California needs clean firm power, and so does the rest of the world

Three detailed models of the future of California's power system all show that California needs carbon-free electricity sources that don't depend on the weather.

JCS Long[a], E Baik[b], JD Jenkins[c], C Kolster[d], K Chawla[d], A Olson[d], A Cohen[e], M Colvin[a], S M Benson[b], RB Jackson[b], DG Victor[f,g], SP Hamburg[a]

Affiliations:

a: Environmental Defense Fund, b: Stanford University, c: Princeton University, d: Energy & Environmental Economics, e: Clean Air Task Force, f: UC San Diego, g: The Brookings Institution

Summary

California has committed to achieve a net-zero carbon economy by 2045. To meet the state's carbon-neutral goal, California will need to rely primarily on forms of energy that do not emit greenhouse gases.

Rapid expansion of wind and solar power and electrification of transportation and heating underlie an affordable path to a net-zero carbon economy. At the same time, extensive electrification and increased reliance on weather-dependent renewable energy sources could create new reliability challenges requiring proactive planning. Solar and wind supplies drop by some 60% from summer to winter. In some cases, the state can get little output from solar and wind generation for weeks at a time. These lulls can also coincide with periods of increased demand, further exacerbating the challenge. Today, California relies on natural gas power plants (and heating) during these periods. If a net-zero carbon economy cannot continue to depend on natural gas to meet this demand, what will the state use instead?

Batteries can be very useful in dealing with the variation in solar and wind power over hours-long periods, such as daily cycles in solar power output, but today's battery technologies cannot cost-effectively store enough energy to pull the state through a big winter storm lasting many days. Without another source of energy to generate electricity during these periods, California's electrified economy could come to a halt. As renewable energy expands, and as use of natural gas for electric generation is eliminated, the state could face a situation much like what Texas recently went through in February 2021. Luckily, California has a track record of planning for these types of events, and with proactive effort, the state can secure an affordable *and reliable* carbon-free electricity future.

California's relationship with natural gas is in transition. To ensure grid reliability, California needs to replace today's carbon-emitting gas-fired power plants, which supply over 40% of the state's electricity, with some alternative source of clean electricity that is available on demand, for as long as it is needed, whenever it is needed. This type of electricity resource is known as "*clean firm power*." Many choices could fulfill this need. Geothermal power takes energy from heat in the ground and is available as needed. California's geology has provided the largest geothermal plant in the world and California might expand this resource. Nuclear power can

provide very large amounts of energy steadily in a small footprint. California could even continue to use gas power if the CO_2 emissions were captured and sequestered underground. Alternatively, gas power plants could be converted to burn clean fuels, such as hydrogen, which might be made via electrolysis with solar power, reformed from natural gas while leaving waste CO_2 to be sequestered underground, or produced from gasification of agricultural and forestry residues or crops. All of these clean firm power sources (and perhaps others) would provide critical reliability that could prevent a Texas-sized tragedy.

Even though these clean firm power technologies currently cost more per kilowatt hour than solar and wind, this study shows that these resources also deliver greater value, which justifies their higher cost. A robust investment in a portfolio of clean firm power options will obviate the need for otherwise-redundant renewable energy. As a result, our modeling finds that California can reach a 100% carbon-free clean electricity supply by 2045 while keeping consumer costs similar to those paid today. An ambitious but achievable investment in clean firm power, with installed capacity similar in magnitude to our existing gas fleet—or roughly 25-40 gigawatts—could eliminate the need for ten times that amount of wind and solar capacity, and significantly reduce associated transmission expansion and the land area required for electricity generation facilities. What will cost a lot more—both in consumer costs and in reliability—will be *not* having clean firm power at all. A strong portfolio of clean firm power will add reliability to the grid, and if California can help utilities recover costs for their clean firm power investments now, we can help keep the lights on in the future without incurring a significant increase in electricity prices.

Introduction

California's government has set ambitious goals to eliminate greenhouse gas emissions, starting with electricity. A 2018 law, Senate Bill 100 (SB100), mandated that all retail sales of electricity must be provided from carbon free sources by 2045. Jerry Brown, who was then the governor, issued a companion executive order Executive Order B-55-18 requiring the entire state, not just the electric sector, to zero-out net emissions also by 2045.

Policymakers in California and also throughout the world have to figure out how to achieve similar goals. In recent years, wind and solar power have become much cheaper. They have improved more quickly than even optimistic experts thought possible a decade ago, in part due to aggressive government mandates for purchase that have created larger markets and allowed rapid learning, induced incremental innovation, and rewarded economies of scale. Furthermore, markedly improving batteries can store the electricity created by wind and solar for later use, and California, of course, benefits from good renewable resources, especially sunshine.

But how far can wind and solar power alone get us on the path to deep decarbonization of the economy through clean electricity? More generally, can California find a decarbonization strategy that not only cuts emissions, but also does not markedly increase the cost of electricity while preserving the reliability of the electric grid—without sacrificing other environmental goals along the way? Recent blackouts in Texas and California especially highlight the need to attend to reliability. If such a strategy succeeds in California, it might be imitated around the globe.

This challenge is growing. California's energy planners project that electricity demand in California will nearly double from today to 2045, as more end uses in our economy currently powered by fossil fuels, from cars to the heating of building, transition to electricity. Electrification would increase California's peak demand for electricity from about 50 gigawatts today to about 100 gigawatts midcentury. How will California maintain the affordability and reliability of electricity supplies while tackling the twin tasks of decarbonization and electrification?

To answer these questions, we convened a group of energy system experts who used three different optimization models of California's electricity system to quantify the costs of a number of different future scenarios for new sources of clean, reliable electric power. Groups from Princeton and Stanford Universities ran the first two models; the third was by a group from the consulting firm Energy and Environmental Economics (E3).[1]

Each model sought to estimate not only how much electricity would cost under a variety of scenarios, but also the physical implications of building the decarbonized grid. How much new infrastructure would be needed? How fast would the state have to build it? How much land would that infrastructure require? Although each of these models offered their own depictions of the California electricity system and independently explored the ways it would be optimized, they all used the same data with respect to past conditions and they all used the same estimations of future technology costs. Despite distinct approaches to the calculations, all the models yielded very similar conclusions.

Sun and wind and challenges

Wind and solar have become mature technologies and enjoy substantial public support. Batteries have also significantly improved. Consequently, wind and solar power and batteries can be the cornerstones in an affordable, carbon-free California electricity system.

However, relying to a much greater extent on solar and wind power also present challenges as these resources depend on the weather and weather is variable on time frames spanning minutes to seasons. Average daily output from current California solar and wind infrastructure in the winter declines to 30-40% of the maximum summer production, for example. Periodic large-scale weather patterns extending over 1,000 kilometers or more, known as "*dunkelflaute*" (the German word for dark doldrums) drive wind and solar output to low levels across the region and can last days, or even several months. Average wind and solar outputs also vary from year to year, particularly for wind power. Batteries can help make up for fluctuations that last for multiple hours, but they cannot make up for these longer-duration variations in wind and solar availability. For this reason, having enough wind and solar power to meet demand during the slack periods would necessitate building an enormous amount of capacity that would otherwise exceed the grid's demand during more abundant periods.

[1] Appendix A provides a key to the scenario names and Appendix B provides supplemental material for each of the modeling efforts. Data spread sheets are also found at www.edf.org/cleanfirmpower.

Since wind, solar and batteries are the most mature and affordable clean energy technologies available today to help reach California's carbon-free electricity goals, our project first sought to figure out just how much overcapacity would be needed to ensure reliable electricity availability—and how much it would all cost—assuming that wind and solar power and battery storage were the only options available for new capacity. We thus modeled a carbon-free electricity system with wind, solar and batteries as the only new resources available, and tested this system to ensure reliability over hundreds of possible scenarios for the weather over the course of a year.

We found that reliably generating the electricity needed in 2045 from wind and solar power would require building up to nearly 500 gigawatts of power-generating capacity (along with 160 gigawatts and 1000 gigawatt-hours of new storage). This is roughly half the capacity of the entire U.S. electricity generating system today and about six times the current total generating capacity now serving California (about 80 gigawatts), including nuclear, gas and coal generating stations, hydroelectric dams, and everything else.

All of this excess capacity would be expensive. We estimate that wholesale electricity rates would increase by about 65% over today if currently available renewable energy and storage technologies alone were to be utilized to meet demand in 2045. It may not be possible to build wind and solar facilities at this scale, even if consumers were willing to pay that premium. Solar development will likely dominate the renewable energy portfolio in California, and getting to nearly 500 gigawatts by 2045 would require expanding solar capacity at a rate 10 times higher than has ever been done before. There may not be enough people, supplies, or land to do this.

This is the great challenge with weather-dependent energy sources. On a dollar per kilowatt hour basis, wind and solar power are now cheaper than carbon-intensive sources of electricity like coal or even gas. They can thus play a central role in delivering an affordable carbon-free grid. But if wind and solar are pushed to do all of the heavy lifting themselves, the system requires a lot of excess generating capacity and storage (most of which is seldom used) to provide reliable electricity and completely drive out greenhouse emissions. As a result, this strategy ends up being much more expensive that it might appear at first glance.

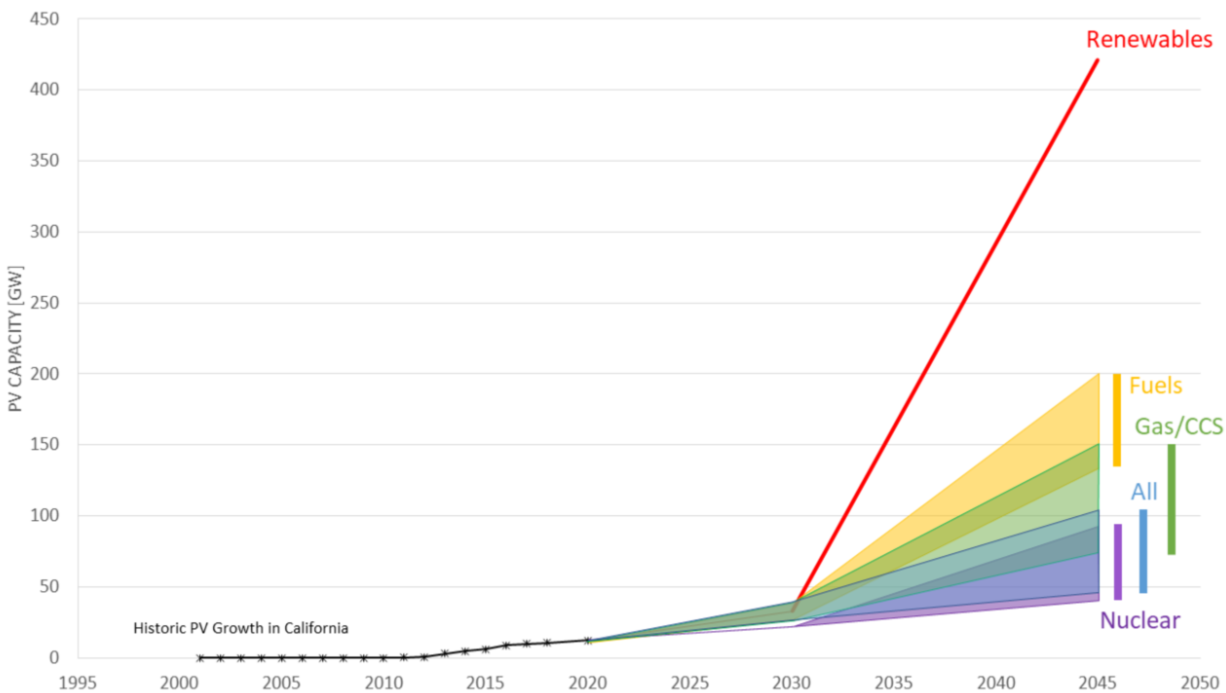

Figure 1. The growth of photovoltaic (PV) capacity dedicated to California across a range of scenarios deliverying 100% carbon-free and reliable electricity supplies by 2045. All cases shown include variable renewable energy and batteries. The case in red labeled "Renewables" did not allow any clean firm power to be built. Other cases allow both renewable energy, batteries and the labeled form of clean firm power. Results shown for mid-range capital cost cases and \$33/MMBtu generic zero-carbon fuel. The renewable and batteries-only case was only solved by E3's RESOLVE and RECAP models and includes otherwise redundant solar capacity necessary to ensure reliability through all weather-years. All other cases show the range of outcomes from the ensemble of three models (RESOLVE, GenX, and urbs).

A clean firm solution

There is a better solution. Solar and wind do not need to do the job alone. There exist carbon-free alternatives that do not depend on sunshine or wind. We call these resources "clean firm power" defined as zero-carbon power that can be relied on whenever it is needed for as long as it is needed. Clean firm resources do not depend on the weather like solar and wind do, and these resources do not have limitations in how long they can produce power, as batteries do.

For example, geothermal power takes energy from heat in the ground and is available when needed. California's geology already provides the Geysers, the largest geothermal plant in the world. Advances in geothermal technology could plausibly expand this resource beyond the special conditions found at the Geysers. Clean firm power might include "green" hydrogen split from water using renewable electricity or hydrogen split from gas or biomass gasification, leaving CO_2 to be sequestered underground, or it could entail biofuels made from sustainably-harvested agricultural or forestry waste or crops. California could continue to use gas-generated power if the greenhouse gas emissions were captured and safely stored permanently underground. Nuclear power can provide very large amounts of energy steadily in a small footprint; ongoing advances in nuclear technology could allow the deployment of lower cost, much-diminished accident risk with less waste.

Our modeling finds that almost any combination of these resources (or others with supply chains that do not result in greenhouse emissions) could deliver a 100% carbon-free electricity supply with generation and transmission supply costs of about 7-10 cents per kilowatt-hour, which compares well to today's average generation and transmission costs for California's investor-owned utilities (9 cents per kilowatt-hour, Figure 2). Renewable energy can inexpensively provide at least half of the carbon-free energy needed by 2045—and more in most cases (Figure 4)—but clean firm technologies provide a critical complement to weather-dependent renewable energy that ensures reliability while keeping whole system costs low. We also find that having more than one clean firm power option helps reduce costs even further (Figure 2). This key insight will help decision makers planning a decarbonized grid, not just in California, but in other parts of the world as well: opening the portfolio to clean firm power as well as wind and solar energy goes a long way to keeping the total costs and impacts down.

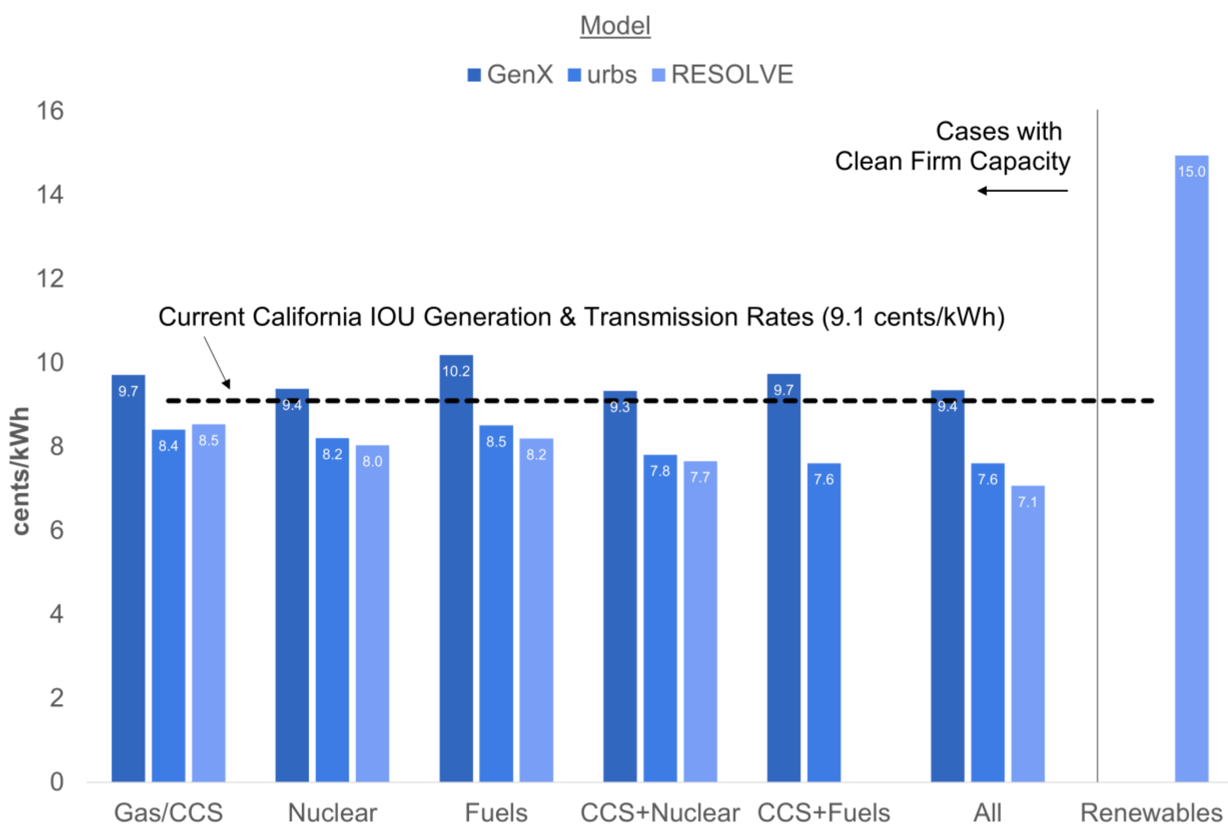

Figure 2. The wholesale generation and transmission costs for 100% carbon-free electricity for the year 2045. All cases shown include variable renewable energy and batteries. The case in red labeled "Renewables" did not allow any clean firm power to be built. Other cases allow both renewable energy, batteries and the labeled form of clean firm power. Results shown for mid-range capital cost cases and $33/MMBtu generic zero-carbon fuel. The renewable and batteries-only case was only solved by E3's RESOLVE and RECAP models to ensure reliability of this portfolio through all weather-years.

A range of sensitivity cases demonstrate that the substantial cost savings from having one or more clean firm resources is robust to a range of possible future technology costs (Figure 3). Across all modeled sensitivity cases, portfolios with at least one clean firm power option are 32-53% cheaper than the renewable energy and batteries only portfolio.

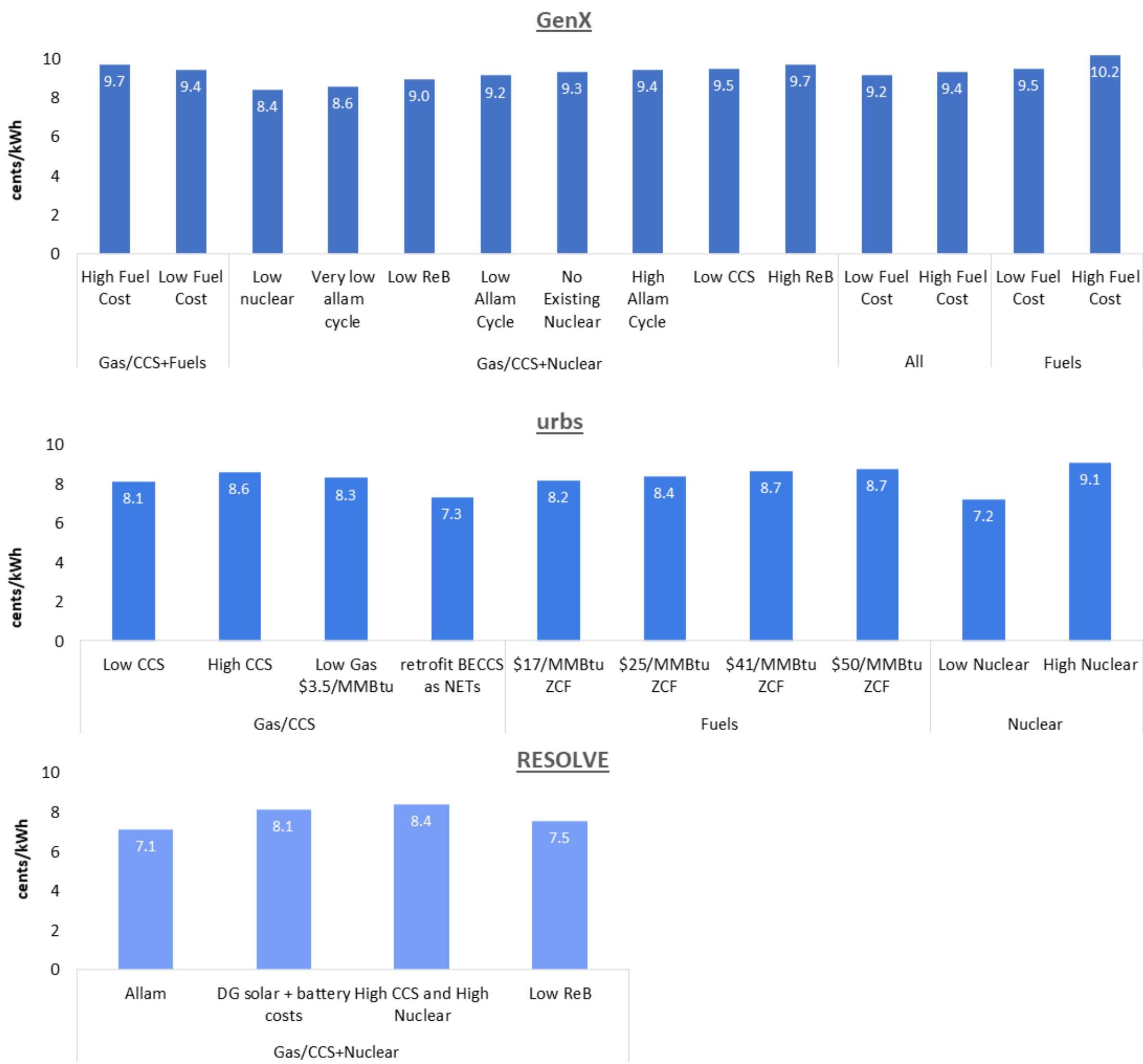

Figure 3: Price sensitivity results show that modeled 2045 California electricity system costs are relatively insensitive to the cost of clean firm power; all cases with at least one clean firm power option are 32-53% cheaper than the variable renewable energy and batteries only portfolio (see Figure 2).

We find that most of the energy supplying California in 2045 comes from inexpensive renewable resources (Figure 4), mainly solar in California. But when the sun doesn't shine for many days at a time, the clean firm resources are worth their relatively expensive price.

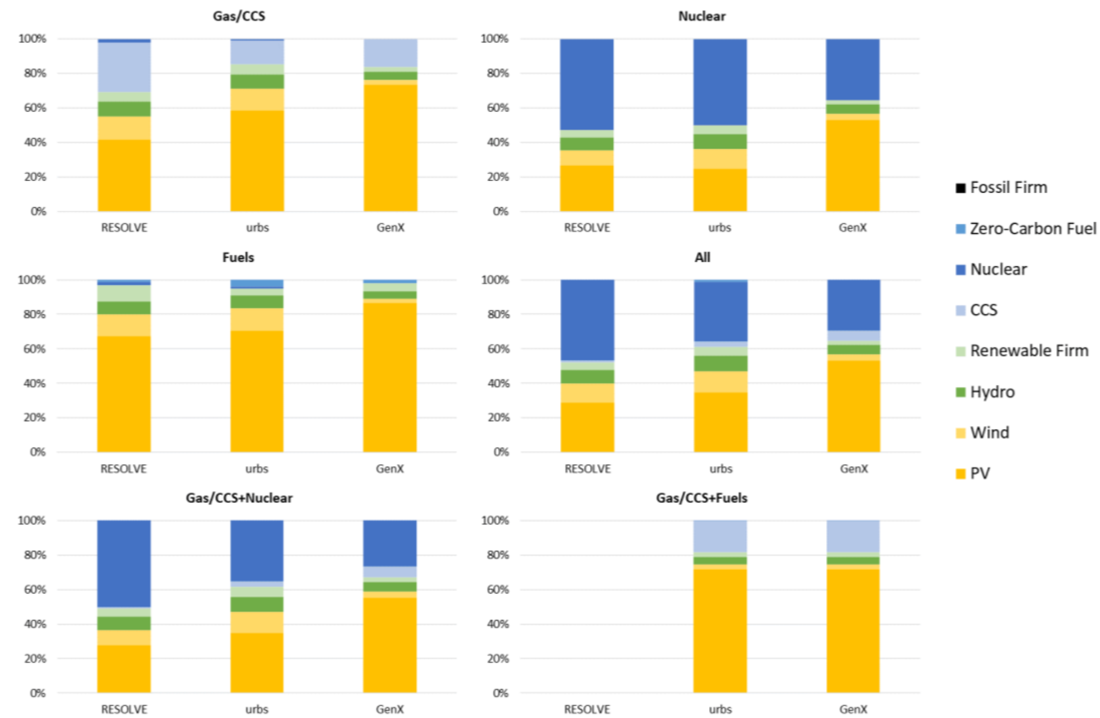

Figure 4. Percent of modeled 2045 California electricity supply coming from various resources for portfolios with clean firm power.

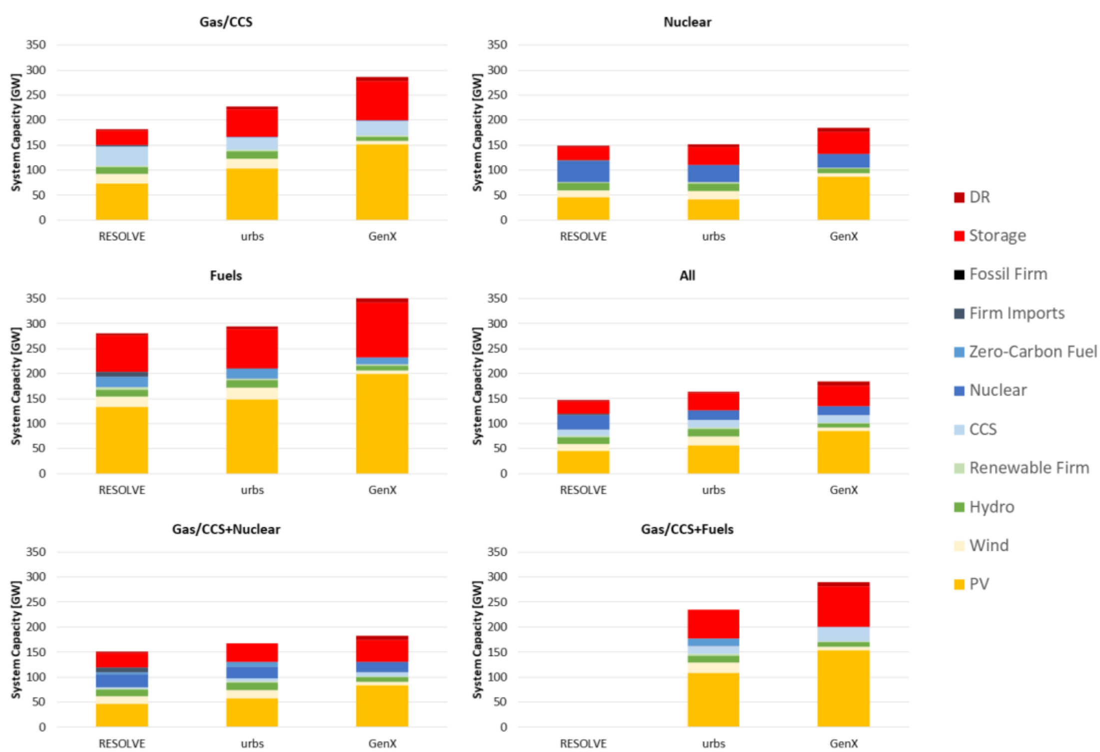

Figure 5. Installed capacity of California electricity resources in 2045 for portfolios with clean firm power.

A clean firm power portfolio

California today has 48 gigawatts of total firm power capacity, most of which (42 gigawatts) come from natural gas fired powerplants. The remaining gigawatts come from nuclear power, geothermal and a small amount from coal. California plans to decommission its last nuclear power plant at Diablo Canyon in 2025 taking 2.2 gigawatts of firm and zero-carbon capacity offline.

Our modeling concludes an ambitious but achievable investment in clean firm power capacity, essentially replacing the gas fleet with 25-40 gigawatts of clean firm power will minimize costs while maintaining reliability (Figure 6) and substantially reduce the amount of renewable energy capacity that must be deployed (Figures 1 & 5 above). By 2045 the clean firm power portfolio could eliminate the need for some 250 to 400 gigawatts of additional renewable energy.

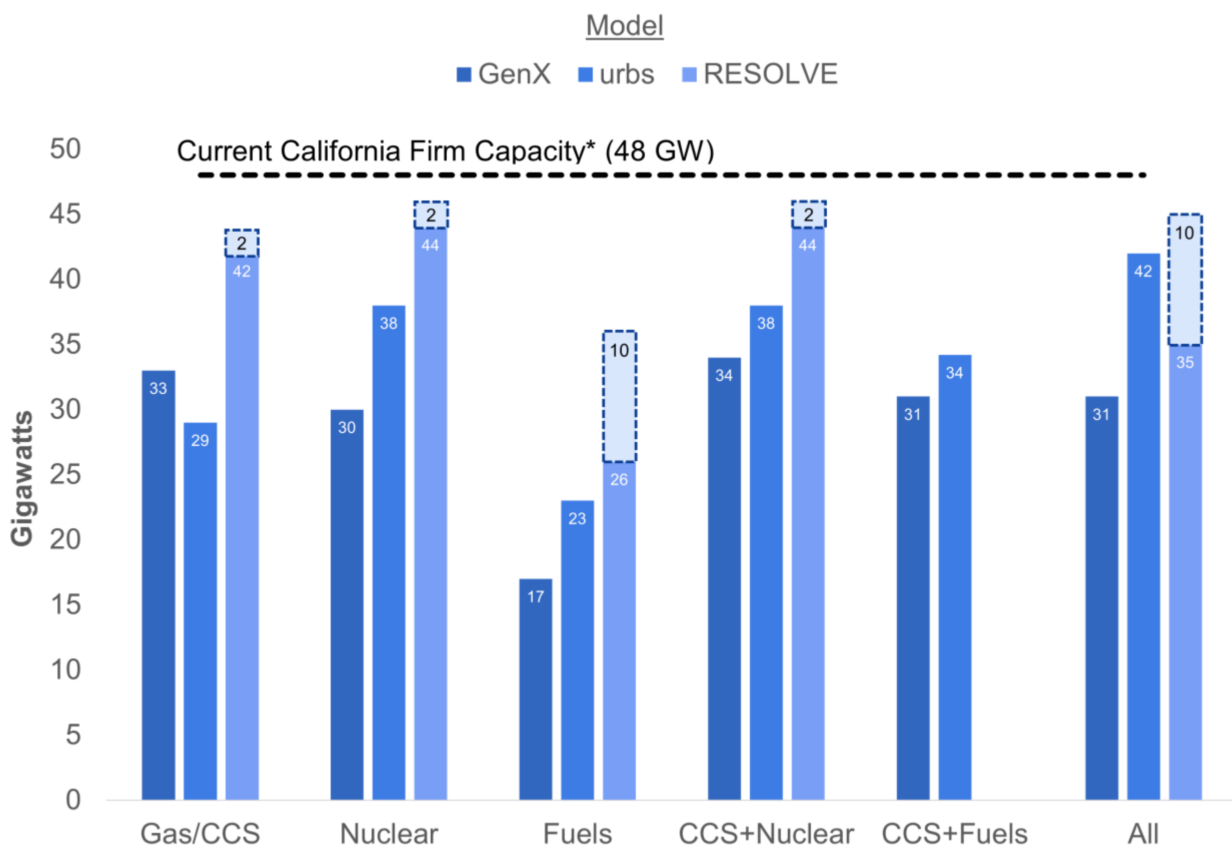

Figure 6. Clean firm power capacity needed to ensure reliability and affordability in 100% carbon-free cases. All models include variable renewable energy and batteries and account for existing contracts. Results shown for mid-range capital cost cases and $33/MMBtu zero-carbon fuel. GenX optimizes Western Interconnect-wide dispatch and thus generally requires less firm capacity in California than other models.

Each of these clean firm power resources would play a different role in eliminating overcapacity (Figure 7). For example, nuclear power would act as a “flexible base” power source, generally providing a steady amount of electricity but reducing output during the height of solar output, enabling nuclear plants to conserve their fuel for longer refueling cycles. Although we did not model geothermal generation explicitly, we would expect it to act quite similarly to nuclear power as it also has large up-front costs and minimal variable expenses. The models find it economical to ramp output from natural gas plants with CO_2 capture and storage down and up from day to night and to shut these plants down for longer stretches in the spring. Power plants using more costly carbon-free fuels would be utilized only occasionally when solar, wind and storage options were unavailable. As a result, we find that having many options for clean firm power available results in the least cost solutions because each resource is able to operate at the ideal utilization rate, resulting in the lowest-cost mix of clean firm resources (Figures 7 & 7).[2] Any of these resources could adjust to fill the gap during times of *dunkelflaute*, resulting in the substantial cost savings shown in Figures 2 & 3.

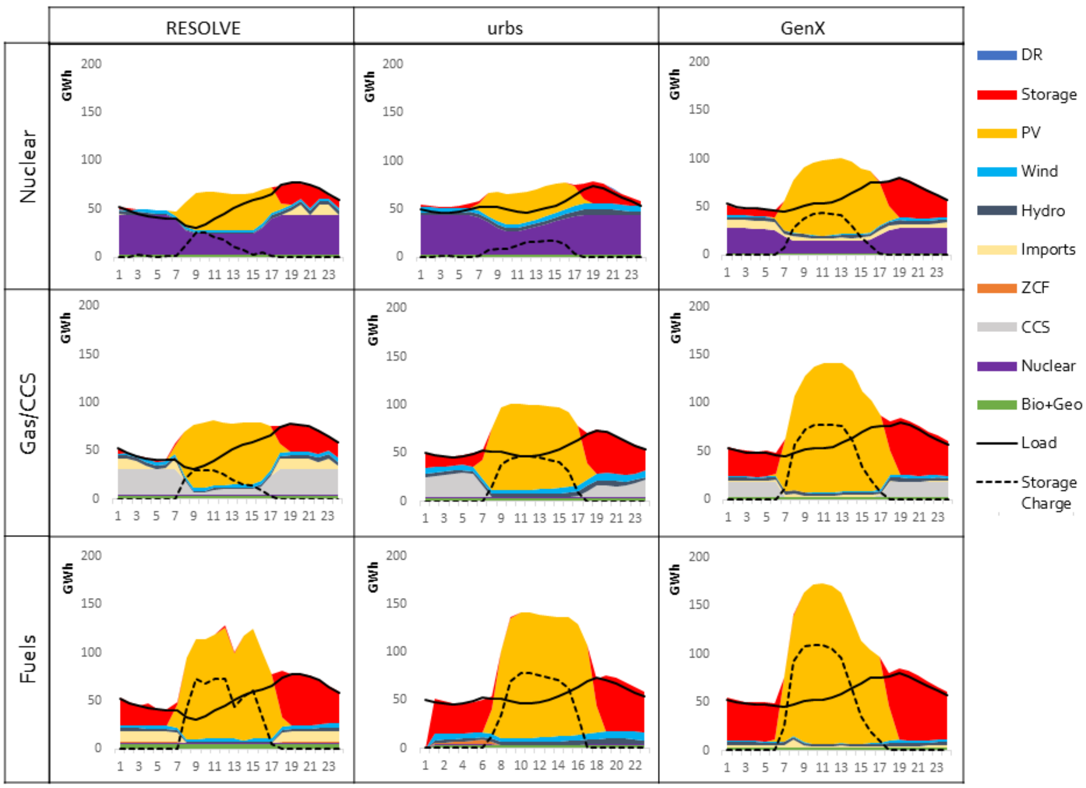

Figure 6. Each type of clean firm power would play a slightly different role in meeting demand. Daily generation pattern of the three models on an example September day for each scenario. Nuclear power would act as a “flexible base” power source but conserving fuel by reducing output during the height of solar output. Natural gas generation with CO_2 capture and storage would ramp up at night when solar ramps down. Use of costly carbon-free fuels would only run when solar, wind and storage options were unavailable. Any of these resources could fill the gap during times of *dunkelflaute.* Each clean firm resource shows distinct daily operations that are consistent across all three models. Note: Representative September day used for RESOLVE, average generation profile for September days used for urbs, and average generation profile of representative September weeks used for GenX. GenX imports indicate net imports into California, and may include imports of power from clean firm resources operating outside of California. (Figure taken from Baik et al. “What is different about different net-zero carbon electricity systems?”, manuscript EGYCC-D-20-00141 (under review) in *Energy and Climate Change*).

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[2] For more, see Baik et al. “What is different about different net-zero carbon electricity systems?” manuscript EGYCC-D-20-00141 (under review) in *Energy and Climate Change.*

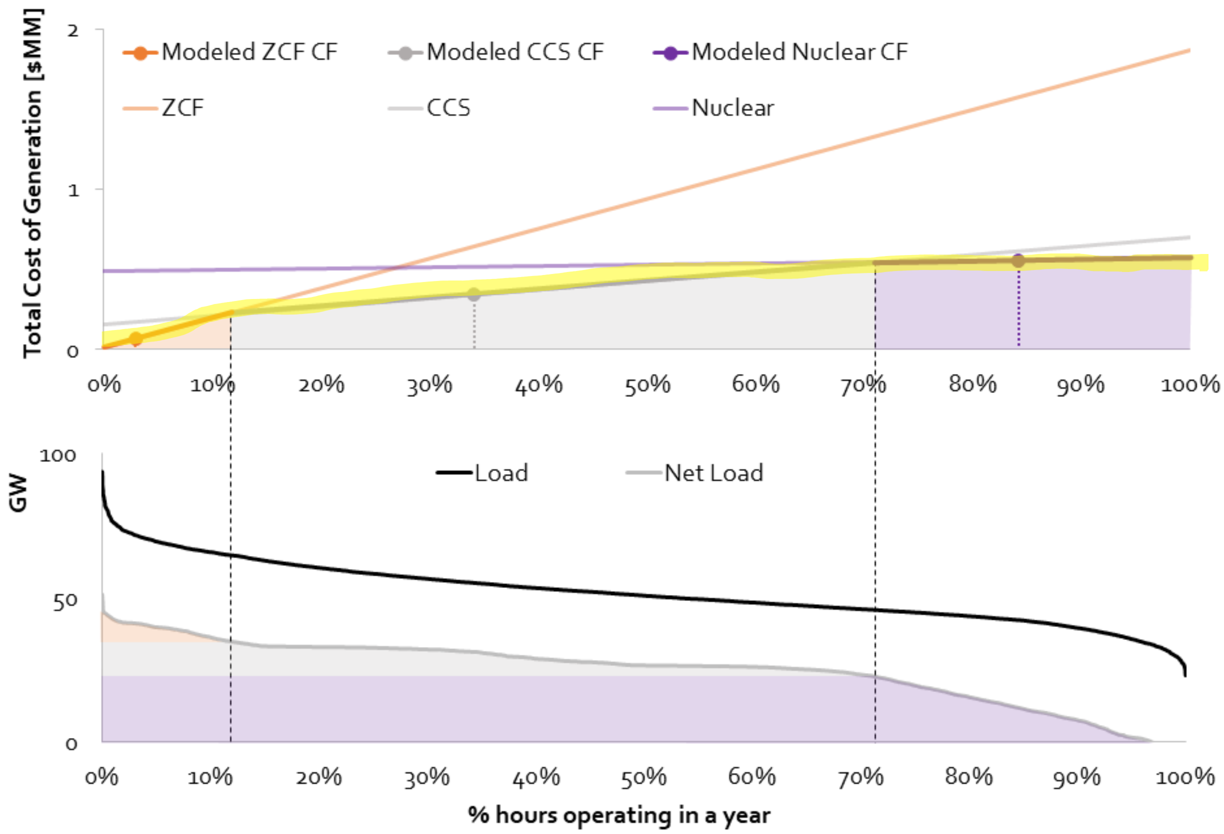

Figure 8. Operating shares of various resources in a year. ZCF is gas turbine power plants using zero-carbon fuel; CCS is natural gas power plants with carbon capture and storage. The least cost solution is achieved when many options are available for clean firm power so that the marginal cost curve can follow the lowest cost resource at each utilization rate. The lowest cost portfolio is highlighted. The more types of clean firm power that are available, the lower the total cost. At one end, power plants burning high cost zero carbon fuels but with low capital costs are suited to act as quick flexible response and to operate only occasionally when needed. At the other end, nuclear power or other options with high fixed costs and low variable costs are suited to operating at high utilization rates (above 70% of the hours of the year). In the middle, CCS provides a good way to regularly provide the least expensive power option at night and will generally back off during the day when solar is available. Net load is the load net renewables and storage that these clean firm resources have to meet. The figure shows that each of the clean firm resources takes a chunk of the net load that has to be met. In the net load graph – the shaded area under the curve (MW * % hours operating) multiplied by 8760 hours in a year should approximately be the MWh of electricity each resource generates. (Figure taken from Baik et al. “What is different about different net-zero carbon electricity systems?”, manuscript EGYCC-D-20-00141 (under review) in *Energy and Climate Change*).

Advantages of a portfolio with Clean Firm Power

Decarbonized electricity systems with clean firm power have other key advantages over systems that are solely based on variable renewable energy and batteries (Table 1). Portfolios that include clean firm power alongside renewables in a 100% carbon-free electric system require between 625 and 2500 square miles dedicated to utility scale solar and wind. Without clean firm power, 3-10 times as much land would be required — more than 6250 square miles. Recent assessments of the solar resource in California indicate that 6250 square miles may exceed the amount of land fit for utility-scale solar not subject to legal restrictions and without high conservation value. Other limitations that will make 100% renewable systems difficult to deploy include difficulty in obtaining transmission right of ways or spatially explicit deployment needs or geographic challenges that have yet been factored in and these would amplify the value of clean firm capacity. These conclusions would become even more extreme should the existing out-of-state supplies of hydro and nuclear power become unavailable.

Table 1. Summary of issues related to the need for clean firm power.

Issue		With Clean Firm Power	Without Clean Firm Power
Costs for generation and transmission *California transmission and distribution costs are currently about 9 cents/kWh*		~9 cents/kWh	~15 cents /kWh
Solar and Wind Capacity *Entire U.S. electric generating capacity is ~1100 GW*		25 – 200 GW	470 GW
New Storage* *Largest battery facility now being built is 0.6 GW /2.4 GWh.* *CA expects to have 2 GW battery capacity in 2021*	**New short-term battery power capacity**	20 -100 GW	160 GW
	New short-term battery energy storage capacity	100-800 GWh	1000 GWh
Land Use *CA land area is ~164,000 sq miles*		625- 2500 sq miles	6250 sq miles
Transmission *CA currently has ~ 15 million MW-miles (26,000 circuit miles) of transmission*		2 – 3 million MW-Miles	~9 million MW Miles

**Energy storage beyond existing pumped hydro*

Including clean firm power also reduces the need for millions of megawatt-miles of transmission lines. California currently has approximately 15 million megawatt-miles of transmission. All portfolios that include clean firm power add 2-3 million megawatt-miles of new in-state transmission lines to meet the goal of zero emissions by 2045. Some of this might be built along existing right of ways, but any siting and permitting this amount of transmission for timely build out will present challenges. Eschewing new clean firm power could at least triple this need to 9 million megawatt-miles even with West-wide coordination of electricity supplies.

Our models built a significant amount of battery storage in addition to California's existing pumped hydro storage capacities. Models with clean firm power built approximately 20-100 gigawatts of new battery storage with 100-800 gigawatt-hours of energy storage capacity. Without clean firm power, the models built about 160 gigawatts of short-term battery storage to deliver nearly 1000 gigawatt-hours of energy. California has a large battery-focused policy under way, and some of the world's biggest battery installations have followed. California will have about 2 gigawatts of battery storage in 2021; the largest single battery storage facility being built anywhere has a capacity of 0.6 gigawatts at Morro Bay and will be able to provide power for 4 hours, or 2.4 gigawatt-hours. Portfolios that depend solely on wind and solar build the equivalent of nearly 1000 energy storage facilities of this size and, even with clean firm power, the models build hundreds of facilities this size. Future energy storage facilities will likely include a lot of batteries but might also include different configurations of technologies, including pumped hydro or novel systems.

Increasingly better batteries play a key role in a carbon-free grid, but like all resources, forcing them to play roles they are ill-suited to adds cost and challenge. Batteries provide flexibility on hourly and diurnal time scales, and all three modeling approaches choose to install storage—modeled as batteries, though in the real world an array of options would be used. But in none of these solutions do batteries economically fill the entire need for clean firm resources. Batteries make sense for shorter duration uses (e.g, shifting solar from midday into the evening) but cannot cost-effectively sustain discharge for weeks at a time. We did examine a class of technologies called "long duration storage" to see if these could substitute for clean firm power. Long duration storage technologies, such as electrolysis and underground storage of hydrogen or advances in ultra-cheap metal-air batteries could potentially provide storage for longer than a few days. Modeling for this study and other recent work indicates these resources play their best role as partial substitutes or even complements, rather than true alternatives to clean firm power; they provide another useful arrow in the quiver, but systems with clean firm power remain meaningfully less expensive (Figure 9).

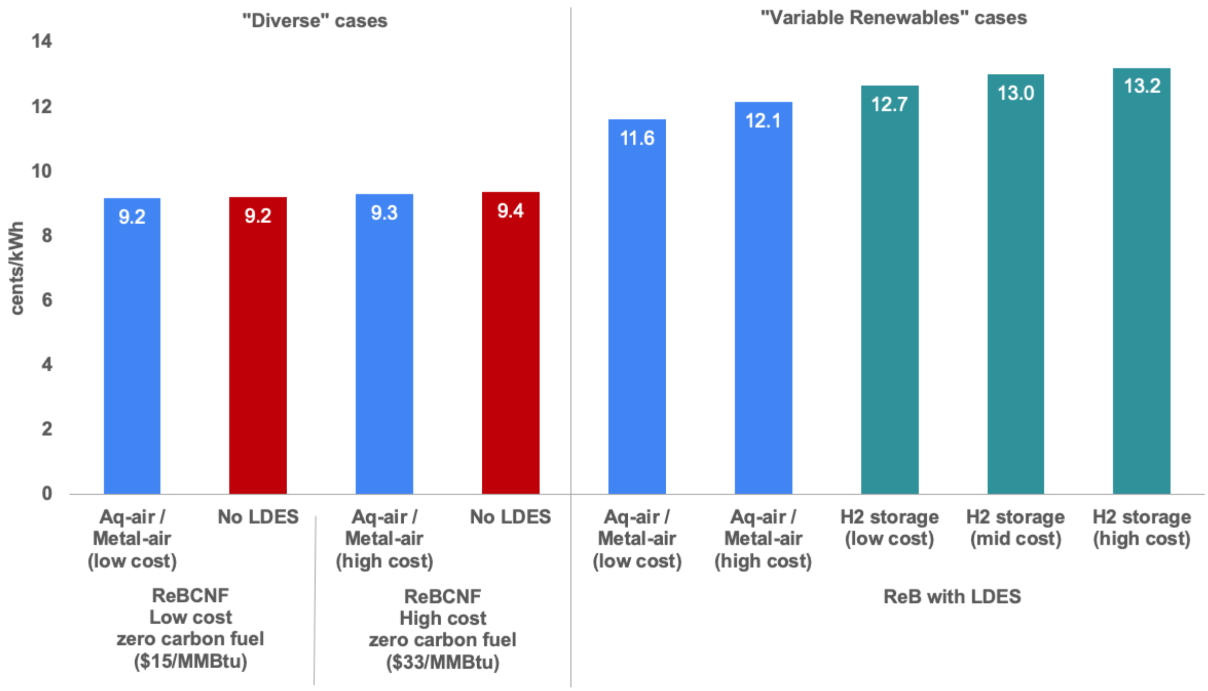

Figure 9. The impact of long duration energy storage (LDES) on 2045 California electricity generation and transmission cost. Costs on the left are for systems that either have clean firm power or clean firm power plus LDES. Those on the right have only variable renewable energy, batteries and long duration storage. Having LDES does not substantially reduce costs if clean firm power is available, but low-cost long-duration storage options can diversify the portfolio of options and reduce reliance on clean firm capacity moderately. Systems which substitute LDES for clean firm power entirely are significantly more expensive. Note that these scenarios without clean firm power were not modeled across multiple weather years, which could require additional storage and renewable energy capacity (and greater cost) to meet reliability requirements across years.

Finally, some have argued that California could continue to deploy its existing gas fleet to provide firm, but not clean, power and then offset the resulting emissions with negative emission technologies (NETs) such as direct air capture and sequestration or bioenergy with carbon capture and storage (BECCS) to meet its economy-wide carbon neutrality goal. We found this solution will likely cost more and produce more direct CO_2 emissions than a system that includes both NETs and clean firm power. Even if the state wants to consider NETs, developing clean firm power is a "no regrets" strategy that positions California to meet its economy-wide decarbonization goals by retaining available NETs to offset more-difficult-to-decarbonize sectors such as agriculture, industry, or heavy-duty transport. Also, NETs technologies have common ground with CCS and hydrogen from gas or biomass for clean firm power in that they all require sequestration of CO_2. Having CO_2 sequestration capacity in California will therefor enable both clean firm power and several negative emission technology options.

Conclusion

Weather-dependent renewable resources like wind and solar will play a starring role in California's low carbon energy future. Even with substantial clean firm power installations, our models generally find that at least 60% of California's electricity in 2045 could be produced with renewable resources. Our model results show that, moving towards 2045, even without clean-firm power, California can abate a lot of emissions by building out renewable energy and providing firm, but not clean, power from gas plants. Until then, existing natural gas-fired generators could act as firm power, albeit with continued emissions, and thus used only when these generators are essential. But by 2045, emissions need to drop to zero and California will need to replace these carbon-emitting resources or retrofit them to either capture and store CO_2 or burn clean fuels in a zero-carbon economy. Our model results show that squeezing out the last increments of CO_2 from power generation while maintaining affordability and reliability will require clean firm power.

An ambitious but achievable investment in clean firm power, on the order of California's existing gas fleet could, on the upside, eliminate the need for ten times that amount of renewable energy and thus help keep generation and transmission costs in line with today, cut the land area needed for utility scale solar facilities and energy storage by a factor of ten, and reduce transmission infrastructure needs by a factor of four by 2045. These advantages will help increase the likelihood of achieving climate goals in California.

California needs to start planning early to obtain clean firm power supplies. It may seem as though 2045 is a long way off, but from an infrastructure investment and technology development perspective, it is really the day after tomorrow. California could initially target deployment of approximately 30 gigawatts of clean firm power by 2045, with interim milestones along the way in order to avoid high system costs and loss of reliability in the future. Deployment will require policy support because these technologies are currently more expensive per kilowatt hour than wind and solar energy and all face implementation challenges. Managing this issue requires early innovation, investment, and political conversations to choose viable clean firm power systems. It takes a long time to develop new technologies and to get regulators to approve them; waiting a decade to get to work will put California at risk of failure. As all these technologies keep costs low, California can work to scale several of these clean firm options simultaneously and expand whichever ones ultimately prove most feasible and cost-effective.

We don't yet know the best choices and mixes of clean firm power. Consequently, the state should design an adaptive investment strategy—one that proactively deploys and tests a diverse portfolio of clean firm power choices until experience identifies the best and most feasible choices. A broad portfolio approach increases chance of success, helps to avoid technological cul-de-sacs, and thus will help ensure affordability and reliability in the long run. California's government could require utilities to build some form of clean firm power now and allow cost recovery for their implementation. Leaving the form of clean firm power up to the utilities themselves—with oversight from California's regulators focused on evaluating what the utilities do on the ground—will allow experimentation and learning.

The federal government can also help, not just California, but the entire nation, by making sizeable investments in clean firm power—including investment in innovations needed for the next generations of these sources.

There's a lot at stake not just for California. Across the planet—in diverse places such as India, China, Chile, Europe and many others—governments and electric system planners are pushing hard to deploy vast quantities of renewable power. California can help the planet achieve those visions—and thus help the planet cut global emissions and slow climate change—by showing how these power sources can be integrated reliably with clean firm power while meeting other goals such as wise land stewardship, environmental justice, and containment of costs.

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Appendix A. Scenario definitions

Scenario Names	Technologies allowed for expansion
Renewables (ReB)	Solar PV+Wind+Battery Storage
Gas/CCS (ReBC)	Solar PV+Wind+Battery Storage+CCS
Nuclear (ReBN)	Solar PV+Wind+Battery Storage+Nuclear
Fuels (ReBF)	Solar PV+Wind+Battery Storage+Zero Carbon Fuel
All (ReBCNF)	Solar PV+Wind+Battery Storage+CCS+Nuclear+Zero Carbon Fuel
Gas/CCS+Nuclear (ReBCN)	Solar PV+Wind+Battery Storage+CCS+Nuclear
Gas/CCS+Fuels (ReBCF)	Solar PV+Wind+Battery Storage+CCS+Zero Carbon Fuel

Supplementary Information

Contents

A. Common Modeling Assumptions

All three models shared common assumptions on load, future resources availability and future resource costs. The following section summarizes the common assumptions made across all three models. All common assumptions are derived from E3's RESOLVE modeling work.

1. Load Growth Assumptions

California electricity loads and hourly load shapes assumed in this study result from sector allocated emissions based on E3's modeling of economy-wide greenhouse gas emissions reduction targets as set by California to achieve an 80% greenhouse gas emissions reduction below 1990 levels by 2050 [3]. Table 1 shows loads expected to be considerably higher in 2030 and 2045 than today due to electrification of vehicle and building loads.

Table 1: Load growth assumptions for modeled years

California Load Growth Assumptions	2019[4]	2030	2045
Annual Load [TWh/yr] (includes BTM PV)	~250	317	475

2. Resources Considered for Expansion

California has several resources that can be considered for its future decarbonized electricity sector. All three models' optimization capabilities allow them to select from among a wide range of potential new resources. In this study, the options for new investments considered are defined by the scenarios and include technologies that are commercially available today as well as technologies that are assumed available in the near and long-term: by 2030 or 2045. The full range of resource options considered in this study is shown in **Error! Reference source not found.**.

Table 2: Candidate resource options considered

Candidate Resource Option	Available Options	Functionality
Natural Gas Generation	- Simple cycle gas turbines - Reciprocating engines	- Dispatches economically based on heat rate, subject to ramping limitations

[3] https://www.ethree.com/wp-content/uploads/2018/06/Deep_Decarbonization_in_a_High_Renewables_Future_CEC-500-2018-012-1.pdf
[4] https://efiling.energy.ca.gov/Lists/DocketLog.aspx?docketnumber=20-IEPR-03

	- Combined cycle gas turbines (CCGT) - Combined cycle gas turbines with Carbon Capture & Storage (CCS)	- Contributes to meeting reserve requirements and ramping needs - CCGT combined with CCS is an RPS eligible resource - CCGT with CCS has flexible ramping constraints and can capture 90-100% of greenhouse has emissions
Nuclear Generation	- New advanced nuclear generation	- New nuclear plants are assumed to be dispatchable pressure-water-reactors[5]
Renewable Generation	- Geothermal - Wind (inc. Out-of-State and Offshore) - Utility Scale Solar PV (inc. Out-of-State) - Distributed Solar PV	- Variable generation generates as available; geothermal assumed to run as baseload - Dynamic downward dispatch of variable renewable resources to help balance load
Energy Storage	- Batteries (> 1 hour) - Pumped hydro storage (> 12 hours)	- Stores excess energy for later dispatch - Contributes to meeting reserve requirements and ramping needs
Flexible Loads	- Advanced shift demand response (e.g., controllable AC)	- Allows the model to shift load from one timepoint to another

[5] https://www.eia.gov/outlooks/aeo/pdf/electricity_generation.pdf

The modeling exercise includes the following generation technologies[6]:

- **''Fuel-saving'' variable renewable energy (VRE) resources**. They harness renewable energy inputs (wind, solar insolation, water) that vary on timescales ranging from seconds to hours to seasons, have zero (or near-zero) variable costs, and have no fuel costs. At lower penetration levels, they may displace the need for firm capacity, but, at higher shares, capacity needs are driven by periods with low VRE availability. At high energy shares, these technologies therefore contribute value primarily by displacing other higher variable cost generating technologies whenever available and reducing the total fuel consumption and variable costs of the system. These include
  - wind power,
  - solar photovoltaics (PV),
  - concentrating solar power
  - run-of-river hydropower.
- **''Fast-burst'' balancing resources**. These are either energy constrained (storage, demand flexibility) or have very high variable cost (demand curtailment). These technologies are therefore poorly suited to operating continuously over long periods of time and are better used during high-value periods when relatively fast bursts of power or quick demand adjustments are needed to balance supply and demand. These include
  - short-duration energy storage (e.g., Li-ion batteries),
  - flexible demand (or schedulable loads), and
  - demand response (or price-responsive demand curtailment).
- **''Firm'' low-carbon resources**. These are technologies that can be counted on to meet demand when needed in all seasons and over long durations (e.g., weeks or longer) and include
  - nuclear power plants capable of flexible operations,
  - hydro plants with high-capacity reservoirs,
  - coal and natural gas plants with CCS and capable of flexible operations,
  - geothermal power, and
  - biomass- and biogas-fueled power plants.

3. Technology Costs

Most technology cost assumptions for available resources are taken from NREL's 2018 Annual Technology Baseline. Assumptions on capital and fixed O&M costs for resources, as well as associated financing assumptions are included in Supplementary Information file *Cost and Financing Assumptions.xlsx*. An example of assumed costs for resources in 2045 are summarized in Table 3.

Note that modeled costs for the modeled timesteps are taken as averages of capital costs for the time frame for which they are being modeled. For example, for modeling time frames from 2030 to 2045, capital costs assumptions for 2031-2045 are averaged and are input into the model.

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[6] This taxonomy was originally developed in Sepulveda, et al. 2018, "The Role of Firm Low-Carbon Electricity Resources in Deep Decarbonization of Power Generation," *Joule* 2(11). https://doi.org/10.1016/j.joule.2018.08.006

Table 3: Candidate cost assumptions for 2045

Resource Costs in 2045

	Overnight Capital Cost 2045 ($2016/kW)				
Resource Type	**Benchmark**	**Low**	**High**	**Operating Assumptions**	**References**
Utility-Scale Solar PV (in-state avg.)	**$903**	$502	$1,540 (Distributed Solar Cost)	No fuel cost; Single axis tracking; ~33% CF	NREL ATB 2018
Onshore Wind (in-state avg.)	**$1,563**	$794		No fuel cost; TRG6 ~ 36% CF	NREL ATB 2018
OOS Transmission Cost Adder (Wyoming & New Mexico Wind)	**$1,330**			No fuel cost; ~42% CF	NREL ATB 2018
Offshore Wind (Floating)	**$2,059**			No fuel cost; TRG8 ~ 52% CF	NREL ATB 2018
Geothermal	**$4,692**			No fuel cost	NREL ATB 2018
CCGT with CCS at 90% Capture	**$1,700**	$1,360 (-20%)	$2,040 (+20%)	NG Cost ~ 7 $/MMBTU w/o carbon adder	NREL ATB 2018 with ~ 3$/MWh for T&S. Non-Allam Cycle 100% capture cost assumption from Feron et al. 2019
CCGT with CCS at 100% Capture	**$1,816**	$1,000 (Allam Cycle Net Power Scaccabarozzi et al. 2017)	$2,180 (+20%)	Same as above	
Advanced new nuclear (SMRs)	**$5,210**	$3,650 (-25%)	$6,770 (+25%)	Low fuel cost Uranium ~0.7$/MMBTU	NREL ATB 2018
New CCGT	**$1,099**			Natural Gas Cost ~ 10$/MMBTU (incl. carbon adder)	NREL ATB 2018
Li-Ion Battery (Capacity $/kW/Energy $/kWh)	**$85/$118**	$71/$89	$113/$253(BTM Li-Battery)	Round trip efficiency of 92%; number of hours selected in optimization	Lazard LCOS v.4.0
Pumped Storage	**$2,350**			Limited to 4,000 MW	Lazard LCOS v.4.0

While California has a wide variety of resources for its decarbonization, it has limited capacity of some resources. Notably, onshore wind, geothermal, and offshore wind resources are limited, so most of future capacity growth in-state is dominated by solar PV and battery storage. Assumed availability of future resources are summarized in Table 4.

Table 4: Resource Assumptions

Category	Assumption	Study Assumption
Candidate Resource Limits	Solar PV	Limited to 266,963 MW in-state and 45,684 MW out-of-state (UT/NV/NM/AZ)
	Wind	Limited to 2,586 MW in-state and 12,000 MW out-of-state (WY/NM/PNW)
	Geothermal	Limited to 1,808 MW in-state and 1,152 MW out-of-state (NV/PNW)
	Pumped storage	Limited to 4,000 MW
	Battery storage	Unlimited availability
	Demand Response	Up to 4.9 GW
	CCS	Available in specific scenarios
	Zero Carbon Fuel	Incremental cost of $33/MMBtu in 2045
Other	Behind-the-meter PV	Baseline installed capacity of 15,335 MW by 2030 and 24,742 MW by 2050 (forced in). Model can select up to 36,749 MW of additional BTM PV.

Table 5: Three models used and summary of key differences

	RESOLVE	urbs	GenX
Model Type	Linear Programming Model	Linear Programming Model	Linear Programming Model with linear relaxation of unit commitment constraints
Temporal Resolution	37 representative days	1 year in hourly time steps (8760 hours)	16 representative weeks with hourly resolution time steps (2,688 hours)
Spatial Resolution	3 zones: CA, SW, NW	10 CA zones; 2 out of state zones (SW, NW)	2 CA zones; 7 out of state WECC zones
Capacity Decisions Optimized	California	California	WECC-wide
Policy Assumptions for Neighboring Regions	Neighboring states assumed to adopt deep decarbonization measures, which are reflected in their assumed resource build	Neighboring states assumed to adopt deep decarbonization measures, which are reflected in their assumed resource build	All states within WECC adopt the same energy and carbon policies
Imports/Exports to/from CA	2000 MW of firm imports assumed Unspecified imports are treated as gas resources with a CA carbon adder applied at 0.43 tCO_2/MWh	Firm imports modeled and unspecified imports treated as gas resources with a CA carbon adder applied at 0.43 tCO_2/MWh	Co-optimized subject to inter-regional transmission network flow constraints and endogenous transmission capacity expansion

B. RESOLVE

E3's RESOLVE (Renewable Energy Solutions) is a resource investment model that is well known to utilities and utility commissions across the US, having been used extensively for resource planning needs including most recently: in California (CPUC 2017), the Northwest (Energy Northwest 2020, PSE IRP 2017), Hawaii (PSIP 2016), the Southwest (El Paso Electric Utility 2020), the Midwest (Xcel Minnesota 2019 IRP) as well as jurisdictions on the East Coast. RESOLVE is a linear optimization model that identifies optimal long-term generation and transmission investments in an electric system, subject to reliability, technical, and policy constraints such as annual greenhouse gas emissions levels and clean energy portfolio standards (E3 2020, Ming et al 2019). In this study RESOLVE optimizes California's resource portfolio for least system cost while modelling interactions with external regions (including the Northwest and Southwest) based on price signals from their generation profiles. Resource portfolios for neighboring regions are input based on E3's Aurora Market Pricing work for the WECC assuming environmental policy constraints like that of California by 2045. E3 also complements this analysis using their Renewable and Energy Capacity Planning Model (RECAP) to develop a zero carbon-emitting portfolio built solely on renewables and battery-storage additions (duration of 4-8 hours), referred to in the text as "ReB" scenario. RECAP assesses generation resource adequacy for a power system based on loss of load probability analysis and through an iterative process can be used to build a portfolio of variable and storage resource that will meet its probabilistic limits on reliability. All E3 portfolios presented in this study are assessed for their reliability using RECAP and meet the 2.4 hours per year loss of load hours electric reliability standard.

RESOLVE is a resource investment model that identifies optimal long-term generation and transmission investments in an electricity system, subject to reliability, technical, and policy constraints. In this study, it is used to develop least-cost resource portfolios for California that meet SB100 defined by achieving 100%+ RPS by 2045 and meeting various decarbonization targets.

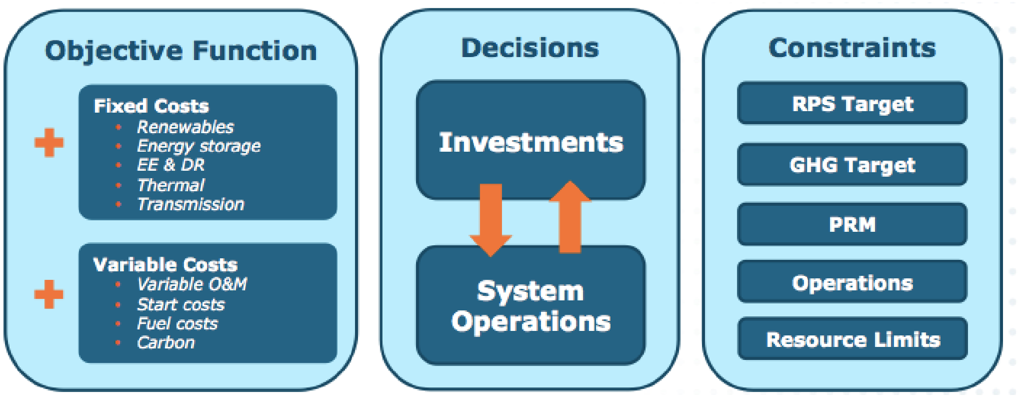
This study utilizes the California-wide RESOLVE version that was developed for the CEC's deep decarbonization project to evaluate long-run (2045) electricity portfolios for the state. A separate version of RESOLVE is used by the California Public Utilities Commission (CPUC) to evaluate near-term (2030) optimal resource portfolios for the CAISO footprint within the context of the CPUC's Integrated Resource Planning (IRP) proceeding[7]. The principal differences between the models are the footprint (state of California vs. CAISO area) and the time frame (2045 vs. 2030) over which resource investment is optimized.

Neighboring regions to California, the Northwest (NW) and Southwest (SW), are also modelled as part of the system with optimized investment. Given recent policy adoptions by Washington State, Colorado, New Mexico and Arizona, we assume that these regions will have a resource build that matches an equivalent to California's 80% greenhouse gas emissions reduction target by 2050 from 1990 levels. RESOLVE assumes that 10,000 MW of resources from out of state regions can contribute to meeting Resource Adequacy needs in California.

[7] http://cpuc.ca.gov/General.aspx?id=6442457210

RESOLVE considers both the fixed and operational costs of different portfolios over the lifetime of the resources and is specifically designed to simulate power systems operating under high penetrations of renewable energy and electric energy storage. By co-optimizing investment and operations decisions in one stage, the model directly captures dynamic trade-offs between them, such as energy storage investments vs. renewable curtailment/overbuild. The model uses weather-matched load, renewable and hydro data and simulates interconnection-wide operations over a representative set of sample days in each year. The objective function minimizes net present value (NPV) of electricity system costs, which is the sum of fixed investment costs and variable plus fixed operating costs, subject to various constraints. Figure 1 provides an overview of the model.

Figure 1: Overview of RESOLVE Model



RESOLVE scenarios are designed to ensure reliability under all high renewable penetration cases with the following features:

- **Economic Retirement Functionality:** This logic allows RESOLVE to retire existing resources if the going-forward costs of maintaining the resources is greater than the fuel, O&M, ancillary service and capacity savings the resources produce when operating.

- **Seasonal Energy Sufficiency Requirement:** This constraint ensures the system can produce sufficient energy across extended periods (up to 3 weeks) and anomalous periods of low renewable output that are not captured in the limited set of sample days used for operations in the model. In most electricity systems today, which meet significant shares of demand with firm resources that can be dispatched throughout the year when needed, this type of constraint is not significant. However, in a system that relies heavily on intermittent renewables, the capability to serve load during prolonged periods of low renewable output is a key reliability consideration.

In addition to the common assumptions and resources modeled, E3 considers 55 GWh/day of flexible loads in the form of Advanced shift demand response (e.g., controllable AC) that allows the model to shift load from one timepoint to another.

It is worth noting that RESOLVE is not designed to answer detailed reliability questions in systems without sufficient firm capacity. The RESOLVE modeling framework is limited to a set of 37 representative sample days, which does not have enough data points to make robust conclusions on reliability events that happen infrequently, potentially less than once per year. In addition, the sample days are independent (not connected) and therefore do not capture the potential need for multi-day or seasonal storage.

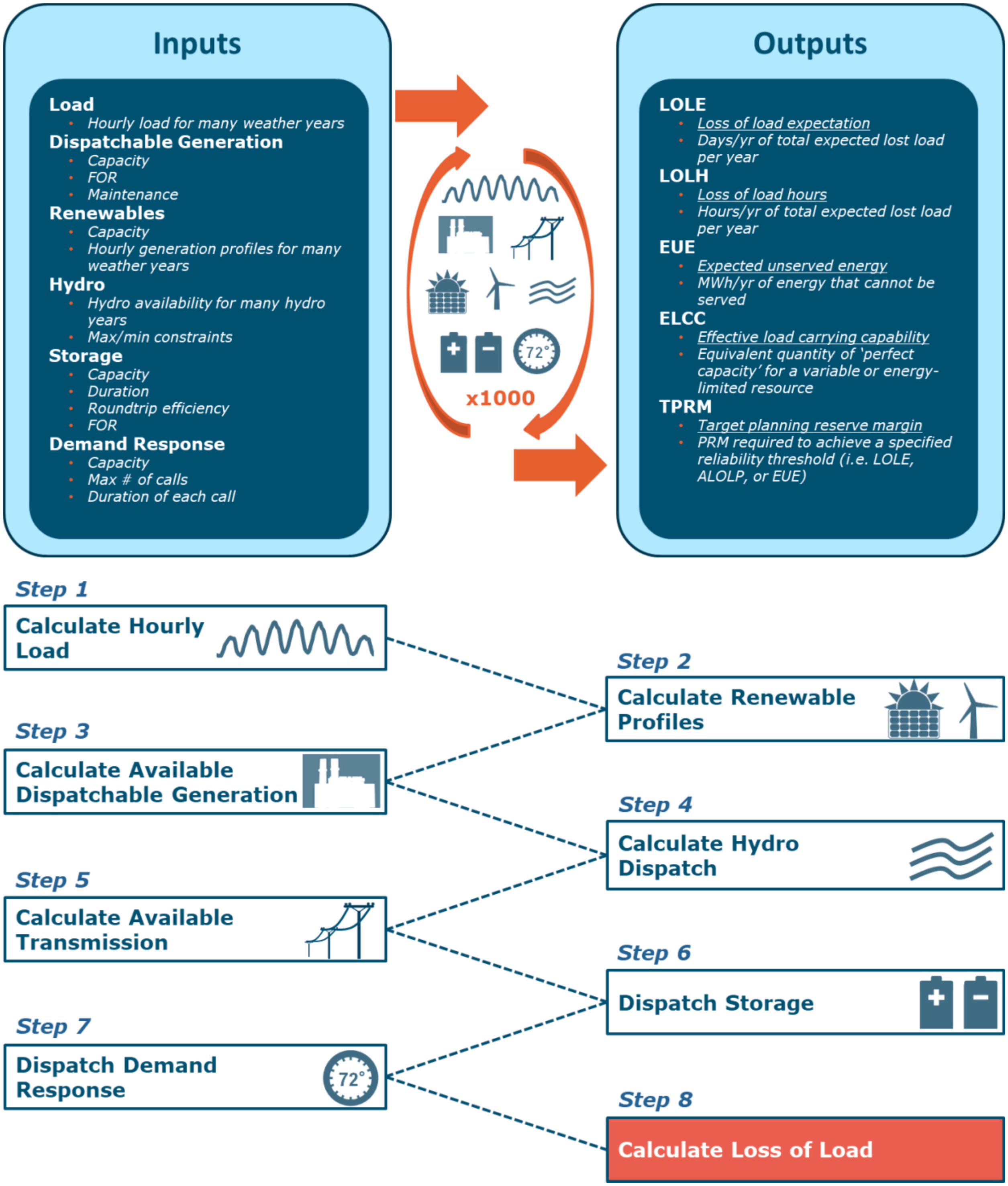
RESOLVE does however include both a Planning Reserve Margin (PRM) constraint to ensure that sufficient resources are maintained to meet an assumed long-run reliability standard as well as an Energy Reserve Margin (ERM) constraint to ensure an equivalent loss of load expectation (LOLE) below 2.4 hours/year (per CAISO's definition of a reliable system). The PRM and ERM standards are developed exogenously and incorporated into RESOLVE as an assumption. For systems in which firm capacity is available to be selected, the capacity expansion model selected sufficient resources to meet energy and capacity needs plus a defined reserve margin to ensure sufficient capacity during adverse weather events.

For the ReB scenario in which firm capacity was not available for selection, a more robust approach to resource adequacy was required in which a much wider range of potential load, wind and solar conditions was considered. For this case, E3 used RESOLVE to develop an initial portfolio that meets energy needs during the 37 selected days. E3 then used its RECAP model, which combines loss-of-load-probability modeling with a capacity expansion heuristic, to identify additional wind, solar and battery resources needed to meet a 1-day-in-10-year Loss-of-Load Expectation standard. This more exacting approach was not utilized for all scenarios because (1) the analysis is very time- and resource-intensive and was beyond the scope of this project, and (2) E3's experience in prior studies has been that the simpler reserve margin approach generally produces portfolios that meet resource adequacy standards when sufficient firm capacity is available for selection by the capacity expansion model.

The Renewable Energy and Capacity Planning (RECAP) model is a loss-of-load-probability model developed by E3 that has been used extensively to test the resource adequacy of electric systems across the North American continent, including California, Hawaii, Canada, the Pacific Northwest, the Upper Midwest, Texas, and Florida. RECAP was developed specifically to address the needs of a changing electricity sector by incorporating the unique characteristics of dispatch-limited resources such as wind, solar, hydro, battery storage, and demand response into the traditional reliability framework.

RECAP calculates a number of reliability metrics by simulating the electric system with a specific set of generating resources and loads under a wide variety of weather years, renewable generation years, and stochastic forced outages of electric generation resources and imports on transmission. Correlations enforced within the model capture linkage among load, weather, and renewable generation conditions. Time-sequential simulation tracks the state of charge and energy availability for dispatch-limited resources such as hydro, energy storage, and demand response. By simulating the system thousands of times with different combinations of these factors, RECAP provides a robust, stochastic estimation of loss of load expectation (LOLE), target planning reserve margin (PRM), individual resource effective load carrying capability (ELCC), and other reliability statistics. An overview of this process is provided below. RECAP conducts a Monte-Carlo time-sequential simulation of loads and resource availability, and the general steps in RECAP's algorithm are shown below.

Figure 2. Overview of RECAP model



C. urbs

urbs is a dispatch and capacity expansion model that designs large-scale power systems to meet policy standards while minimizing total costs. For capacity expansion, urbs determines what type and how much of generation, transmission, or storage capacities need to be added to each region to construct the optimal power system in California. For hourly dispatch, urbs utilizes generation, transmission, or storage resources from all regions cost-optimally to cost-optimally meet the hourly demand profiles in each region. Modeling reliability on urbs is limited to meeting the given load in the modeled year.

The model solves a linear optimization problem that is formulated in Python and solved by Gurobi. The optimization goal is to minimize the societal costs of the system which involves annualized capital cost for new capacities built, as well as fuel costs, and fixed and variable operational costs for a given year. The optimization is subject to operational constraints of generation, transmission, and storage technologies, as well as policies such as a RPS, a CO2 tax, or a CO2 regulation. In this study, urbs is used to model California's power system to meet it 2045 SB100 goals. A more detailed description of the model can be found on the *urbs* GitHub page (TUM, 2017).

1 Geographical Extent

Within the model, the California power system is represented by ten distinct regions. Each region is a set of contiguous counties that are grouped to resemble California's balancing authority areas and local reliability areas. The designated regions also take into consideration the distribution of transmission networks such that there are well-connected transmission lines within a single region. Electricity transmission and distribution within a region is assumed to be lossless. Each region has its own distinct set of generation capacities, transmission line capacities, storage capacities, and demand load profile.

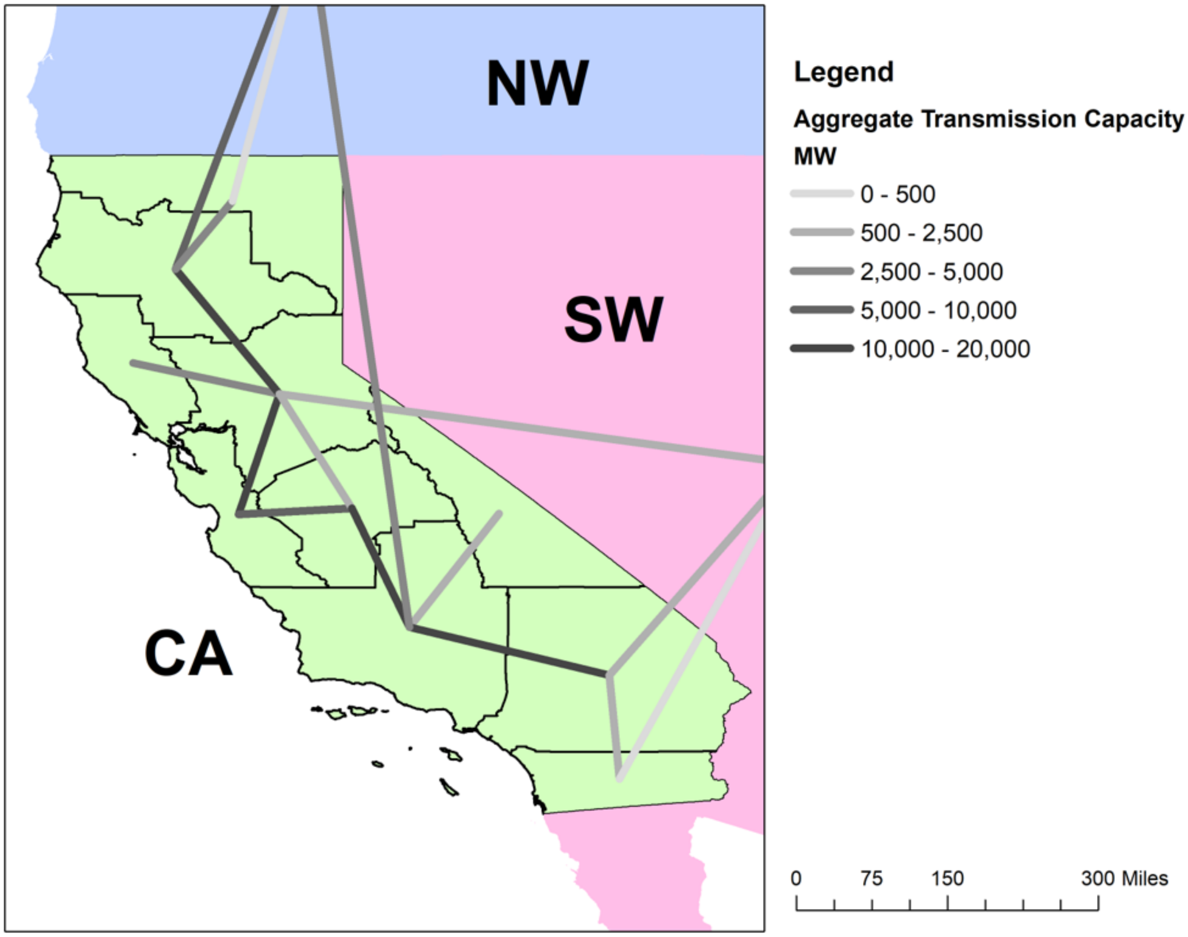


Figure S1. Modeled extent of California and its surrounding regions in urbs

The out-of-state (OOS) regions are divided into two separate regions: the Northwest (Washington, Oregon, Montana, Idaho, and Wyoming) and the Southwest (Arizona, Nevada, and Utah). Energy imports from these regions occur through import from out-of-state power plants owned by California balancing authority areas, power purchase agreements, and general electricity imports from which the generation source is unknown. The California Air Resources Board (CARB) imposes an 0.428 ton/MWh emissions intensity for unspecified imports. Two additional OOS regions are modeled to capture defined imports from the Northwest and Southwest, which don't have an emissions intensity involved such as hydro and wind power from the Northwest, and PV imports from the Southwest. The transmission capacity between an out of state region and California is divided equally for defined and undefined resources. Existing and future generation and storage technology capacities for the out of state regions are taken from E3's assumptions, which assume 80% emissions reduction in the Northwest and Southwest regions by 2045 relative to 1990 levels.

Expansion of resources dedicated to California in out of state regions are limited to 10,000 MW of wind (5,000 MW each from the Northwest and Southwest) and 10,000 MW of Southwest PV. Additional 1,152 MW of geothermal from the Northwest is also allowed as an expansion candidate.

2 System Scenarios

The modeling is conducted in a two-step process- one from 2020-2030 and another from 2030-2045. A single 2020-2030 capacity expansion and dispatch model is run with a policy constraint of meeting expected load in 2030 as well as the 60% RPS requirement as set out by SB100. The results of the 2030 modeling run are then utilized as inputs for the 2045 capacity expansion modeling. Figure S2 summarizes the results of the 2030 modeling.

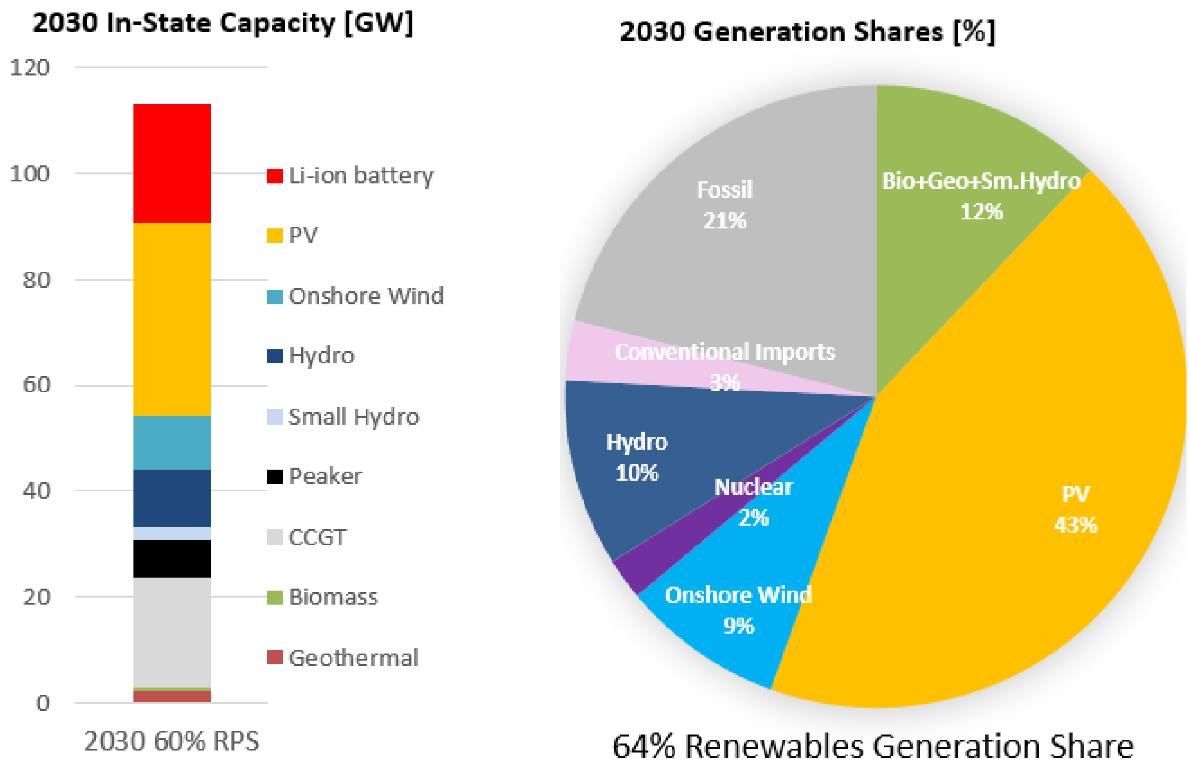


Figure S2. Optimized system capacity and generation in California 2030.

3 System Data and Assumptions

3.1 Generation

Generation technologies are divided into dispatchable and non-dispatchable resources. Dispatchable generation sources are conventional energy sources such as coal, nuclear, gas, biomass, geothermal, and CCS-enabled power plants from which generation can be controlled from an operator's perspective. Non-dispatchable generation resources, such as solar and wind, are generation resources that cannot be turned on or off to meet the operator's needs. For non-dispatchable generation sources, hourly capacity values are provided for generation source and region. Generation technologies are also divided between renewable and non-renewable resources as defined under California's Renewable Portfolio Standard, and is summarized in Table S5.

Table S1. Delineation of renewable generation under California's RPS

Renewable	Solar, Onshore Wind, Biomass, Geothermal, Offshore Wind, Small Hydro (<30 MW), Biomass-CCS
Not Renewable	Gas, Coal, Large Hydro, Nuclear, Gas-CCS

Regional distribution of generation resources are based on EIA's 2018 Form 860, information on generators in 2018 (EIA, 2018). The capacities of generating power plants are aggregated based on regions and generation source as defined by *urbs*. In cases when the total capacity did not match RESOLVE inputs, the overall capacities in each region were scaled to match the total generation capacity in RESOLVE. A 15% planning reserve margin is included in the analysis as well.

Hydro is modeled in a two step-process to represent its seasonal variation and limitations, but also the flexibility in generation. 70% of the total hydro capacity in a region is considered a non-dispatchable resource that has must-run generation patterns based on historical 2018 generation from EIA (US Energy Information Administration, 2018). 30% of the total hydro capacity is modeled as a flexibly dispatchable resource, only limited in operation by an annual capacity factor of 25%.

3.2 Transmission

Transmission lines between regions are distinguished between Alternating Current (AC) and Direct Current (DC) lines, and existing transmission line capacities above 115kV are aggregated to one large transmission corridor between two different regions. Depending on the length of the transmission lines between regions, AC transmission lines have a range of efficiency loss of 89-99%, while the DC transmission lines have a range of efficiency loss of 93-97% (Clair, 1953). Existing transmission line data in Western U.S. is obtained from Hart Energy Publishing (Hart Energy Publishing, 2015). Transmission line capacities above 115 kV are used and the capacities of the transmission lines are calculated based on voltage level and length (Kerala State Electricity Board Engineers' Association, 2015). The transmission capacities between regions are aggregated as a single corridor between regions. See attached modeling input excel sheet to see transmission capacities between modeling regions. Spur line costs for solar and gas-CCS are calculated based on GenX spur line cost assumptions and added to the total system cost post optimization.

3.3 Translating E3 RESOLVE Resources Zones in urbs

Each region in urbs has 1-2 wind and solar profiles that are consistent with E3 RESOLVE's candidate renewable resource zones. Table S2 summarizes the how the solar and wind resources from E3 RESOLVE's candidate zones were applied to modeling regions in urbs. For an urbs region with two RESOLVE zones, additional solar and wind profiles are modeled as 'Added Solar' and 'Added Wind'.

Table S2. Wind and Solar profiles from E3 utilized in urbs model per region. Two zones that are applicable two possible potentials and resources profiles were input.

Urbs region	RESOLVE ZONE 1	RESOLVE Zone 2
CCT	Solano	Greater Carrizo
CVA	Central Valley North Los Banos	
ECA	California	
ELU	Riverside East Palm Springs	Southern California Desert
FRE	Westlands	Tehachapi
LAX	Tehachapi	Kramer Inyoken
NCT	Northern California	
NVA	Northern California	
PAC	Northern California	
SDG	Greater Imperial	
SW	SW	Arizona
NW	NW	Utah

3.4 Load

The load in each region is assessed by dividing the aggregate California load assumptions from E3, by the population density in each region as summarized in Table S3. The aggregate capacity for distributed solar is also proportionally attributed to each region by its population. In each region, the net load profile is obtained by subtracting the assumed distributed PV generation (based on regional solar profiles from E3) from the overall load.

Table S3. Population distribution across urbs regions

urbs region	% of Population
CCT	18.2%
CVA	11.4%
ECA	0.1%
ELU	19.7%
FRE	4.0%
LAX	33.2%
NCT	2.7%
NVA	1.7%
PAC	0.3%
SDG	8.9%

Figure S3 shows the location of each region modeled in urbs.

Figure S3. Location of each region modeled in urbs

3.5 Calculating System Cost

The total system cost calculated for California consists of capital, fixed, and variable costs for in-state generation and out of state resources dedicated to California. In addition, costs/revenues from import and export of electricity with neighboring state is assessed. In each region the marginal cost of generation in that region is multiplied by the energy level of exports in that region to find the system import/export costs. For California, exports from California are considered a net revenue, while imports from Northwest and Southwest regions are considered costs. Note that in 2045, there are no unspecified imports due to the CARB carbon adder, so only net revenue from exports is considered within the total system cost.

4 Additional Technology Assumptions

4.1 CCS Retrofit Cost Assumptions

In addition to building new NGCC units, urbs allows California's existing NGCC units to be retrofit with post-combustion carbon capture. Capital costs for retrofitting existing NGCC plants with carbon capture and storage (CCS) is assumed to be the difference in capital costs between and NGCC units and NGCC units with CCS. The capital cost assumptions for NGCC-CCS are consistent with RESOLVE and GenX, while the capital cost for NGCCs are based on NREL's 2018 Annual Technology Basis for NGCCs. Other fixed and variable operational costs for retrofit CCS plants are assumed to be consistent with RESOLVE and GenX. Once retrofit, the NGCC power plant that was retrofit has its peak capacity reduced by 25% to account for the energy penalty of carbon capture. New NGCC-CCS units are modeled by allowing the system to build more NGCC capacity that can then be retrofit by the system.

4.2 Offshore Wind Assumptions

The capacity factors and generation profiles are taken from a BOEM analysis on potential offshore resources in California (Musial et al., 2016). Average capacity factors for each region is taken from the BOEM study and the offshore wind generation profiles for the five regions that have potential (CCT, LAX, NCT, NVA, PAC) taken from Renewable.Ninja is scaled to match the capacity factor identifies in the BOEM study.

4.3 BECCS Assumptions

In modeling BECCS, only existing biomass power plants in California are allowed to be retrofit with carbon capture, and so expansion capacity is limited by the existing biomass capacity in-state. Cost assumptions for bioenergy retrofit with carbon capture are taken from the 2012 NETL Analysis on coal and biomass analysis. Fixed O&M costs for BECCS power plants are taken from the fixed costs for case P.A.1 power plant with 100% biomass feed with 90% Capture. Retrofit capture costs are taken to be the difference in overnight capital costs from Case P.A.1. (100% biomass feed) and Case P.N.1. (100% biomass feed with 90% Capture).

All 2007 $s are converted to 2018 $ to be consistent with capital cost assumptions for other generation and storage resources. No learning curve is assumed for BECCS across time.

Table S4. Modeling assumptions for BECCS in urbs

Description	Values
Overnight Capital Costs	$2,483,000/MW (NETL, 2012)
Fixed O&M	$128,000/MW-year (NETL, 2012)
Variable O&M	$12.4/MWh (NETL, 2012)
CRF	0.095
Heat Rate	15,100 MMBtu/MWh (NETL, 2012)
CO2 emissions	-841 kg/MWh (NETL, 2012)
Retrofit Power Penalty	25%

5 Cost Sensitivities

A range of cost for expansion technologies were assessed as sensitivity cases. The high, low, and reference cost cases assessed are summarized in Table S5. Additional lower and higher zero carbon fuel prices at $16.5/MMBtu and $50/MMBtu were also modeled.

Table S5. Range of cost sensitivities for technologies considered for expansion. The costs are representative average capital costs between 2030 and 2045.

	High/Low relative to reference costs
Nuclear Capital Cost	+/- 25%
CCS (retrofit) Capital Cost	+/- 20%
Zero Carbon Fuel Fuel Cost	+/- 25%, 50%
Solar Capital Cost	Based on NREL's High and Low cost estimates
Wind Capital Cost	Based on NREL's High and Low cost estimates
Battery Capital Cost	+25% /-33%

Reference

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D. GenX

GenX Model Overview

GenX is an electricity resource capacity expansion planning model. It is a highly configurable optimization modeling framework designed to incorporate a wide range of state-of-the-art methods to provide improved decision support capabilities for a changing electricity landscape. For a detailed description of the model, including complete mathematical formulation, see Jenkins and Sepulveda (2017) and Jenkins (2018) Chapter 3. A brief description of the model and its configuration and use in this study follows.

GenX is a constrained optimization model that simultaneously optimizes the mix of electricity generation, storage, and demand-side resource investments and retirement decisions, network investment decisions, and operational decisions (at hourly resolution) to meet electricity demand and maximize social welfare in a future planning year. The objective of the model is to minimize the cost of electricity supply subject to hourly demand-balance constraints at all locations in the system and a set of engineering and policy-related constraints on power system operations and investments.

GenX uses a least cost optimization framework as a proxy for maximizing social welfare by including the opportunity cost of any non-served electricity demand in the objective function. The hourly own-price elasticity of electricity demand is approximated through a series of price responsive demand segments, each representing a set of consumers with different willingness to pay for electricity consumption. In other words, if the marginal cost of supply rises above the willingness to pay of any segment in a given hour, demand is reduced by the aggregate consumption of that segment of consumers, and the foregone utility of consumption is incorporated as a cost in the objective function.

GenX is a 'static' investment planning model, in the sense that its objective is not to determine when investments should take place over time, but rather to produce a snapshot of the minimum-cost generation, storage, and transmission capacity to meet some future planning year. The model can be run sequentially and myopically (without foresight), with outputs from one planning period serving as inputs (e.g. starting generation, storage, and network capacity) for subsequent planning periods. In this study, we run the GenX model in sequence for the period from 2020-2030 and then use results from the 2030 planning year as inputs for a 2031-2045 planning period. In this paper, we only present the results for 2045.

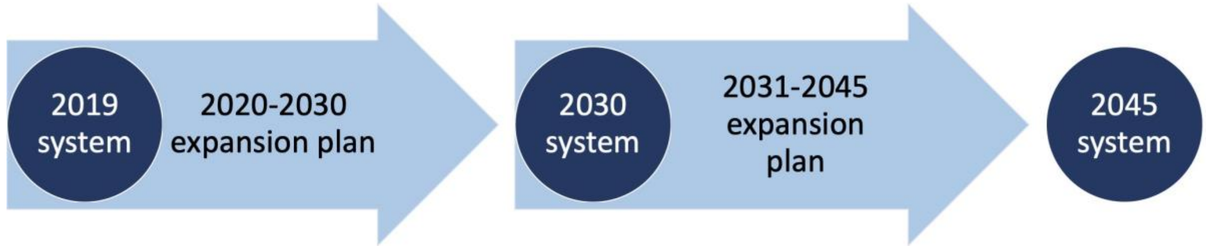

Fig 1: Diagram of sequential (myopic) expansion planning periods used in GenX SB100 Pathways Project cases

The appropriate level of model resolution with (1) regards to chronological variability of electricity demand and renewable energy availability; (2) power system operational detail and unit commitment constraints; and (3) transmission and distribution network representation each vary for a given planning problem or policy question. As such, GenX is designed to be highly configurable, with several different degrees of resolution possible on each of these three key dimensions.

In this study, we employ a simplified zonal transport model, which explicitly represent key transmission network constraints between zones or regions (with 9 regions, as detailed in Section 1.1). Transmission power flows between regions are constrained to a maximum transfer capacity, which can be expanded via endogenous transmission expansion decisions. As these paths represent a simplified abstraction of real AC networks, we do not apply optimal power flow constraints (e.g. parallel flow constraints or voltage angle limits). We do not model distribution networks in this study (e.g. modeled demand represents bulk power system demand at the primary transmission substation level, inclusive of estimated losses in distribution voltage levels).

Additionally, to improve computational tractability we configure the model herein to consider a reduced number of representative hours within the future planning year, selected using k-means clustering technique along with a selection of peak period based on the method in Mallapragada et al. (2018). We first identify the week containing the peak load and remove it from the original time series data. We then apply k-means clustering on the remaining time series to obtain the set of typical time periods. Instead of selecting the center of the cluster as the typical period, we track the data point that is closest to the center. The k-means clustering algorithm provides the weight of each cluster, which signifies the total number of hours in the year represented by each hour in the cluster (with the sum of weights in each hour equal to 8,760, or a full year of operations). In this study, we select 16 representative 7-day periods (weeks), based on analysis of a 3-zone Western Interconnect model using the same inputs as this study that demonstrated that with 16 representative weeks, cost results are accurate within 0.5% of the cost of a case using a full year (52 weeks) and capacity results for any resource type are accurate within 2% of peak demand (Figure 2).

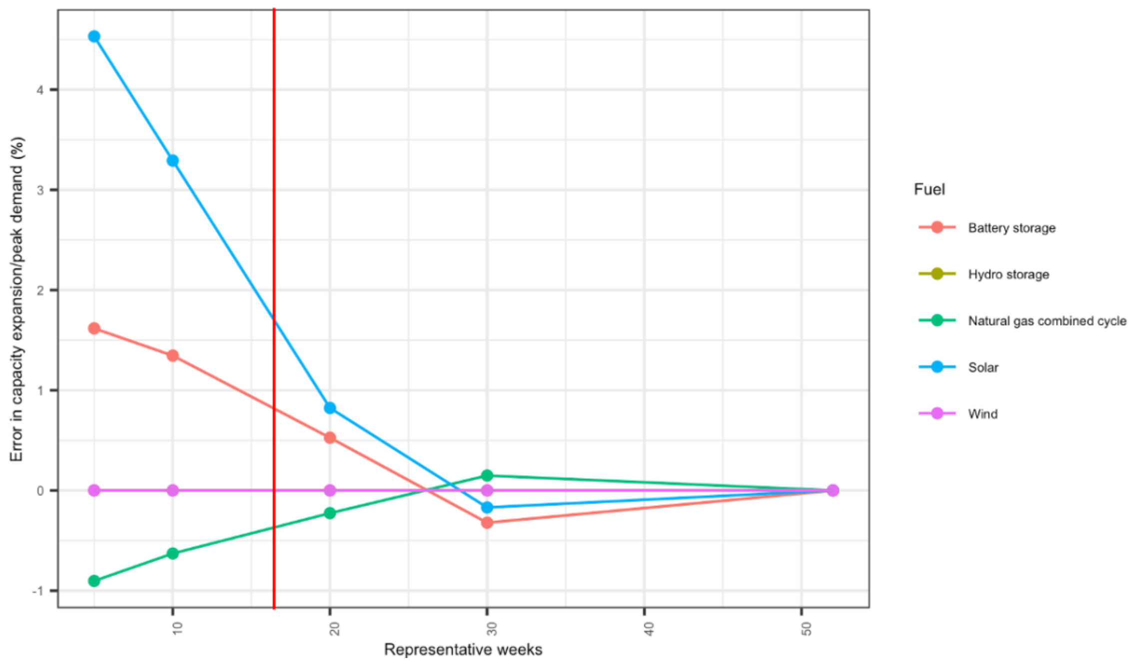

Fig 2: Abstraction error by resource for western electricity coordinating council (WECC) wide system Finally, we employ a linear relaxation of discrete unit commitment decisions for thermal generators

Thermal power plants (e.g. large coal, gas, and nuclear power plants) face important constraints on cycling decisions (start-up and shut-down) and minimum operating levels when online or "committed." In addition, large thermal units can only be added in discrete increment sizes (e.g. a 450 MW combined cycle power plant of 1,100 MW nuclear reactor), are thus most accurately modeled as integer expansion decisions. In this study, these integer unit commitment and capacity addition variables for thermal units are replaced with continuous variables while maintaining the full set of unit commitment constraints (e.g. minimum up and down times after cycling, minimum stable output levels while committed) and incorporating start-up costs in the objective function. That is, the model is configured as a linear program (LP) where the feasible region represents the convex hull of the mixed integer linear programming (MILP) formulation inclusive of discrete unit commitment and investment decisions for thermal units. Jenkins (2018) demonstrates that this linear relaxation of unit commitment decisions offers a significant improvement in computational tractability (run-times are improved by roughly 60-80%) with minimal error in key outcome variables (e.g. less than 0.25% error in total cost and capacity outcomes within 1% of peak demand for most resources, see Jenkins (2018), Chapter 3). Additionally, by employing the full set of unit commitment constraints and associated costs, this linear relaxation produces more accurate results than a simple linear economic dispatch formulation that entirely ignores unit commitment decisions more typically applied in capacity planning models (i.e., ignoring start-up, shut-down, minimum output, etc. and constraining only ramp rates and maximum output).

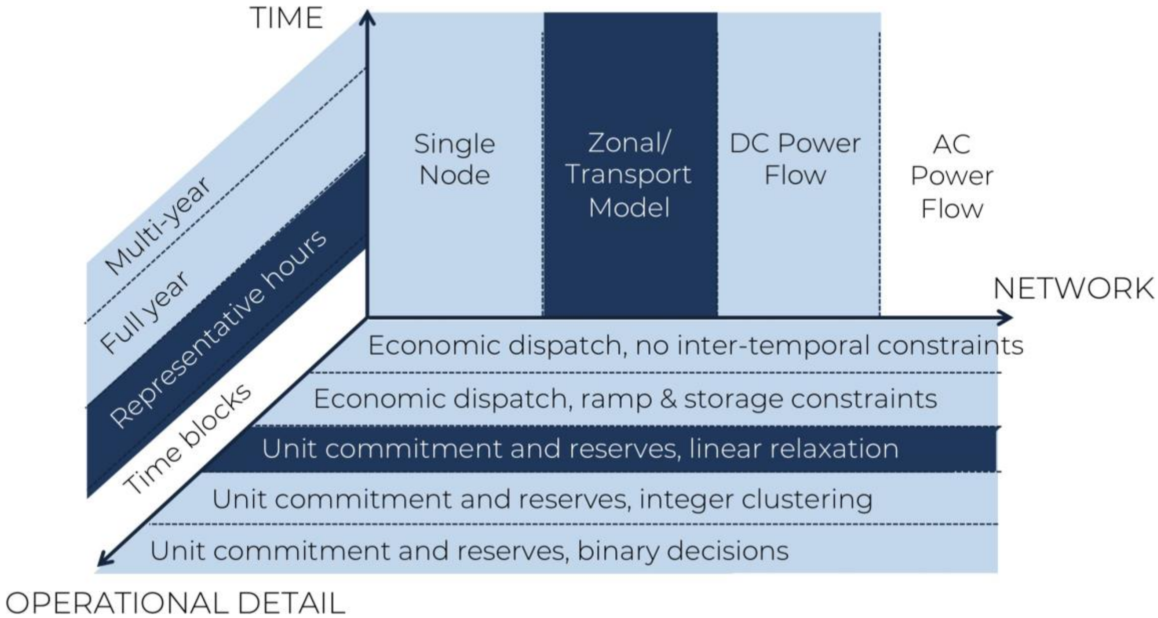

Fig 3: Summary of GenX model configuration for this study. Possible configurations are depicted in light blue, and the specific configuration used in this study in dark blue.

1.1 *Data and Assumptions*

The power system model analyzed in this paper is a case study that approximately represents the U.S. portion of the Western Electricity Coordinating Council (WECC) or Western Interconnection that includes California, New Mexico, Oregon, Washington, Montana, Arizona, Utah, Wyoming, Nevada, Idaho, and Colorado. We divide WECC into 9 transmission zones or regions as shown in Figure 4. Each region represents an aggregation of the base model regions in the EIA IPM model database (EPA, 2018). Table 1 provides the mapping between IPM zones and the regions defined for the modeling of WECC system.

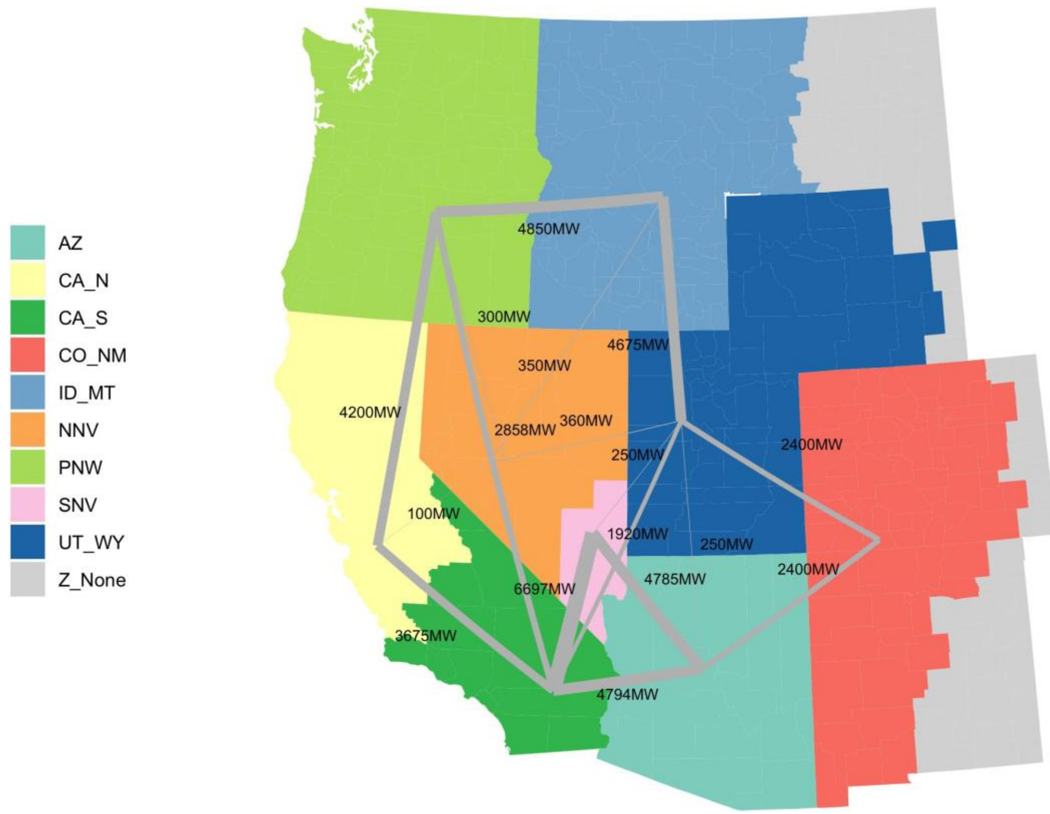

Fig 4: Western Electricity Coordinating Council map aggregated into 9 zones with transmission paths showing inter-regional transmission limits for the existing network

Table 1: Mapping from IPM zones to GenX model regions for this study

Model Region	IPM zones
CA_N	WEC_CALN, WEC_BANC,
CA_ S	WECC_SCE, WEC_LADW, WEC_SDGE, WECC IID
AZ	WECC_AZ
CO_NM	WECC_CO, WECC_NM
ID MT	WECC_ID, WECC_MT
NNV	WECC_NNV
SNV	WECC_SNV
PNW	WECC_PNW
UT WY	WECC_UT, WECC_WY

1.2 *Transmission data*

The power flow within each zone is unconstrained and power flow between the zones is subject to explicit transmission flow constraints. The 9 regions are connected by 17 transmission paths. We define length, existing capacity, transmission loss and maximum potential reinforcement for each transmission line. Based on Cohen et al. (2019), we assume transmission losses are 1% per 100 miles, transmission expansion cost is 1350 $/MW-mile and weighted average cost of capital is 7%. The cost assumption in Cohen et al. (2019) is converted from reported 2013 USD to 2018 USD using 1.0792 inflation rate based on the BLS Consumer Inflation Index. We assume that the financial asset life of transmission lines is 40 years. We apply a cost multiplier for transmission reinforcement cost within California of 2.25 times the cost in the rest of WECC based on (Cohen et al., 2019). The reinforcement cost for transmission paths between California and other regions in WECC is assumed to be average of the the within California and rest of the WECC costs. The following table 2 provides details of the transmission network considered in this study. We limit transmission capacity expansion to 200% of the starting capacity along each path in each of the two sequential planning periods (2020-2030 and 2031-2045). As such, a path can be expanded by no more than 400% (but only if the model chooses to expand the line to the maximize extent allowed in both planning periods).

Table 2: Transmission network details for WECC

Transmission Path Name	Path Max Flow [MW]	Path distance [Miles]	Transmission Loss [%]	Path Max Re-inforcement [MW]	Path Reinforce-ment Cost [2018 USD/MW-yr]
CA N - CA S	3675	309.33	3.1	7350	81716
CA N - NNV	100	319.46	3.2	200	60950
CA N - PNW	4200	248.80	2.5	8400	47469
CA S - AZ	4794	387.22	3.9	9588	73878
CA S - PNW	2858	401.48	4	5716	76598
CA S - SNV	6697	159.78	1.6	13394	30484
CA S - UT WY	1920	591.06	5.9	3840	112767
AZ - CO NM	2400	393.32	3.9	4800	46179
AZ - SNV	4785	237.18	2.4	9570	27847
AZ - UT WY	250	247.67	2.5	500	29078
CO NM - UT WY	2400	232.19	2.3	4800	27261
ID MT - NNV	350	347.23	3.5	700	40767
ID MT - PNW	4850	541.91	5.4	9700	63625
ID MT - UT WY	4675	255.44	2.6	9350	29991
NNV - PNW	300	307.56	3.1	600	36110
NNV - UT WY	360	533.89	5.3	720	62683
SNV - UT WY	250	431.34	4.3	500	50643

1.3 *Load data*

To model the hourly load variation for 2030 and 2045, the historical load data for year 2011 from EPA (2018) are scaled up using region-specific growth rates. To consider the regional variation in demand growth, we aggregate the 9 modeled zones into 3 broader regions: California (CA), WECC Northwest (WECC NW) and WECC Southwest (WECC SW). WECC NW includes Oregon, Washington, Montana, Utah, Wyoming, Northern Nevada, and Idaho while WECC SW includes Arizona, New Mexico, Southern Nevada, and Colorado. To synchronize inputs with RESOLVE and urbs models, we use the same regional growth rates for WECC NW and WECC SW from E3, assumed to be 14.8% and 17.6% through 2030 and 31.7% and 38.3% through 2045, respectively. For these two regions, we use historical demand profiles and increase demand each hour by the regional percent growth rate, which reflects a business as usual growth projection.

For California, demand projections are also from E3 (the same as used in RESOLVE and urbs modeling for this study) and assume significant end-use electrification of transportation and heating loads. As such, we cannot use the historical demand profiles from EPA (2018), and instead use the hourly per unit profiles from E3's RESOLVE inputs for this study. As E3 input data is for total California load, we disaggregate the total statewide load into CA N and CA S model regions based on each region's share of total 2011 demand in EPA (2018). As a result, CA N and CA S has the same load profile shape and growth rates with different absolute load value. Figure 5 depicts the total annual modeled load in each model region in 2030 and 2045 planning years.

To consider distributed generation (DG) adoption reflective of solar policies in California, Arizona and Colorado, we remove estimated production from DG solar from the load profile (as modeled demand reflects load at the transmission substation). E3 assumes total T&D losses of 7.33% for California and EPA's IPM model assumes 2.88% transmission losses in WECC. As such, we model the reduction in transmission-level load from behind the meter solar production assuming average avoided distribution losses of 4.53%. The total capacity of DG solar for California is assumed to be same as E3 RESOLVE assumptions used in this study while the capacity for Arizona and Colorado is assumed to be sufficient to meet DG solar carve-out requirements in the existing state RPS policies. We assume 35 degree fixed tilt, south facing systems, with 15% system losses and generate DG solar profiles from Renewables.Ninja for weather year 2009 (Pfenninger and Staffell, 2016). The modeled locations for DC solar in CA N, CA S, WECC AZ and WECC CO are Sacramento, Los Angeles, Phoenix and Denver, respectively.

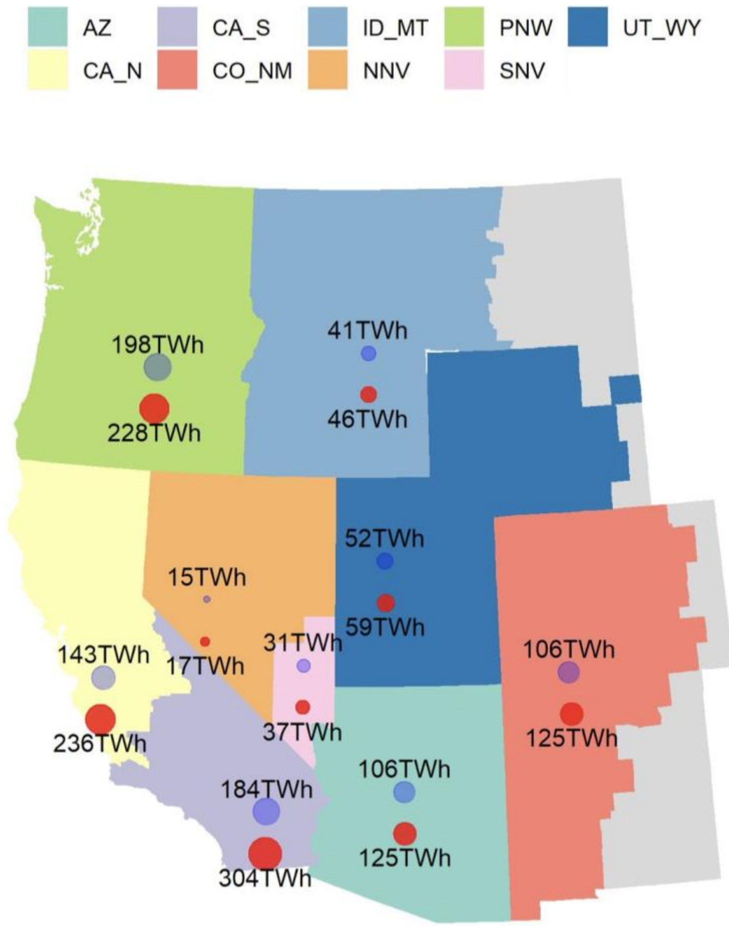

Fig 5: Total annual modeled load in 2030 (purple) and 2045 (red) by model region

We assume that the value of lost load (or involuntary demand curtailment) is 9000 $/MW. Additionally, we assume 7.5% of load in each hour is willing to voluntarily curtail demand (demand response) at an opportunity cost of 600$/MWh, as per the 'CA Shed DR' resources modeled by RESOLVE.

1.4 Generation and Storage

For this analysis, we model the existing generator fleet by clustering individual generators within each model region into 10 generator types and one storage type per model region based on 2018 installed capacity data from (EIA, 2018): coal, nuclear, natural gas combined cycle (NGCC), natural gas 'peakers' (combining existing combustion turbine, steam turbine, and reciprocating engine generators), geothermal, solar PV (single axis tracking), onshore wind, small hydro (run of the river units less than 30 MW), large hydro (combining reservoir and run-of-river units), biomass and hydroelectric pumped storage. We create two clusters each of NGCC and peaker plants for CA N and CA S to consider the variation in heat rates. We omit less than 2 GW of installed concentration solar power (CSP) capacity to reduce model dimensionality. We also model all existing small hydro, biomass, and geothermal energy resources as must-run generators with modeled capacity equal to the average output of these units to reduce decision variables.

Additionally, we consider new build construction of onshore wind (10 different locations/profiles across all model regions), solar PV (20 different locations/profiles across all model regions), offshore wind (3 locations/profiles, one each in PNW, CA N, and CA S), geothermal (4 locations/profiles in CA N, CA S, PNW, and SNV), and lithium-ion batteries (all regions) in all cases. In select cases, we also permit construction of natural gas combined cycle (NGCC), natural gas combustion turbine (NGCT), natural gas combined cycle with post-combustion carbon capture and sequestration (NGCCS) at both 90% and 100% net capture rate, natural gas Allam cycle with CCS (Allam cycle NG) at 100% net capture rate, new advanced nuclear (small modular reactors), long-duration hydrogen storage, and long-duration aqueous-air/metal-air storage. Due to geological constraints (lack of available geologies suitable for underground storage), NGCCS and Allam cycle NG are not permitted in AZ, NNV, SNV or PNW and hydrogen storage is not permitted in the low cost cases (which assume underground storage) in ID MT, NNV, and PNW.

Finally, in zero-carbon fuel (ZCF) sensitivity cases, we assume existing or new build NGCC and NGCT plants can be reconfigured (at nominal cost) to run on biogas, hydrogen (e.g. produced via electrolysis or methane reforming with CCS) or another zero-carbon fuel (e.g. ammonia or synthetic methane) (see Section 1.5 for cost details).

The following table 3 shows the availability of new build technologies for each model region. Depending on the sensitivity case, the resulting WECC power system model has up to 179 eligible resources with 75 thermal units subject to linearized unit commitment constraints, 14 energy storage resources, 9 long duration energy storage resources, 9 large hydro resources, 22 biomass, geothermal and small-hydro resources (modeled as must-run generators), and 50 dispatchable variable renewable resource sites/profiles.

Table 3: Availability of new technologies by region

Technology	CA N	CA S	AZ	CO NM	ID MT	NNV	PNW	SNV	UT WY
Onshore wind	✓	✓	✓	✓	✓	✓	✓	✓	✓
Offshore wind	✓	✓					✓		
Solar PV	✓	✓	✓	✓	✓	✓	✓	✓	✓
Geothermal	✓	✓					✓	✓	
NGCC	✓	✓	✓	✓	✓	✓	✓	✓	✓
NGCT	✓	✓	✓	✓	✓	✓	✓	✓	✓
Li-ion battery	✓	✓	✓	✓	✓	✓	✓	✓	✓
NGCC CCS*	✓	✓		✓	✓				✓
Allam cycle NG*	✓	✓		✓	✓				✓
Nuclear*^	✓	✓	✓	✓	✓		✓	✓	✓
Hydrogen long duration energy storage*$	✓	✓	✓	✓	✓	✓	✓	✓	✓
Aq-air/Metal-air long duration energy storage*	✓	✓	✓	✓	✓	✓	✓	✓	✓

* - Available only in select cases; ^ - only available in California after 2030. $ - hydrogen storage is not permitted in the low cost cases (which assume underground storage) in ID MT, NNV, and PNW.

The projected capital, fixed and variable operations and maintenance (O&M) costs for most new-build resources are consistent with those detailed above for E3 RESOLVE inputs and generally based on NREL (2018). Lithium-ion battery storage costs are based on Lazard (2018). Costs are converted to region-specific costs using NREL Annual Technology Baseline regional cost multipliers (NREL, 2019).

In addition to the mid-range cost scenarios included in RESOLVE runs, we model low nuclear cost and low CCS cost sensitivity cases with investment costs 25% and 20% lower than the base case assumptions, respectively. We also consider three scenarios with availability of Allam cycle natural gas plants with CCS (at 100% capture rate). Our high-cost Allam cycle scenario uses investment cost (2014 $/kW), fixed O&M cost (54 $/kW), and heat rate (7.08 MMBtu/MWh) from White and Weiland (2018), with reported costs converted from 2011 to 2018 USD using 1.13 factor (based on BLS CPI). The variable O&M cost for Allam cycle is assumed to be 70% of the variable O&M for NGCT with post combustion CCS based on the ratio of O&M costs for Allam cycle and post-combustion capture reported in White and Weiland (2018) (or 4.42 $/MWh). A low-cost Allam cycle scenario assumes 25% lower investment and fixed O&M costs than the mid-cost case, and an improved heat rate (6.82 MMBtu/MWh) based on Scaccabarozzi et al. (2017). A very low-cost Allam cycle case is run based on installed cost (1000 $/kW) and heat rate (6.42 MMBtu/MWh) claims from NET Power, an Allam cycle developer, for Nth of a kind installations.

We scale up the fixed O&M of existing power plants by 1.5 times the cost for new build plants to reflect increased costs of maintenance for aging units, and we scale variable O&M of existing power plants proportionate to the ratio of heat rate for existing thermal unit clusters and the heat rate of new build units of the same type.

We also assume minimum output power for thermal units with unit commitment decisions, which is 20%, 30%, 50% and 60% for NGCC, NGCT, nuclear and NGCC CCS plants, respectively, consistent with E3 RESOLVE assumptions. Moreover, thermal units, biomass plants, geothermal and small hydro are assumed to have 100% availability.

A full description of all cost and performance parameters for the new generation technologies are given in the "Resources 2030" and "Resources 2045" worksheets of the GenX input data supplement provided along with this SI. Long duration energy storage assumptions are detailed below in Section 1.8 below.

1.5 *Fuel data*

Regional values for fuel cost for coal, natural gas, and uranium and their CO_2 content are consistent with E3 RESOLVE inputs and taken from EIA Annual Energy Outlook (EIA, 2018) and defined for 3 aggregated regions: California (CA), WECC Northwest (WECC NW) and WECC Southwest (WECC SW). Table 4 presents fuel price and CO_2 content for fuels by region. Biomass fuel costs are assumed to be 10 $/MMBtu as per E3 RESOLVE assumptions.

In select cases, we also model two levels of zero-carbon fuel (ZCF) costs. A high cost scenario assumes a ZCF cost of approximately 33 $/MMBtu reflective of E3's RESOLVE cost assumptions for marginal biomethane prices in 2045. Additionally, low-cost ZCF cases with prices of approximately 15 $/MMBtu are based on techno-economic assessment of potential hydrogen production costs from steam methane reforming of natural gas with carbon capture and sequestration (so-called "blue hydrogen") based on IEA GHG Pro- gramme (2017) and assuming a 50% reduction in CAPEX for the carbon capture module by 2040. While modeled based on a techno-economic study of hydrogen from methane reforming with CCS, this low cost ZCF case is consistent with any clean hydrogen supplied at a delivered cost of approximately $1.60-1.75/kg (e.g. including renewable electrolysis). Regional hydrogen fuel costs in this low-cost case parallel natural gas regional price differences to reflect similar cost of fuel delivery. CO_2 emissions for hydrogen are assumed to be zero based on direct combustion emissions (note that upstream GHG emissions for natural gas-based hydrogen production paths may be non-zero). For derivation of these fuel cost assumptions, see the "Blue H2 Costs" sheet in the GenX input data supplement provided along with this SI.

Table 4: Price and CO_2 content assumptions for fuels by region

Fuel [tons/MMBtu]	Price [$/MMBtu]						CO_2 content
	2030			2045			
	CA	NW	SW	CA	NW	SW	
Coal	2	2	2	2	2	2	0.094
Uranium	0.7	0.7	0.7	0.7	0.7	0.7	0
Natural gas	5.8	5.06	5.3	6.9	6.05	6.3	0.053
Biomass	10	10	10	10	10	10	0
Zero-carbon fuel - High cost (e.g. biomethane)	-	-	-	32.73	32.73	32.73	0
Zero-carbon fuel - Low cost (e.g. H_2 at ~$1.60-1.75/kg delivered cost)	-	-	-	15.84	14.58	15.04	0

SMR w/CCS - Steam methane reforming with carbon capture and sequestration; NW - WECC NW; SW - WECC SW

The fuel prices above are modified by applying a 45 $/ton CO_2 price to all fuels in 2030 based on E3's mid-range CO2 price trajectory from California IRP proceedings (rounded to the nearest whole dollar). Additionally, fuel costs for CCS plants built in 2021-2030 planning period receive a 50 $/ton CO_2 subsidy to reflect the 45Q tax credit for carbon capture and sequestration. For 2045 cases, either a 0 emissions cap is applied (in baseline cases), with no carbon price, or a 200 $/ton CO_2 price is applied to all fuels to reflect the potential marginal cost of negative emissions to off-set residual emissions from natural gas units in 2045 in a net-zero emissions (carbon neutral) economy, consistent with California Executive Order B-55-18.

1.6 *Wind and solar resource clusters*

For potential capacity expansion of solar and onshore wind, we define multiple clusters per region based on E3 RESOLVE inputs (see Table 5). Additionally, three offshore floating wind turbine resource clusters are added with profiles from Pfenninger and Staffell (2016) and maximum capacity per site from Musial et al. (2016). See the "Generator Variability" sheet in the GenX input data supplement provided along with this SI for hourly capacity factor profiles for each resource cluster.

To consider the cost of electricity transmission from solar and wind sites to demand centers, we add spur line costs to inflate the base investment cost. In this way, we implicitly account for transmission costs within model regions, where transmission constraints are not explicitly considered. Spur line distances are based on driving distances from sites to major metropolitan areas as estimated by Google Maps. See comments in "Resources 2045" sheet of the GenX data supplement for route assumption details. We used driving distances (as opposed to straight-line distances) to approximate realistic routes considering topological and jurisdictional constraints that may face transmission routes. Where renewable sites are assumed to deliver to metropolitan areas in another model region (e.g. Montana wind delivering to Portland, Oregon metro area), we subtract the explicitly modeled inter-regional transmission distance from the site to metro distance. Spur line costs per mile are from Cohen et al. (2019), and as per the reference, spur line costs in California are assumed to be 2.25 times more costly than in other regions. Table 5 presents the assumption for the new solar and wind clusters.

(Note that spur line costs are also added to new nuclear and CCS units, reflecting expected siting locations for these resources. See “Resources 2045” sheet of the GenX data supplement for details.)

Table 5: Solar and wind resource clusters

Technology	Region	Cluster	Max Capacity [MW]	Spur Line Distance [miles]	Transmission cost [$/MW-yr]
Onshore wind	CA N	1	643	*	*
	CA N	2	146	*	*
	CA S	1	1094	*	*
	CA S	2	416	*	*
	AZ	1	2897	185	56522
	CO NM	1	10000	150	45829
	CO NM	2	34580	110	33608
	ID MT	1	5633	108	33024
	PNW	1	10048	120	36663
	UT WY	1	33816	223	68024
Solar	CA N	1	78817	20	13749
	CA N	2	14914	20	13749
	CA N	3	5056	20	13749
	CA N	4	28088	20	13749
	CA S	1	15237	20	13749
	CA S	2	4318	20	13749
	CA S	3	17337	20	13749
	CA S	4	15448	20	13749
	CA S	5	14310	20	13749
	CA S	6	36553	20	13749
	AZ	1	15020	20	6110
	CO NM	1	664	20	6110
	CO NM	2	15000	20	6110
	ID MT	1	1065	20	6110
	PNW	1	7556	20	6110
	PNW	2	9211	180	54994
	SNV	1	15000	20	6110
	UT WY	1	15020	20	6110
Offshore wind	CA N	1	2397	75	53160
	CA S	1	3702	34	46970
	PNW	1	5256	144	78700

* - Spur line cost for California wind sites included in annualized wind cluster investment cost provided by E3.

1.7 Hydropower

The input data for reservoir hydro includes initial level of the water in the reservoir, inflow data and minimum reservoir level. We assume that hydro reservoirs are half full at the beginning and constrain the water level at the end of the year to be same as at the beginning of the year. The EIA-923 report provides monthly historical inflow data for reservoir hydro for each state. Due to lack of hourly profiles, we aggregate the state level data into model regions and equally distribute the inflow over each hour. Minimum power share from hydro reservoirs is set equal to the minimum of hourly values. Based on validation of modeled dispatch against historical 2009 CAISO aggregate hydro dispatch, we set reservoir capacity for California resources to 2 times the average hourly average inflow rate. Lacking data for validation for other states, we assume reservoir capacity in the Southwest states (AZ, NV, CO, NM) are equal to that in California (2 times average hourly inflow) and reservoir capacity in the Northwest states (OR, WA, ID, MT, UT, WY) are twice that of California (4 times the average hourly inflow) based on the relative flexibility of hydro units in E3's RESOLVE inputs (expressed in RESOLVE as daily water budgets). See the 'Hydro Variability' sheet in the GenX data supplement for more detail.

1.8 Long duration energy storage

In select sensitivity cases, we include two types of potential long duration energy storage technologies. First, we model a long duration hydrogen energy storage pathway. Capacity decisions are made independently for charge power capacity (electrolysis), energy storage capacity (underground or tank H_2 storage), and discharge power capacity (combustion turbine). Three cost assumption levels are considered for hydrogen electrolysis and storage capacity costs. Low storage capital costs represents underground storage in large salt caverns based on estimate from Lord et al. (2014); Mid cost represents underground storage based on "future" underground cost estimate from Steward et al. (2009). High cost represents above ground steel tanks "future" cost from Steward et al. (2009). Electrolysis costs for 2040 represent interpolation of 2025/2030 and 2050 cost projections from the literature. Low electrolysis cost is based on 2030 estimate from Saba et al. (2018) (397 EUR/kW) and 2050 forecast from Dolf Gielen and Miranda (200 $/kW). Mid cost is based on the lowest 2025 estimate from Taibi et al. (480 EUR/kW) and lowest 2050 estimate from Michalski et al. (2017) (334 EUR/kW). High cost is based on the highest 2025 estimate from Taibi et al. (700 EUR/kW) and highest 2050 estimate from Michalski et al. (2017) (607 EUR/kW). EUR converted to USD at an exchange rate of 1.11:1. Electrolysis fixed operations and maintenance costs vary across sensitivity scenario as well, based on Michalski et al. (2017). As discharge costs reflect mature combustion turbines, no cost sensitivity is considered for this cost component and capital, fixed O&M and variable O&M costs are the same as those modeled for new build stand-alone combustion turbines from NREL (2018). Capital cost and performance assumptions for hydrogen storage are summarized in Table 6.

Table 6: Cost and performance sensitivity assumptions for hydrogen long duration energy storage

Attribute	Low	Mid.	High
Storage component (underground caverns or above-ground tanks)			
Capex [$/kWh]	1	5	10
Asset Life [years]		30	
Energy to power ratio permitted		48–2000	
Charge power component (electrolysis)			
Capex [$/kW]	321	452	726
OpEx [$/kW-yr]	14	30	46
Single-trip Efficiency [%]		67	
Asset life [years]		25	
Discharge power component (combustion turbine)			
Capex & Opex [$/kW-yr]		123	
Single-trip Efficiency [%]		40	

Additionally, we model cases exploring a speculative range of cost and performance assumptions that may be achieved by low-cost aqueous-air or metal-air electro-chemical long duration energy storage technologies, as detailed in Table 7. These technologies are assumed to have use the same capacity for charging and discharging and have independently sizable energy storage capacity decisions.

Table 7: Cost and performance sensitivity assumptions for aqueous-air or metal-air electro-chemical long duration energy storage

Attribute	Low	High
Energy Capex [$/kWh]	4	12
Power Capex [$/kW]	300	1300
Energy to power ratio permitted	100-200	12-48
Round Trip Efficiency [%]	45	50
OpEx [$/kW-yr]	30	40
Lifetime [years]	25	25

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Data sets

- Data Supplement Inputs on GenX
- Data Supplement Inputs on URBS
- Data Supplement Inputs on Resolve
- Data Supplement Results on GenX
- Data Supplement Results on URBS