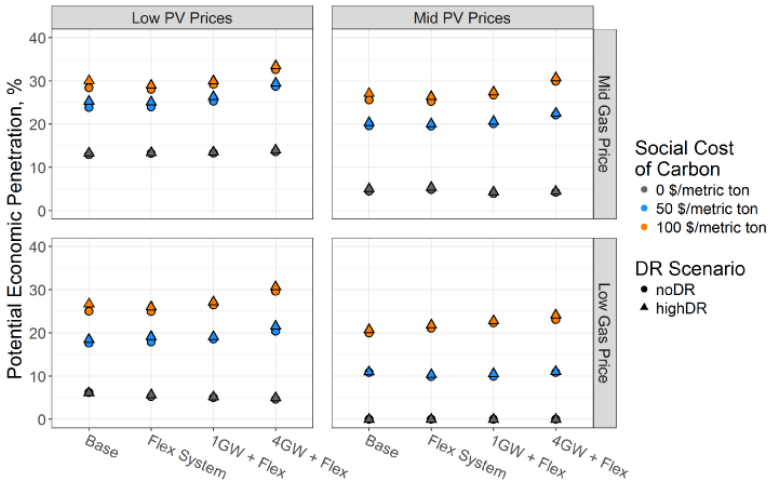

Figure 10: Potential economic penetration of PV in FRCC in 2026 under different flexibility, PV price, gas price, and carbon cost assumptions.

If no costs are assigned to carbon emissions, the potential economic penetration in 2026 under mid PV prices is zero if natural gas prices are also low. However, either higher natural gas prices or lower PV prices are enough to make PV an attractive investment up to penetrations of at least 5%–and up to 13% if both conditions hold–even if carbon emissions and other reasons to prefer PV over other types of generation remain fully externalized. Energy-shifting flexibility, such as that provided by battery storage and certain types of DR, increases economic carrying capacity more at higher PV penetrations and thus only comes into play in the 2026 timeframe if conditions are favorable enough for PV. Under mid PV and low natural gas prices, assumed carbon costs must be around $100/metric ton for this flexibility to make a significant impact in our modeled 2026 system. Under other conditions, our baseline assumption of $50/metric ton is sufficient for system flexibility to have a positive effect on PV deployment potential in 2026.

3.4. Emissions Impacts of Flexibility Depend on Gas Price and PV Penetration

Reducing carbon emissions is important owing to both climate impacts and the correlation of carbon with other emissions that impact air and water quality. However, because there is no national carbon tax or other explicit

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price on emissions, we do not include emission costs in the production cost optimization. Thus the lowest-cost operations simulated by our models may increase system emissions when flexibility is added (Figure 11).

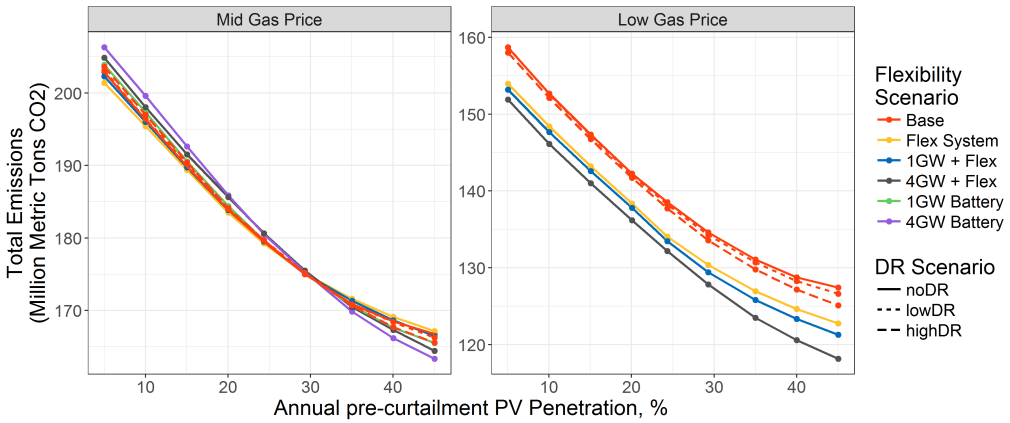

Figure 11: Total carbon emissions in the combined FRCC-SERC system by natural gas price regime and for several flexibility scenarios

All mid-gas-price scenarios with batteries or DR, except for the 1GW + Flex System scenario, increase emissions over the baseline scenario for PV penetrations up to 30%, a result similar to that in Fares and Webber (2017). This means that any emissions reductions achieved by reducing PV curtailment are canceled out by other effects, including increased load required to compensate for battery roundtrip efficiency losses and the tendency to shift generation from natural gas peaking plants to lower-cost conventional sources, such as coal. Above 30% PV penetration, batteries can charge and DR can increase load almost exclusively during times of PV curtailment and then shift this energy use to other times of the day, thus lowering overall system emissions. Flexibility reduces emissions for all low-gas-price scenarios, because in this regime flexibility predominantly reduces coal generation in favor of natural gas. The size of this effect for scenarios including the Flex option is approximately equivalent to increasing the PV penetration by 5%.

In general, at PV penetrations lower than those that result in significant curtailment, the effect of system flexibility on externalized emissions depends highly on the current makeup of the generator fleet and relative fuel prices. If coal generators have a marginal price advantage over CC units, for instance, energy storage is likely to increase, rather than reduce, emissions when PV

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penetrations are modest. On the other hand, at least in the FRCC system we studied, flexibility generally reduces emissions when gas prices are low or the PV penetration is high.

4. Conclusions

Our modeling study determines the value of PV in FRCC under a wide range of conditions finding that Florida should prepare for penetrations of at least 5%, and more likely 10-24%, within the next decade under all but the most pessimistic of conditions for PV deployment. At the higher end of these central estimates, our modeling shows the emergence of some duck curve challenges in Florida, the associated loss of PV value under baseline flexibility assumptions, and the ability of flexibility options to preserve some of this value and thereby enable higher levels of PV deployment. DR is one effective option; our High DR option preserves enough value to boost the economic carrying capacity of PV by 1-2 percentage points at mid gas prices. This impact is comparable to the impact of implementing 1 GW of battery storage, whereas adding 4 GW of storage expands the economic carrying capacity by up to 6 percentage points at low PV prices. Batteries, however, are likely to cost substantially more than at least some forms of DR even in the 2026 timeframe, depending on the required energy capacity (Nykvist and Nilsson, 2015; Cole et al., 2016b; Alstone et al., 2016). Among the options we analyze, enhanced operational flexibility–a combination of reducing CC minimum generation, allowing PV to provide contingency and regulation reserves, and improving balancing authority cooperation–typically has little impact on the ECC of PV with a tendency to reduce it at higher PV prices.

By applying PV price projections, we calculate Florida's economic PV potential to be 20%-24% of annual generation in 2026 without flexibility options, at mid gas prices and assuming a carbon cost of $50/metric ton. With flexibility options, this potential penetration rises to 20%-30%. The benefits of flexibility options become more significant after incremental curtailment rates start to climb at PV penetrations around 15%-20%.

We also analyze the sensitivity of economic PV deployment potential with and without flexibility options under varying natural gas prices and carbon

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costs. Both are significant drivers of PV value. Lower natural gas prices reduce the value of avoided fuel and emissions, such that the economic deployment potential drops to 11%-18% without flexibility options and 10%-22% with them. The ex-post assumed social cost of carbon has a particularly large impact, yet it is highly uncertain; our literature review revealed estimates of \$8-\$284 per metric ton for the mid-2020s timeframe. Under most conditions, however, if a carbon cost of at least \$50/metric ton were to emerge from the public discourse, that would be sufficient to support PV penetrations at or above the point where flexibility options enhance potential PV penetration.

Future work could include expanding the range of flexibility options considered. For example, it would be worthwhile to examine under what conditions energy storage cost trends warrant larger storage buildouts than our 4-GW option. In addition, a wider range of DR possibilities could be explored, particularly the large potential of scheduled electric vehicle charging. DR modeling methods could be refined to account realistically for all relevant physical phenomena such as the time-varying roundtrip efficiencies for thermal mass-based energy shifting seen for individual end-uses in Beil et al. (2015); Cole et al. (2014); O'Connell et al. (2015).

5. References

Alstone, P., Potter, J., Piette, M. A., Schwartz, P., Berger, M. A., Dunn, L. N., Smith, S. J., Sohn, M. D., Aghajanzadeh, A., Stensson, S., Szinai, J., Apr. 2016. Interim Report on Phase 1 Results. Technical Report, California Public Utilities Commission (CPUC).
URL http://www.cpuc.ca.gov/General.aspx?id=10622

Beil, I., Hiskens, I. A., Backhaus, S., 2015. Round-trip efficiency of fast demand response in a large commercial air conditioner. Energy and Buildings 97, 47–55.
URL http://www.sciencedirect.com/science/article/pii/S0378778815002200

Bloom, A., Townsend, A., Palchak, D., Novacheck, J., King, J., Barrows, C., Ibanez, E., O'Connell, M., Jordan, G., Roberts, B., Draxl, C., Gruchalla, K., Aug. 2016. Eastern Renewable Generation Integration Study. Tech. Rep. NREL/TP-6A20-64472, NREL, Golden, CO.
URL http://www.nrel.gov/docs/fy16osti/64472.pdf

Pursuant to the DOE Public Access Plan, this document represents the authors' peer-reviewed, accepted manuscript. The published version of the article is available from the relevant publisher.

Borchers, A. M., Duke, J. M., Parsons, G. R., Jun. 2007. Does willingness to pay for green energy differ by source? Energy Policy 35 (6), 3327–3334.
URL http://www.sciencedirect.com/science/article/pii/S0301421506005131

Brinkman, G., Jorgenson, J., Ehlen, A., Caldwell, J., Jan. 2016. Low Carbon Grid Study: Analysis of a 50% Emission Reduction in California. Technical Report NREL/TP-6A20-64884, NREL (National Renewable Energy Laboratory (NREL), Golden, CO.
URL http://www.nrel.gov/docs/fy16osti/64884.pdf

CAISO, 2016. Fast Facts: What the duck curve tells us about managing a green grid.
URL https://www.caiso.com/Documents/FlexibleResourcesHelpRenewables_FastFacts.pdf

Chow, L., Brant, S., Gannon, J., Sellden, C., Jan. 2017. The 2015 Resource Adequacy Report. Tech. rep., California Public Utilities Commission (CPUC).

Claudy, M. C., Michelsen, C., O'Driscoll, A., Mar. 2011. The diffusion of microgeneration technologies – assessing the influence of perceived product characteristics on home owners' willingness to pay. Energy Policy 39 (3), 1459–1469.
URL http://www.sciencedirect.com/science/article/pii/S0301421510009183

Cole, W., Mai, T., Logan, J., Steinberg, D., McCall, J., Richards, J., Sigrin, B., Porro, G., Nov. 2016a. 2016 Standard Scenarios Report: A U.S. Electricity Sector Outlook. Technical Report NREL/TP-6A20-66939, National Renewable Energy Laboratory, Golden, Colorado.
URL http://www.nrel.gov/docs/fy17osti/66939.pdf

Cole, W. J., Marcy, C., Krishnan, V. K., Margolis, R., 2016b. Utility-scale lithium-ion storage cost projections for use in capacity expansion models. In: North American Power Symposium (NAPS), 2016. IEEE, pp. 1–6.
URL http://ieeexplore.ieee.org/abstract/document/7747866/

Cole, W. J., Powell, K. M., Hale, E. T., Edgar, T. F., 2014. Reduced-order residential home modeling for model predictive control. Energy and

Pursuant to the DOE Public Access Plan, this document represents the authors' peer-reviewed, accepted manuscript. The published version of the article is available from the relevant publisher.

Buildings 74, 69–77.
URL http://www.sciencedirect.com/science/article/pii/S0378778814000711

Denholm, P., Margolis, R., Aug. 2016. Energy Storage Requirements for Achieving 50% Solar Photovoltaic Energy Penetration in California. Technical Report NREL/TP-6A20-66595, National Renewable Energy Laboratory, Golden, Colorado.
URL http://www.nrel.gov/docs/fy16osti/66595.pdf

Denholm, P., Novacheck, J., Jorgenson, J., O'Connell, M., Dec. 2016. Impact of Flexibility Options on Grid Economic Carrying Capacity of Solar and Wind: Three Case Studies. Technical Report NREL/TP-6A20-66854, National Renewable Energy Laboratory, Golden, Colorado.
URL http://www.nrel.gov/docs/fy17osti/66854.pdf

Denholm, P., O'Connell, M., Brinkman, G., Jorgenson, J., Nov. 2015. Overgeneration from Solar Energy in California: A Field Guide to the Duck Chart. NREL Technical Report NREL/TP-6A20-65023, National Renewable Energy Laboratory, Golden, CO.
URL http://www.nrel.gov/docs/fy16osti/65023.pdf

EIA, Apr. 2013. Annual Energy Outlook 2013 with projections to 2040. Tech. Rep. DOE/EIA-0383(2013), U.S. Energy Information Administration.
URL https://www.eia.gov/outlooks/aeo/pdf/0383(2013).pdf

EIA, Apr. 2014. Annual Energy Outlook 2014 (with projections to 2040). Tech. rep., U.S. Energy Information Administration.
URL https://www.eia.gov/outlooks/aeo/pdf/0383(2014).pdf

EIA, 2015. Electric power sales, revenue, and energy efficiency Form EIA-861 detailed data files: Annual data for 2013. Tech. rep., U.S. Energy Information Administration.
URL https://www.eia.gov/electricity/data/eia861/

EIA, Aug. 2016a. Annual Energy Outlook 2016 (with projections to 2040). Tech. Rep. DOE/EIA-0383, U.S. Energy Information Administration.
URL https://www.eia.gov/outlooks/aeo/pdf/0383%282017%29.pdf

Pursuant to the DOE Public Access Plan, this document represents the authors' peer-reviewed, accepted manuscript. The published version of the article is available from the relevant publisher.

EIA, Nov. 2016b. Electric Power Annual 2015. Tech. rep., U.S. Energy Information Administration, Washington, D.C.
URL https://www.eia.gov/electricity/annual/pdf/epa.pdf

EIA, 2016c. Electric power sales, revenue, and energy efficiency Form EIA-861 detailed data files: Annual data for 2015. Tech. rep., U.S. Energy Information Administration.
URL https://www.eia.gov/electricity/data/eia861/

Exemplar, E., Oct. 2014. PLEXOS, Version 6.4.
URL http://energyexemplar.com/software

Fares, R. L., Webber, M. E., Jan. 2017. The impacts of storing solar energy in the home to reduce reliance on the utility. Nature Energy 2, 17001.
URL http://www.nature.com/articles/nenergy20171

Gagnon, P., Margolis, R., Melius, J., Phillips, C., Elmore, R., Jan. 2016. Rooftop Solar Photovoltaic Technical Potential in the United States: A Detailed Assessment. Technical Report NREL/TP-6A20-65298, National Renewable Energy Laboratory, Golden, Colorado.
URL http://www.nrel.gov/docs/fy16osti/65298.pdf

Greenstone, M., Kopits, E., Wolverton, A., Jan. 2013. Developing a Social Cost of Carbon for US Regulatory Analysis: A Methodology and Interpretation. Review of Environmental Economics and Policy 7 (1), 23–46.
URL https://academic.oup.com/reep/article/7/1/23/1577964/Developing-a-Social-Cost-of-Carbon-for-US

Heeter, J., Belyeu, K., Kuskova-Burns, K., Nov. 2014. Status and Trends in the US Voluntary Green Power Market (2013 Data). Technical Report NREL/TP-6A20-63052, National Renewable Energy Laboratory, Golden, Colorado.
URL https://www.nrel.gov/docs/fy15osti/63052.pdf

Hummon, M., Palchak, D., Denholm, P., Jorgenson, J., Dec. 2013. Grid Integration of Aggregated Demand Response, Part 2: Modeling Demand Response in a Production Cost Model. Technical Report NREL/TP-6A20-58492, NREL (National Renewable Energy Laboratory (NREL), Golden, CO.
URL http://www.nrel.gov/docs/fy14osti/58492.pdf

Pursuant to the DOE Public Access Plan, this document represents the authors' peer-reviewed, accepted manuscript. The published version of the article is available from the relevant publisher.

Ibanez, E., Brinkman, G., Hummon, M., Lew, D., 2012. Solar Reserve Methodology for Renewable Energy Integration Studies Based on Sub-Hourly Variability Analysis: Preprint. Conference Paper NREL/CP-5500-56169, 2nd Annual International Workshop on Integration of Solar Power Systems Conference, Lisbon, Portugal.

Interagency Working Group, Feb. 2010. Technical Support Document: Social Cost of Carbon for Regulatory Impact Analysis Under Executive Order 12866. Tech. rep., Interagency Working Group on Social Cost of Carbon.
URL https://www.epa.gov/sites/production/files/2016-12/documents/scc_tsd_2010.pdf

Lazard, Dec. 2016. Lazard's Levelized Cost of Energy Analysis – Version 10.0. Tech. rep.
URL https://www.lazard.com/media/438038/levelized-cost-of-energy-v100.pdf

Longo, A., Markandya, A., Petrucci, M., Aug. 2008. The internalization of externalities in the production of electricity: Willingness to pay for the attributes of a policy for renewable energy. Ecological Economics 67 (1), 140–152.
URL http://www.sciencedirect.com/science/article/pii/S0921800907006064

Lopez, A., Roberts, B., Heimiller, D., Blair, N., Porro, G., Jul. 2012. U.S. Renewable Energy Technical Potentials: A GIS-Based Analysis. Technical Report NREL/TP-6A20-51946, National Renewable Energy Laboratory, Golden, Colorado.
URL http://www.nrel.gov/docs/fy12osti/51946.pdf

Madaeni, S. H., Denholm, P., Sioshansi, R., Jul. 2012a. Comparison of Capacity Value Methods for Photovoltaics in the Western United States. NREL Technical Report NREL/TP-6A20-54704, National Renewable Energy Laboratory.
URL http://www.nrel.gov/docs/fy12osti/54704.pdf

Madaeni, S. H., Denholm, P., Sioshansi, R., Jul. 2012b. Comparison of Capacity Value Methods for Photovoltaics in the Western United States.

Pursuant to the DOE Public Access Plan, this document represents the authors' peer-reviewed, accepted manuscript. The published version of the article is available from the relevant publisher.

NREL Technical Report NREL/TP-6A20-54704, National Renewable Energy Laboratory.
URL http://www.nrel.gov/docs/fy12osti/54704.pdf

Margolis, R., Feldman, D., Boff, D., 2017. Q4 2016/Q1 2017 Solar Industry Update.
URL http://www.nrel.gov/docs/fy17osti/68425.pdf

Nordhaus, W., Mar. 2014. Estimates of the Social Cost of Carbon: Concepts and Results from the DICE-2013r Model and Alternative Approaches. Journal of the Association of Environmental and Resource Economists 1 (1/2), 273–312.
URL http://www.journals.uchicago.edu/doi/abs/10.1086/676035

Nordhaus, W. D., Feb. 2017. Revisiting the social cost of carbon. Proceedings of the National Academy of Sciences 114 (7), 1518–1523.
URL http://www.pnas.org/content/114/7/1518

NREL, Jan. 2014. System Advisor Model (SAM).
URL https://sam.nrel.gov/

NREL, Sep. 2016. 2016 Annual Technology Baseline. Tech. rep., National Renewable Energy Laboratory (NREL), Golden, CO.
URL http://www.nrel.gov/analysis/data_tech_baseline.html

Nykvist, B., Nilsson, M. a., 2015. Rapidly falling costs of battery packs for electric vehicles. Nature Climate Change.
URL http://www.nature.com/nclimate/journal/vaop/ncurrent/full/nclimate2564.html

Obi, M., Bass, R., May 2016. Trends and challenges of grid-connected photovoltaic systems – A review. Renewable and Sustainable Energy Reviews 58, 1082–1094.
URL http://www.sciencedirect.com/science/article/pii/S136403211501672X

O'Connell, N., Hale, E., Doebber, I., Jorgenson, J., Jul. 2015. On the Inclusion of Energy-Shifting Demand Response in Production Cost Models: Methodology and a Case Study. Technical Report NREL/TP-6A20-64465, National Renewable Energy Laboratory, Golden, Colorado.

Pursuant to the DOE Public Access Plan, this document represents the authors' peer-reviewed, accepted manuscript. The published version of the article is available from the relevant publisher.

Olsen, D. J., Matson, N., Sohn, M. D., Rose, C., Dudley, J., Goli, S., Kiliccote, S., Hummon, M., Palchak, D., Denholm, P., Jorgenson, J., Ma, O., Sep. 2013. Grid Integration of Aggregated Demand Response, Part 1: Load Availability Profiles and Constraints for the Western Interconnection. Technical Report LBNL-6417E, Lawrence Berkeley National Laboratory, Berkeley, California.

Steward, D., Doris, E., 2014. Effect of State Policy Suites on the Development of Solar Markets. Technical Report DOE/GO-102014-4477, National Renewable Energy Laboratory, Golden, Colorado.
URL http://www.nrel.gov/docs/fy15osti/62506.pdf

Tol, R. S. J., 2008. The Social Cost of Carbon: Trends, Outliers and Catastrophes. Economics: The Open-Access, Open-Assessment E-Journal 2 (2008-25).
URL https://papers.ssrn.com/abstract=1726820

Wilcox, S., Aug. 2012. National Solar Radiation Database 1991–2010 Update: User's Manual. Technical Report NREL/TP-5500-54824, National Renewable Energy Laboratory, Golden, Colorado.
URL http://www.nrel.gov/docs/fy12osti/54824.pdf

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Supplementary Information

6. Additional Information on Methods

6.1. Production Cost Model

PLEXOS is a commercial production cost model that minimizes the total operational cost of meeting a power system's time varying load on a rolling horizon basis, subject to generator, transmission, and reliability constraints. For this analysis, we modeled the projected generation mix in Florida Reliability Coordinating Council (FRCC) in the year 2026. All transmission lines and bulk power level generators are included in the model (Denholm et al., 2016). Figure 2 shows the total installed capacity of FRCC for increasing photovoltaic (PV) penetrations and for each demand response (DR) scenario. The scenarios with batteries added 1 GW or 4 GW of battery capacity for the small and large battery scenarios, respectively. The demand response capacity is measured as the non-coincident sum of each virtual generator's peak capacity for providing contingency reserves.

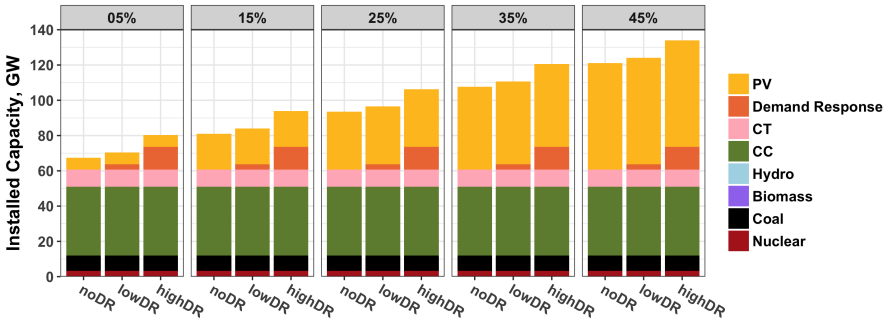

Figure 12: Installed capacity in FRCC at increasing PV penetration for each DR scenario.

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Relevant generator operational constraints were modeled, including maximum capacity, minimum operational levels, minimum up and down times, ramp rates, planned and forced outages, and start costs. Transmission lines were modeled using a DC power flow formulation, with line limits enforced on all lines with voltages at or above 200 kV.

For this analysis we modeled the commitment of all generators in the day ahead market at hourly resolution. We did not include a second phase of real-time dispatch for the system; thus the impact of forecast errors does not appear in the results. The model optimizes one day at a time, computing the optimal solution for all 24 hours simultaneously. It additionally has 24 of "look-ahead", where the model has some foresight of the future but is not attempting to optimize those time periods. This allows us to represent constraints with daily time horizons in the model, such as the number of hours per day a DR provider is willing to operate. Longer-term constraints, such as monthly hydropower limits, are modeled using a mid-term optimization, which runs before the day ahead market and optimizes the full year at a monthly resolution using a load-duration curve method. The results of this optimization are used to formulate shorter-term constraints for the hydropower generation, such that it can be optimized each day but still adhere to the longer-term requirements on its operation.

One important source of flexibility in the model is the transmission connection between FRCC and the SERC Reliability Corporation (SERC). Previous work modeled the market friction between FRCC and SERC with a hurdle rate, a price on energy exchanged between regions. These hurdle rates have been adjusted since Denholm et al. (2016) to better represent the actual flexibility of the FRCC-SERC connection. Additionally, a price on ramping across the interface was added to limit the flexibility associated with imports and exports between FRCC and its neighbors to better measure the impacts of increased flexibility within FRCC.

6.2. Demand Response Resource Models

The demand response resource scenarios were built up by applying time varying fractional filters to an estimate, by utility, of the electricity load broken down by end use. An example week of this load data for all of FRCC

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is shown in Figure 13.[7] The first filter applied to transform this data into a flexible resource is the shed filter, which represents the amount of load that could be subtracted from or added to the baseline load level absent any limitations on communications, or control, or customer incentives. The methodology for estimating this filter is largely unchanged from that in Olsen et al. (2013). For this project the dataset was extended to cover all of the United States, and to be time synchronous with our production cost model, whose weather year is 2006.

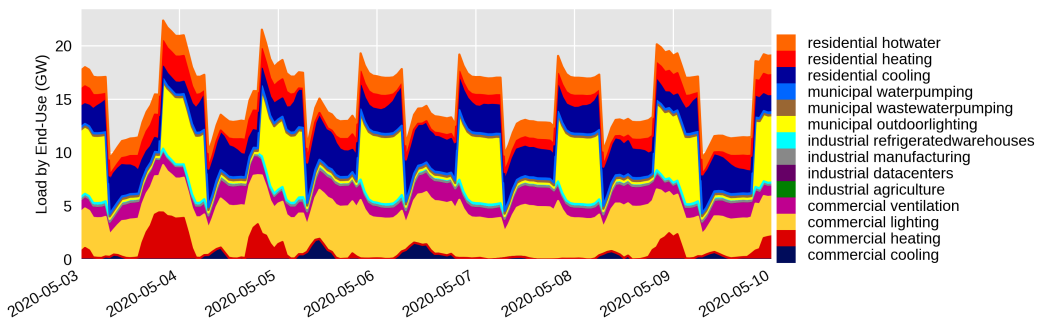

Figure 13: Load timeseries data for end-uses modeled as providing demand response for one spring week.

Further filters were applied to construct two demand response scenarios: Low DR and High DR. The methods for doing this differed depending on whether the end-use was categorized as a direct load control (DLC), or energy management system (EMS) resource. DLC resources are assumed to be directly controlled by the utility or other demand response aggregator. EMS based demand response may also receive signals from a utility or other aggregator, but the control is more sophisticated, perhaps holistically actuating a number of different systems and appliances spread across an entire building or site, and able to take in information about owner and occupant preferences.

As mentioned in the Methods, for DLC end-uses, after accounting for sheddability, the amount of load able to provide demand response was further

[7]The load data was built up from 2013 EIA Form 861 data (EIA, 2015), and many other data sources as described in Olsen et al. (2013). The load data shown in the figure, and the demand response resource data used in this work, was increased by 10.4% based on a 0.826% annual growth rate (EIA, 2013) to better match the 2026 load levels modeled in the FRCC production cost model.

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limited by the U.S. Energy Information Administration (EIA) Form 861 data on current proportions of customers enrolled in DLC programs (EIA, 2016c). Based on tuning the Low DR scenario to approximately match current demand response levels in Florida and looking for an aggressive, yet achievable High DR scenario, we used the 95th percentile of fractional non-zero participation rates in DLC programs in the FRCC utilities for Low DR, and the 95th percentile of fractional non-zero participation rates in DLC programs in the entire United States for High DR, both on a by-sector basis. The resulting filter values are shown in Table 3. For the end uses listed below that are marked as municipal, the average of the commercial and industrial filter values are applied. Since there is no additional customer interaction once DLC is installed, no further filters reducing the amount of load able to provide demand response were constructed, except for an additional multiplicative factor of 0 and 0.05, respectively, on the amount of residential cooling load able to provide regulation reserves in the Low DR and High DR scenarios.

Table 3: Demand Response Resource Filters Derived from EIA Form 861 Data

End-Use Type	DR Scenario	EIA Form 861 Participation Rate	Residential	Commercial	Industrial
DLC	Low	DLC, 95th Percentile of Non-Zero Values, FRCC Utilities	0.25	0.003	0.04
	High	DLC, 95th Percentile of Non-Zero Values, All Utilities	0.64	0.64	1.00
EMS	Low	AMI, 80th Percentile of All Utilities	0.99	0.88	1.00
	High	N/A	1.00	1.00	1.00
EMS	Low	DR Program, 95th Percentile of Non-Zero Values, FRCC Utilities	0.25	0.18	0.17
	High	DR Program, 95th Percentile of Non-Zero Values, All Utilities	0.64	0.94	1.00

EMS controlled end-uses are limited by both the fraction of customers assumed to be able to implement such controls and communicate with a utility or aggregator (controllability), and the degree to which end-users might be willing to sign up for demand response programs that would modify how their loads operate (acceptability). Controllability is estimated using EIA data on advanced metering infrastructure (AMI) penetration. The 80th percentile values of all utility AMI rates used for the Low DR scenario are already

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fairly high, so AMI/advanced communications and controls is assumed to be universally available in the High DR scenario. Acceptability is modeled based on current reported participation in demand response programs. Similar to the DLC participation rates, we use the 95th percentile of non-zero values across the FRCC utilities and all U.S. utilities for the Low and High DR scenarios, respectively. The values are reported by sector in Table 3. Regulation reserves are further limited by an additional multiplicative filter of 0.02 for Low DR and 0.15 for High DR. Finally, for EMS end-uses located in buildings, we apply a filter that is inversely proportional to an occupancy proxy, and equal to 1.0 at lowest occupancy and 0.5 at highest occupancy. For commercial end-uses, we use lighting load as the occupancy proxy. Our residential occupancy proxy is water heating, since our load dataset does not include residential lighting.

Table 4: Demand Response Resource Summary by End-Use

					Proportion of End-use Load Able to Provide the Service (%), Range Listed for Time-varying Filters					
					Energy		Contingency		Regulation	
Sector	End-Use	Resource Type	Control Type	Proportion of FRCC Load by End-Use (%)	Low DR	High DR	Low DR	High DR	Low DR	High DR
Residential	Cooling	Storage	DLC	17	18	44	18	44	0	2
	Heating	Storage	EMS	6	2-5	6-13	2-5	6-13	0-0.1	1-2
	Water Heating	Schedule	DLC	10	6	16	6	16	6	16
Commercial	Cooling	Storage	EMS	4	4-9	24-51	3-7	20-42	0-0.1	4-6
	Heating	Storage	EMS	9	4-9	27-54	3-7	20-42	0-0.1	3-6
	Lighting	Shed	EMS	24	0	0	2-3	11-19	0-0.1	2-3
	Ventilation	Shed	EMS	9	0	0	3-6	20-34	0-0.1	3-5
Municipal	Outdoor Lighting	Shed	DLC	18	0	0	0.1	4	0.1	4
	Wastewater Pumping	Schedule	DLC	1	0.1	4	0.1	4	0	0
	Water Pumping	Schedule	DLC	1	0.1	4	0.1	4	0	0
Industrial	Agricultural Pumping	Schedule	DLC	<0.5	4	100	4	100	4	100
	Datacenters	Schedule	DLC	<0.5	0.1	3	0.1	3	0.1	3
	Manufacturing	Schedule	EMS	<0.5	0.8	5	2	10	0	0
	Refrigerated Warehouses	Storage	DLC	2	0.2	5	0.4	10	0.4	10

The result of categorizing and applying filters to all the end uses is summarized in Table 4. Example availability stacks for each grid service are shown in Figure 14 for the same week as the load data plotted in Figure 13. To turn these resources into virtual generators to be dispatched by our production cost model, we apply assumptions appropriate to each end-use's categorization as sheddable, thermal storage, or schedulable. The end result is

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generators modeled with some amount of storage capacity and no fuel use that are used to shift energy use or provide reserves. The generators are also modeled as having zero variable cost, consistent with most demand response costs being capital or fixed, rather than tied to the exact amount of demand response used from day-to-day.

Sheddable resources, such as the commercial ventilation load available in our model to provide contingency and a limited amount of regulation reserves, as shown in Figure 15a, are modeled as simple reserves-only generators without storage. Under the assumption that contingency reserves are always held, but rarely (up to several or a dozen times per year) called, and that any load providing regulation reserves experiences very little to no degradation of the main service it is providing, we do not apply any constraints on the use of these reserves beyond enforcing their availability profiles. Availability profiles are enforced by product. The sum of services provided is also required to be less than the maximum availability across all offered products. Thus, for our commercial ventilation example, if one MW-h of regulation reserves is provided in a given hour, this reduces the amount of contingency capacity available in that hour by one MW-h.

Thermal storage and schedulable resources are modeled as generators with storage (that is, similar to pumped hydro) to capture their energy-shifting abilities. Their availability for reserves is modeled similarly to the sheddable resources, and the sum of all services provided in a given hour must be less than the max capacity across all services offered, including energy. For lack of better data, 100% round-trip efficiency is assumed for all energy-shifting,[8] but otherwise the storage constraints differ depending on the specific end use being modeled. These typically include a constraint on the number of hours a resource can be used per day, a total number of times a resource can be called per day, and a restriction on which hours it may be used. One difficulty we had modeling these resources originates from the fact that the methodology used to estimate the size of the demand response resource did not explicitly account for the capacity of end-uses to increase load. We thus estimate the ability of the resources to increase load, referred to as pumping capacity in Table 5, based on assumptions applied to the energy service timeseries

[8] O'Connell et al. (2015); Beil et al. (2015) are end-use specific examples showing variations in round-trip efficiency from demand response used as storage.

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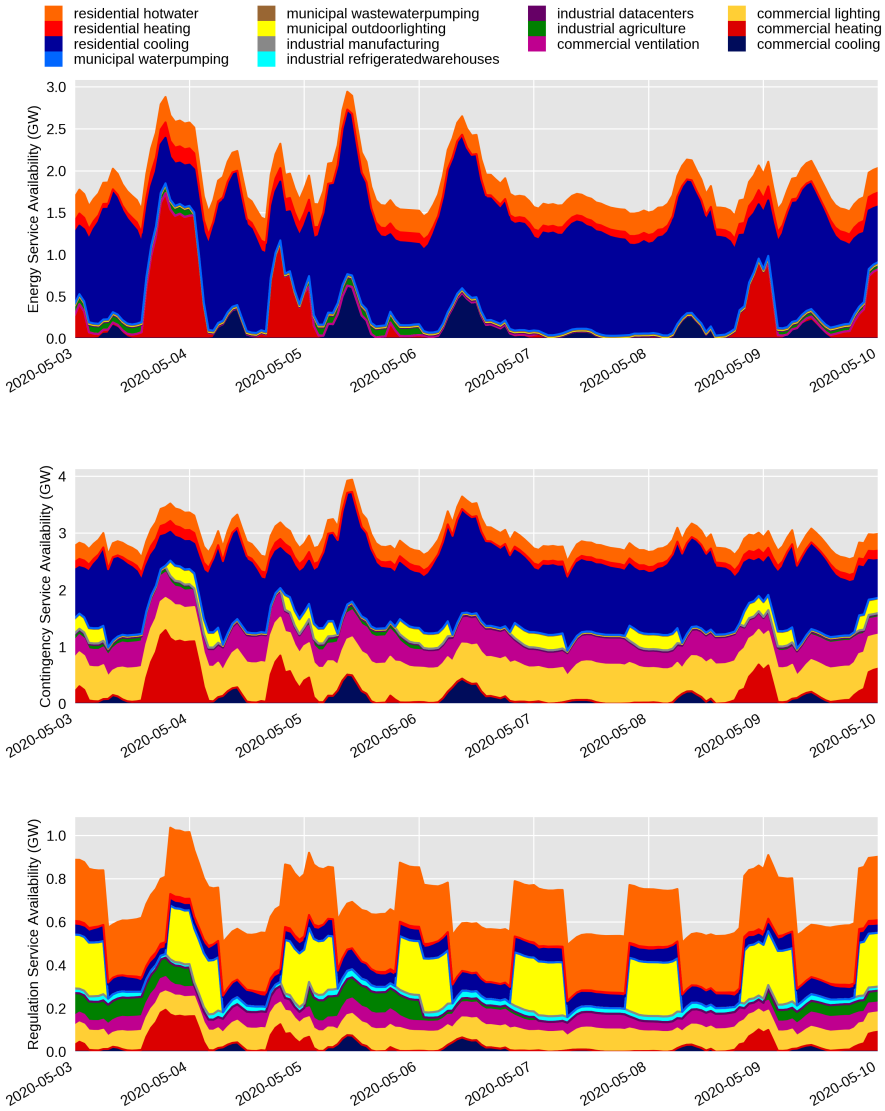

Figure 14: Demand response resource for the High DR scenario by end use and grid service for one spring week.

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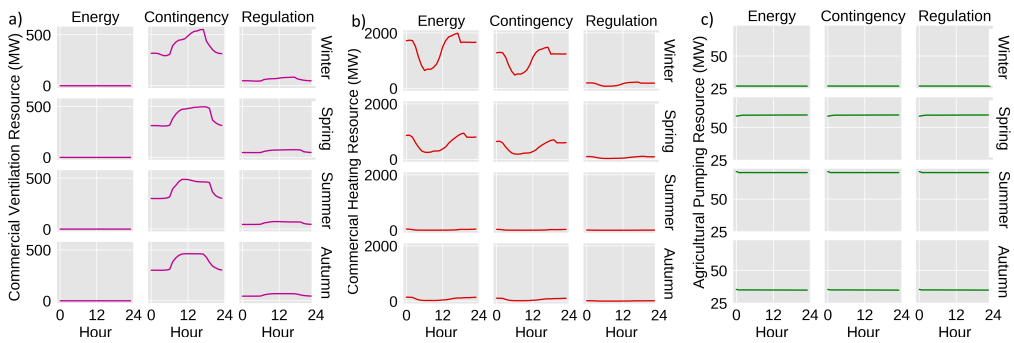

Figure 15: Example demand response resources from the High DR scenario, average values by hour and season. a) Commercial ventilation, a shed resource, b) Commercial heating, a thermal storage resource, and c) Agricultural pumping, a schedulable resource.

data. These estimates are provided in Table 5 with E_i being the energy service availability at time i, $\bar{E} = \max_j E_j$ the maximum of energy service availability taken over the whole year, and D_i the set of all time indicies that fall on the same day as i.

The virtual pumping capacity is thus limited by the overall capacity implied by the energy service timeseries, if that timeseries contains significant variability, as it does for heating and cooling. For less volatile loads more blunt assumptions for the pumping capabilities, such as the ability to double load from baseline levels, are used. Finally, limitations based on the maximum amount of energy service available from a given end use on a given day are used to prohibit unseasonable operation, such as shifting heating energy use when the predominant form of space conditioning is cooling.

The final column of Table 5 specifies a maximum number of hours a resource is allowed to be used per day. Since such a restriction should be applied to individual sites, which are generally much smaller than the overall capacity of the aggregated resource, and the capacity of the resource may vary by hour, this constraint is implemented as

$$\sum_{j \in D_i} \frac{G_i}{E_i} \leq T_{\text{day}}, \tag{1}$$

where G_i is the amount of load reduction dispatched in hour i, E_i is the amount of energy shifting resource available in hour i (as above), and T_{day} is the number of hours that the resource may be used per day. Note that only

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Table 5: Modeling Details for Thermal Storage and Schedulable Demand Response Resources

Sector	End-Use	Resource Type	Pumping Capacity	Pumping Time Restrictions	Balancing Frequency (days)	Daily Duration Restriction (h)
Residential	Cooling	Storage	$\min(\bar{E} - E_i, \max_{j \in D_i} E_j)$	5 am-6 pm	1	1
	Heating	Storage	$\min(\bar{E} - E_i, \max_{j \in D_i} E_j)$	3 am-7 pm	1	1
	Water Heating	Schedule	$\min(2E_i, \bar{E}) - E_i$	-	1	-
Commercial	Cooling	Storage	$\min(\bar{E} - E_i, \max_{j \in D_i} E_j)$	5 am-6 pm	1	2
	Heating	Storage	$\min(\bar{E} - E_i, \max_{j \in D_i} E_j)$	3 am-7 pm	1	2
Municipal	Wastewater Pumping	Schedule	$\min(2E_i, \bar{E}) - E_i$	-	1	3
	Water Pumping	Schedule	$\min(2E_i, \bar{E}) - E_i$	-	1	2
Industrial	Agricultural Pumping	Schedule	$\min(2E_i, \bar{E}) - E_i$	-	7	8
	Datacenters	Schedule	$\min(\bar{E} - E_i, \max_{j \in D_i} E_j)$	4 am-8 pm	1	4
	Manufacturing	Schedule	E_i	-	1	-
	Refrigerated Warehouses	Storage	$\min(2E_i, \bar{E}) - E_i$	-	1	4

load reduction duration is limited by T_{day}. Make up, or pumping, energy is then constrained to balance within its own parameters.

The demand response models are programmatically created and applied to the PLEXOS FRCC model with a Python package called beetle. That package has the option to spread DR out to the top n load nodes per region, in proportion to their relative load participation factors. One new generator per DR end-use is created at each such node. Based on runs with DR placed on the top 1, 2, 5, and 10 load nodes, we moved forward with models that place DR at the top two load nodes per region, that is, at 12 nodes in total throughout FRCC. We found this level of dispersion to be a good balance between computational complexity and model realism.

6.3. Capacity Cost Assumption

This study assumes a capacity price of \$75/kW-year, based on the Annual Energy Outlook (AEO) reported annualized costs for combustion turbines. The 2016 AEO gives combustion turbine costs of \$78.40/kW-yr for 2020,

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$74.4/kW-yr in 2030, and $71.75/kW-yr in 2040. We performed a sensitivity over this assumption, but that level of variability is not enough to significantly impact the value of PV, having less than 1% impact, and less than 0.5% impact at penetrations above 20% PV. However, it can be argued that $75/kW-yr should be considered an upper bound on capacity price, since systems with excess capacity often report significantly lower capacity prices. For example, California has made capacity payments ranging from $5/kW-yr to $100/kW-yr, with an average price paid of $35.50/kW-yr in 2016 (Chow et al., 2017). Even using this lower capacity price only impacts lower PV penetrations, with a median impact of 5-8% change at low PV penetrations, and 1-3% change at higher penetrations. This is due to the rapid decline of the incremental capacity value of PV, such that at higher penetrations, PV capacity value is not a significant factor in the overall PV value.

6.4. Photovoltaic Cost Projections

The Annual Technology Baseline (ATB) provides low, mid, and high cost projections for many developing technologies through 2050 (NREL, 2016). For this analysis, we used the midline and low cost trajectories for utility scale photovoltaics. To match the $/MWh units of our PV value outputs, and the average capacity factors of the PV facilities in our model, we pulled levelized cost of energy (LCOE) trajectories for 20% capacity factor plants. Figure 16 shows those projected trajectories, which both start at $118/MWh, but then quickly diverge to $84/MWh and $65/MWh in 2020, $60/MWh and $43/MWh in 2030, and $50/MWh and $28/MWh in 2050 for the mid and low cost trajectories, respectively. For the analysis presented in the paper, we used the mid and low cost projections for the year 2026, the year represented in our model.

7. Additional Results

In this section we present some additional results that may be of interest to readers. In particular, we present more details on our natural gas price sensitivities, describe how the value of PV results change with different social cost of carbon assumptions, take a closer look at the extent to which demand response may be able to support PV integration in Florida, and more explicitly connect incremental curtailment rates with incremental PV value.

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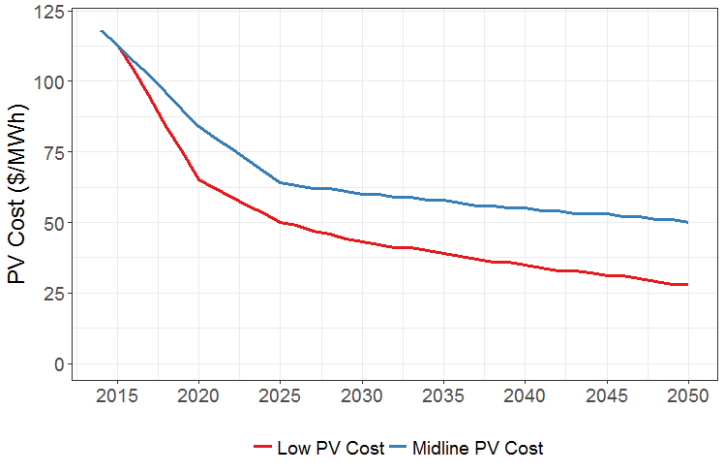

Figure 16: PV cost trajectories from the 2016 ATB

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7.1. Natural Gas Price Sensitivity

Our natural gas prices are based on the South Atlantic region price trajectories from the Annual Energy Outlook. These prices vary by month based on historical patterns and are the same prices used in the Eastern Renewable Generation Integration Study (Bloom et al., 2016). The original analysis was performed using the reference case gas prices for 2026 from AEO 2014 (EIA, 2014). The low natural gas price sensitivity was performed by scaling the reference monthly gas prices by the ratio of the AEO 2016 low natural gas price scenario (EIA, 2016a) to the original AEO 2014 value. For this sensitivity, we did not change the prices of coal, nuclear, or oil. This led to a change in the merit order of generators, such that more efficient gas combined cycle (CC) units came to have a lower marginal cost relative to most coal plants. Coal plants went from being the marginal plant 71% of the time to being the marginal plant 25% of the time. Gas CC units increased to being the marginal unit 72% of the time from 26% of the time. The merit order of gas combustion turbine (CT) units did not change significantly. Gas CT units were marginal 3% of the time in both cases. All values are calculated as the median across all scenarios by gas price.

We ran all flexibility scenarios, except the battery-only scenarios, using low natural gas prices and analyzed the ways in which lower natural gas prices changed our results. The changes are quite significant, starting with which generators are impacted by the various flexibility measures. As shown in Figure 17, almost all flexibility options tend to increase gas CC generation and reduce coal generation, to take advantage of the CC generators' marginal price advantage in this low gas price environment. The Flex System package of options is especially consequential, because it includes a reduction in the minimum generation level of gas CC units that allows more of them to stay on through the mid-day solar peak. All of the Flex System scenarios show a remarkable increase in the amount of natural gas used, replacing nearly all coal with gas CC generation, as shown in Figure 18. On its own, demand response tends to increase the use of natural gas and decrease the use of coal at low PV penetrations, but increases PV generation over both gas and coal at high PV penetrations. As with the mid gas price scenarios, demand response alone and paired with other flexibility options reduces the use of gas CT units.

Low natural gas prices also reduce the value of the next increment of PV by

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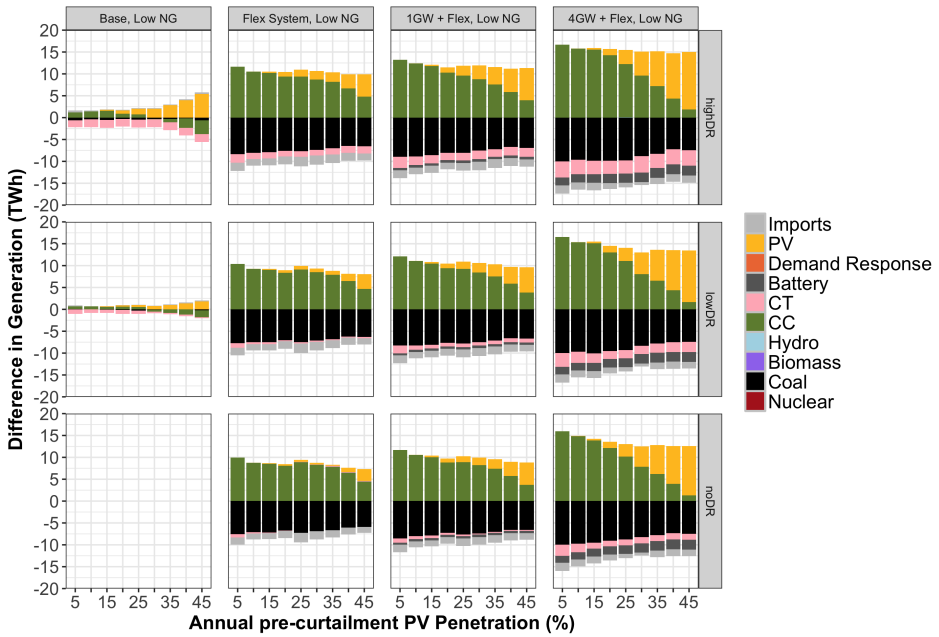

Figure 17: Annual generation differences by technology between the various low natural gas price scenarios and the Base, low natural gas price, no DR scenario with the same PV penetration.

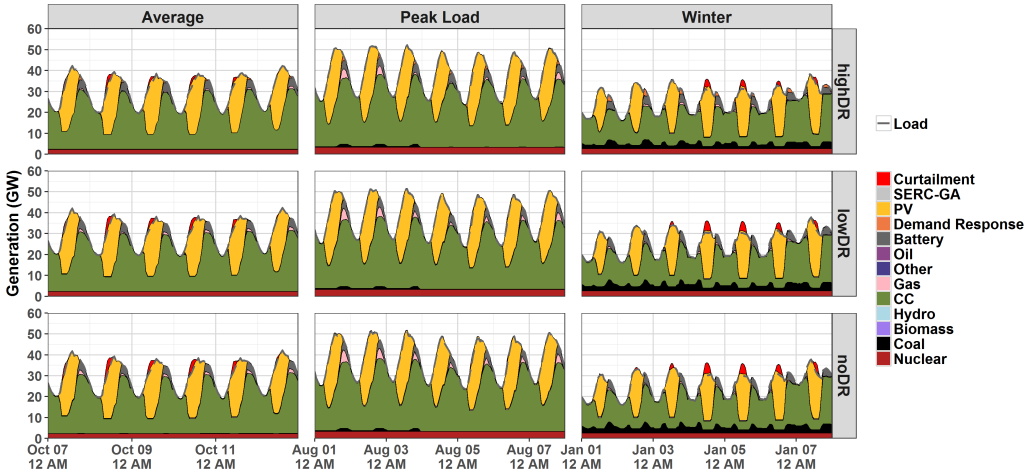

Figure 18: Dispatch stacks for the scenario with 30% pre-curtailment PV penetration, low natural gas prices, and the Flex + 4 GW package of flexibility options.

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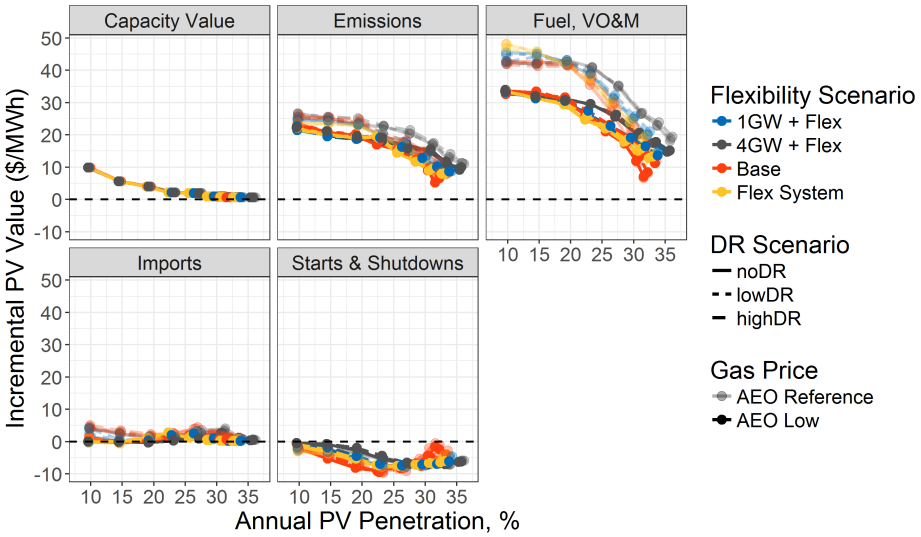

Figure 19: Component-wise incremental value of PV for all scenarios. The low natural gas scenarios are shown in brighter colors than the corresponding mid gas price scenarios.

reducing the value of fuel and emissions avoided per unit of PV generation. Figure 19 shows this by plotting each component of incremental PV value for the low (in bright colors) and midline (in lighter colors) natural gas price scenarios. Low natural gas prices have no impact on the capacity value, and very little impact on the value of imports or starts and shutdowns; however the impact on value derived from avoided fuel and emissions is clear. The net impact of flexibility options in the low gas price scenario are shown in Figure 20. Flexibility options are able to preserve PV value at high penetrations in this case, just as they are with mid natural gas prices, but the effect is muted to the extent that flexibility also increases gas CC generation, see especially the Flex System curve. Overall, 4 GW of battery capacity in FRCC is able to increase the economic penetration of PV by three to five percentage points at low PV cost. The impact of DR is similar to that of the mid gas price scenario, increasing the economic carrying capacity of PV by one to two percentage points.

7.2. Social Cost of Carbon Sensitivity

The central results of this paper use a \$50 per metric ton of CO_2 social cost of carbon based on the Interagency Working Group analysis for the year 2030

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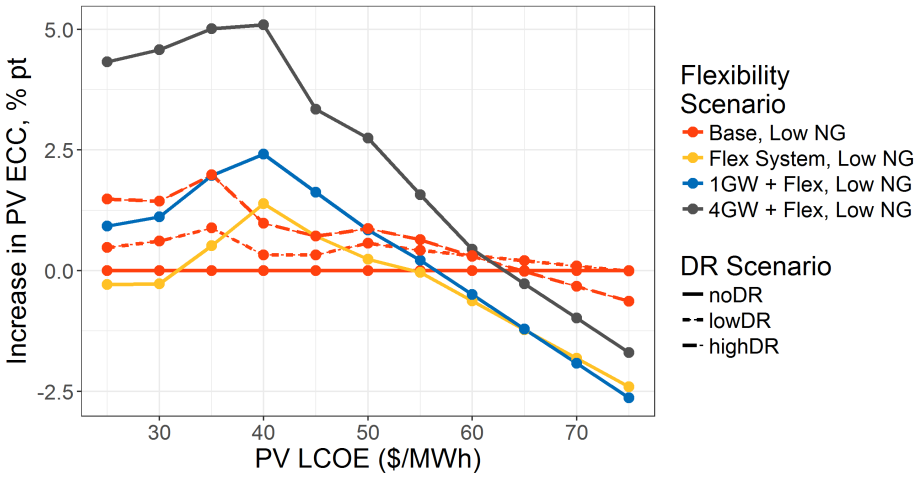

Figure 20: Percentage point increase in economic PV penetration when flexibility options are applied to the low natural gas price base scenarios.

and a 2.5% discount rate (Interagency Working Group, 2010). As described in the Methods, we also consider a range of cost values covering the literature, from \$8.2 per metric ton CO_2 to \$284.1 per metric ton. In the main paper we show the effects of a narrower range, \$0 to \$100 per metric ton, on the economic carrying capacity of PV in FRCC in 2026. Figure 21 shows the impacts of this range of carbon costs on the overall incremental value of PV to the system. The range assumed in the paper is shown in the shaded area, the 95th percentile social cost of carbon, \$284.1, is shown as a line at the top of the plot. This figure makes it clear that assuming a high cost of carbon emissions translates into PV being cost competitive today, and further implies an accelerated timeline for the importance of system flexibility, especially as it relates to preserving PV value at higher penetrations. Alternatively, if no cost is assigned to carbon emissions, PV costs must drop below \$50/MWh or even \$40/MWh to match PV incremental value.

7.3. Demand Response Impacts

Demand response (DR) is an intuitively attractive form of system flexibility based on its relatively low capital costs as compared to other flexible technologies like pumped hydro and battery storage. We thus set out in this study to determine to what extent DR may be able to help integrate PV into the Florida system via flexible load operations.

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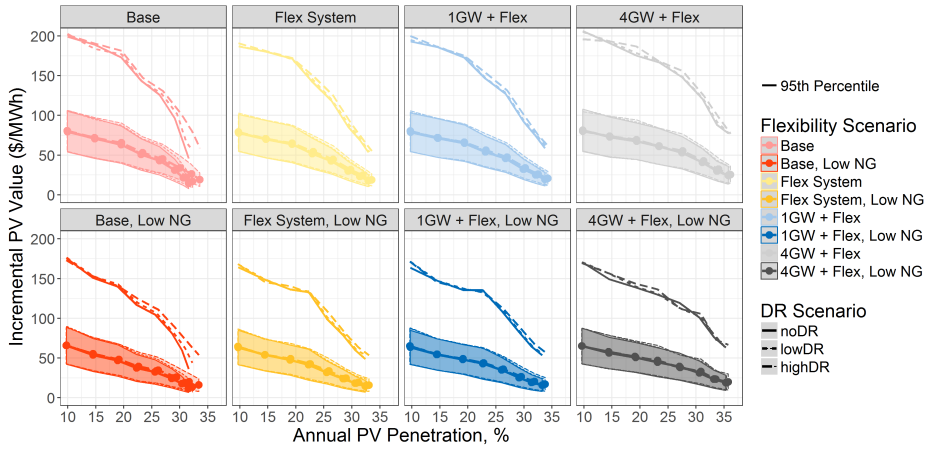

Figure 21: Sensitivity of PV value to the social cost of carbon. The shaded area shows the impact of a social cost of carbon ranging from \$0 to \$100 per metric ton. The 95th percentile social cost of carbon, \$284.1, is shown as an outlier line. The assumed cost of carbon has a high impact on the overall value of PV to the system.

In the main body of the paper, annual generation differences by technology show that our High DR scenario is able to elicit generation changes of a magnitude similar to that achieved by 1 GW of battery capacity spread throughout FRCC. It is also apparent that the mechanisms through which the two technologies reduce system costs are different, because DR tends to reduce CT generation to a much greater extent than does battery capacity. In fact, the demand response resources we model contribute mostly by providing reserves, rather than explicitly shifting energy. As shown in Figure 22, the commitment of DR greatly exceeds is dispatch most of the time, which is in contrast to the commitment and dispatch patterns for battery capacity in that same plot. We also see that the peak generation and charging for the two resources are similar, at around 1 GW, while the peak commitment for DR generally ranges higher, between 3 GW and 6 GW. These patterns reflect the fact that the use of demand response for energy shifting is highly restricted; a number of end-uses are not allowed to provide energy shifting at all, and those that do are subject to various energy constraints related to how much energy the end-use requires over a given period of time and what level of deviation from baseline operations is allowed.

Figures 23-24 show the by-technology provision of annual reserves for contingency and regulation for each mid natural gas price scenario. With no

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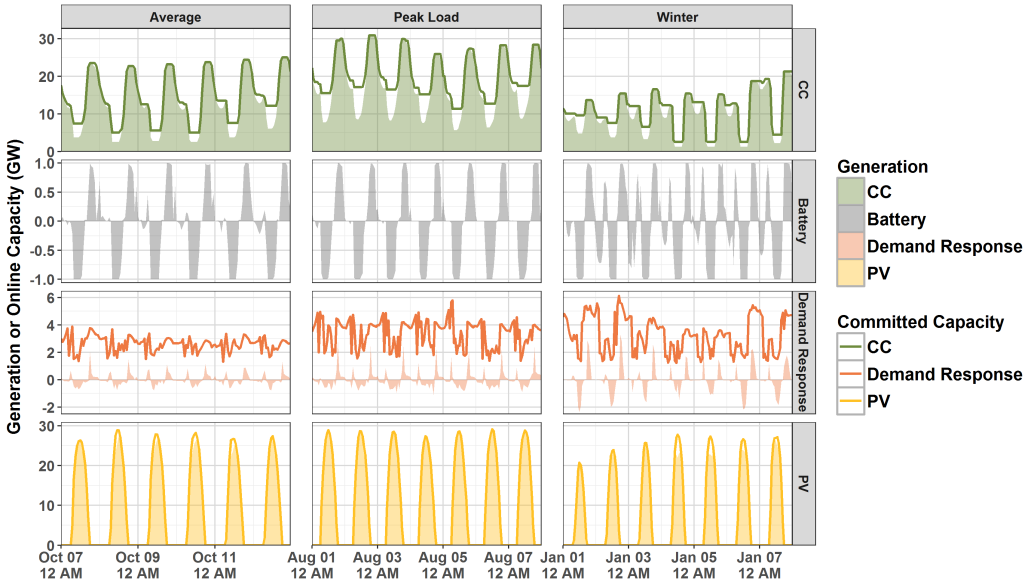

Figure 22: Commitment and dispatch for the 1GW, High DR, mid gas price, 30% PV scenario

demand response in the system, batteries are able to provide a substantial amount of the required reserves, both contingency and regulation. However, with demand response modeled as a no-variable cost resource, when present even at low levels it can provide nearly all contingency reserves. In the High DR scenarios, demand response can also provide most of the regulation reserves, especially at low to intermediate levels of PV. For those scenarios including the Flex System package, the ability for PV to provide reserves was only significantly utilized at PV penetrations above 30%, and was most predominantly used to provide regulation reserves. Low natural gas prices did not substantially alter these findings. As Figure 23 and Figure 24 visually indicates, in this study we did not model any caps on the proportion of reserves that could be provided by demand response, storage, or PV, either alone or in combination. As such caps are in place in multiple jurisdictions, these results should be interpreted as an upper bound on the possibilities for flexible technologies providing reserves.

As shown in the main body, the operational changes induced in the system by DR do increase the economic carrying capacity of PV in FRCC once sufficiently high PV penetrations are reached. Figure 25 shows the analogue

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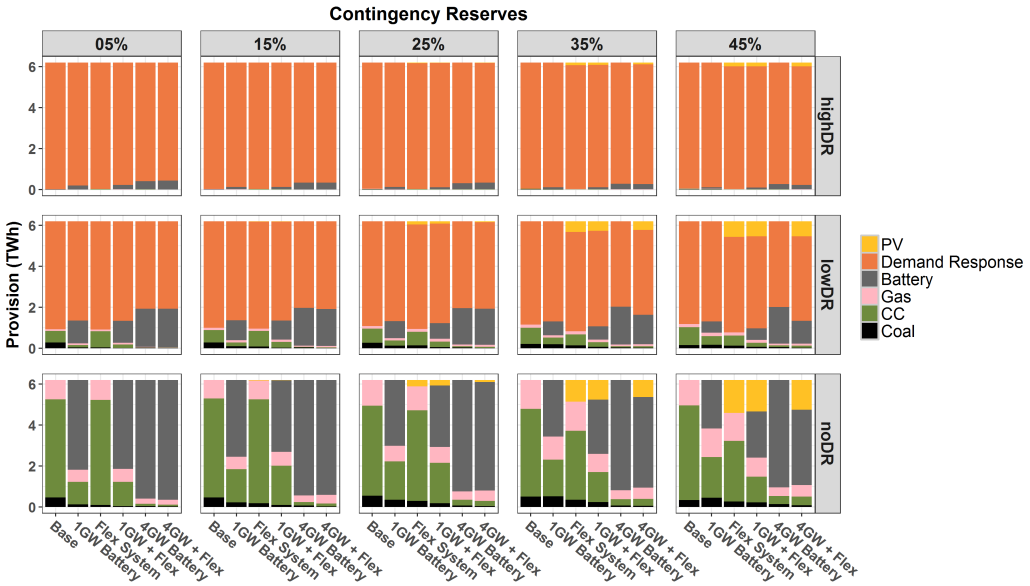

Figure 23: Contingency reserves provision by generator type for each flexibility and DR scenario

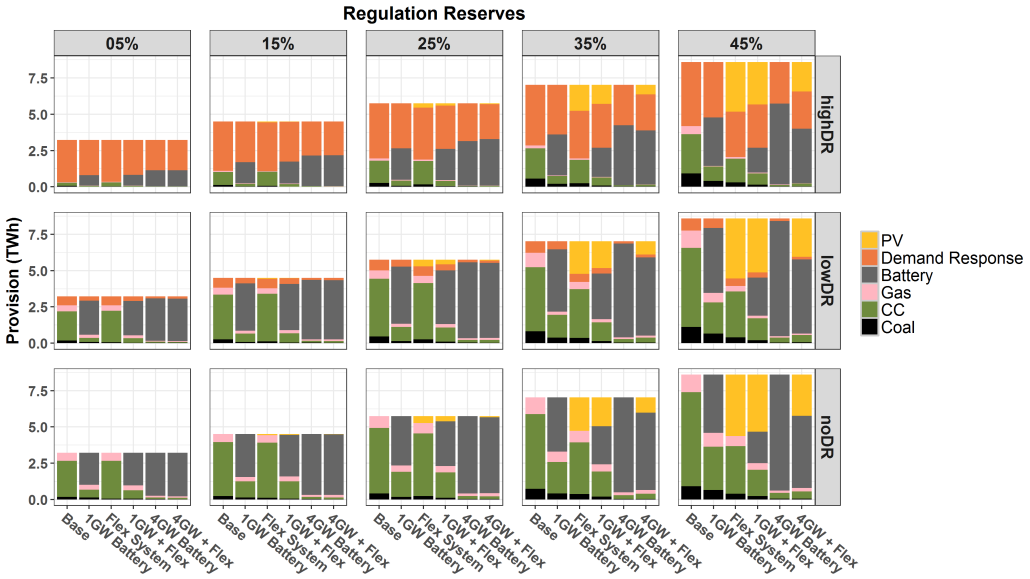

Figure 24: Regulation reserves provision by generator type for each flexibility and DR scenario

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of Figure 9 and Figure 20 just for DR, that is, it shows the amount by which DR increases the economic carrying capacity of PV compared to the analogous scenario without DR, holding PV costs constant. Overall, we can see that DR usually increases the ability of FRCC to integrate PV, even in combination with other forms of flexibility like battery storage. The presence of those other technologies does depress the impact of DR, albeit with varying levels of effect depending on the underlying conditions. In general, at low PV costs the efficacy of the Low DR scenario at increasing PV penetration drops from about 0.75 % pt to about 0.25 % pt when battery storage capacity is added. The analogous change for the High DR scenario is from about 1.5 % pt without storage to about 0.75 % pt with storage.

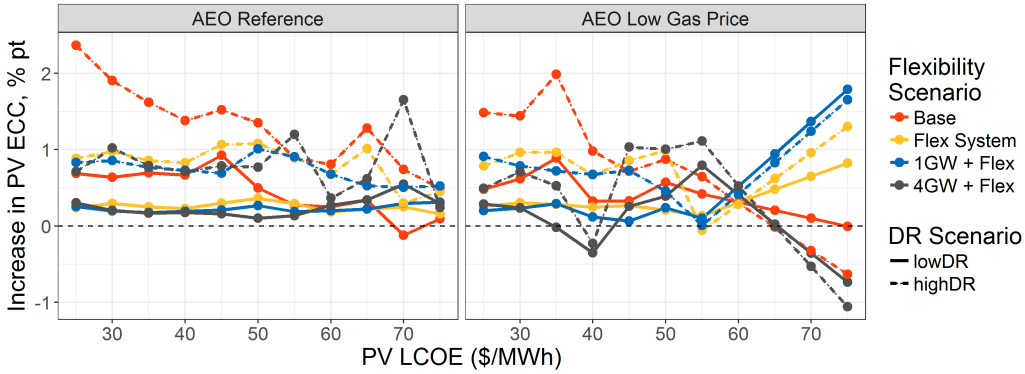

Figure 25: Percentage point increases in economic carrying capacity of PV due to demand response. The figure on the left shows mid natural gas prices. The figure on the right shows low natural gas prices.

7.4. Curtailment Impacts

The marginal curtailment of solar PV units is important as this represents the amount of the total energy produced by new plants that is actually unusable by the power system as a whole. In the baseline scenario with mid gas prices and no flexibility options, 80% of the final increment of PV, which corresponds to increasing the pre-curtailment penetration from 40% to 45%, is curtailed. The flexibility options considered in this study are able to reduce marginal curtailment to 55%, but this is still a large amount of energy to throw away from a new PV plant, and requires very low cost PV to make such installations economically attractive. Figure 26 shows that the 4 GW

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of battery storage is most effective at reducing curtailment in this system, demonstrating that the combined economics of PV and battery storage are important future considerations.

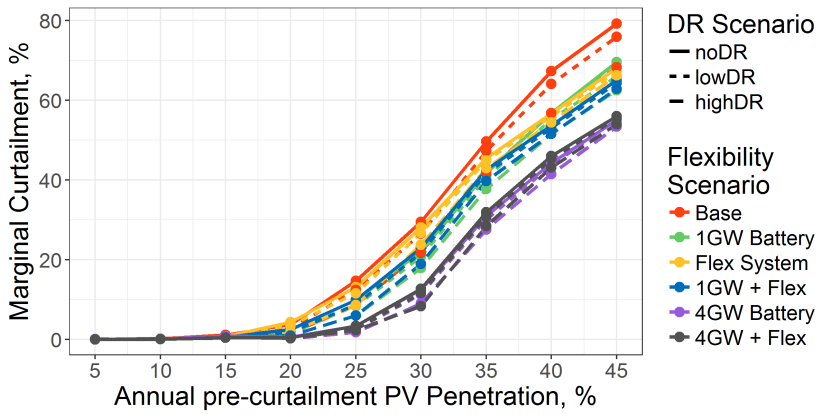

Figure 26: Marginal curtailment by pre-curtailment penetration for each flexibility scenario in the mid natural gas price scenario.

Curtailment reduction is a large piece of the additional value flexibility options bring to PV. The ability to increase the fraction of utilized solar energy allows for higher benefits from the resource. As such, we analyzed the correlation of reduced marginal curtailment with increased PV value for each of the scenarios in our analysis. Figure 27 shows this correlation

We found R^2 values ranging from 0.56 to 0.87 for the reference natural gas price scenarios. The low natural gas price scenarios typically had lower correlation, with R^2 values ranging from 0.18 to 0.87. The median R^2 values were 0.75 and 0.58 for the reference and low natural gas price scenarios, respectively.

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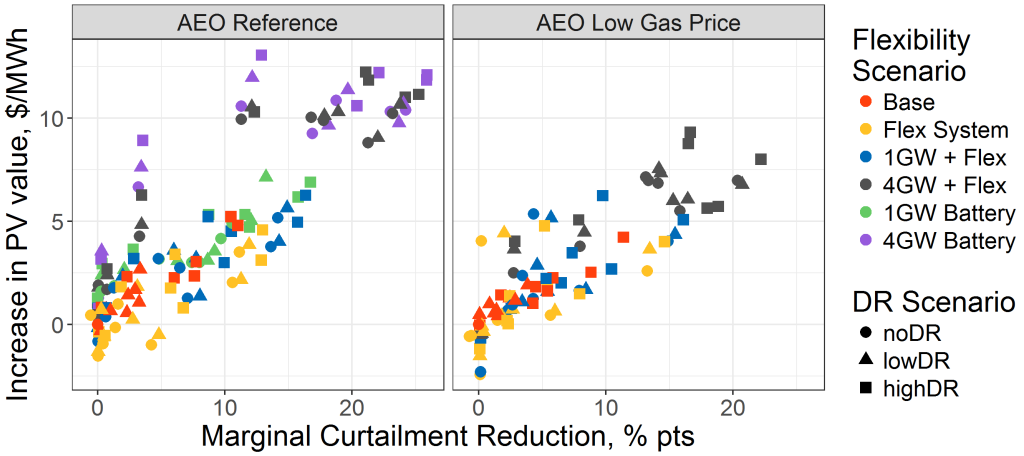

Figure 27: Marginal curtailment vs increased PV value from the baseline scenario, for each pre-curtailment penetration.

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