The Economics of Flexible Solar for Electricity Markets in Transition

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EXECUTIVE SUMMARY

High renewable energy penetrations require new ways of managing electricity markets and system operations. Successful integration will include more system flexibility to manage the increase in variability and uncertainty inherent in renewable energy production. An electricity system's flexibility is determined by many characteristics of its underlying value chain. As such, the overall ability of a market to efficiently integrate renewable energy depends on the flexibility of many components in the system. Areas to improve flexibility include adjustments to power plant operations, changes in market dispatch rules, increased transmission connections, new flexible consumption technologies, and more energy storage. One important source of electric system flexibility that is not yet being utilized in markets around the world is from renewable energy plants themselves. Primarily seen as the source of variability and uncertainty, a renewable energy plant's ability to be dispatched to enhance integration is often overlooked. This is no longer due to technology barriers, since control systems on modern solar photovoltaic plants are capable of accurately following highly granular dispatch instructions from its operator, just like a conventional power plant.

This project studies the value of flexible solar operation in a high-renewable system by constructing and analyzing a computational model of the California electricity market. California is a good place to study because it is a large, relatively competitive market with a large and fast-growing solar energy penetration. It provides a useful test case for other large electricity markets that follow in California's steps with growing solar penetrations. The model behavior assumes power plants competitively bid into the market and an independent system operator chooses production levels and transmission flows to meet electricity demand at the lowest possible cost. A baseline scenario is calculated that replicates California's 2019 supply mix and production levels, followed by scenarios that simulate rising solar penetrations. In the initial scenarios, solar is assumed to produce as a must-take resource, so the operator does not have the ability to adjust its output beyond the expected production levels determined by its insolation levels. The results from these inflexible solar scenarios are compared to equivalent scenarios where solar plants are operated flexibly. Flexible solar plants can be dispatched at any level below their expected energy output, and the system operator in the model instructs them to produce in a way to minimize total system costs.

At a 30% annual solar penetration, flexible solar operation reduces annual production costs in California by at least $172 million compared to a scenario with inflexible solar operation. Including markets in neighboring states results in total regional savings of at least $268 million per year. Limited results from a more granular model that better captures solar variability suggests that these savings are conservative estimates, and actual value from flexible solar operation could be 2 or 3 times as large. To give a sense of scale, the CAISO electricity market cleared approximately $10 billion of energy transactions in 2018. The largest value from flexible operation comes from handful of solar plant clusters located 1) in northern Los Angeles County at the western edge of the Mohave Desert, 2) in the Imperial Valley in southern California near the border with Mexico, and 3) near the Las Vegas metropolitan area. The modeling shows flexible solar value is often realized by strategically dispatching solar plants below their maximum output levels at particular times of the day to mitigate severe system ramps. This saves the operator from needing additional fast-ramping resources with high operating costs to meet the swing in net demand, lowering total system costs. It also reduces greenhouse gas emissions via reduced reliance on natural gas plant for ramping support. Additional value from flexible solar operation can be gained due to the operator's increased ability to respond to production forecast uncertainty. However, the deterministic model used in this study is unable to quantify the option value from flexibility associated with growing uncertainty in electricity markets. This is certainly a topic suitable for further study.

Modeled market operations in California change in a variety of ways as solar penetrations rise. Growing solar energy primarily replaces energy from natural gas combined cycle plants and imports. Significant changes occur when solar penetration reaches 30% of total annual energy. Most power plants that cannot handle significant daily ramps are no longer dispatched. Solar production often exceeds California demand, at which point excess power is exported until transmission capacity or demand in neighboring states is saturated, after which the remaining solar is curtailed. Bulk power flows in California reverse direction as the state increasingly exports solar power during the day, learning on neighboring markets to help balance the grid.

After reporting the numerical results, a discussion is provided on market design to incent efficient levels of flexible operation. The modeling shows how operating a solar plant below its maximum expected energy output can lower total system costs at high penetrations. However, existing market structures compensate solar plants based on their total energy production. This creates a market failure. An independent system operator tasked with minimizing total production costs will sometimes want to operate a solar plant below its maximum energy output, reducing the energy market revenue earned by the solar plant owner. A solar owner acting rationally under the existing market paradigm is incentivized to maximize its energy output, even when doing so leads to higher system costs. To align market incentives with the socially efficient outcome, flexibility products should be implemented in competitive markets that compensate all resources providing valuable flexibility services for their opportunity cost of foregone energy revenue. In addition to market rules that incent efficient real time operation, long-term contract structures need to adjust by moving away from compensating solar plants based on total energy produced. Instead, contracts should reward plant operation that maximizes its full value to the system. Contracts that pay solar plants according to their nameplate capacity or expected energy output prior to adjustments for flexibility services can shift revenue away from volumetric energy production, enable flexible operation, and align the incentives facing solar plant owners and independent system operators.

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1. INTRODUCTION

Background

A significant body of research points to the importance of increasing electricity system flexibility to support high penetrations of renewable energy.[1–5] The literature has tackled this topic from numerous angles. For example, recent work has developed system metrics and indices to quantify system flexibility in ways that can be used to inform applications ranging from real-time operations, resource planning models, and high-level policymaking.[6–12] These metrics often describe the system's ability to respond to contingency events at various time scales. For example, an important metric might be the amount megawatts available to ramp up in response to an unexpected outage or supply reduction from a resource. Relatedly, research has sought to understand how flexibility requirements evolve as renewable penetrations rise,[13–17] along with implications for market design in high renewable systems.[18–20] An important insight from this work is that flexibility can be enhanced throughout the entire electricity system. For example, minimum operating levels on conventional power plants can be adjusted,[21,22] markets can be integrated across regions to facilitate balancing,[23] storage can be deployed,[24] and price signals can better reflect location- and time-varying market conditions.[25] Admittedly, an electricity market's flexibility is an emergent property determined from many components of the system: Papaefthymious et al. (2018) identified 80 different indicators that jointly define an electricity system's flexibility level. [26] Alongside the growth of research on this topic is a flurry of regulatory and market development efforts to improve flexibility across the electric sector.[27] Clearly, there are many areas throughout the value chain that policymakers can focus on for improving flexibility. The most effective flexibility solutions will vary by region and depend on the local fuel mix, renewable energy penetration, and market structure.

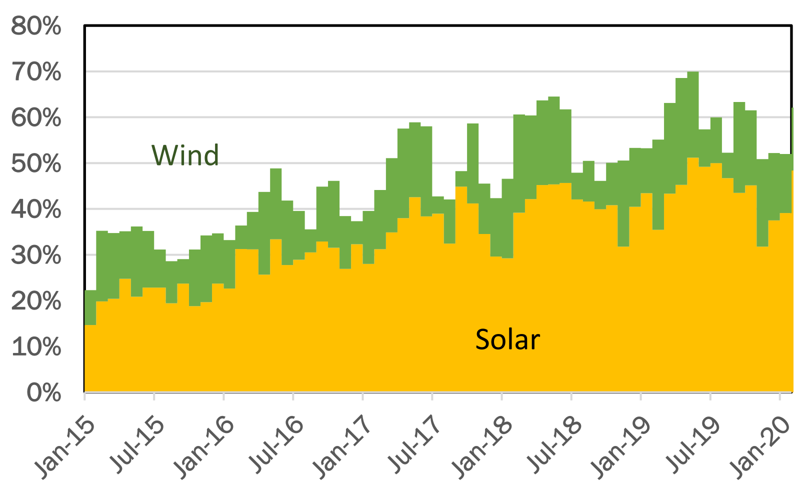
An important source of electric system flexibility not yet adequately addressed in the broader literature is from solar plants themselves. Inverters and control systems on modern utility-scale PV plants can follow automated dispatch instructions from the operator just like other power plants. A recent study performed a detailed electricity market simulation for the Tampa Bay electricity system in Florida, US, and found flexible PV operation is an important component for cost-effectively managing high solar penetrations on this system.[28] The study also showed how PV flexibility can reduce short-term reserves needed in a market with a growing renewable penetration. In contrast, conventional thinking has operators treating variable renewable energy as a must-take resource whose output is determined exogenously by the sun or other factors. If the operator cannot balance the rest of the fleet, then renewable generation is often fully curtailed, despite it typically being a zero-marginal cost resource. Current operating procedures, market tariffs, public policy, and power purchase agreements have been built around this restrictive way of solar operation.

Solar plants need not be operated as must-take resources. A utility-scale solar PV plant consists of multiple inverters, each of which is connected on one side to solar arrays, and on the other side to the transformer that puts electricity onto the grid. The plant's control system monitors and adjusts electricity coming through each inverter such that the total output of the plant at the single point of interconnection is controlled, similar to a conventional power plant. Modern controls on solar PV plants can reliably adjust output in response to an unexpected contingency elsewhere in the system, or to help regulate the grid's frequency in real time by operating at levels below its maximum output. For example, California Independent System Operator (CAISO), First Solar, and the National Renewable Energy Laboratory (NREL) recently demonstrated a large PV plant capable of providing a full suite of reliability and ancillary services.[29] This includes solar PV participation in automatic generation control (AGC), primary frequency control, ramp rate control, and voltage regulation. In this demonstration, the solar PV plant followed the automated control signals for AGC with 27% more accuracy than the best-performing thermal generation.[30] In addition to real-time reliability and ancillary services, a solar plant can perform slower, incremental adjustment over the course of an afternoon to facilitate load following. This can help the operator mitigate difficulties associated with large solar ramps and associated net load following in the mornings and evenings, offsetting the need to rely on more expensive fast-ramping thermal generators.

The case for studying California

This project models the California electricity market to research flexible solar operation. The state provides a good case to study because it's a relatively competitive, large market with a fast growing solar penetration. California's annual peak demand ranges between 45-50GW, approximately equivalent in size to the United Kingdom or France.[31] Furthermore, the state's grid operator has recently experienced renewable penetrations (over 5 minutes) as high as 70% and is curtailing renewable energy at an increasingly growing rate. Figure 1 plots the monthly maximum renewable penetration from the CAISO 5-minute market. It also illustrates the growth in renewable energy over the last several years.

Figure 1 CAISO monthly maximum percent of load served by renewables in the 5-minute market over last 5 years.[32]



Growing solar penetrations are impacting electricity prices throughout the state. Figure 2 shows the average CAISO system price by time of day from 2013, when solar generated less than 2% of

California's total annual electricity, and 2019 when solar was over 11%.[33] In 2019, there were relatively lower prices during the day, but prices spiked in the evening to $100/MWh on average. This "duck curve" is consistent with growing solar operational challenges. All the solar production goes offline in the evening, right before demand peaks in the evening as people come home from work. A visual example of this is provided in Figure 3, which plots the CAISO supply mix on February 24, 2020. The net load, which is the total load minus the renewables, has a significant ramp in the evenings when solar goes offline. During this period, the operator relies on more expensive, fast ramping resources to balance supply with demand, raising prices during the evening. It is during these shoulder periods that present the greatest operational challenges, and when additional flexibility is most valuable.

Figure 2 CAISO average system prices by time of day for years 2013 and 2019.[34]

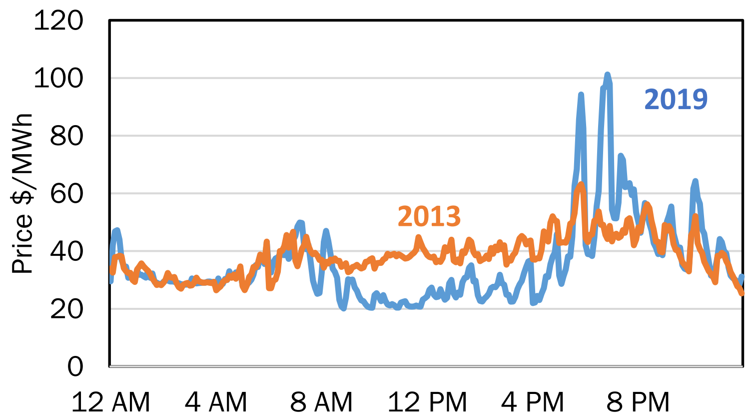
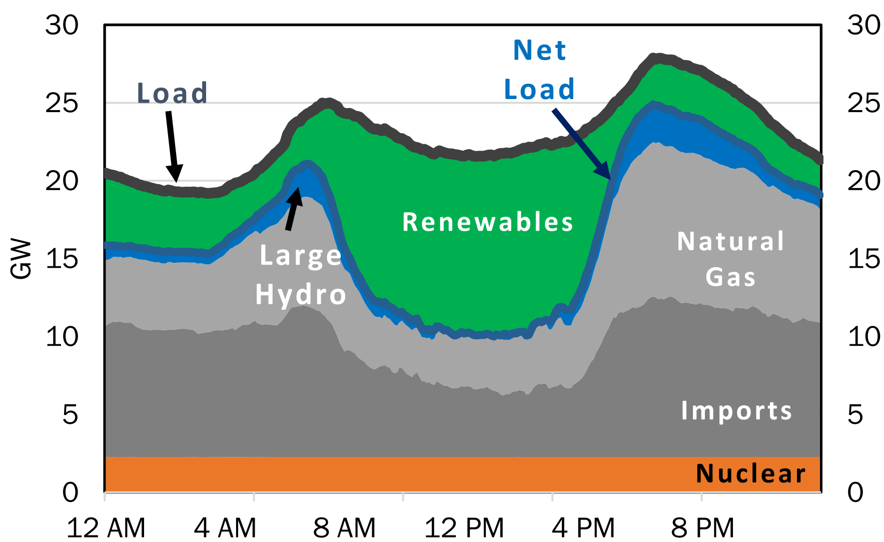


Figure 3 CAISO supply mix, 2/24/2020.[35]



Despite today's challenges, solar generation in California is expected to grow well into the future. In late 2018, California passed a law requiring 50% of the electricity mix to be powered by renewable resources by 2026, and be 100% powered by zero carbon resources by 2045.[36] While the specific relative contributions of solar, wind, and other renewable resources to this future target remain uncertain, it is likely that solar in California will play a major role and continue to grow for decades to come. This makes the state a good case to use for an in depth study on the economic and operational impacts of flexible solar operation.

A simple economic model for flexible PV

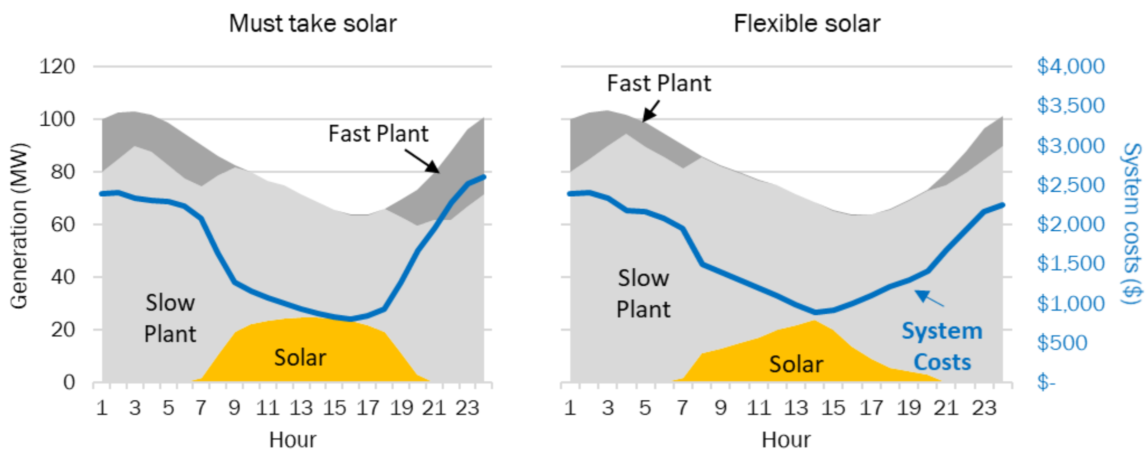
In order to build intuition into the value of flexible solar operation, this section develops a basic market model to demonstrate in a simple manner how flexible solar can lower system costs by providing ramp support and load following. The model includes three power plants operating for 24 hours to supply power for a typical daily demand profile. One plant is ramp-constrained, the second plant is not-ramp constrained but more expensive to operate, and the third is a solar plant. These parameters are listed in Table 1. In the first scenario, solar is treated as a "must-take" resource, while in the second scenario it can produce at any level less than or equal to its maximum output. An independent operator is tasked with dispatching these three plants to meet demand while minimizing total system costs. These scenarios are solved for a market with solar levels reaching a maximum instantaneous penetration of approximately 37%, plus a high-penetration case where solar output is doubled to a maximum penetration of 75%. The mathematical program underlying this model is provided in Appendix 1.

Table 1 Model parameters

Plant type	Production cost ($/MWh)	Ramp constraint (MW/hr)
Slow	20	5
Fast	40	Unconstrained
Solar	0	Unconstrained

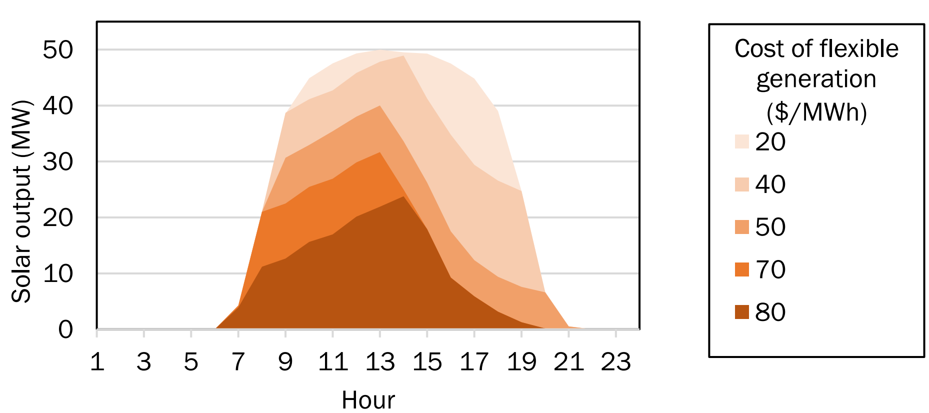
The solutions for the baseline scenario are displayed as stacked area plots in Figure 4. Production from the lower-cost, ramp constrained plant is represented by the blue region, which is used as much as possible to meet demand. The left panel shows the conventional situation where the operator treats solar as a "must-take" resource, and optimizes its remaining fleet around the solar. In the morning and evenings, the lower-cost, ramp-constrained plant cannot adjust quickly enough to meet the system ramps as solar comes on and offline. It is during these periods when the fast plant comes online to make up the difference, represented as the gray regions. When solar is operated flexibly, the operator cuts back on solar production to provide load following support in the morning and evening, so that the rate of change in residual demand better matches the lower-cost plant's ramp rate. This lowers system costs by shifting generation from the fast plant to the slow plant, which can be seen as a reduction in the gray regions in the flexible solar scenarios, and a subsequent drop in the hourly production cost line during the morning and evenings. The black line shows hourly system costs, and total system costs are reported below each panel's title. In this simple model, system costs are reduced by approximately 2% by operating the solar resource flexibly for this particular day.

Figure 4 Solutions for must take and flexible solar in simple model



These results suggest an economic tradeoff exists between providing energy and net load support for a flexible solar plant. The choice facing the system operator is how much to dispatch down the low-cost solar in order to minimize morning and afternoon ramps. As the fast plant becomes more expensive, the operator more aggressively reduces solar output for ramping services. To analyze this tradeoff, the model is re-optimized as the cost of the fast plant is varied. The change in solar outputs for a high solar penetration level as the cost of the fast plant (C_{flex}) varies are shown in Figure 5. The yellow shape next to $C_{flex} = 40$ replicates the solar output from panel 4 of Figure 4. The value of ramping support increases as C_{flex} increases, resulting in more aggressive solar dispatch down. Thus, when the cost of the fast resource is high, solar is more aggressively dispatched down to mitigate the net load ramp and shift additional production to the slow plant.

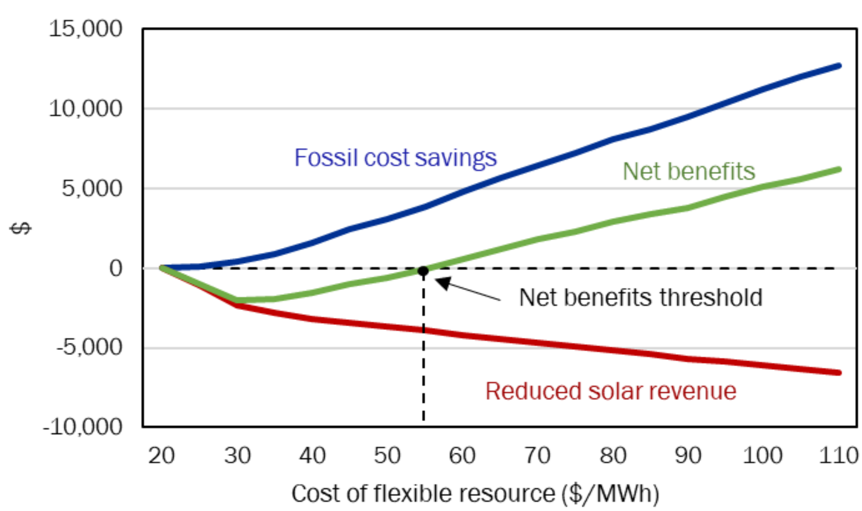
Figure 5 Solar output as the production cost of the flexible plant varies.



This simple model shows that cost savings arise when flexible solar operation reduces the need for the more expensive resource. The operator's incentive to cut back on flexible solar output is greater when the cost of the marginal generator during shoulder periods is high. When solar plants are dispatched down to provide ramp support, they incur an opportunity cost of foregone energy market revenue. It is beneficial to dispatch down solar output when the system benefits outweigh the opportunity cost. The difference between production cost savings and lost solar revenue yields a flexible solar system net benefits metric.

To illustrate, Figure 6 plots production cost savings through reduced fossil generation, solar revenue losses, and the associated net benefits curve as functions of the fast plant's production costs (C_{flex}) in the base scenario of the simple model. Net benefits are negative for when the fast plant has low costs of production. The point where the green line crosses zero is the flexible solar net benefits threshold. The space to the right of this threshold in the positive quadrant represents system benefits for ramping down solar output that are greater than the opportunity cost. In competitive energy markets, solar producers are currently unable to internalize the system benefits from flexible solar operation. Instead they only experience reduced revenue as the system operator dispatches them down. Existing contracts reinforce the "must-take" paradigm for solar production because they typically compensate plants based on their energy produced and not for flexibility services. The next section builds on this modeling intuition by describing a larger, more realistic economic dispatch model used to study flexible solar operation in the California electricity market.

Figure 6 Flexible solar net benefits illustration.

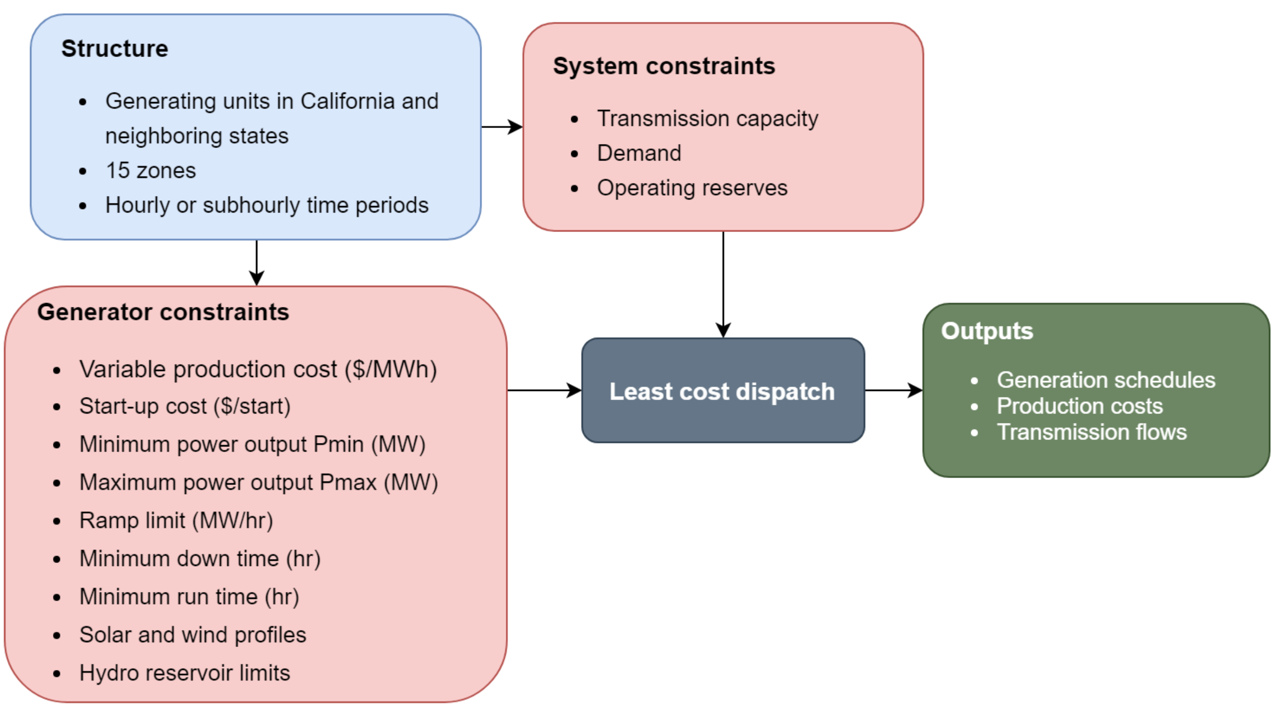


2. ECONOMIC DISPATCH MODEL

Overview

The computer model built for this study incorporates generating unit-level information for power plants in California and its neighbors. The spatial structure is made up of 15 zones, 4 of which represent markets external to California. The generating unit-level information in the model includes production costs, minimum and maximum power outputs, ramp limits, and minimum down times. Solar and wind plants produce according to spatially matched renewable energy production profiles, and overall energy limits are placed on hydro plants to represent reservoir limits. These data are fed into a production cost minimizing optimization algorithm that calculates unit-level generation schedules and transmission flows across the state. Figure 7 summarizes this structure. An hourly version of the model is solved for a base year that replicates the 2019 California supply mix. These scenarios are solved for solar penetrations starting at a base level of 10% of total annual supply, increasing to a high solar penetration of 30% annual supply. A detailed, 25-page documentation of the modeling methods, assumptions, and data is provided in Appendix 2. It is worth noting that a 30% solar penetration results in solar production levels that exceed demand on most days of the year. From a technical perspective, increasing solar penetration above 30% will require significant investments in energy storage. This is a crucial component of high solar integration that is widely studied, and not a focus of this report.

Figure 7 Model overview.



Several model scenarios are solved to study rising solar penetrations. The ensuing results presentation will mostly focus on two scenarios, a base- and a high-solar level, summarized in Table 2. The maximum solar penetration of 43% modeled in the base case is approximately equivalent to the observed maximum penetration levels from 2019 as plotted in Figure 1. Seven additional scenarios were solved with intermediate solar levels, the results of which fall in between these two scenarios. In Table 2, annual penetrations represent the share of total annual generation in California provided by solar according to their generating profiles before curtailments or dispatch down is applied. The maximum penetration level represents the period with the highest share of solar generation relative to demand at 5-minute granularity, which occurs during a low-demand period in the spring. The base scenario is equivalent to California's 2019 solar penetration.

Table 2 Simulation scenarios with rising solar penetrations.

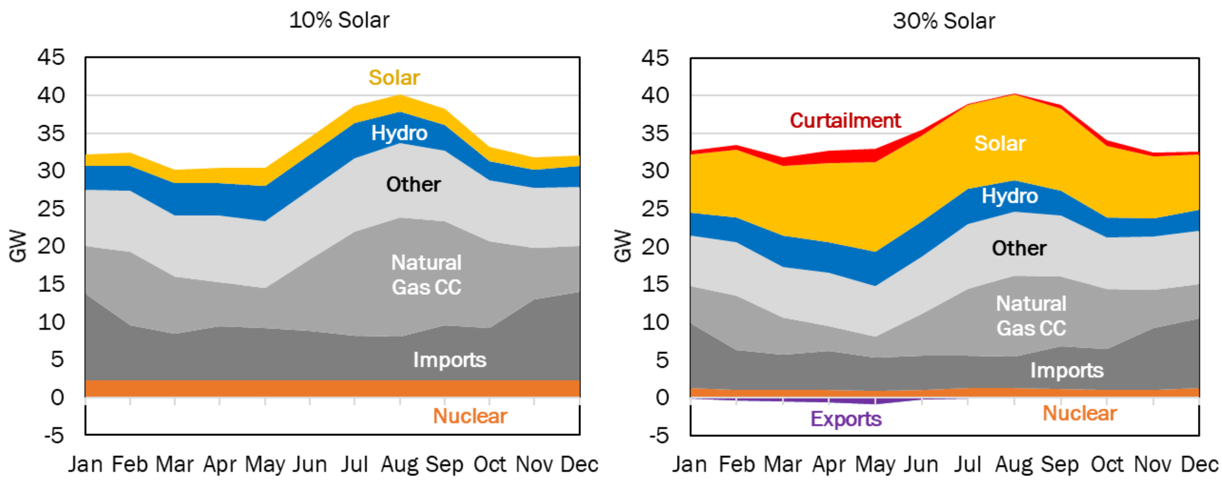
Scenario	Annual Penetration	Max Penetration
Base	10%	43%
High	30%	144%

Inflexible solar

Initially, the model treats solar as a must-take resource. In these "inflexible solar" scenarios, the operator takes solar energy as it is produced and does not actively adjust its output via dispatch signals. The operator then balances the net demand with the remaining supply resources. The operator is allowed to curtail solar only after all available resources are in use and supply and demand do not balance. This modeling approach approximates the existing practice and incentives that the system operators and market participants utilize today, where solar is curtailed primarily for reliability reasons. The "must-take" scenarios will be compared to flexible solar scenarios where solar can be dispatched down to provide ramping support, mitigate the net load curve, and lower system costs.

Figure 8 displays monthly-averaged generation in the base and high solar scenarios. These charts provide broad insights regarding seasonal trends and the fuel mix. The growth in solar primarily replaces natural gas combined cycle and imports that are on the economic margin. Hydro generation stays relatively constant as solar penetration rises, because it is low cost and can ramp quickly to help match daily swings in solar output. The "other" category includes wind, biomass, geothermal, solar thermal, and fossil-fueled peaking units. These generators are also mostly low-cost and/or flexible units and stay online as solar production grows. California starts exporting electricity in the high solar scenario. Exports are concentrated during the day as neighboring states are sent California's abundant, low cost solar. Notable levels of curtailment also show up in the high penetration scenario, increasing to an average of approximately 1.5GW during spring months.

Figure 8 California generation mix by month for 10% and 30% solar scenarios.



In summary, the operational response to a 30% solar penetration relative to today's level involves a decrease in natural gas combined cycle plants and imports as well as increased exports and solar curtailments. Figure 8 shows these impacts are most concentrated in spring months when solar production is relatively high and electricity demand is low. Conversely, operational challenges from solar are least concentrated in the summer with higher demand.

To see the daily operational characteristics of growing solar penetration, Figure 9 zooms in on a single week in mid-April, for both the base and high solar scenarios. Here it is possible to see the ramping and startup/shutdown challenges facing generators in the high solar case. Plants that cannot handle significant ramps on a daily basis are eliminated, reducing the overall amount of fossil generation. The only plants still producing in the middle of the day are low-cost nuclear and a variety of plants in the "other" category including wind, geothermal, and solar thermal plants. The operator chooses to leave some of these plants online during the days with high solar production because of start-up constraints. In this inflexible scenario, the operator treats solar and wind as must-take resources. Solar in excess of demand is exported out of state until demand in neighboring markets and transmission capacity is saturated, after which the remaining solar is curtailed.

Figure 9 Modeled California electricity supply for one week in the spring, base solar (left) and high solar (right) penetrations.

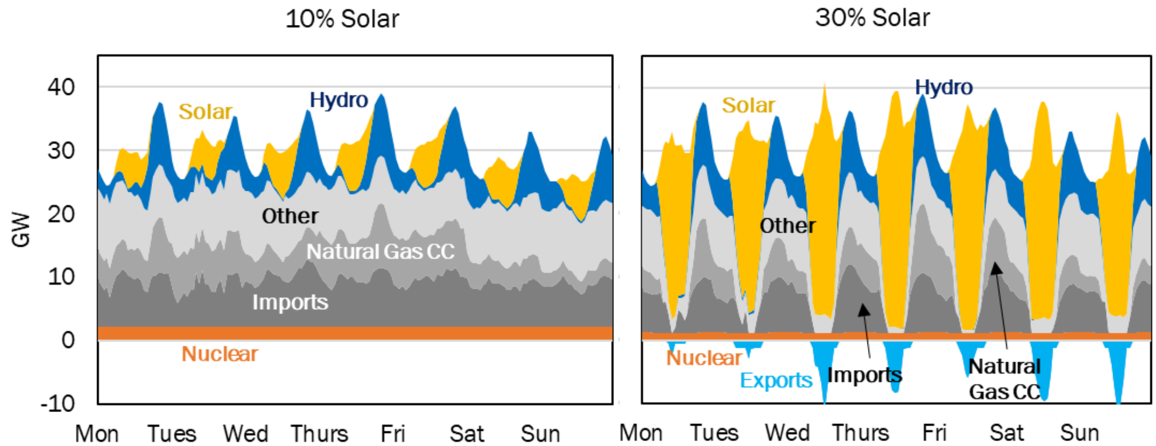
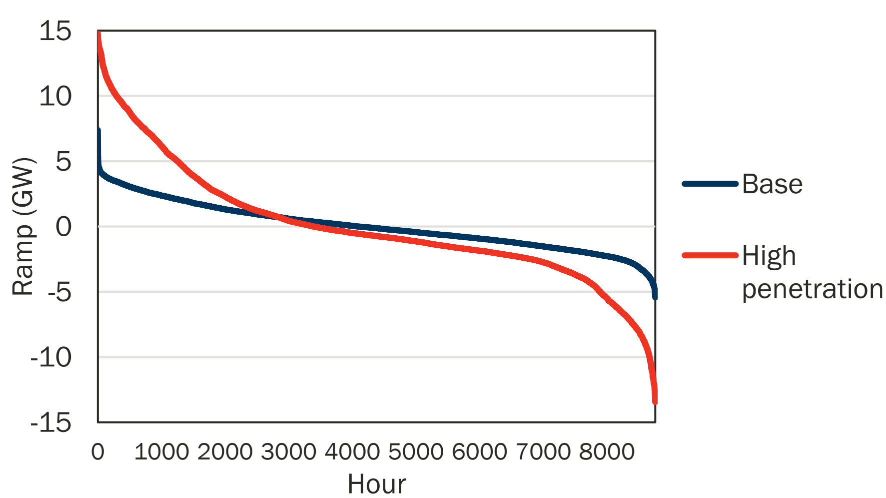


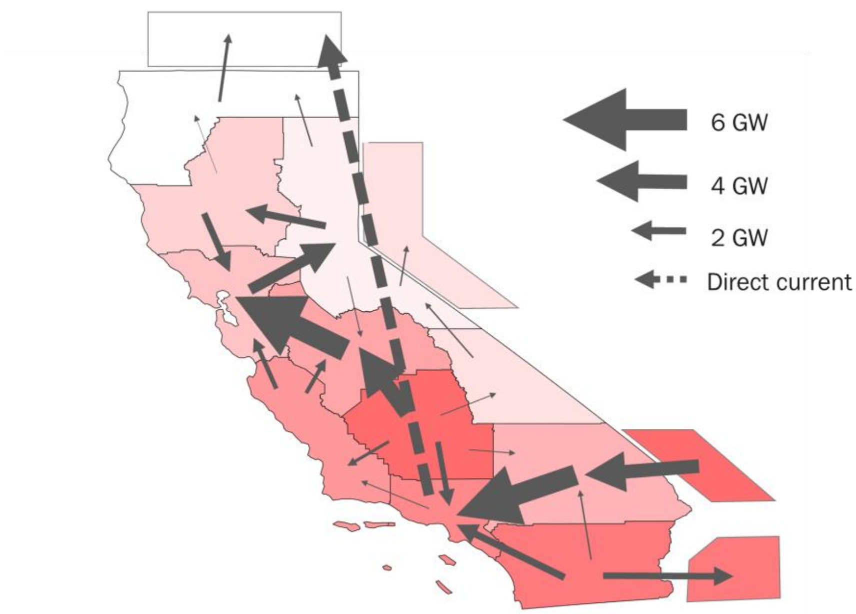
Figure 9 shows how increasing solar penetrations creates operational challenges from large system ramps in the morning and evenings. The ramp duration curves in Figure 10 are another way to investigate the system ramping needs as solar penetration rises. These curves are constructed by calculating California's hourly net load for the year, equal to total demand minus wind and solar. The first difference of the net load series yields a set of hourly ramps, which are sorted from largest to smallest and plotted as the duration curve. The fact that the red curve is above the blue curve in the positive direction and below in the negative direction represents the higher magnitudes and frequency of system ramps at high solar penetrations. In the high solar scenario, the maximum hourly net load ramp is 14.8 GW and the minimum is -13.4 GW. In comparison, the maximum and minimum hourly net load ramps in the baseline scenario are 7.4 and -5.4 GW, respectively. When considering morning and evening ramps, operators will also pay attention to the 3-hour ramp metric. In this model, the maximum and minimum 3-hour net load ramps are 13.6 and -14.4 GW in the base case. In the high solar case, they are 33.3 and -29.1 GW.

Figure 10 Net load hourly ramp duration curves for baseline and high solar penetraions.



Transmission flows on the California grid adjust as solar penetrations rise. Historically, power has typically flowed into California from the north and west. The imports largely consist of hydro and natural gas generation. As solar in California grows, these flows reverse and the state begins to export electricity during the day. Modeled flows at noon on a spring day with a high solar penetration are displayed in Figure 11. It shows significant electricity flows from the southern part of the state where solar production is concentrated into the Los Angeles region and then northward along the state's transmission infrastructure "backbone" through the Central Valley and into the San Francisco region. Flows are reversed as electricity is exported to Arizona consumers from the solar-rich southern zone, and on the large direct current transmission connecting the Los Angeles area with the Pacific Northwest. These model results demonstrate how electricity flows will change in California, which has historically been a significant importer of power. As California's solar penetration rises, bulk power flows will reverse as the state increasingly exports power during the day, leaning on neighboring markets to help balance its grid.

Figure 11 Midday transmission flows in spring for high solar scenario.
Zones are shaded according to relative solar penetrations.



Flexible solar

The previous section described the model scenarios that treated solar as a must-take resource. This section describes model scenarios in which the operator can flexibly dispatch solar plants at any level below their expected output. Technically, operators could do this in the inflexible solar scenarios through curtailment, after all available supply is exhausted. In the inflexible solar scenarios, curtailment only occurred for reliability purposes, if it was necessary keep supply and demand in balance after all other existing resources were utilized. The key difference with flexible solar operation is that solar dispatch can be adjusted at any time if doing so reduces total system costs.

In the deterministic model, flexible solar operation will occur primarily through dispatching down the plants. Scaling solar back during shoulder periods with significant system ramps enables lower-cost resources that are ramp constrained to replace higher-cost units. This is the same underlying mechanism presented in the simple model from Section 1, although modeled in higher dimensions to more realistically capture the California market. Dispatching solar production flexibly comes with an economic tradeoff, as it tends to reduce the amount of low-cost solar energy supplied. In fact, dispatching down solar energy when there isn't an expensive ramp constraint will tend to increase system costs, as the reduced solar energy is replaced by more expensive supply. In this way, the cost-minimizing operator will adjust flexible solar output at times and locations where there is a positive net benefit. This occurs during periods of large system ramps that are otherwise expensive to balance. The operator chooses to use flexible solar for ramping support more frequently as solar penetrations rise, because in these scenarios the marginal resources needed for ramp support are significantly more expensive. Figure 12 displays the flexible solar model results for the high penetration during the same spring week from Figure 9. Figure 13 zooms in on a single day and compares it to the same day from the inflexible solar model results. These figures show the operator scaling back solar during the day relative to the inflexible scenario, With flexible solar, the operator strategically shaves off the solar peak during the day to manage the net system load at high penetrations. Doing this reduces the overall system ramp by 3.5 GW, allowing lower cost resources that are ramp constrained to operate and increase total system value.

Figure 12 Supply for high penetration with flexible solar, same spring week as Figure 9.

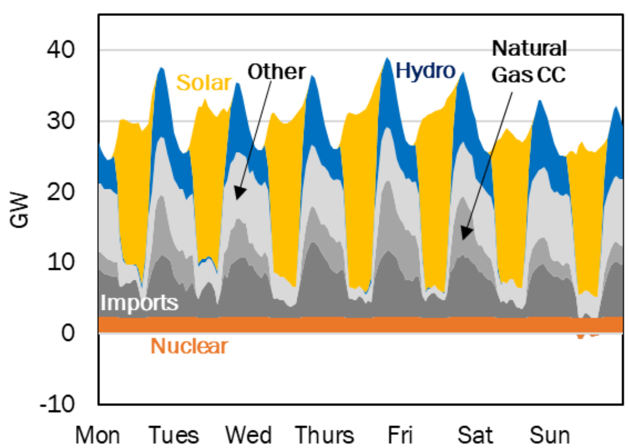
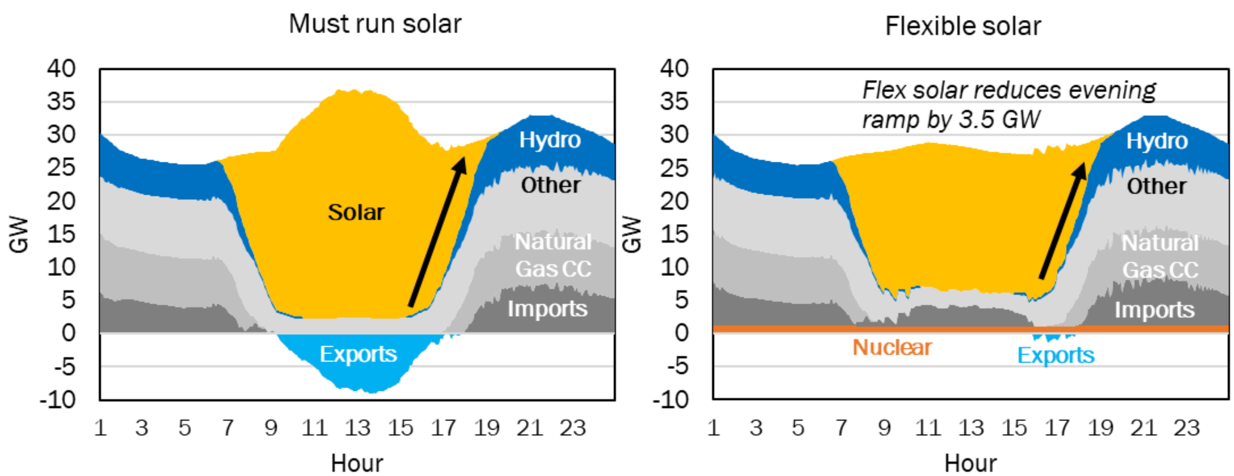
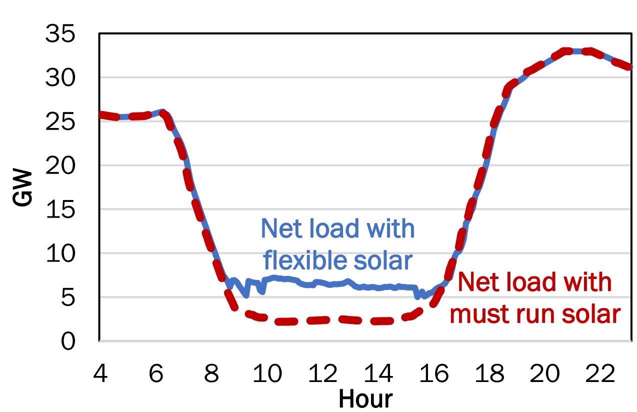


Figure 13 Must run and flexible solar scenarios for a single fall day.



Nuclear generation was completely shut off in the must-run scenario during the day presented in Figure 13. The operator made the decision that it was too expensive to operate nuclear during the system conditions presented by must-take solar operation, given nuclear plant start-up and shut-down costs and ramping constraints. Exports during the day are mostly eliminated in the flexible solar scenario. Imports increase, and the change in non-California generation mostly consists of out-of-state hydro, solar thermal, and nuclear. Flexible solar operation also enables geothermal and solar thermal units to increase output. These are low-cost ramp-constrained units that increase production when the ramping needs of the system are reduced. Increasing output from these units lowers total system costs by replacing high-cost fast-ramping fossil units that were required when solar is operated on a must-run basis. For example, Figure 13 shows that nuclear is unable to be dispatched at all during these 24 hours with must run solar because it cannot sufficiently ramp down during the day. With flexible solar, nuclear can remain online for the full 24-hours, which replaces fossil generation at night. The impacts of flexible solar are shown another way in Figure 14, which plots net load curves for the must run and flexible solar scenarios. When solar is operated flexibly, it is scaled back to enable some inflexible low-cost resources to remain online during the day, replacing natural gas generation during the night.

Figure 14 Daily net load curves for must run and flexible solar scenarios.



Stepping back, at a 30% solar penetration, modeled electricity system operation with flexible solar reduces total annual production costs for the California system by $172 million dollars compared to must-take solar operation. Including generators in neighboring states leads to total regional savings $268 million per year. For scale comparison, the CAISO market cleared approximately $10 billion of energy transactions in 2018.[37] These cost savings occur as flexible solar is strategically scaled back in certain hours to mitigate system ramps, enabling ramp-constrained power plants that produce at lower cost to remain online. Table 20 and Table 21 in Appendix 3 provide detailed overviews of the changes in generation and production costs between the must run and flexible solar scenarios.

Figure 14 plots the aggregate changes in generation by technology after switching to flexible solar operation, broken out by month to consider seasonal effects. The green bars in the negative direction represent the net solar energy that is reduced once it operates flexibly. Note that the largest solar scale-backs occur in the spring months when operational and ramping issues are largest. Solar is scaled back the least during the summer, despite there being relatively high solar production. Figure 14 shows how flexible solar operation enables less reliance on flexible fossil generation, the majority of which is natural gas combined cycle plants (grey) plus peaking units. The reduction in these units is offset by increasing output from less costly, slower-ramping generators, consisting of nuclear, imported power, geothermal, and solar thermal. The increases in this lower-cost yet ramp-constrained supply are unlocked by dispatching solar flexibly to reduce system ramps. Average monthly electricity consumption in California is approximately 25,000 GWh, so the magnitude of the generation shifts depicted in Figure 14 represent approximately 7-10% of the total energy supplied, depending on the particular month.

Figure 15 Change in California generation from flexible solar by month.

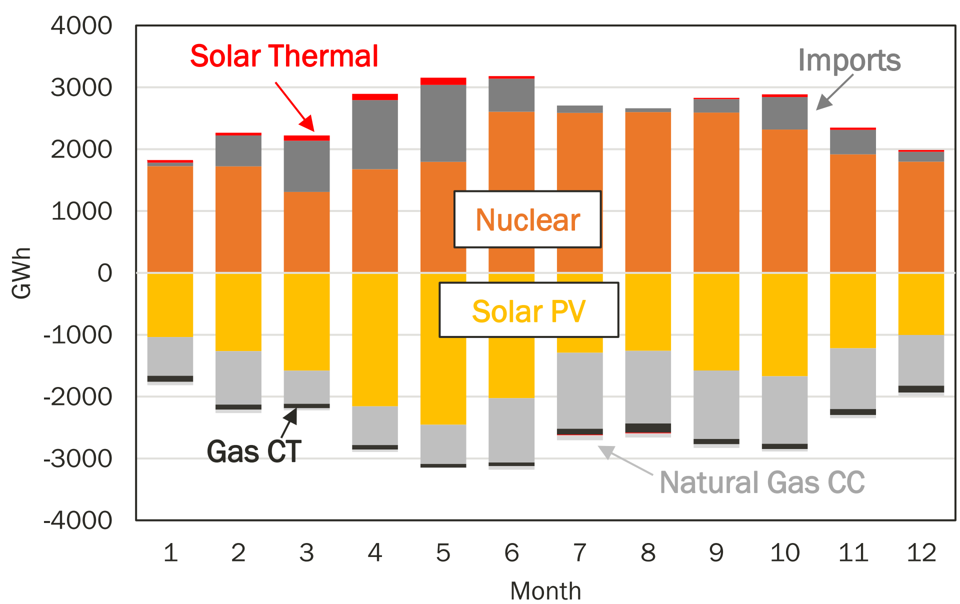
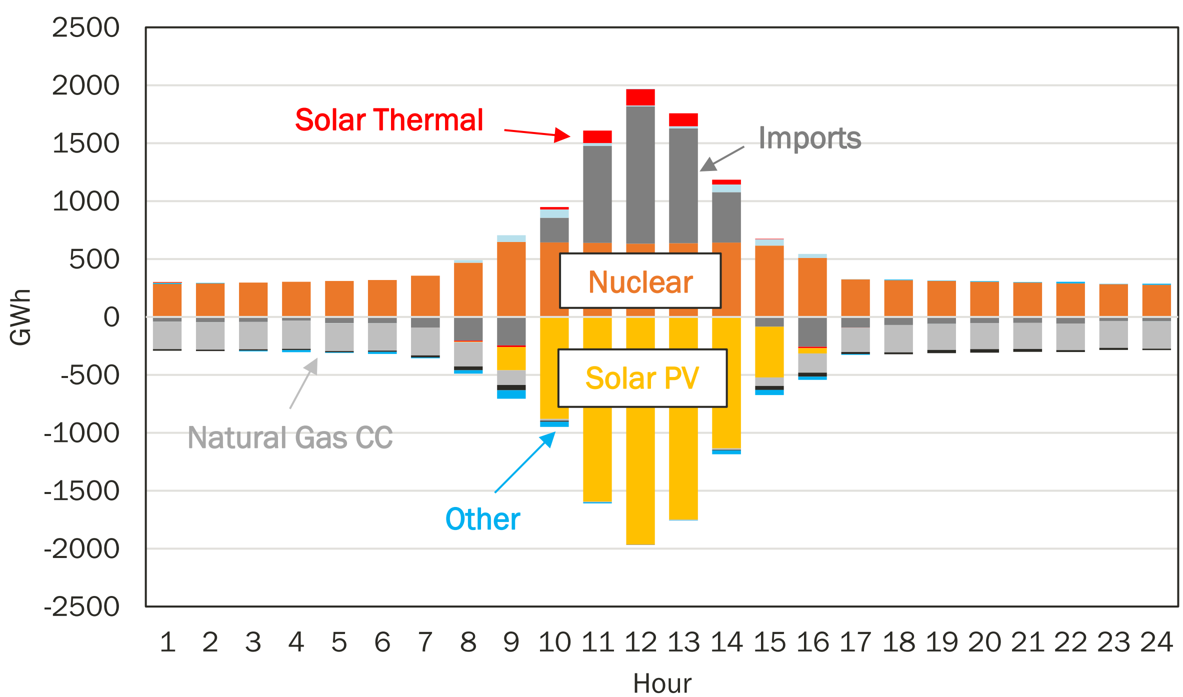


Figure 15 yields additional insights by showing the same flexible solar effects by generation type except broken out by hour of day. First, this plot shows there is a baseload shift from natural gas CC to nuclear that occurs in morning, evening, and night hours. When solar is operated as a must-take resource, more natural gas CC was required by the operator to remain online during the night in order to maintain ramping capabilities that were needed during the morning and evening. With flexible solar, these ramping requirements are reduced, enabling some of it to be replaced by lower-cost, slower-ramping nuclear units that had start-up constraints preventing their nighttime operation with must-take solar. Gas combustion turbine (CT) and other oil-based peaking units decrease when solar is operated flexibly during the morning and afternoon as solar is ramping up and down. These are high-cost flexible units that were relied on more heavily in the must-take solar scenario. When solar is operated flexibly, geothermal and solar units increase output during daytime hours.

Figure 16 Change in annual California generation from flexible solar by hour of day.



Both Figure 14 and Figure 15 show increasing imports with flexible solar operation. Changes in out of state generation primarily are made up of additional hydro from the Pacific Northwest, nuclear from the Pheonix area, and solar thermal from plants in both Nevada and Arizona. These out-of-state generators are part of an integrated network serve demand in both their local market and neighboring markets, including California. However, it is difficult to separate imports by fuel type because both generators and end-users produce onto and consume from an interconnected electricity network.

Flexible solar operation in these scenarios reduces carbon dioxide equivalent (CO_2e) in California by approximately 1.9 million metric tons (MMT), compared to the baseline. For scale comparison, total electric sector emissions in California in 2017 were 38 MMT.[38] Emissions in neighboring states also declined in the flexible solar scenario. Although solar photovoltaics declines overall, their flexible operation enables a reduced reliance on natural gas plants. This is offset by other zero-emitting sources, including nuclear, hydro, and solar thermal.

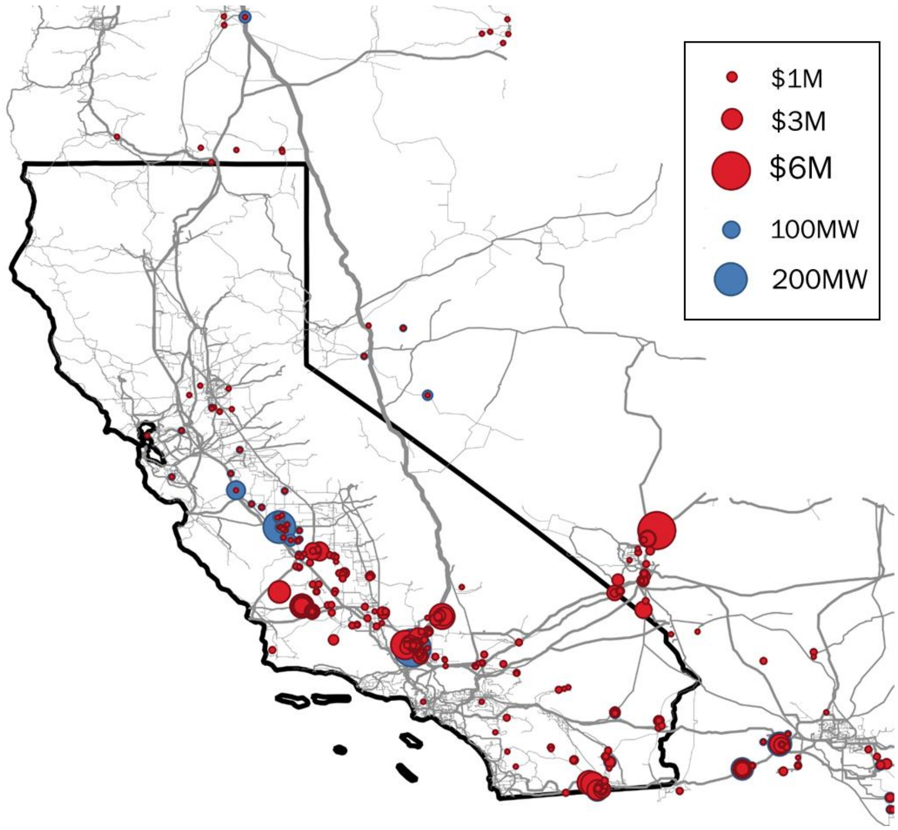
Locational value of flexible solar

Another way to analyze the value of flexible solar is to examine the flexible solar shadow values. In the model, each solar plant has a constraint requiring production at its expected energy output. Many optimization algorithms will produce shadow prices, or dual variables, associated with each constraint. In this case, the shadow prices on the must run solar constraints in the downward direction represent the marginal reduction in system costs that would be achieved if the plant operated flexibly. Thus, these shadow prices represent the locational marginal value of flexible operation for each solar plant for each period in the model. This is similar to how locational marginal prices in wholesale electricity markets are equivalent to the shadow price on the load constraint and represent the marginal value of energy at each node. Technically, a linear-program relaxation estimate of this model was solved to estimate locational shadow values, because the open-sourced mixed-integer problem solver used to calculate the baseline model did not produce shadow values.[39]

The flexible solar shadow price is non-zero at a solar plant during periods when flexibly operating the plant produces net system cost reductions. During those periods, it is equal to the marginal reduction in system costs that would be achieved if the must-run constraint were relaxed. When the system operator cannot physically balance the system due to the must-run constraint, the shadow price binds at the value of lost load. This is set to $2,000/MWh, equal to CAISO's administrative power balance penalty.[40] These values are summed across the year to estimate an annualized value of flexible solar at the plant level.

Figure 16 maps the value of flexible solar for solar plants in the model region. It shows clusters of value from a handful of large solar plants north of the Los Angeles region. Additional value clusters are observed from solar plants in southern California near the border, and in the area surrounding Las Vegas. In the map, the red circles represent the value from flexibly operating these plants. The blue circles represent the plant's nameplate capacity on a scale matching the red circles, and are set behind the red circles. This means that a visible blue circle on the map indicates the associated solar plant provides less value when operated flexibly relative to what would be expected based on its size, compared to the rest of the solar fleet. There are a couple large solar plants visible in the map that show blue in central California closer to San Francisco, including a 205 MW plant in Fresno county and a 108 MW plant in Merced county. These large solar plants show less value from flexible operation. They are located in areas with less ramp-constraints and less access to lower-cost power plants that stand to benefit from flexible solar operation, including nuclear, solar thermal, and geothermal.

Figure 17 Annual flexibility value by solar plant, millions of dollars. Visible blue circles highlight plants that have lower flexibility value relative to its size. Grey lines represent the high voltage transmission network.



Nuclear sensitivities

The results of this modeling exercise for California depend to a significant extent on the operation of two large nuclear power plants: the Diablo Canyon plant north of Los Angeles and the Palo Verde plant in the Phoenix area. Given this, the general results were compared with a couple nuclear-related sensitivity scenarios to more deeply understand their effects on flexible solar operation in the California market. The first sensitivity is focused on the flexibility of nuclear plant operation, while the second is on nuclear plant retirement.

The primary model results assumed the nuclear plants were operated relatively inflexibly. Specifically, nuclear unit ramp rates were restricted to 1% of nameplate capacity per hour, minimum operating levels were set to 50% of nameplate capacity, and minimum down times at 8 hours. To be clear, at high renewable penetrations these constraints typically bind, and the nuclear plants are operating more flexibly in the model than they typically do at current solar levels. Occasionally, California nuclear units show an ability to operate more flexibly, more details on this topic are provided in Appendix 2 on page 47. In addition, nuclear plant operation in Europe and a variety of technical literature suggest pressurized water nuclear reactors can operate much more flexibly than how they are operated in California. The flexible nuclear model sensitivity examined the impact of reducing the minimum operating limits to the plants' reported levels, reducing the minimum down times to what is estimated from observed plant data, and setting the ramp limits to 25% of nameplate capacity per hour.

The Diablo Canyon nuclear plant in California is currently planned for retirement in 2025.[41] For this reason, another model sensitivity without this plant operational was calculated. The impacts of flexible solar on the generation fleet for these scenarios are summarized in Table 3. Both of the nuclear sensitivity scenarios mitigate the effects that nuclear units have on the overall flexible solar results. In the first case, nuclear is a large flexible resource that is utilized in the base case when solar is operated as must run. This reduces the overall impact on the generation fleet when solar is allowed to operate flexibly. In the second case, a significant portion of the total nuclear generation in the model is now offline. As a result, less solar is scaled back for ramping support in the flexible scenario. The decrease in nuclear availability mitigates flexible solar's impact on natural gas combined cycle and peaking units. Conversely, these nuclear scenarios result in partially-offsetting increases in other lower-cost resources for ramping support including hydro, geothermal, solar thermal, and imports.

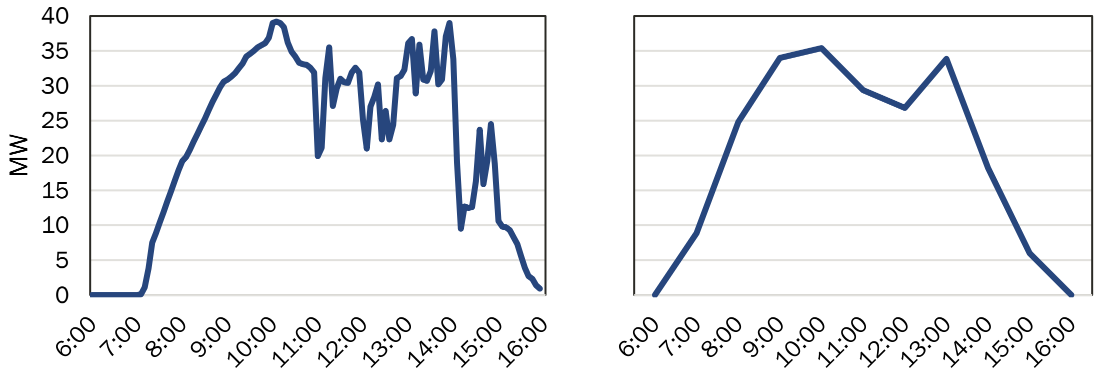
Table 3 Change in California generation (GWh) at 30% penetration with flexible solar operation for nuclear sensitivities.

Technology	Base	Flexible Nuke	Retired Nuke
Conventional Hydroelectric	118	215	215
Gas CT and Oil Peakers	-1,026	-115	-22
Geothermal	-353	-3	70
Natural Gas Fired Combined Cycle	-10,739	-670	-139
Nuclear	24,643	1,616	314
Solar Photovoltaic	-18,539	-8,567	-8,081
Solar Thermal	529	1,201	1,182
Imports	5,778	6,413	6,462
All Other	-388	-89	-1

Sub-hourly model

This study highlights how flexibility benefits are closely tied to increased system ramping needs in markets with growing solar. System variability from solar comes from large ramps in the morning and evening and short-term fluctuations in output throughout the day. A model with hourly profiles aggregates away from this variability and doesn't capture all the benefits from short-run flexibility. Figure 17 displays an example daily solar profile for a 50 MW plant used in the model. The left panel plots 5-minute output data, while the right panel shows the same data aggregated to hourly averages. There is significant subhourly variability that is lost in the hourly model.

Figure 18 Example solar output data at 5-minute granularity (left) and hourly granularity (right). Grey dotted line represents peak from 5-minute data.



There is a tradeoff between balancing model granularity and computation time. It was not feasible for this study to calculate a sub-hourly model for a full year of market dispatch for California and neighboring states. Instead, an annual model was solved at hourly granularity, and one week in mid-April was solved at 5-minute granularity. The results from the 5-minute model suggest there are substantial benefits from flexible solar operation that are not captured in the hourly model. Flexible solar operation in the 5-minute model yielded 3.4 times more production cost savings compared to the hourly model for the week studied. These results suggest the $268 million annual production cost savings captured in the hourly model are an underestimate. True cost savings could be 3.4 times higher, at $911 million. However, this is likely an overestimate because operational challenges from high solar penetrations are concentrated in the spring, the period during which the 5-minute model was calculated.

3. LOOKING FORWARD

Market design for flexible solar

The modeling in this study shows how flexible solar operation can provide ramping and load-following support while reducing the need for more expensive fossil-based flexible resources. Previous work has shown how flexible solar operation can also provide the system short term reliability and ancillary services including frequency and voltage regulation.[29] These ancillary services have been used historically in competitive electricity markets, and adequate remuneration and provision frameworks exist in most markets today. Compensation mechanisms for ramping support do not widely exist in competitive electricity markets. In the case of flexible solar, the plant reduces system costs by dispatching below its expected maximum output, but will lose revenue in competitive energy markets when doing so. This leads to a market failure, as the incentives facing individual plant owners do not lead to the efficient system outcome. Conversely, in non-competitive markets, vertically-integrated electric utilities and their customers are often able to internalize the system value of flexible solar because it lowers the cost of electricity delivery from the utility's supply portfolio. For this reason, regulated utilities in areas with high solar penetrations are the first to move towards flexible solar operation. Hawaii Electric Company recently issued large RFPs for dispatchable solar resources to support the operation of its high-solar grid.[42]

Properly-designed flexibility market products can enable solar PV plants to internalize the system benefits from flexible operation in competitive markets.[43,44] Technology neutrality and a focus on the service provided is a core principle in electricity market product design. As such, a solar plant that adjusts its dispatch to mitigate a ramp in net load is equivalent to a fossil plant being dispatched in response to the same ramp need. Furthermore, if the solar plant can manage the ramp at a lower marginal cost than the fossil plant, an efficient market would deploy the flexible solar plant. A properly designed ramp product would involve a payment to a solar plant that dispatches down to offset the need for a more expensive ramping resource. An efficient price for the ramp product would derive from the equilibrium between two components: 1) the marginal cost of solar flexibility, which is the opportunity cost of foregone energy revenue, and 2) the marginal system benefit from the solar plant's flexible operation, which comes from a reduced need for a more expensive ramping resource.

Dispatchable renewable energy should be an option for system operators when they procure capacity for ramping services. It is economically efficient to procure flexible solar when the marginal benefit of providing flexibility service exceeds the marginal cost of foregone energy revenue. Put another way, it is economic when the next marginal ramping resource that would be replaced by the deployment of flexible solar has a production cost greater than the current energy price. In this case, an efficient market would lead to the solar plant being dispatched down, the more expensive ramping resource will not need to be used, and the solar plant would be compensated somewhere between the current energy price and the marginal cost of the avoided plant. To illustrate this concept further, consider the following example: suppose the system operator determines a need to procure additional ramping capacity to help manage an upcoming net load increase in the evening. Suppose further that the expected marginal energy price during this period is $50/MWh. Finally, suppose the operator has only two options to solve the ramping need: 1) it could dispatch a flexible combustion turbine (CT) plant that has a production cost of $75/MWh, or 2) it could dispatch down the solar plant below its expected output, which costs the solar plant $50/MWh in lost energy revenue. Clearly, option 2 is the lower-cost solution. If the operator dispatches the CT because of "must-run" solar rules, market clearing would lead to the plant receiving at least $75/MWh to cover its production cost. Rather, the operator should dispatch down the solar plant and compensate it at least $50/MWh but less than $75/MWh. Doing this yields lower system costs compared to the CT solution, and incents the flexible solar plant to provide needed ramping support rather than operate as a must-run plant.

More generally, properly priced flexibility products that reflect the system's marginal cost of procuring the needed flexibility will incent all resources to supply efficient levels of flexibility services. Well-designed market products lead to efficient real time operation and provide accurate price signals for investors of flexible supply. Moreover, competitive and transparent market prices inform efficient contracting between owners and off-takers. With well-functioning flexibility markets, power purchase agreements can add provisions that incorporate spot prices for flexibility services to improve economic efficiency. Most solar projects are developed under long-term contracts that specify upfront the terms of operation throughout the plant's lifetime. Existing solar PV contracts reinforce the historic "must-take" paradigm of solar production because they typically compensate based on total energy produced, and do not consider flexibility services. Under these contracts, a solar plant will lose revenue if they forgo energy production to provide system flexibility. In this way, flexible solar operation requires a structural redesign of long-term power purchase contracts.[45] One way to do this is to move some or all of the compensation mechanism in the contract from one that is energy based ($/MWh) to capacity-based ($/MW).[46] In exchange for making a capacity payment, the off-taker is able to operate the PV plant flexibly.

The capacity based PPA approach is appealing in its simplicity. However, the nameplate capacity of a solar plant on its own does not fully reflect the plant's capabilities. For example, two solar plants may both have a total capacity of 100MW, but one may be worth more because it is located in an area with higher solar insolation. Or, one may have a higher capacity factor on average due to superior panel technology or through the use of tracker technology. Another contracting approach that deals with this issue is to compensate the solar plant based on its expected energy output (MWh). Expected energy output would be an estimate of what the plant's total energy production would be prior to any output adjustments for flexibility services. The expected energy payments would remain constant while allowing the system operator the option to operate the plant flexibly when doing so is beneficial for the system. Thus, if two plants had the same nameplate capacity but one had a higher capacity factor, this type of contract would value the more efficient plant higher while also allowing for flexible operation by separating compensation from the plant's final energy output.

Conclusion

This paper explored the economics, operation, and market design for flexible solar operation in electricity systems. More flexibility is needed to manage systems with increasing variability as the electric industry decarbonizes. Understanding the value from flexible solar operation to support efficient renewable energy integration is the primary focus of this study. A review of the research literature reveals how flexibility can be enhanced at many different components of the electricity system, including through adjustments to conventional power plants, energy storage, transmission interconnection, and demand side technologies. The available literature on the use of solar or wind plants directly as a source of flexibility is relatively sparse but growing.

For this research, market optimization models were built and used to study the value from flexible dispatch of large solar photovoltaic power plants in a competitive electricity market. First, a stylized model was described to show how a solar plant can provide load-following support during the morning and evening system ramps on a simple, hypothetical system with three power plants. Next, the bulk of work that went into this study consisted of constructing a large computer model of the California electricity market designed to study the value of flexible solar operation, the details of which are described in Appendix 2. The modeling concludes that at a relatively high solar penetration of 30%, flexible solar operation lowers total system costs on the order of hundreds of millions of dollars per year in California and neighboring states, compared to a system which operates solar as a must-take resource. The primary source of economic value from solar plant flexibility derives from the operator's ability to strategically adjust solar output to mitigate large swings in net load and thereby reduce the need for fast-responding plants that have high production costs.

For the most part, electricity markets and contracts are not currently able to take advantage of this flexibility value inherent in modern solar PV plants. From a technical perspective, automated control systems at utility-scale solar PV plants and in modern electricity system operations centers are able to control power output in a precise and automated fashion. However, market dispatch procedures largely do not consider these capabilities when determining day ahead and real time schedules. Instead, they rely primarily on conventional generation to provide ramping support combined with renewable curtailment procedures. Furthermore, current long-term power purchase agreements typically incent solar plants to maximize its energy production, even when reducing production would provide highly-valued relief to the system. New contracts should implement provisions that don't make financially penalize solar plants when they provide valuable system flexibility. Market designers will need to implement new flexibility products that reflect the technical capabilities of all available resources, including solar, while incorporating resources' opportunity costs into their pricing. This evolution of competitive electricity markets will enable efficient operation of the system in a high renewable future.

APPENDIX 1. MATHEMATICAL FORMULATION FOR SIMPLE MODEL

The simple model includes the following choice variables and parameters and is solved for $T = 24$ periods.

<u>Decision variables</u>

x_{1t} Production for slow plant

x_{2t} Production for fast plant

s_t Production for solar plant

<u>Parameters</u>

c_1 Production cost for slow plant

c_2 Production cost for fast plant

$\bar{s}_t$ Maximum solar output

$start$ Starting level for slow plant

$ramp$ Ramp limit for slow plant

The optimization problem is as follows:

$$\underset{x_{1t}\ x_{2t}\ s_t}{\text{minimize}}\ c_1 x_{1t} + c_2 x_{2t} \tag{1}$$

subject to:

$$x_{1t} + x_{2t} + s_t = d_t \quad \forall t \tag{2}$$

$$s_t = \bar{s}_t \quad \forall t,\ \text{or}\ \ s_t \leq \bar{s}_t \tag{3}$$

$$x_{11} = start \tag{4}$$

$$-ramp \leq x_{1t} - x_{1t-1} \leq ramp \tag{5}$$

$$x_{1t}, x_{2t}, s_t \geq 0 \quad \forall t \tag{6}$$

The objective function (eq 1) is to minimize total production costs. The first constraint (eq 2) establishes that total generation meets demand in every period. Equation 3 fixes solar output to its predetermined level in the non-flexible scenarios, and allows it to be dispatched below and up to this maximum output in the flexible scenarios. Equation 4 establishes a starting point for the slow generator. Equation 5 bounds the change in output for the slow generator to within its ramping limit. Equation 6 ensures that generation levels are non-negative.

APPENDIX 2. ECONOMIC DISPATCH MODEL DETAILED DOCUMENTATION

This technical appendix describes the methodology underlying the flexible solar economic dispatch model. It begins by describing the sources and methodologies for the input data. It ends by defining sets, parameters, and variables along with the mathematical formulation of the optimization problem characterizing the model. The data preparation was largely done using Python-based open source scientific computing software,[47] while the spatial analysis was done using QGIS.[48]

Model topology

Zones

The purpose of developing a zonal model of the California electricity market is to generate useful spatial insights while minimizing unnecessary or unreasonable computational complexity. For this general study on the value of flexible solar in California, the model should have sufficient spatial detail to represent high-level differences in demand patterns and capture transmission constraints important for solar generation across the state. The ensuing 15-zone structure was built by aggregating a county-level shape file from the US Census Bureau.[49] The underlying counties in each zone are listed in Table 4 at the end of this section.

California relies on significant levels of electricity imports from neighboring states, with approximately 1/3 of its total generation from out of state sources.[50] Thus, it is important for the model to represent supply external to the California market. Figure 18 maps power plants and their transmission connections in California and neighboring states. Figure 19 shows the model's California zones with a regional transmission overlay. In Figure 19, the thick lines represent 500 kV transmission facilities, while the single thickest line going north-south and entering California in zone 3 is a 1000 kV DC line. Together, these two maps suggest the external regions could be reasonably organized into four regions of interconnections with California:

1. The northern interconnection with Oregon hydro and gas plants and zone 1.
2. The connections with plants in the Reno, NV area and zone 3.
3. The connections with solar and other external plants between southern Nevada and zone 10.
4. Connections with solar and gas plants in the Phoenix region with zone 11.

These regions motivate the creation of four external zones. The external zones are numbered 12-15 and graphically shown in Figure 20.

Figure 19 Power plants and transmission in California and neighboring states.[51,52]

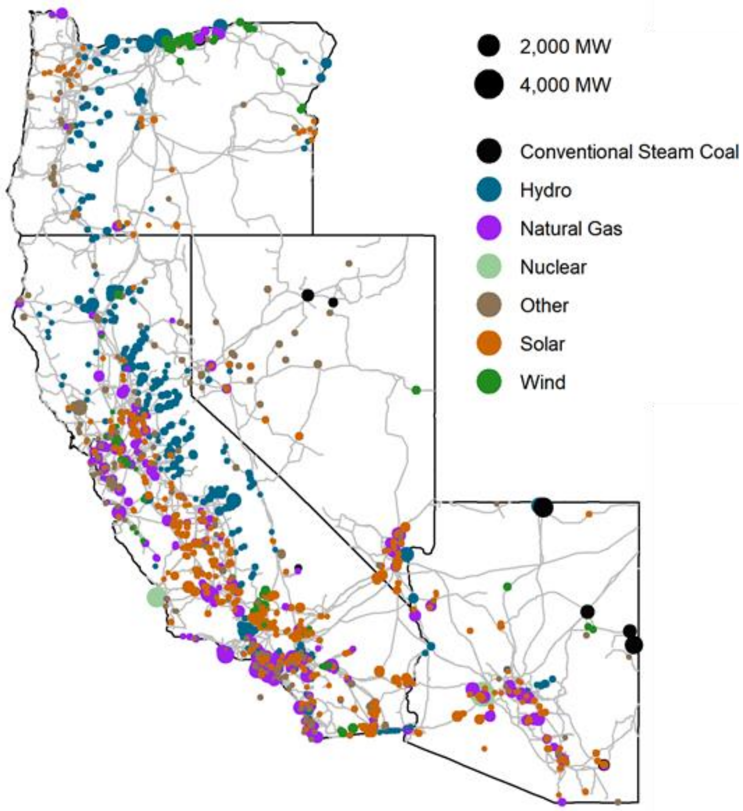


Figure 20 Model zones with transmission overlay.

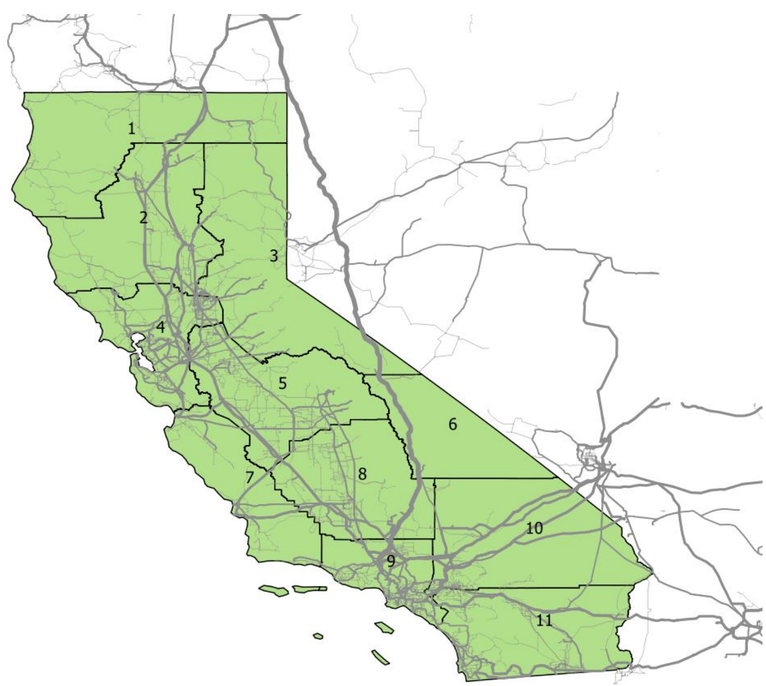


Figure 21 Map of model region with external zones.

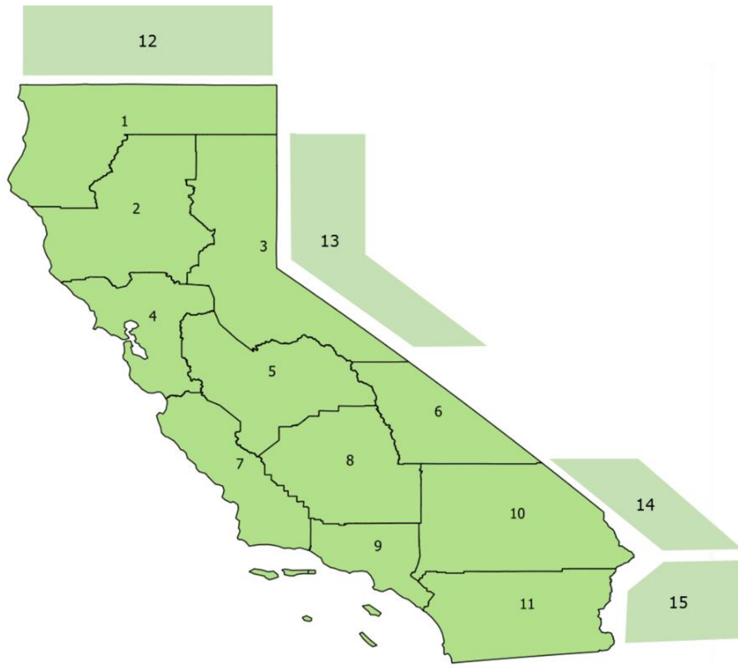


Table 4 Counties by model zone.

Zone	Counties
1	Del Norte, Humboldt, Trinity, Sikiyou, Modoc
2	Shasta, Tehama, Butte, Glenn, Lake, Colusa, Sutter, Yuba, Mendocino
3	Lassen, Plumas, Sierra, Nevada, Placer, El Dorado, Amador, Alpine, Calaveras, Tuolumne, Mono
4	Sonoma, Napa, Yolo, Marin, Solano, Sacramento, Contra Costa, San Francisco, San Mateo, Santa Cruz, Alameda, Santa Clara
5	San Joaquin, Stanislaus, Merced, Mariposa, Madera, Fresno
6	Inyo
7	San Benito, Monterey, San Luis Obispo, Santa Barbara
8	Kings, Tulare, Kern
9	Ventura, Los Angeles, Orange
10	San Bernardino
11	Riverside, Imperial, San Diego

Transmission

The analysis utilizes a zonal pipe-flow model to represent the state's electric transmission capabilities. This method simplifies the transmission system for computational tractability while characterizing the high level power flow capabilities across the state. It assumes power can be transferred as if it were done through simple pipes, without considering the details of Kirchoff's voltage laws for circuits nor reactive power constraints. A recent overview of these transmission modeling methods is provided by Sun and Cole (2017).[53]

Transmission capacities between each zone are calculated by summing up the capacities of individual lines that cross the corresponding zones' shared border. The transmission data is from the US Department of Homeland Security[52] and contains voltage levels for each line. The points where transmission lines cross zone borders are displayed in Figure 21. Transfer capacities between each zone are calculated as the sum of line-flow limits that cross each zonal border. Individual line flow limits can be estimated as a functions of the line's voltage and length using the methods described by Molzahn et al. (2015)[54] and Gutman et al. (1979)[55]. The method involves relating a line's length with its surge impedance loading (SIL), which is the MW loading at which natural reactive power balance occurs. SIL is a function of the line's voltage and impedance. A range of SIL values by voltage from Molzahn et al. (2015) using typical impedance values are displayed in Table 5.

Figure 22 Transmission border crossings used for calculating zonal transmission capacities.

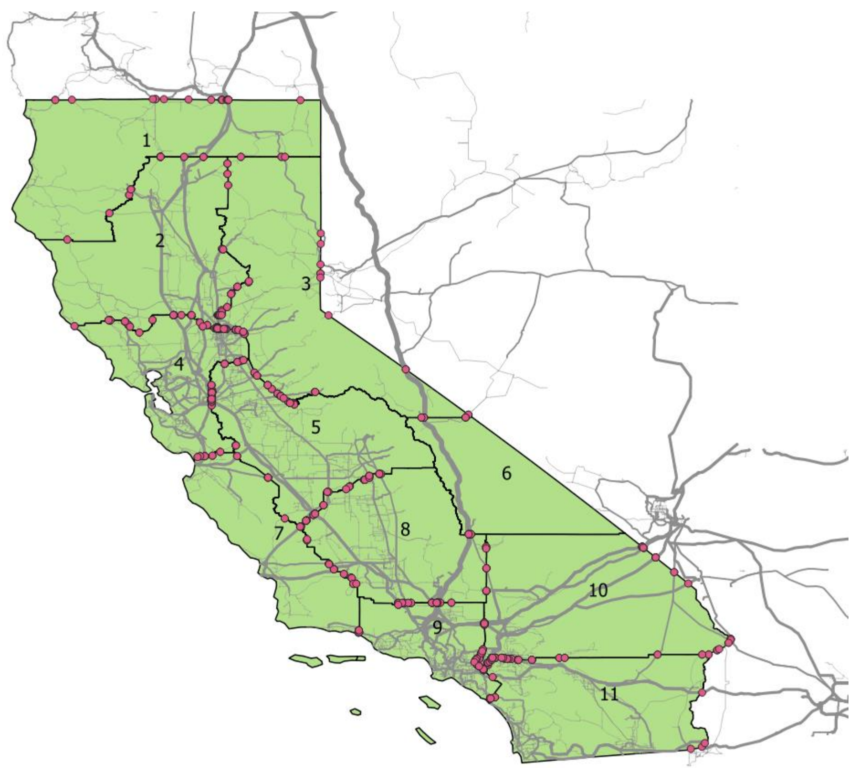


Table 5 Typical surge impedance loading (SIL) values by line voltage.[54,55]

Voltage (kV)	SIL (MW)
69	12.5
138	50.5
230	132
345	390
500	910
765	2210

Some transmission lines have voltage levels different than the discrete values provided by the references in Table 5. For these, a 2nd degree polynomial interpolation is used, equal to $SIL = 0.0042kV^2 - 0.3444kV + 10.318$. The data from Table 5 along with this fitted curve are plotted in Figure 22. Reliable data on individual line lengths cannot be derived from the data's transmission line segment shapefiles, so it is assumed that maximum transmission capacities are equal to the corresponding SIL values. There is a large DC line called the Pacific HVDC Intertie that directly connects supply in northern Oregon (zone 12) with the Los Angeles area (zone 9). This line has a capacity of 3100 MW according to a document from the Bonneville Power Administration.[56] The estimated transmission capacities for lines that cross zone borders are summed by zone pair to obtain zonal transmission capacities. These are presented graphically in Figure 23 and listed in Table 6.

Figure 23 Polynomial interpolation for SIL values by line voltage.

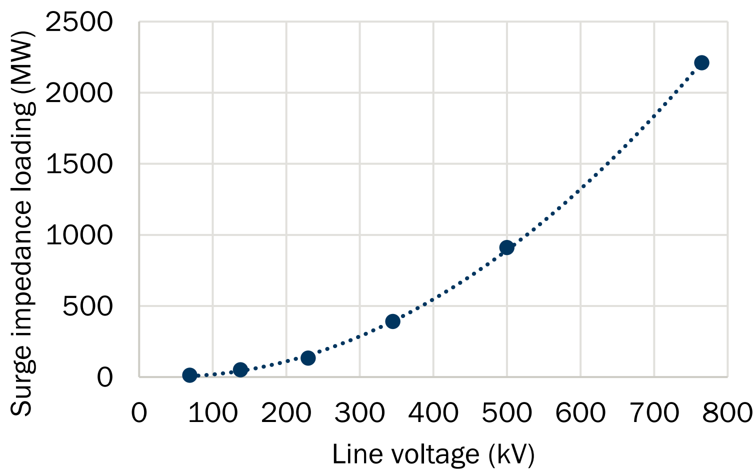


Figure 24 Aggregate transmission connections by zone.

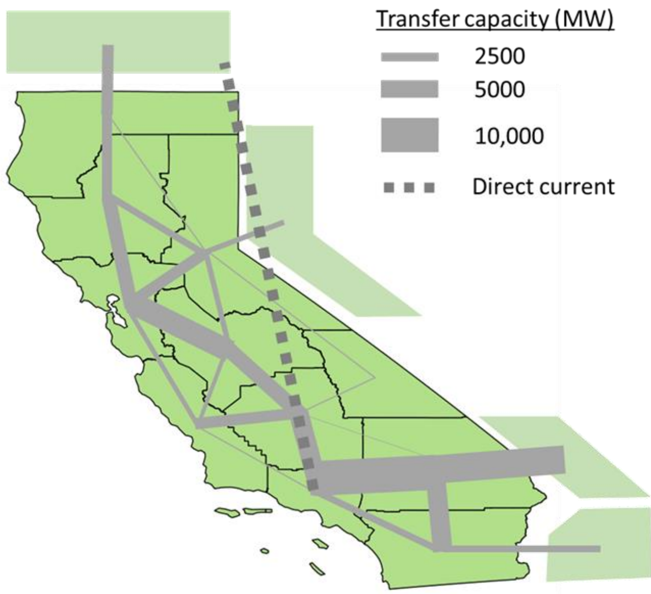


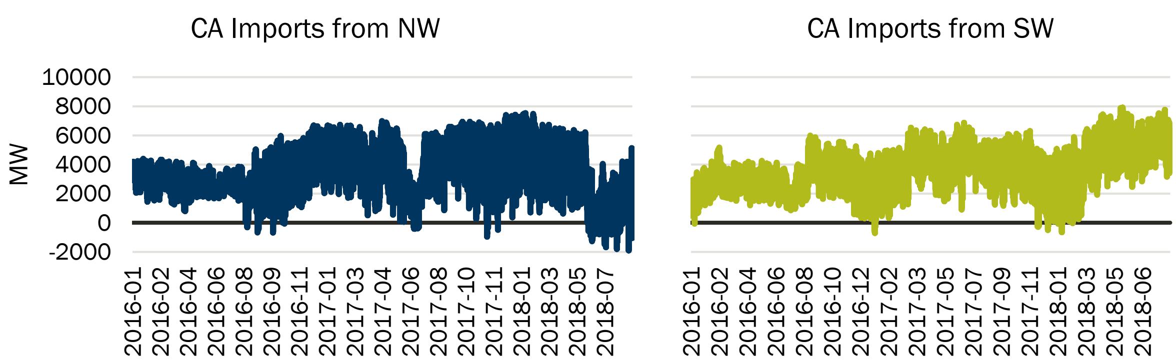
Table 6 Transmission capacity by zone pairs.

From	To	Tx Capacity (MW)
1	2	2939
1	3	405
1	12	3269
2	3	1999
2	4	4000
3	4	3338
3	5	1533
3	6	366
3	13	1480
4	5	6413
4	7	1278
5	7	1199
5	8	4432
6	8	336
7	8	3383
7	9	324
8	9	5555
8	10	285
9	10	10068
9	11	2010
9	12	3100
10	11	5706
10	14	8094
11	15	1904

Imports

The model incorporates a simplified representation of external markets importing into California via the external zones described previously. The US EIA collects historic electricity trade within the US, tracking hourly interchange between California and two neighboring aggregated balancing regions.[57] These neighboring regions are labeled "Northwest", which includes Oregon and a northern section of Nevada, and "Southwest", which includes the remaining southern part of Nevada and Arizona. The NW region corresponds to zones 12 and 13, while the SW region corresponds to 14 and 15. The hourly time series for these regions are shown in Figure 24. These data show that California's neighboring regions have almost always been exporting into California. There is a negligible amount of trade between California and Mexico (75 MW per hour on average from 2016-2018), which is ignored in this model.

Figure 25 Hourly California imports from Northwest and Southwest regions, 2016-2018.[57]



From these series, the average total imports by month and region were calculated and shown in Table 7. These are included in the model as monthly import limit constraints such that imports from external zones 12 and 13 don't exceed the NW limits and zones 14 and 15 don't exceed the SW limits. Furthermore, the model requires that external zones meet local demand first before exporting generation to California. The monthly limits are put in place so that the model doesn't import more energy into California than levels observed in the recent past. Without these limits, the model will tend to over-import because of real-world administrative costs and barriers associated with trading across balancing regions that are not captured in the model.

Table 7 Average imports by month into California from Northwest and Southwest regions, MWh, 2016-2018.[57]

Month	NW	SW
1	7,917,788	7,824,682
2	7,367,736	6,569,943
3	8,155,572	6,721,708
4	8,524,310	4,908,699
5	9,999,037	5,097,259
6	9,556,792	5,957,612

7	8,550,265	8,031,921
8	7,275,088	9,229,512
9	7,711,500	8,809,882
10	5,024,622	9,070,072
11	4,697,309	8,585,035
12	6,234,082	9,439,071

Demand

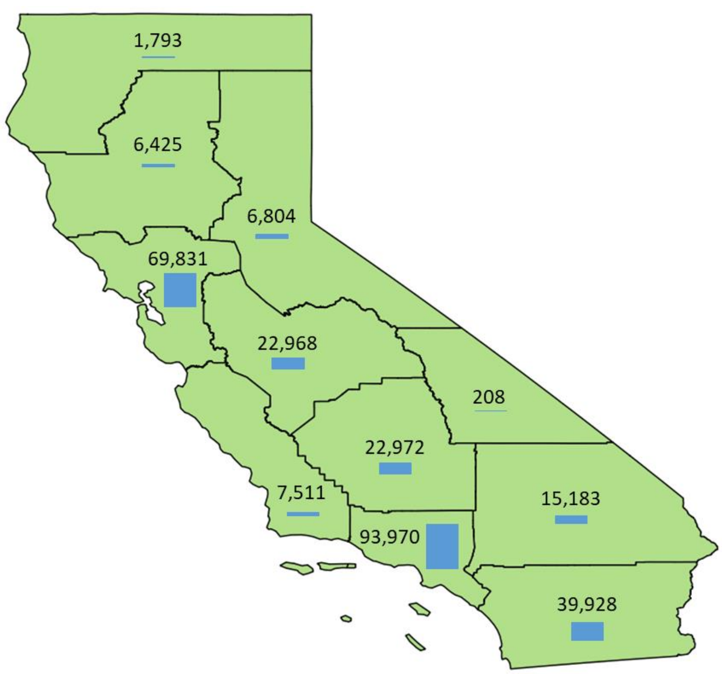
Overview

Hourly demand data for balancing areas across California and its neighbors were collected. The service territories of these entities do not match the model zones. To deal with this, county-level annual energy consumption data is used to calculate annual demand by zone. Then, each balancing area with hourly data is assigned to the zones that overlap its territory as closely as possible. The hourly demand shapes from each balancing authority data series are then scaled to match the annual demand level for the corresponding zone.

Annual demand by zone

County-level annual electricity consumption data from the California Energy Commission was downloaded and aggregated to the zonal level.[58] Average annual consumption from 2015-2018 is displayed in Figure 25.

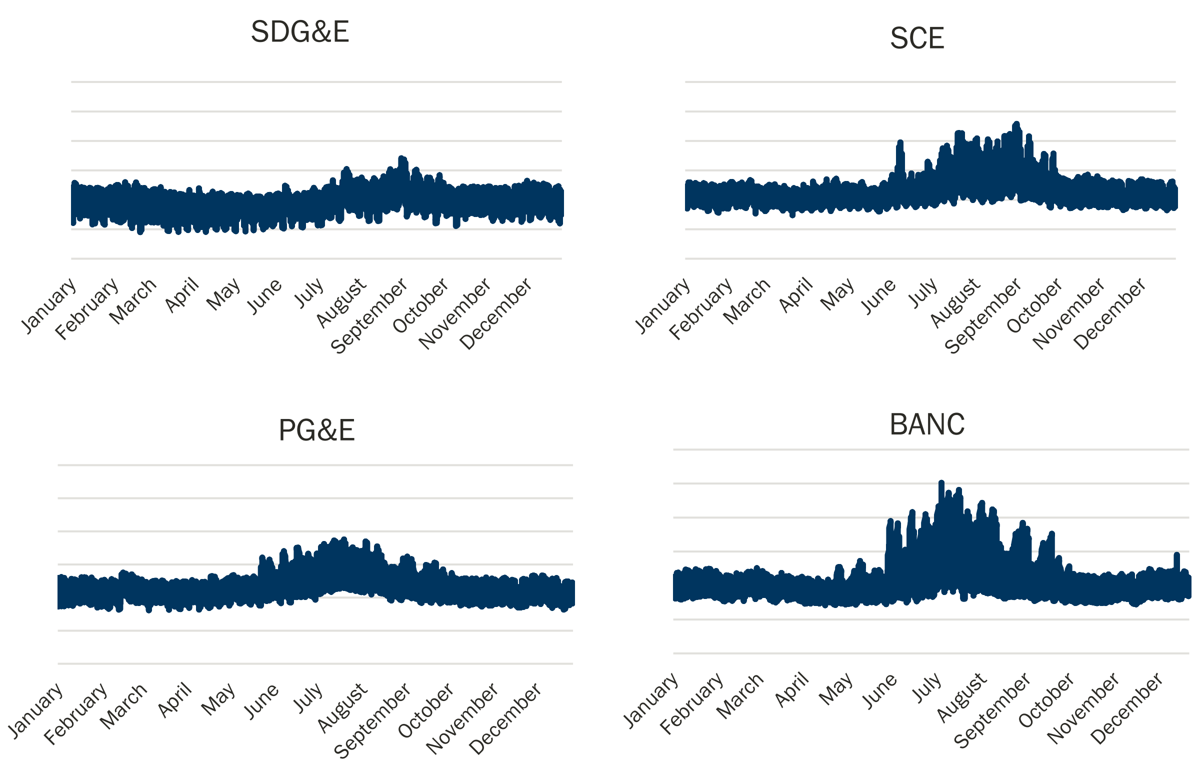
Figure 26 Average annual energy consumption by zone (GWh), 2015-2018.[58]



Demand shapes

Electricity demand profiles vary across California. For example, peak energy consumption in the north occurs earlier in the year than in the south. Also, the variance of electricity consumption depends on the customer type. For example, industrial consumers tend to have lower peak loads relative to off-peak compared to residential and commercial consumers. To illustrate, Figure 26 presents demand series for four California service areas from 2018. The axes are scaled to unity to show relative changes, so the variation is directly comparable across series. The levels of these shapes will later be calculated by the annual consumption value corresponding to the zones from Figure 25. Pacific Gas & Electric (PG&E) and the Balancing Area of Northern California (BANC) in the northern part of CA have peak summer demand in July. In the south, San Diego Gas & Electric (SDG&E) and Southern California Edison (SCE) peak demand occurs in late August or September. Furthermore, SDG&E and, to a lesser extent, PG&E have flatter demand profiles than BANC and SCE.

Figure 27 Relative demand profiles for California balancing authorities.[57]



To reflect demand variation across the state, balancing areas (BAs) for which demand data are available are assigned to zones according to Figure 27. This assignment approximates as best as possible the geographic variation in consumption profiles across the model zones. The BA acronyms are defined in Table 8. The low consumption, rural zones in northern California are assigned to BANC, the urban and coastal zones that include the Bay Area and Sacramento are assigned to PG&E, and so on. External balancing authorities are also assigned to the appropriate external zones, characterizing the markets that can import into CA. The demand profiles for each BA, some of which are shown in Figure 26, are then scaled so that annual consumption in each zone matches the levels displayed in Figure 25.

Figure 28 Balancing authority assignment to model zones for demand shapes.

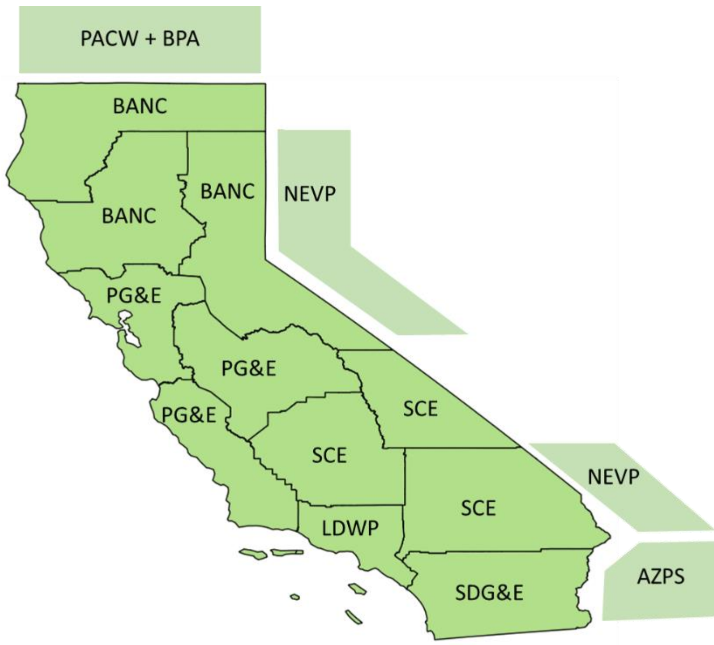


Table 8 Balancing authority names.

BANC	Balancing Authority of Northern California
BPA	Bonneville Power Administration
LDWP	Los Angeles Department of Water and Power
NEVP	Nevada Power Company
PACW	PacifiCorp West
PG&E	Pacific Gas and Electric
SCE	Southern California Edison
SDG&E	San Diego Gas & Electric

Operating reserves

In real time market operation, reserves are required to be available in case demand or supply do not realize as predicted. This is driven by uncertainty in electricity consumption, wind and solar output, and the possibility of unplanned generator or transmission outages. Operating reserve requirements are a complex function of these variables, but the authors of the 2010 Western Wind and Solar Integration study showed that a “3+5” heuristic equal to 3% of demand plus 5% of wind and solar output provides a relatively good, simple estimate of a system’s operating reserve requirement.[59] For this model, hourly zonal operating reserves are calculated as 3% of each zone’s demand plus 5% of nameplate wind and solar capacity in that zone, discounted by an aggregate capacity factor. The wind capacity factor is 34% and is a plant-weighted average from recent production in the western U.S. reported by LBNL (2019).[60] The solar capacity factor is 22% and is the aggregated west-coast value from NREL’s ATB (2019).[61]

Plant characteristics

Overview

Table 9 summarizes the power plants in the baseline model by production technology. This includes generation in California and neighboring states. The core information on plants in the model, including size, technology, and location were collected from the EIA’s electricity datasets.[62]

Table 9 Summary of generating units by technology in baseline model.

Technology	Capacity (MW)	Number of units
Natural Gas Fired Combined Cycle	45,008	362
Conventional Hydroelectric	22,282	691
Natural Gas Fired Combustion Turbine	16,475	375
Solar Photovoltaic	13,156	925
Natural Gas Steam Turbine	10,099	50
Onshore Wind Turbine	9,500	181
Conventional Steam Coal	7,759	21
Nuclear	6,533	5
Geothermal	3,576	165
Solar Thermal	1,775	16
Wood/Wood Waste Biomass	1,163	62
Natural Gas Internal Combustion Engine	749	135
Petroleum Liquids	682	137
Landfill Gas	402	171
Other Gases	270	15
Other Waste Biomass	184	77
All Other	121	10
Municipal Solid Waste	85	4
Other Natural Gas	52	45
Petroleum Coke	27	1

Installed capacities are summed at the zonal level and compared to zonal demand levels. Total capacity and peak demand by zone in the baseline scenario are displayed in Table 10. Note that wind and solar capacities are not discounted. While imperfect, this comparison provides insight into balancing patterns across the model. For example, zones 4 and 9, representing the San Francisco and Los Angeles metropolitan regions respectively, have significantly less installed capacity than peak demand. These urban zones will rely on import connections with neighboring zones to meet demand. This includes excess capacity in zones 2 and 3 in northern California to sell to zone 4 (San Francisco), and excess capacity in zone 8 to sell into zone 9 (Los Angeles).

Table 10 Installed capacity and peak demand by model zone.

Zone	Capacity (MW)	Peak demand (MW)
1	452	475
2	5,371	1,702
3	4,048	1,801
4	10,707	15,235
5	5,409	5,012
6	358	49
7	4,945	1,647
8	11,096	5,477
9	15,108	22,410
10	4,862	3,565
11	10,955	8,232
12	16,796	14,635
13	3,120	4,274
14	9,015	4,288
15	29,758	7,261

Costs

Fuel

Monthly-averaged fuel costs reported to EIA for coal and natural gas plants from 2015-2017 are used in the model.[63] Fleet-level monthly averages were assigned to coal and gas plants with missing fuel data, shown in Figure 28. During the sample period, natural gas fuel costs have tended to be higher during winter months, while coal costs have remained stable throughout the year. Plant level fuel costs are missing for petroleum plants in California; the average 2017 value for petroleum plants in neighboring states of Arizona, Nevada, and Oregon is used. Plant-level nuclear and biopower are not available in the EIA data, and aggregate values from the NREL Annual Technology Baseline (ATB) were assigned to these plants. Table 11 presents the annually-averaged fuel costs by technology used in the model.

Figure 29 Monthly average fuel costs for model fleet, 2015-2017.

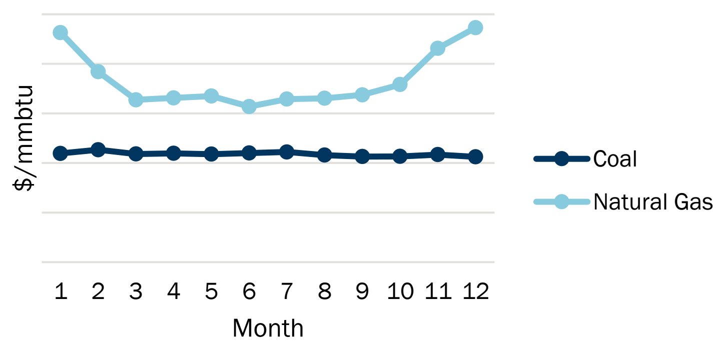


Table 11 Average fuel costs by technology in model fleet.

Technology	$/mmbtu
Coal	2.18
Natural gas	4.33
Nuclear	0.64
Biopower	3.10
Petroleum	13.61

Thermal plant fuel costs are converted to $/MWh values using measured plant-level heat rates from the EPA EGrid dataset.[64] For the few plants with missing heat rate data, capacity-weighted average heat rates from the rest of the model fleet are used. Nuclear plant heat rates are not tracked by the EPA so an average heat rate reported in NREL's Annual Technology Baseline is used. Aggregate heat rates by technology are presented in Table 12.

Table 12 Capacity-weighted average heat rates by technology in model fleet.[64]

Technology	Average heat rate (mmbtu/MWh)
Natural Gas Fired Combined Cycle	7.23
Natural Gas Fired Combustion Turbine	9.93
Natural Gas Steam Turbine	12.00
Conventional Steam Coal	11.04
Wood/Wood Waste Biomass	11.04
Natural Gas Internal Combustion Engine	9.03
Nuclear	10.46
Petroleum Liquids	13.50
Landfill Gas	29.56
Nuclear	10.46
Other Gases	5.74
Other Waste Biomass	74.62
Other Natural Gas	148.13

Operations and maintenance

Average variable operations and maintenance (O&M) costs by technology class from the 2019 NREL ATB are used, and shown in Table 13.[61] These represent the per-unit, non-fuel expenses associated with producing energy. They include expenses associated with water use, disposal, chemicals, lubricants, and other materials that are used when a generator is producing electricity. Natural gas internal combustion engines and petroleum plants are assumed to have O&M costs similar to natural gas peaking plants, and are assigned those values.

Table 13 Variable operations and maintenance costs by technology.[61]

Technology	Variable O&M ($/MWh)
Biopower	5.17
Coal	5.00
Geothermal	0.00
Hydropower	0.00
Natural gas combined cycle	2.77
Natural gas combustion turbine	7.14
Nuclear	2.31
Solar	0.00
Solar Thermal	0.00
Wind	0.00

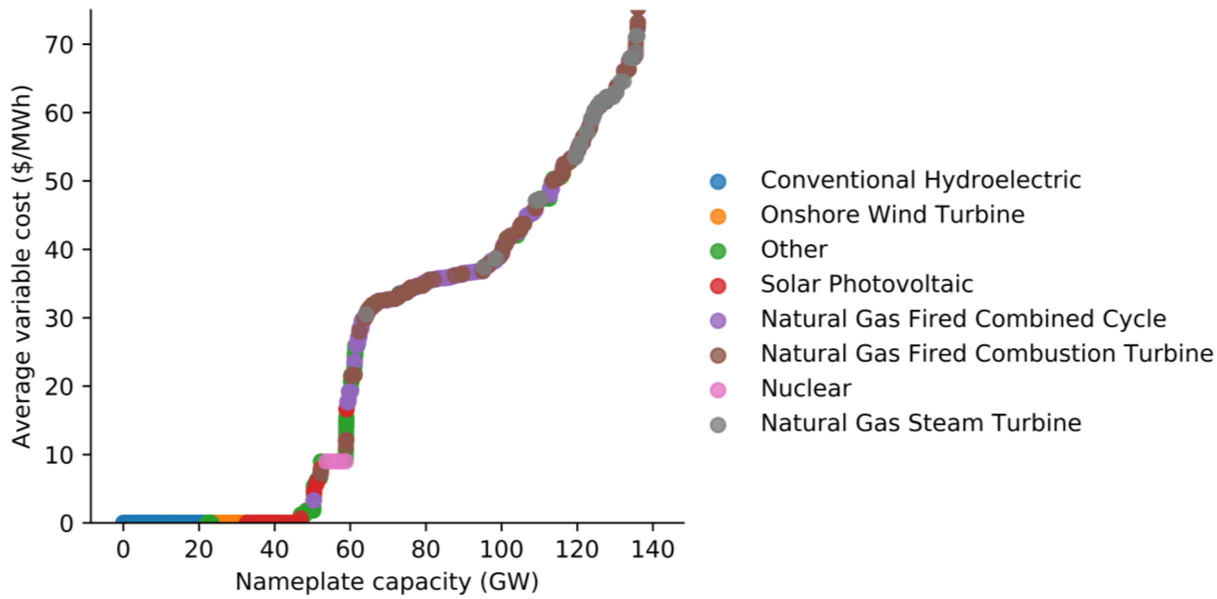
Emissions costs

The model incorporates plant-level EPA-measured CO_2-equivalent emissions rates.[64] Emissions costs are calculated using the most recent carbon auction settlement price available for California; $16.80 per ton of CO_2, as of November 2019.[65] Table 14 summarizes average emissions rates by technology as reported by EPA. Plant-level fuel, O&M, and emissions costs estimates are summed to determine variable costs. The plants in the model fleet are sorted in order of increasing variables costs and plotted as a supply curve in Figure 29.

Table 14 Average emissions rates by technology for model fleet.[64]

Technology	CO_2e rate (ton/MWh)
Coal	1.04
Natural Gas Combined Cycle	0.38
Natural Gas Combustion Turbine	0.54
Geothermal	0.07
Petroleum Liquids	0.93
Wood/Wood Waste Biomass	0.06

Figure 30 Supply curve for plants in the base model.



Start-up costs

Start-up costs for thermal power plants include the cost of startup auxiliary power as well as required input materials including start-up fuel, chemicals, water, additives, and more. Aggregate estimates of these costs for coal and gas plants were published by Intertek APTECH on a $/MW basis, and displayed in Table 15.[66]

Table 15 Start-up costs.

Technology	Start-up cost ($/MW)
Coal	29.78
Gas Combustion Turbine	1.77
Gas Steam Turbine	37.13

Flexibility parameters

Plant-level flexibility parameters used in the model include minimum operating load, ramping limits, minimum down times, and minimum run times. Minimum operating levels are reported by the US Energy Information Administration.[51] Empirical estimates of ramp limits, minimum down times, and minimum run times for fossil plants are used, specifically the 95th percentile values from the plant-level distributions described in the next section. These aggregated values are presented in Table 16. Parameters for steam turbines fueled by nuclear, biomass, and geothermal energy are assumed to be technically similar to the average of coal-powered steam turbines. Natural gas internal combustion engines and petroleum plants are assumed to have parameters equal to the average gas combustion turbine plants.

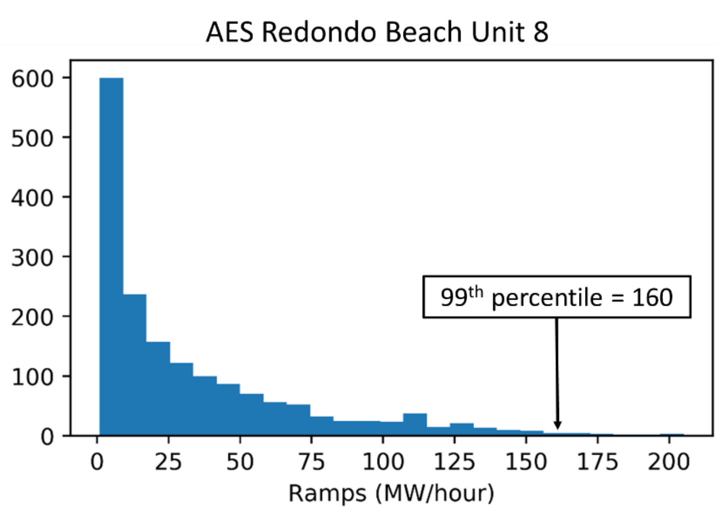
Table 16 Average flexibility characteristics of fossil generators in the model fleet, weighted by generator size. Ramp limits are the maximum ramp rate (MW/hr) divided by generator capacity.

Technology	Minimum load (% capacity)	Ramp limit	Minimum down time (hrs)	Minimum run time (hrs)
Conventional Steam Coal	0.32	0.14	1.18	5.25
Natural Gas CC	0.31	0.29	2.33	3.44
Natural Gas CT	0.36	0.48	3.72	1.81
Natural Gas Steam Turbine	0.17	0.32	3.93	6.54

Parameter estimation

The ramp limits and run times are primarily derived from generation data in the U.S. Environmental Protection Agency's (EPA) Continuous Emissions Monitoring System (CEMS) data. Other research has used similar methods for making similar calculations for subsets of the US.[67,68] Hourly data for all covered units from 2015-2018 were downloaded via EPA's Air Markets Program Data portal using scripts written by the Catalyst Cooperative's Public Utility Data Liberation Project.[69,70] The ramp limits and run times were calculated by compiling the distributions of hourly ramps, down times, and run times for each unit and deriving values at the tail ends of these distributions. Maximum ramp rates are from the high end of the ramp distributions, while minimum down and run times are from the low end of their respective distributions. For example, Figure 30 plots the observed distribution of hourly ramps for a generating unit in California over the data sample. Each ramp in the distribution is calculated as the absolute difference in MW observed from the plant when it changes its output from one hour to the next. The high end of this distribution suggest a reasonable ramp rate for this plant would be 160 MW/hr. Utilizing the 99th percentile (or the 1st percentile in the case of minimum run times and down times) makes the estimates robust to outliers and observations more extreme than the plant's preferred technical limits.

Figure 31 Frequency distribution of hourly ramps for one generator, 2015-2018.



As described in the previous paragraph, a simple absolute first difference is used to derive the historic ramps. The compilation of distributions for observed down times and run times requires a slightly more complicated logic, defined in the subsequent pseudo-code. The code records a unit shut-down if it is observed to be offline in an hour and generating in the previous hour. Conversely, it records a start-up if the unit is observed to be generating while being offline the previous hour. It then counts the number of hours until the switches statuses again, and records that number as the down time or run time. More specifically, if i and t index all generating units and hours in the dataset, respectively, and $gen_{i,t}$ represents the observed generation level (in MW) for plant i in hour t, then the following program will record the down times and run times.

Pseudo-code to calculate unit run times and down times:

For each plant i and hour t:

1. If $gen_{i,t} < gen_{i,t-1}$ and $gen_i = 0$ *# unit turns off*
   a. $down_i = 1$
   b. store run_i
2. Else if $gen_{i,t} > 0$ and $gen_{i,t-1} = 0$ *# unit turns on*
   a. $run_i = 1$
   b. store $down_i$
3. Else if $gen_{i,t} = gen_{i,t-1} = 0$ *# unit remains off*
   a. $down_i = down_i + 1$
4. Else if $gen_{i,t} > 0$ *# unit remains on*
   a. $run_i = run_i + 1$

The script that implements the steps described above records the observed down times and run times for each unit and records them in data objects labeled $down_i$ and run_i. Lines 1 and 2 test if the plant turns off or on in each hour, respectively. If either of these situations occur, the computer resets $down_i$ or run_i, and stores the previously-recorded run_i and $down_i$ objects. In lines 3 and 4 it begins counting the hours for which the unit remains in this state. Once all the down times and run times are compiled for each unit, the minimum and percentile values are calculated from the distributions.

Matching datasets

After estimating the unit-level parameters as described in the previous section, our modeling application requires merging in generator-level technical characteristics from the EIA data. EIA focuses on electric generation and provides their data at the generator level, while EPA focuses on emissions and provides data at the boiler level (EPA documentation also refers to these as “units”). A mapping between EIA generators and EPA boilers was required to merge the data. In several cases a single boiler serves multiple generators. A common example of this situation is with combined cycle (CC) power plants. A CC configuration may have multiple gas turbines with separate boilers, plus a steam turbine that draws energy from all the boilers via the gas turbines. In this case, the steam turbine is associated with multiple boilers. Parameter values for generators like this not assigned to a single boiler are given the average values of the other generators within the same plant.

The boiler-to-generator mapping is available as the data file "epa_eia_crosswalk.csv". In some cases the naming conventions differed between boilers and generators at the same plant. The specific assignments for these plants were based off the authors' best guesses after reviewing technical and generating characteristics across the units. This is the first publicly-available crosswalk between EPA CEMS units and EIA generators as far as the authors know. However, the EPA likely has matched their units with EIA data to create their Emissions & Generation Resource Integrated Database (eGRID).[71] Past researchers have merged EPA CEMS with EIA datasets, requiring a similar mapping effort.[72–74] It is a labor-intensive task to match the differing naming conventions between EPA units and EIA generators. Our cross walk file can benefit researchers who conduct future analyses requiring a unit-level matching between hourly generation and emissions information from EPA data with the electricity generation technical characteristics from EIA datasets. Researchers would further benefit if EPA and EIA collaborated to publish an official crosswalk between their datasets that is updated as units retire and come online. This would improve the quality of future research because the matching would no longer include educated guesses by researchers not affiliated with the US government.

Reference comparison

Capacity-weighted fleet averages of representing the distribution tails for ramp rates and minimum down times are compared to reference values for coal and natural gas power plants obtained from Hentschel et al., 2016.[75] This comparison is summarized in Table 17. One insight from this comparison is that the ramp rate reference values are notably larger than the average ramp rates limits observed in the data. This suggests that most fossil plants in the US did not ramp near their technological reference limits during the data sample period. Nevertheless, the reference limits are not impossible to achieve, as a small number of plants were observed to ramp at or above the reference limits. This includes 12 coal units (out of 456), 21 combined cycle units (out of 1421), and 36 combustion turbine units (out of 1417).

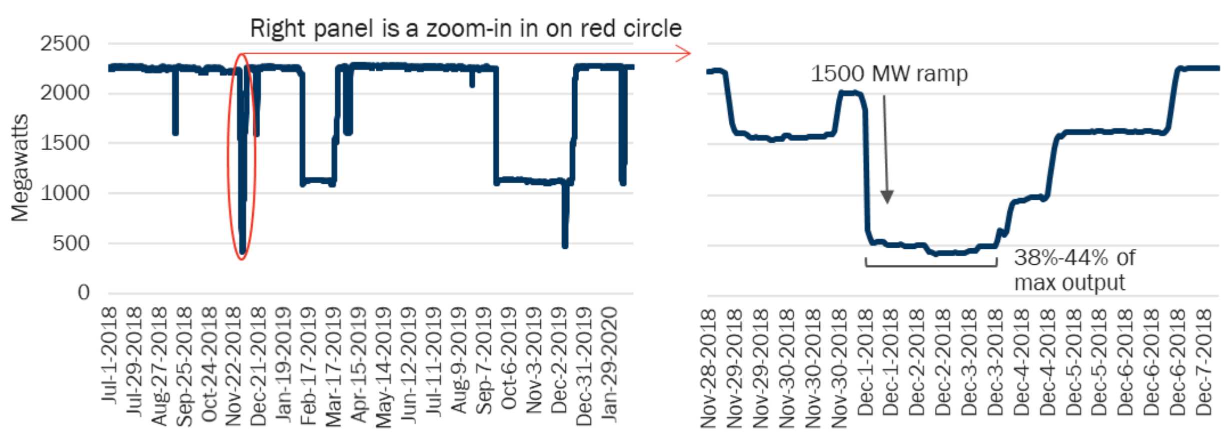
Table 17 Estimated ramp rates and minimum down times compared to reference values.[75] Estimated values are smaller than reference because most plants never ramp near their technical limits during the sample period.

	Coal	Gas CC	Gas CT
Ramp max (%cap/hr)	88	116	97
Ramp 99pct (%cap/hr)	26	59	73
Ramp 95pct (%cap/hr)	18	34	58
Ramp 90pct (%cap/hr)	14	24	47
Ramp reference (%cap/hr)	171	360	600
Down min (hr)	1.44	1.75	1.75
Down 01pct (hr)	1.94	1.57	3.26
Down 05pct (hr)	4.61	3.29	7.04
Down 10pct (hr)	10.00	4.59	9.80
Down reference (hr)	1.5	<1	<1

Nuclear flexibility

There are 5 nuclear generating units included in this model – two within California at the Diablo Canyon plant, and 3 in Arizona at the Palo Verde plant. All of these units report to US government statistical agencies a low minimum operating level below 10% of total capacity. Furthermore, a variety of sources indicate these pressurized water reactors have a demonstrated capability of ramping relatively quickly at or above 5% of nameplate capacity per minute.[76–78] In practice, however, nuclear plants in the United States are not generally operated flexibly on a daily basis. Figure 31 shows generation for the Diablo Canyon nuclear plant in California. The left panel displays hourly generation for the past couple years. The right panel zooms in on a particular event that took place over a few days in late 2018 in which the generating units displayed considerable ramping capabilities. This plant consists of two pressurized-water nuclear reactor generating units, each of which produces about 1135 MW at full capacity.

Figure 32 Historical generation for Diablo Canyon nuclear plant in California. [57]



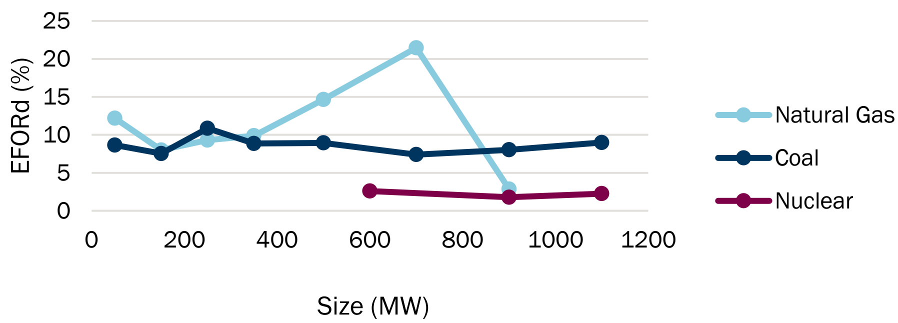
An examination of the plant's historic output shows it has the ability to ramp quickly, although it has done so infrequently over the past few years. For example, the right panel of Figure 31 shows multiple significant ramping events over a period of several days. On December 1, the plant decreased output by approximately 1500 MW over a single afternoon, including an 1183 MW drop in a single hour. After this drop, one of the generating units operated between 38%-44% of nameplate capacity for approximately 3 days, before the plant ramped up output again. For our market simulation, the main scenarios will assume to be relatively non-flexible. This includes nuclear ramp rates restricted to 1% of nameplate capacity per hour, minimum operating levels are set to 50% of nameplate capacity, and minimum down time and run times are set to 8 hours.

Outages

Plant capacity limits are discounted by their Equivalent Forced Outage Rate – Demand (EFORd) to reflect outage probabilities. EFORd is the probability of a generator experiencing an outage when they are demanded to run.[79] Historic EFORd rates by aggregated by fuel type and size from 2014-

2018 from the North American Electric Reliability Council (NERC) are used, and shown in Figure 32.[80]

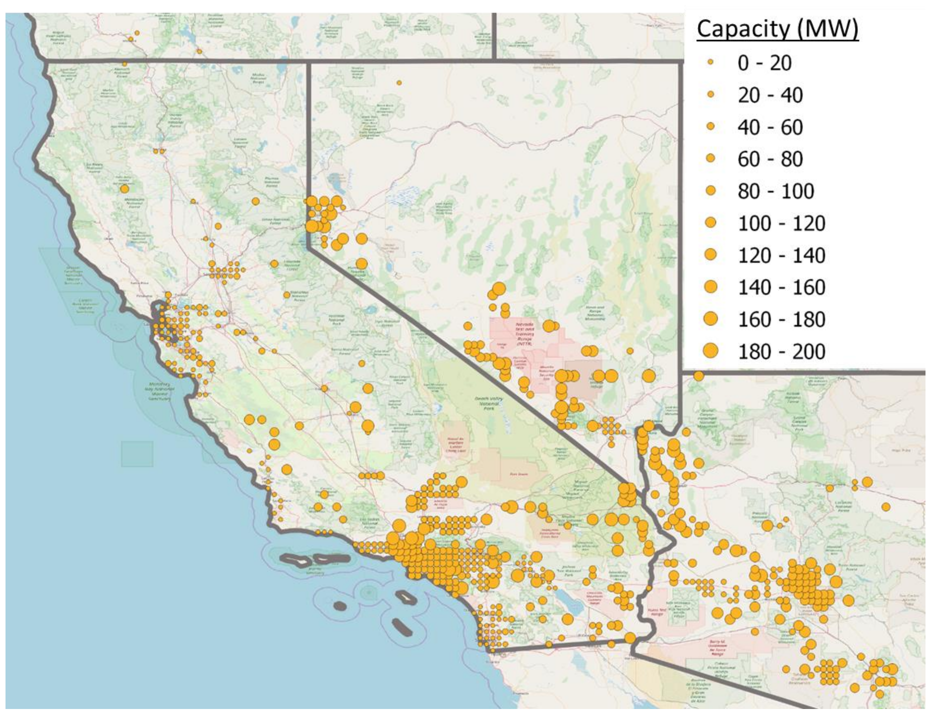
Figure 33 Average equivalent forced outage rates - demand (EFORd) by fuel type, 2014-2018.[80]



Solar profiles

Detailed solar output simulations with 5-minute output granularity for modeled PV plants are available from NREL.[81] The NREL-modeled solar locations in California and neighboring states are displayed in Figure 33. Each operational solar plant from EIA's data is spatially matched to the nearest modeled plant in the NREL dataset. The real-time outputs from the NREL data are then scaled to match the output capacity for the corresponding operational solar plant.

Figure 34 Modeled solar locations with 5-minute output.[81]



Wind profiles

Within California, most installed wind capacity is located in zones 8, 12, 4, and 11, each with 3305, 3211, 1297, 1134 MW of installed capacity, respectively. Wind energy production profiles at the balancing area (BA) level from EIA are used.[57] This is a simplification from the plant-level profiles used for solar, done in part because solar output is the focus of this analysis and there is significantly more solar production in California than wind. More detailed wind data is available but access would require additional administrative and programming hurdles.[82] Using aggregated BA-level wind profiles tends to negate the severity of ramps at individual plants. Annual hourly wind profiles for CISO and Bonneville Power Authority (BPA), the two balancing authorities with significant wind production, are displayed in Figure 34. For the model, zones 1 through 4 and 12 generate with BPA's wind profile, while the remaining zones use the CISO profile. Plant-level annual capacity factors from 2015-2017 are derived from EIA data,[63] and the aggregated hourly wind profiles are scaled such that each plant achieves its annual capacity factor. Total capacity and average capacity factors by zone for wind plants are displayed in Table 18.

Figure 35 Hourly annual wind profiles for California Independent System Operator and Bonneville Power Authority.[57]

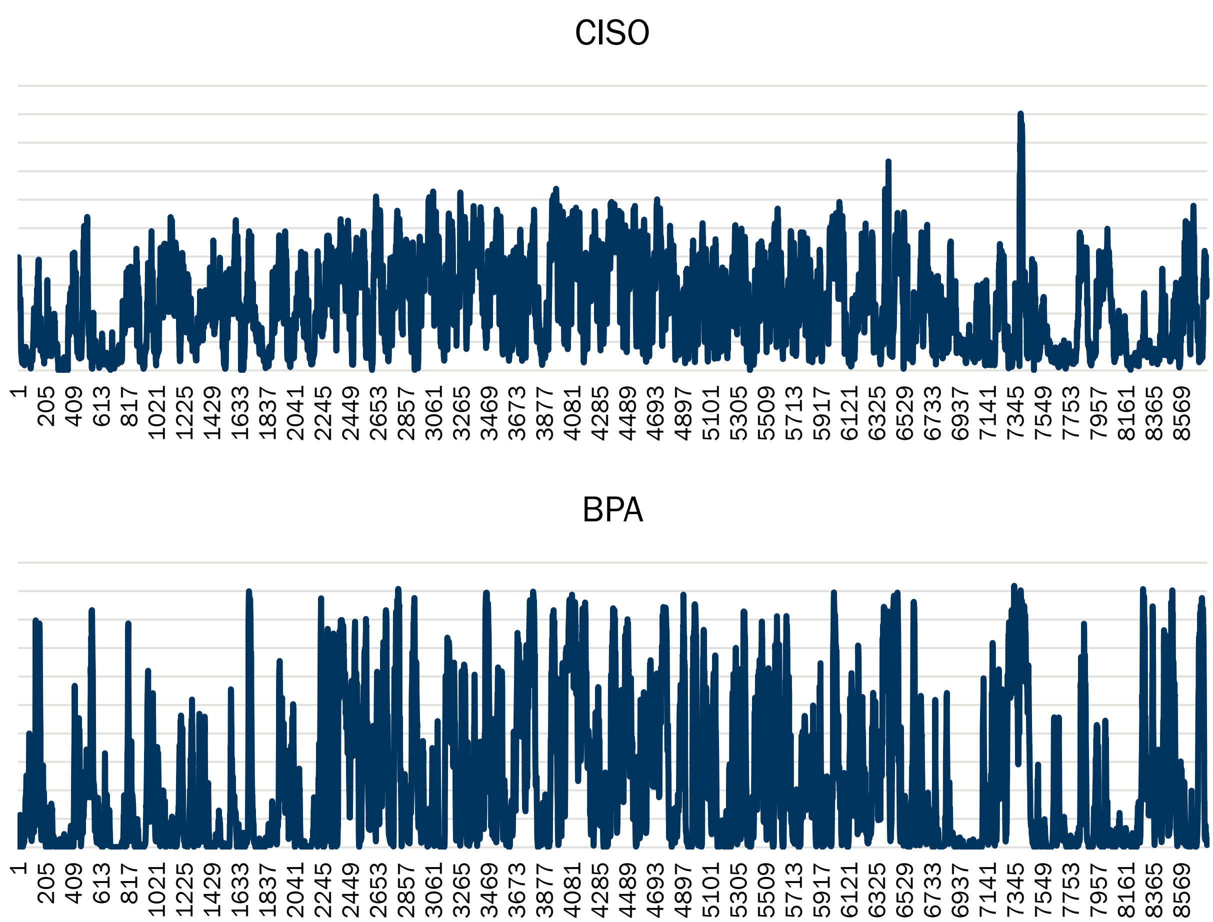


Table 18 Summary of wind characteristics by model zone.

Zone	Capacity (MW)	Number of plants	Average capacity factor
1	0	0	N/A
2	102	2	0.27
3	0	0	N/A
4	1297	22	0.26
5	20	3	0.17
6	0	0	N/A
7	4	3	0.27
8	3305	57	0.22
9	2	1	0.00
10	7	5	0.10
11	1134	38	0.26
12	3211	44	0.25
13	150	1	0.26
14	0	0	N/A
15	267	5	0.23

Hydro constraints

Historic monthly generation totals for each hydro plant are collected from EIA[63] and used to calculate hydro energy constraints. This method allows hydro plants to flexibly adapt to changes in solar output across model scenarios while assuming their aggregate outputs are limited to reflect reservoir constraints similar to what the plants faced in the recent past. Specifically, the average monthly generation levels from 2015-2017 for each plant were used as a maximum output constraint in the model. Plant-level generation data was downscaled to the unit-level, assuming that each unit produced at its nameplate capacity-weighted share of the total plant's output. There were a few plants with missing generation data. These were assigned a size-normalized average output calculated from the rest of the hydro fleet. The idea for this method was inspired by the work of Fonseca et al. (2019).[83]

Model formulation

Overview

The economic dispatch model underlying the flexible solar analysis is a unit commitment (UC) optimization problem. The objective of the dispatch model is to determine the lowest-cost schedule for power plants across the system, given the constraints reflected in the model. The UC problem can be formulated and reliably solved as a deterministic mixed-integer program (MIP).[84,85] An introduction to the MIP optimization method is available in Bradley et al., 1977.[86] For this particular model, the zonal demand and transmission constraints are similar to what was used in Dahlke, 2019,[87] and the binary start-up / shut-down and minimum run / down time constraints are similar to the constraints used in Van Den Bergh et al., 2015.[88]

Model

The sets, parameters, and variables are defined in Table 1.

Table 19 Model definitions

Sets	
$I(i)$	Generators
$Z(z)$	Zones
$Ex(z)$	The subset of zones that are outside of California
$T(t)$	Time periods
Parameters	
$MinC_i$	Generation cost at minimum output ($/MWh)
$VC_{i,t}$	Variable generation cost ($/MWh)
SUC_i	Start-up cost ($/start)
$Pmin_i$	Minimum power output (MW)
$Pmax_i$	Maximum power output (MW)
$TX_{z,z'}$	Transmission capacity from z to z'
$Ramp_i$	Ramp limit (MW/hr)
$D_{t,z}$	Hourly demand (MW)
$O_{t,z}$	Operating reserves (MW)
MDT_i	Minimum down time (hr)
MRT_i	Minimum run time (hr)
$\bar{p}_{i,t}$	Baseline generation profile for wind and solar (MW)
$\bar{h}_{i,month}$	Monthly hydro energy limit
Variables	
$p_{i,t}$	Generation above minimum output (MW), $\mathbb{R}^+$
$tx_{z,z',t}$	Transmission from zone z to z'
$y_{i,t}$	On/off status {0,1}
$v_{i,t}$	Start-up status {0,1}
$w_{i,t}$	Shut-down status {0,1}

The equations below mathematically define the model. The objective function (1) minimizes total production costs across all generators and time periods, considering variable operations and start-up costs. The constraints ensure that total generation plus imports satisfy zonal demands (2), generators produce below their capacity limits and above their minimum output limits (3) and ramping limits (4), while transmission flows satisfy zonal constraints (5). Plants will not start-up / shut-down until their minimum down times (6) / run times (7) are satisfied. Equation (8) establishes the binary logic for the model's start-up, shutdown, and generation decisions to ensure that a plant does not produce before it is turned on, and will produce after it is turned on. In the baseline model, solar and wind are dispatched as must-take according to the baseline hourly profiles using location-specific insolation and weather models (9) and (10). In the flexible solar scenario, the equals sign in (9) will be converted to an inequality to allow solar to dispatch down or up when it is cost-optimal. Finally, each hydro plant cannot exceed its monthly energy constraint (11).

$$\text{Minimize} \sum_i \sum_t (y_{i,t}MinC_i + p_{i,t}VC_{i,t} + v_{i,t}SUC_i) \quad \forall i,t \tag{1}$$

Subject to

$$\sum_{i\in z}(p_{i,t} + y_{i,t}Pmin_i) + \sum_{z<z'} -tx_{z,z',t} + \sum_{z>z'} tx_{z',z,t} \geq D_{t,z} + O_{t,z} \quad \forall t,z \tag{2}$$

$$p_{i,t} \leq y_{i,t}(Pmax_i - Pmin_i) \quad \forall i,t \tag{3}$$

$$-Ramp_i \leq p_{i,t} - p_{p,t-1} \leq Ramp_i \tag{4}$$

$$-TX_{z,z'} \leq tx_{z,z',t} \leq TX_{z,z'} \quad \forall z,z' > z,t \tag{5}$$

$$1 - y_{i,t} \geq \sum_{t'=t+1-MDT_i}^{t} w_{i,t'} \quad \forall i,t \tag{6}$$

$$y_{i,t} \geq \sum_{t'=t+1-MRT_i}^{t} v_{i,t}' \quad \forall i,t \tag{7}$$

$$y_{i,t-1} - y_{i,t} + v_{i,t} - w_{i,t} = 0 \quad \forall i,t \tag{8}$$

$$p_{i,t} = \leq \bar{p}_{i,t} \quad \forall i \in solar, t \tag{9}$$

$$p_{i,t} = \bar{p}_{i,t} \quad \forall i \in wind, t \tag{10}$$

$$\sum_{t\in month} p_{i,t} \leq \bar{h}_{i,month} \quad \forall i \in hydro\ , months \tag{11}$$

Implementation

The model was written in the Julia numeric computing language utilizing its JuMP optimization framework and the CBC mixed integer linear program solver.[89–91] The baseline model has 2118 generating units, each of which has four variables ($p, y, v, \& w$), plus another 105 transmission flow variables per hour, or 8577 total variables per hour. Solving this model for a full year is too large a problem for a single laptop computer. Instead, the model is sequentially solved in daily chunks, each of which takes the solver approximately 60-90 seconds to complete with an Intel® Core™ i7-6600U CPU @ 2.6GHz with 16 GB RAM.

APPENDIX 3. DETAILED MODEL RESULTS

Table 20 Annual change in generation by technology and zone with flexible solar and 30% solar penetration, GWh

Zone →	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Total
All Other	0	0	0	-1	0	0	0	0	-3	0	0	0	0	0	0	**-4**
Conventional Hydroelectric	0	4	1	0	0	0	0	-1	0	0	-1	138	0	0	-25	**118**
Conventional Steam Coal	0	0	0	0	0	0	0	0	0	-10	0	-13	-9	0	0	**-31**
Geothermal	0	-13	2	-114	0	-68	0	0	0	0	-169	2	7	0	0	**-353**
Landfill Gas	0	-1	-1	-9	-1	0	-3	0	-48	0	-7	-4	0	-3	-6	**-84**
Municipal Solid Waste	0	0	0	0	-3	0	0	0	-11	0	0	-2	0	0	0	**-16**
Natural Gas Fired Combined Cycle	0	-197	-10	-1175	-219	0	-128	-788	-381	-427	-776	-557	-131	-756	-5195	**-10739**
Natural Gas Fired Combustion Turbine	0	-10	0	-15	-43	0	-11	-110	-71	-13	-43	-2	-3	-148	-85	**-555**
Natural Gas Internal Combustion Engine	-5	-6	-2	-5	-9	0	0	0	-4	-3	-2	-8	-2	0	0	**-45**
Natural Gas Steam Turbine	0	0	0	0	0	0	0	0	-4	0	-2	0	-22	0	0	**-29**
Nuclear	0	0	0	0	0	0	9998	0	0	0	0	0	0	0	14645	**24643**
Onshore Wind Turbine	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
Other Gases	0	0	0	0	0	0	0	0	-1	0	0	0	0	0	0	**-1**
Other Natural Gas	0	0	0	-1	0	0	0	-1	-4	-1	0	0	0	0	0	**-7**
Other Waste Biomass	0	-3	0	-3	0	0	0	-1	-24	0	-3	-1	0	0	0	**-37**
Petroleum Coke	0	0	0	-4	0	0	0	0	0	0	0	0	0	0	0	**-4**
Petroleum Liquids	0	0	-2	-41	-9	0	0	0	-8	0	-6	0	-1	0	-359	**-426**
Solar Photovoltaic	0	-32	-1	-168	-9	0	-2887	-2247	-1848	-208	-611	-14	-39	-25	-10450	**-18539**
Solar Thermal	0	0	0	0	0	0	0	0	7	92	292	0	9	-21	151	**530**
Wood/Wood Waste Biomass	-8	-16	-25	-3	-18	0	0	-30	0	0	-21	-36	0	0	-23	**-180**
Grand Total	**-13**	**-274**	**-43**	**-1543**	**-312**	**-68**	**6968**	**-3179**	**-2402**	**-572**	**-1349**	**-498**	**-195**	**-954**	**-1346**	**-5778**

Table 21 Annual change in production cost by technology and zone with flexible solar and 30% solar penetration, millions of dollars.

	Zone															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Total
All Other	0.00	0.00	0.00	-0.05	-0.02	0.00	0.00	0.00	-13.86	0.00	0.00	0.00	0.00	-0.04	0.00	**-13.97**
Conventional Hydroelectric	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**
Conventional Steam Coal	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.25	0.00	-0.59	-0.40	0.00	0.00	**-1.24**
Geothermal	0.00	-0.02	0.00	-0.21	0.00	-0.08	0.00	0.00	0.00	0.00	-0.16	0.00	-0.02	0.00	0.00	**-0.49**
Landfill Gas	0.00	0.00	0.00	-0.05	-0.01	0.00	-0.02	0.00	-0.30	0.00	-0.04	-0.02	0.00	-0.02	-0.03	**-0.50**
Municipal Solid Waste	0.00	0.00	0.00	0.00	-0.05	0.00	0.00	0.00	-0.12	0.00	0.00	-0.03	0.00	0.00	0.00	**-0.20**
Natural Gas Fired Combined Cycle	0.00	-6.82	-0.35	-42.31	-8.15	0.00	-4.83	-27.93	-13.50	-15.37	-28.32	-18.41	-4.64	-22.93	-145.43	**-338.99**
Natural Gas Fired Combustion Turbine	0.00	-0.22	0.00	-0.58	-1.67	0.00	-0.42	-3.80	-2.77	-0.51	-1.87	-0.06	-0.13	-3.36	-0.65	**-16.03**
Natural Gas Internal Combustion Engine	-0.17	-0.24	-0.09	-0.16	-0.32	0.00	0.00	0.00	-0.15	-0.09	-0.07	-0.32	-0.08	0.00	0.00	**-1.70**
Natural Gas Steam Turbine	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.28	-0.01	-0.05	0.00	-0.84	0.00	-0.01	**-1.18**
Nuclear	0.00	0.00	0.00	0.00	0.00	0.00	90.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	131.87	**221.89**
Onshore Wind Turbine	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**
Other Gases	0.00	0.00	0.00	-0.46	0.00	0.00	0.00	0.00	-0.65	0.00	0.00	0.00	0.00	0.00	0.00	**-1.10**
Other Natural Gas	0.00	0.00	0.00	-0.55	0.00	0.00	-0.01	-0.02	-0.10	-0.02	-0.01	0.00	0.00	0.00	0.00	**-0.71**
Other Waste Biomass	0.00	-0.02	0.00	-0.02	0.00	0.00	0.00	-0.01	-0.21	-0.02	-0.02	-0.01	0.00	0.00	0.00	**-0.30**
Petroleum Coke	0.00	0.00	0.00	-0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**-0.04**
Petroleum Liquids	0.00	0.00	-0.04	-1.18	-0.24	0.00	0.00	-0.01	-0.18	-0.01	-0.13	0.00	-0.02	0.00	-6.97	**-8.78**
Solar Photovoltaic	0.00	-0.02	0.00	0.00	0.00	0.00	0.00	0.00	-0.18	0.00	-0.02	0.00	-0.04	0.00	-2.46	**-2.72**
Solar Thermal without Energy Storage	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.36	0.00	0.00	0.00	-0.01	0.00	**-0.36**
Wood/Wood Waste Biomass	-0.06	-0.10	-0.15	-0.02	-0.11	0.00	0.00	-0.20	0.00	0.00	-0.14	-0.23	0.00	0.00	-0.15	**-1.15**

Total	-2.57	-7.44	-27.05	-68.98	-14.83	-0.12	84.74	-38.09	-38.39	-26.89	-31.95	-19.67	-26.68	-26.35	-23.82	-268.07

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