

Matching Hourly and Peak Demand by Combining Different Renewable Energy Sources

A case study for California in 2020

Graeme R.G. Hoste
Michael J. Dvorak
Mark Z. Jacobson

Stanford University
Department of Civil and Environmental Engineering
Atmosphere/Energy Program
ghoste@stanford.edu

Abstract

In 2002 the California legislature passed Senate Bill 1078, establishing the Renewables Portfolio Standard requiring 20 percent of the state's electricity to come from renewable resources by 2010, with the additional goal of 33% by 2020 (California Senate, 2002; California Energy Commission [CEC], 2004). More recently, some legislative proposals have called for eliminating 80% of all carbon from energy to limit climate change to an 'acceptable level'. At the passing of the 2002 California bill, qualifying renewables provided less than 10% of California's energy supply (CEC, 2007). Several barriers slow the development of renewables; these include technological barriers, access to renewable resources, public perceptions, political pressure from interest groups, and cost, to name a few. This paper considers only one technological barrier to renewables: integration into the grid.

Many renewable resources are *intermittent or variable* by nature—producing power inconsistently and somewhat unpredictably—while on the other end of the transmission line, consumers demand power variably but predictably throughout the day. The Independent System Operator (ISO) monitors this demand, turning on or off additional generation when necessary. As such, predictability of energy supply and demand is essential for grid management. For natural gas or hydroelectricity, supplies can be throttled relatively easily. But with a wind farm, power output cannot be ramped up on demand. In some cases, a single wind farm that is providing power steadily may see a drop in or complete loss of wind for a period. For this reason, grid operators generally pay less for energy provided from wind or solar power than from a conventional, predictable resource.

Although wind, solar, tidal, and wave resources will always be intermittent when they are considered in isolation and at one location, several methods exist to reduce intermittency of *delivered* power. These include combining geographically disperse intermittent resources of the same type, using storage, and combining different renewables with complementary intermittencies (e.g., Kahn, 1979; Archer and Jacobson, 2003, 2007). This paper discusses the last method: integration of several independent resources. In the pages that follow, we demonstrate that the complementary intermittencies of wind and solar power in California, along with the flexibility of hydro, make it possible for a true portfolio of renewables to meet a significant portion of California's electricity demand. In particular, we estimate mixes of renewable capacities required to supply 80% and 100% of California's electricity and 2020 and show the feasibility of load-matching over the year with these resources. Additionally, we outline the tradeoffs between different renewable portfolios (i.e., wind-heavy or solar-heavy mixes). We conclude that combining at least four renewables, wind, solar, geothermal, and hydroelectric power in optimal proportions would allow California to meet up to 100% of its future hourly electric power demand assuming an expanded and improved transmission grid.

1. Electric Grid Basics

Electricity is perhaps the only commodity consumed the instant it is produced. In an idealized case, when someone turns on lights or air conditioning (holding all other loads constant), a power plant somewhere must ramp up its output slightly to meet the increase in demand. Fortunately, California has a sufficiently large number of electricity users that small increases in loads in some places are well balanced by small decreases in loads elsewhere. But aggregate

statewide demand still changes significantly over the day and year, with July demand typically increasing by two thirds from early morning to afternoon, and by about the same amount from January afternoon to July afternoon. These trends are seen below in our estimates of 2020 California statewide electricity demand (Figure 1). These curves were extrapolated from 2006 aggregate demand data taken from Oasis, an online database managed by the California ISO (California Independent System Operator, 2007). Data were averaged over one month to give the average hourly demands for January, April, July, and October. By averaging over a month, unusual demands from unseasonably hot or cold days, holidays, brownouts, etc., were taken into account. To estimate 2020 demand from the 2006 data, a 1.4% annual increase was assumed, consistent with the CEC’s figure of 1.22 – 1.49% per year (CEC, 2001b).

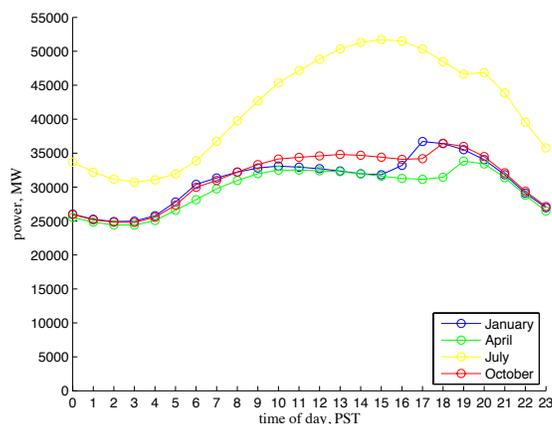


Figure 1: Estimated average hour-by-hour California electricity demands for 2020. Projected from 2006 values assuming 1.4% annual growth. 2006 demand data from California ISO.

2. Methods

As mentioned above, our analysis is performed for the average day in each season, with January, April, July, and October taken as representative months. The average hourly demand curves shown above make up one end of the equation; a well-packaged supply makes up the other. Throughout this report, we show that we can match this average demand in these months with the average supply (calculated from modeled wind speeds and real insolarations, see Section 4) from four different renewable resources—geothermal, wind, solar, and hydro—as well as some conventional baseload generation.

One question raised is whether it is appropriate to draw conclusions for hour-to-hour grid management on any given day from an analysis in which both supplies and demand are averaged over the entire month. Looking at each site individually, this method could pose problems. It is very unlikely that the wind speed at Altamont Pass *every* July day at 3pm will be exactly the *average* 3pm July wind speed, for example. But when looking at the total power generation from wind turbines distributed all over the state, it is much more likely that the aggregate power production, among all sites, at every hour will be very close to the average. As with the example of a single energy user’s increasing load being balanced by another’s decreasing load, below average wind speeds at some farms will be compensated for by above average wind speeds at others. As with demand, the large-scale variation in wind power output over the day will become more noticeable and important than small-scale variations in individual locations. With rooftop

PVs in millions of locations, the chance of simultaneous cloud cover affecting all systems is extremely small. While it would never make sense to use average wind speeds or insolation to predict real hourly outputs from a *single* wind farm or rooftop PV system, we assume for this analysis it is reasonable to use average aggregated statewide renewable supply to predict *aggregate* statewide electric power output. This assumption is reasonable so long as we can also assume that the transmission system will be upgraded sufficiently

3. A Renewable Package to Meet the 33% RPS

Given that the ‘aggressive’ California RPS target is 33% by 2020, an initial step of our model was to estimate the renewable capacities that could be used to meet that goal. The 2007 capacities of California geothermal, wind, solar, and hydroelectric power were:

- 1,870 MW of geothermal in two major developments: the Geysers (north of San Francisco) and various plants in Imperial Valley (CEC, 2002)
- 700 MW of solar power, roughly half rooftop photovoltaics and half solar thermal (Quaschnig and Muriel, 2001)
- 2,421 MW of wind power in five large farms: 710 MW at Tehachapi, 619 MW at San Geronimo Pass, 586 MW at Altamont Pass, 415 MW at the High Winds Energy Center, 16 MW at Pacheco Pass, and 75 MW in smaller, distributed farms (American Wind Energy Association, 2007)
- 13,500 MW of dependable hydro capacity distributed over the state, with an annual output of 4,100 MW (30.4% capacity factor) (CEC, 2001a, 2008a)

Due to growing environmental and social concerns, as well as the fact that large hydro facilities (over 30 MW) do not qualify as renewable under the RPS, we assume that no new hydro plants will be built in California by 2020 (California Senate, 2002).

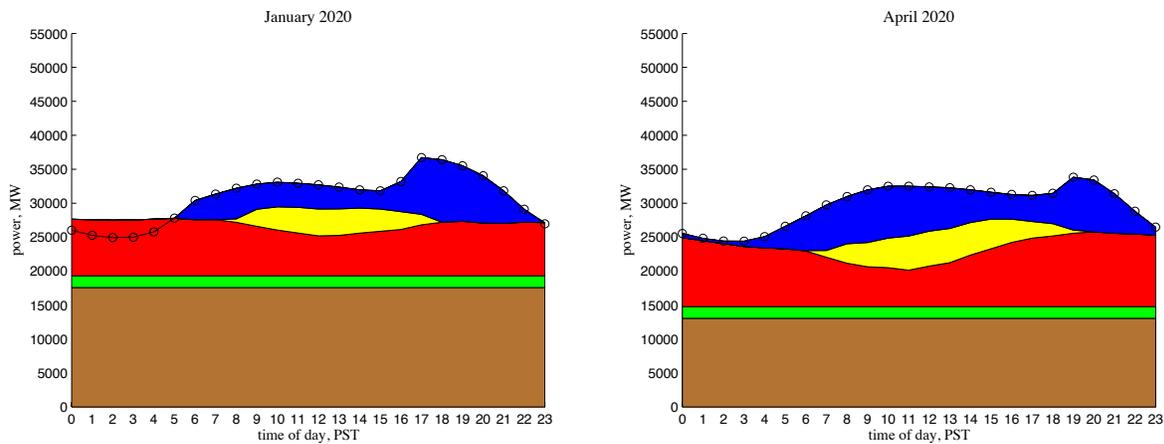
If the only increase in wind and solar capacities through 2020 is from projects already proposed to the California Energy Commission (which includes a 4,500 MW expansion of the Tehachapi wind farm, set to go online by 2010, 2,927 MW of solar thermal projects in Southern California, and 3,000 MW of rooftop PVs as proposed in the California Million Solar Roofs Initiative), we find that the current hydro and geothermal capacities are more than sufficient to meet the low RPS target of 20% by 2020 (California Wind Energy Association, 2007; CEC, 2008b; California Public Utilities Commission [CPUC], 2007a, b).

To scale up to the 33% RPS target, we retain the estimates of geothermal, solar PV and solar thermal capacities from our low scenario and increase total wind capacity until the annual renewable energy generated is 33% of total demanded energy. This condition is met with a statewide capacity of 16,000 MW. Here, the wind capacity is distributed as follows: one new farm of 2,400 MW is added at Eureka (offshore),¹ and the remaining capacity is spread proportionally over the existing farms (except Tehachapi—held constant). This amounts to 5,210

¹ A 2007 paper by Dvorak et al suggests a very good wind resource just offshore of Eureka. This site has consistently high wind speeds over the year, and a reasonable potential of 2,400 MW, taking into account undersea topography and local transmission considerations (Dvorak et al, 2004).

MW at Tehachapi, 3,035 MW at San Geronio, 2,874 MW at Altamont Pass, 2,400 MW at Eureka, 2,035 MW at High Winds, 78 MW at Pacheco Pass, and 368 MW in small, distributed farms. The solar thermal plants are modeled at their actual proposed locations, and the one million rooftop 3 kW systems are distributed across California in the state's most populous regions (see Section 4.3).

Given these estimates of gross statewide renewable capacities and their distributions, we calculated the average hourly generation from each resource and packaged these together into a peaking supply in each month. The figures below show a renewable peaking supply from these resources in January and April 2020 (Figures 2 and 3). A detailed discussion of our calculation of average hourly generation from gross capacities follows in the next section. With these methods clearly defined, it is simple to scale up the renewable capacities to meet even more aggressive targets such as 80% or 100% of renewable electricity supply.



Figures 2 and 3: A renewable peaking supply in January and April 2020: 1,870 MW geothermal (green), 16,000 MW wind (red), 6,271 MW solar (yellow), and 13,500 MW hydro are combined on top of a conventional baseload (brown) to just meet statewide demand (dotted black line). Using this method of combining supplies, the amount of baseload needed varies seasonally (see Section 5.2).

4. Hourly Supplies from Gross Capacities

In the example above, we met one third of statewide electricity demand with renewable resources; later we show cases meeting 80% and 100% of electricity demand. Our method of scaling up these resource portfolios follows three main steps:

1. First we estimate the average hourly power supply from 1 MW at each considered renewable plant; this requires use of modeled and historic data, as explained below. Knowing this, we can easily scale up output from a single farm to any given capacity.
2. Second, we assume some distribution of statewide capacity across our individual locations. From this distribution and the results of (1), we model the expected hourly output from 1 MW of *statewide* wind capacity by summing up the hourly outputs from each individual farm in an appropriate ratio.
3. Finally, this aggregate hourly output from 1 MW of statewide generation can be scaled linearly to any capacity. A key assumption here is that the development of new resources will follow the current distribution.

This section covers the first and second of these steps for each resource. The final step—actually scaling the gross statewide capacities—is covered in Section 5, where we outline our method of optimization.

4.1. Geothermal Power

Geothermal plants typically operate as baseload power. In this analysis, all geothermal plants in 2020 are assumed to provide baseload power with a 92% capacity factor (Geothermal Energy Association, 2007). Thus 1 MW of geothermal capacity contributes 920 kW constantly throughout the day and year.

4.2. Wind Power

The power produced by a wind turbine is a function of the wind speed and the type of turbine. For this analysis we assume the entire statewide capacity to be composed of a single type of turbine. We considered several turbines, but the turbine that consistently produced the highest capacity factors given the wind speeds faced in this analysis was the REPower MM92, a 2 MW turbine with 80 m hub height and a 92.5 m diameter (REPower, 2007). Figure 4 shows the power curve for this turbine, which has a cut-in speed of 3.0 m/s and a rated speed of 11.2 m/s, above which only 2,000 kW is generated. The turbine also has a shutdown speed of 25 m/s at which point the blades are feathered into the wind and no power is generated.

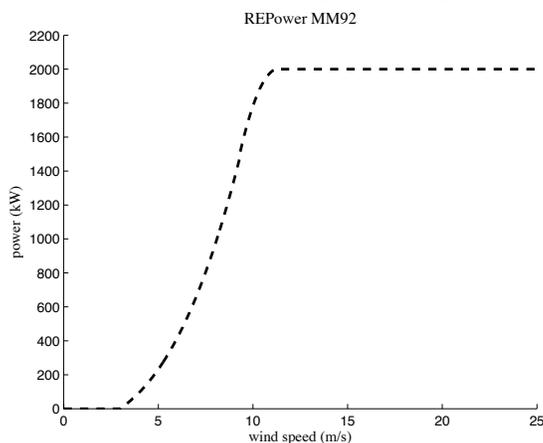
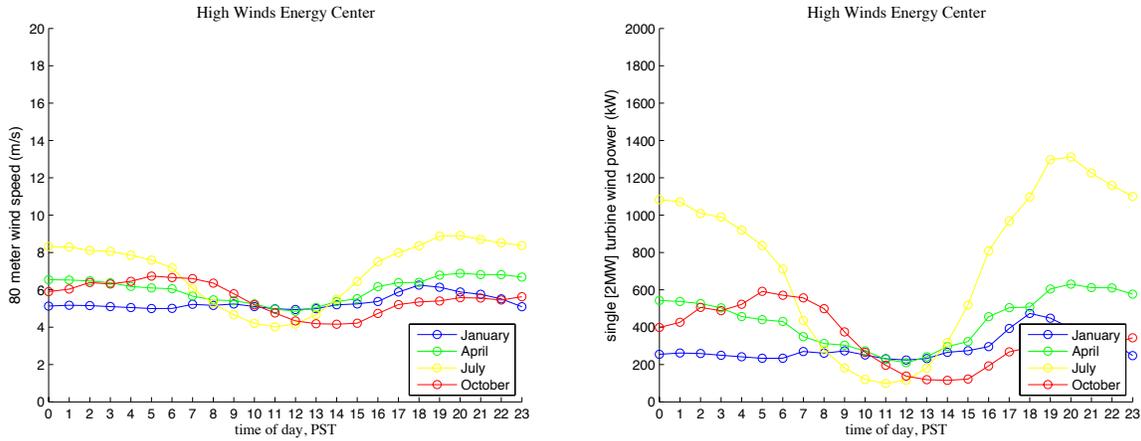


Figure 4: Power curve for the REPower MM92 2 MW wind turbine, showing instantaneous power as a function of wind speed. Manufacturer’s rough data are fitted with two separate polynomials, one for wind speeds below 9.3 m/s and one for speeds above 9.3 m/s (but less than the rated speed of 11.2 m/s). The lower curve has the form $y = 1.3438x^3 + 4.397x^2 + 14.209x - 116.54$; the upper curve $y = -118.08x^2 + 2683.9x - 13247$.

Wind speeds for each location were modeled with the Pennsylvania State University/NCAR *Mesoscale Model version 5* (MM5) with 5-km horizontal resolution. A nested grid with 1-km horizontal resolution was used over the San Francisco Bay Area, and this includes the farms at Altamont Pass, High Winds Energy Center, and Pacheco Pass. The model domain produced hourly wind speeds at 80 meters (along with other meteorological data) over two runs using 2005 and 2006 boundary conditions (Dvorak et al, 2007). These wind speeds were then averaged over the months of January, April, July, and October to get monthly hourly averages at each site. These 80 m wind speeds were combined with the power curve in Figure 4 to estimate the power generated by a single MM92 turbine (2 MW capacity) at each site. Because reliable wind speeds could not be used for the small, distributed farms (2.3% of statewide capacity), their power

production was modeled using the weighted average capacity factor from the other sites. An example of the modeled average hourly wind speeds and power production from the High Winds Energy Center is shown below (Figures 5 and 6). Because instantaneous power varies as the cube of the instantaneous wind speed, the power output at each site is more variable than the wind speed.



Figures 5 and 6: Hourly average wind speeds (m/s) and power output from one MM92 turbine (rated power of 2 MW) at the High Winds Energy Center. Modeled wind speed data courtesy of M. Dvorak.

Table 1 shows the annual average wind speed and capacity factor for each site. Several sites have very high capacity factors, namely Tehachapi with 65.4%. Note that these capacity factors represent the fraction of wind energy generated compared to the maximum deliverable energy from that turbine, given by

$$\text{Maximum Annual Energy (kWh/yr)} = \text{Rated Power (kW)} \times 8.760 \text{ hr/yr}$$

This maximum annual energy is specific to the turbine size, and is not the same as the total energy available in the wind, from which the theoretical Betz limit proposes that a maximum of around 60% can be harvested (Betz, 1920).

FARM SITE	V _{avg} (m/s)	CF (%)	PCT of TOT. CAPACITY HERE
Altamont Pass	5.93	24.3	18.0%
Pacheco Pass	5.32	18.0	< 1%
High Winds	5.97	22.7	12.7%
Tehachapi	8.95	65.4	32.6%
San Geronio	8.59	56.7	19.0%
Eureka	8.26	53.7	15.0%
distributed	-	46.1	2.3%

Table 1: This table summarizes our assumed distribution of wind capacity across the state, as well as the mean wind speed and annual capacity factor (which is dependent on the choice of turbine) at each site.

Given the hourly production from each farm, we can combine them in accordance with our assumed distribution of farms across California (tabulated above). This is the same proportional distribution discussed in our 33% Scenario, above. Figure 7 shows the total wind power generation from 1 MW of statewide capacity with this distribution. This aggregate generation, while still variable over the day, has much smaller swings than the generation from each site

alone. But although daily intermittency is reduced considerably, there is still a large seasonal variation in power output.

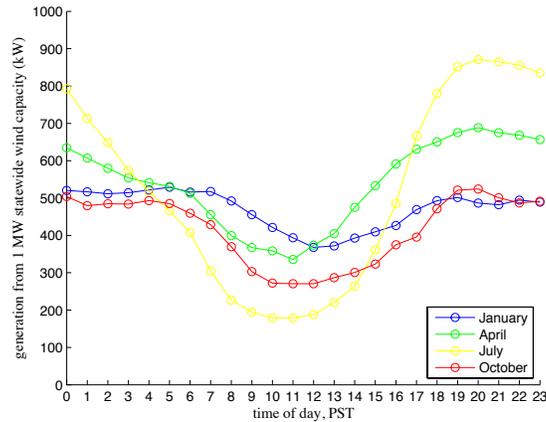


Figure 7: Statewide hourly generation from 1 MW of wind capacity distributed across California as in Table 1. These hourly generation profiles can be scaled up linearly for any assumed gross statewide capacity. Modeled wind speed data courtesy of M. Dvorak.

4.3. Solar Power

Our model uses two types of solar power: photovoltaics and solar thermal. For simplification, we assume total statewide 2020 solar capacity to be half PVs and half thermal. Solar PVs generate electricity directly from incoming radiation, while solar thermal facilities use the sun’s rays to heat a working fluid which then powering a steam turbine. Like wind power, both types of solar power have outputs that are a function of an uncontrollable source, in this case solar insolation.

Solar Photovoltaic Power

All photovoltaic systems in our model are assumed to be south-facing with lat-15° tilt, and to have 80% total power conversion efficiency; this includes losses for dirt and partial shading, module mismatch, and DC to AC inversion. Additionally, we assume the gross statewide capacity for any scenario to be distributed between California’s eight most populous counties, proportionally to their populations. Finally, output from all PV systems within a given county is calculated given insolation data for one reference city within that county. The table below summarizes these data.

COUNTY/REGION	2007 POPULATION	PCT of TOT. CAPACITY HERE	REP. CITY
Los Angeles	10.3 million	33.7%	Los Angeles
SF Bay Area	6.8 million	22.3%	San Francisco
San Diego	3.1 million	10.2%	San Diego
Orange	3.1 million	10.2%	Long Beach
Riverside & San Bernardino	4.1 million	13.4%	Daggett
Sacramento	1.4 million	4.6%	Sacramento
Fresno	917,000	3.0%	Fresno
Ventura	825,000	2.7%	Santa Maria

Table 2: We assume the statewide capacity of solar PVs is distributed between the eight most populous regions in the state, listed here along with their 2007 populations. Additionally, a representative city is chosen to be the modeled site for all PV systems in this region. Population data from California State Association of Counties, 2007.

An 80% efficient system will generate 80% of its rated power under ‘one full sun’ (1000 W/m²) of insolation. For reduced insulations the power output drops linearly. For each reference city, the NREL *Solar Radiation Data Manual for Flat-Plate and Concentrating Collectors* was used to calculate average hourly insulations over the year (Marion and Wilcox, 1994; Masters, 2004). From these insulations we estimated the average hourly power output from a unit capacity at each site; these are combined to get the statewide power generation for 1 MW of gross capacity, seen in Figure 8. The annual combined capacity factor of all these plants is 19%, consistent with measured values on newer rooftop systems, but still below the best available technology (National Renewable Energy Laboratory).

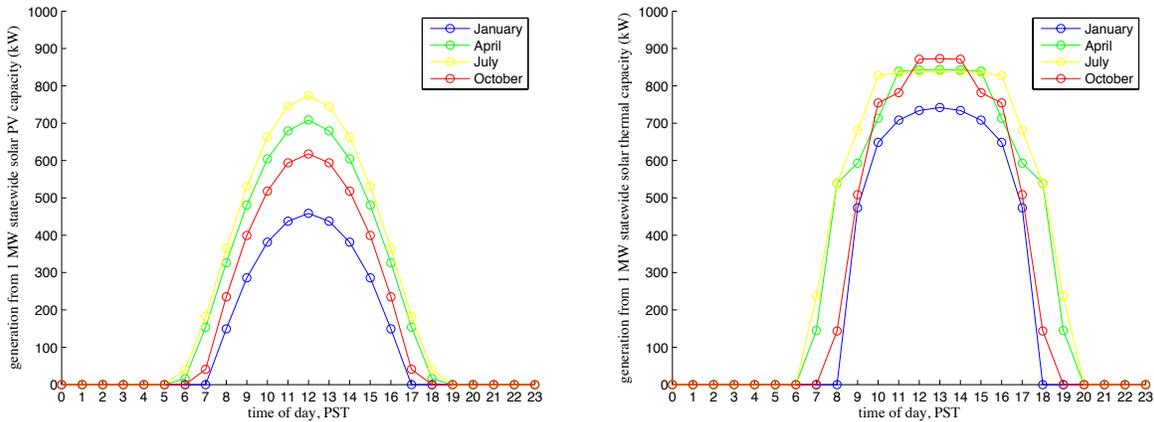
Solar Thermal Power

The average hourly generation from statewide solar thermal facilities is calculated similarly to that for photovoltaics, but with three key differences: 1) we assume thermal facilities to have steam turbines sized for maximum output at one half sun (rather than the full sun for full rated PV power), 2) one or two-axis tracking, direct-beam insolation values are used, and 3) generation lags insolation by one hour, due to warm-up and cool-down of the heat transfer fluid (Carrizo Energy, 2007). In our general model, solar thermal facilities are not assumed to have any long-term (greater than 1-2 hours) storage systems.

As with photovoltaic generation, we used tabulated insolation values to estimate the hourly output from a unit capacity at each site, then combined these into a statewide generation profile, given the total capacity distribution detailed in Table 3. Hourly generation from all the state’s plants are seen in Figure 9.

FACILITY NAME/ SITE	TYPE	PROPOSED CAPACITY (MW)	PCT of TOT. CAPACITY HERE	REP. CITY
Victorville	1-axis trough	50	1.5%	Daggett
Harper	1-axis trough	250	7.6%	Daggett
Hybrid	1-axis trough	50	1.5%	Daggett
Ivanpah	2-axis tower	400	12.2%	Daggett
Stirling 1	2-axis stirling	850	26.0%	Daggett
Stirling 2	2-axis stirling	900	27.5%	San Diego
Beacon	1-axis trough	250	7.6%	Bakersfield
Carrizo	1-axis CLFR	177	5.4%	Bakersfield

Table 3: Currently proposed solar thermal projects in California (CEC, 2008b). These projects form the basis for our modeled distribution of facility types, sizes, and locations.



Figures 8 and 9: Statewide hourly generation from 1 MW of solar PVs (left) and 1 MW of solar thermal (right) distributed across the state as in Tables 2 and 3. Solar insolation data from the NREL Solar Radiation Data Manual (Marion and Wilcox, 1994).

4.4. Hydropower

In this analysis, 2020 hydro capacity remains at 13,500 MW, although the average capacity delivered throughout the year is 4,100 MW. Within the limits of a specific day, the available power from hydroelectricity is extremely flexible. From a ‘cold start,’ with no water flowing through still turbines, a hydro plant can ramp up to its full capacity within a few minutes. If the plant is operating ‘spinning reserves,’ with very little flow spinning the turbines slowly to minimize the inertial jump needed at startup, the full capacity can be reached in less than 30 seconds (D. Freyberg of Stanford University, personal communication, October 10, 2007). Thus within this analysis, the available hydro capacity on each day is assumed to have ultimate flexibility, as long as the maximum statewide capacity of 13,500 MW is not exceeded at any time. A more important consideration for our model is how to determine exactly how much hydropower is available on the average January, April, July, and October days. This is highly dependent on the time of year and also on factors such as precipitation and temperature.

Figure 10, with data taken from the CEC, shows the monthly pattern of hydroelectric generation in California, averaged over 1982-2000 (CEC, 2001a). Generation increases through the spring and into the summer, declining in the fall to its lowest point in November. To a large extent this trend can be explained by current practices of reservoir management (G. Freedman of Pacific Gas & Electric, personal communication, September 21, 2007).

Large reservoirs make up about one third of the state’s nameplate capacity, and because of their size are essentially never in danger of overflowing. In principle they could shift generation to any time of the year, but in reality much of the seasonal flow is dictated by downstream demand for agricultural and municipal water—highest in the summer. Small facilities, on the other hand, have the highest output in winter and spring, when they are filling up with rainfall and snowmelt, and must release water to avoid overflowing (and thus wasting valuable energy). These current reservoir practices could potentially be adjusted slightly, giving hydropower a good deal of seasonal flexibility.

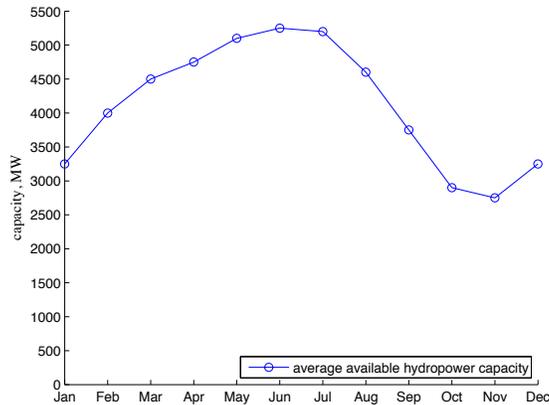


Figure 10: Average hydro capacity used on the California grid in each month over the period from 1982 to 2000 (CEC, 2001a).

5. Scaling up to the Eighty Percent Scenario

At this point we have modeled the average hourly output from a unit capacity of distributed geothermal, wind, and solar (PV and thermal) resources, and laid down some ground rules for how hydro can be used. With the gross hydro capacity fixed, we can scale up the statewide geothermal, wind, and solar capacities to see what is required for any level of renewable portfolio. In this case, we are interested in an 80% renewable electric supply, as motivated by climate change mitigation. But to exactly what levels should we scale each capacity? Not only do we want our renewable portfolio to supply 80% of the total MWh demanded in California over the year, but we also want to show that despite the variability in wind or solar generation over the day and year, our mix can meet or exceed demand in all hours of the day, when packaged with a perfectly flat baseload supply.

5.1. Baseload and Geothermal Supplies

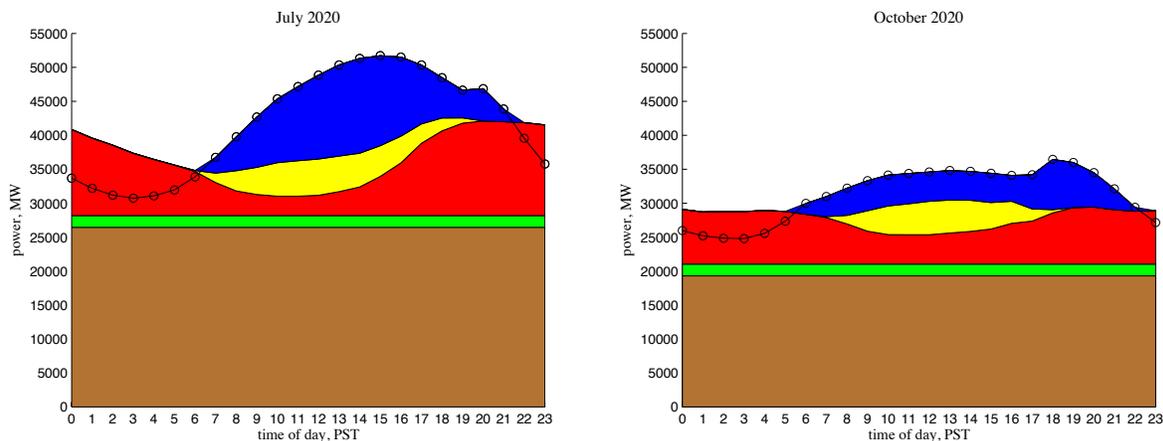
The first step is the baseload supply. For our estimated 2020 demands, 6,678 MW of baseload power is needed to supply 20% of the state’s electricity. For comparison, current nuclear plants in California amount to around 4,100 MW of capacity (Energy Information Administration [EIA], 2009). To simplify our analysis further, we fixed the geothermal capacity (which acts as additional baseload) at 4,700 MW, a realistic estimate of the state’s potential.² Now there are only two free variables, the total statewide wind capacity, and the total statewide solar capacity (again, of which we assume half is PVs, half thermal). To understand the parameters used for optimization, it is worth revisiting the 33% Scenario from Section 3.

5.2. Surplus and ‘Over-Hydro’

In Section 4 we introduced a renewable portfolio that met one third of the state’s electricity demand, and showed an optimized peaking supply from this portfolio in April 2020. April has a much flatter average demand profile than other months, and also benefits from high availability

² 4,700 MW is the ‘most-likely’ estimate of California’s potential capacity as determined by a CEC commissioned geologic survey of the state (CEC, 2005).

of hydropower. This hydro capacity is more than able to account for any fluctuations in demand as well as in the packaged geothermal, wind, and solar supply, and as a result our renewable peaking supply follows the load very well. In other months of the year, this same renewable portfolio does not peak quite as well. The peaking supplies for July and October are shown below (Figures 11 and 12).



Figures 11 and 12: The same renewable peaking portfolio introduced in Section 3, here shown in July and October 2020. This portfolio (green geothermal, red wind, yellow solar, and blue hydro), does not peak quite as well in July as in April. Here there is a significant quantity of surplus renewable energy—where total supply exceeds total demand. This surplus must be shed somehow, whether through EV charging, pumped hydro, ice-making for midday cooling, or export.

In this model, we first packaged the geothermal, wind, and solar supplies together, and then filled in the base beneath these resources, pushing them higher up into the peak until the remaining peak is both small enough to be met with the available hydropower in that month, and not greater than 13,500 MW—the max allowable hydro capacity—in any hour. Because the peak in July demand is so strong—a full two-thirds higher than minimum July demand—this results in a good deal of the renewable wedges being pushed above statewide demand before the peak can be fully filled with hydro. In Figure 11, the monthly surplus is the red wind energy exceeding demand between 10pm and 7am. This amounts to nearly 47 GWh of energy per day in July, or 11.3% of the July renewable energy supply. This surplus renewable generation must be shedded; options include electric vehicle charging, pumped hydro, exporting out of California, and making ice for midday cooling (which will help shave the peak, alleviating the problem). But even with a good use for surplus generation, this solution is still not optimal. Our first optimization condition in selecting a resource portfolio is thus to reduce the monthly surplus (as a percentage of total renewable generation for that month) as much as possible.

In the example above we increased the conventional baseload capacity (the brown block beneath the renewable wedges) until the peak could be filled with available hydro. But in the case of wanting to meet 80% of demand, we have a fixed baseload level. This means that for many renewable capacities, the leftover peak will be too large to be met with the available hydro. The additional amount of hydro that is needed, expressed as a percentage of the actual hydro available in that month, we term the *over-hydro percentage*. Our second optimization condition is to keep the annual over-hydro percentage at or below zero. That is, no more hydro is required over the year than is available. Some seasonal flexibility is allowed however, with a final

restriction being that total hydro capacity needed in any hour on the year does not exceed the total available capacity (13,500 MW).

5.3. Wind and Solar Sweeping

Keeping track of our metrics—maximum monthly surplus (highest out of these four months), annual over-hydro percentages, and total hours (out of these 96) in which required hydro exceeded 13,500 MW—we swept through pairs of wind capacities from 10-50 GW and solar capacities from 3-50 GW. The surfaces below show two of these parameters, the annual over-hydro percentage and the maximum monthly surplus.

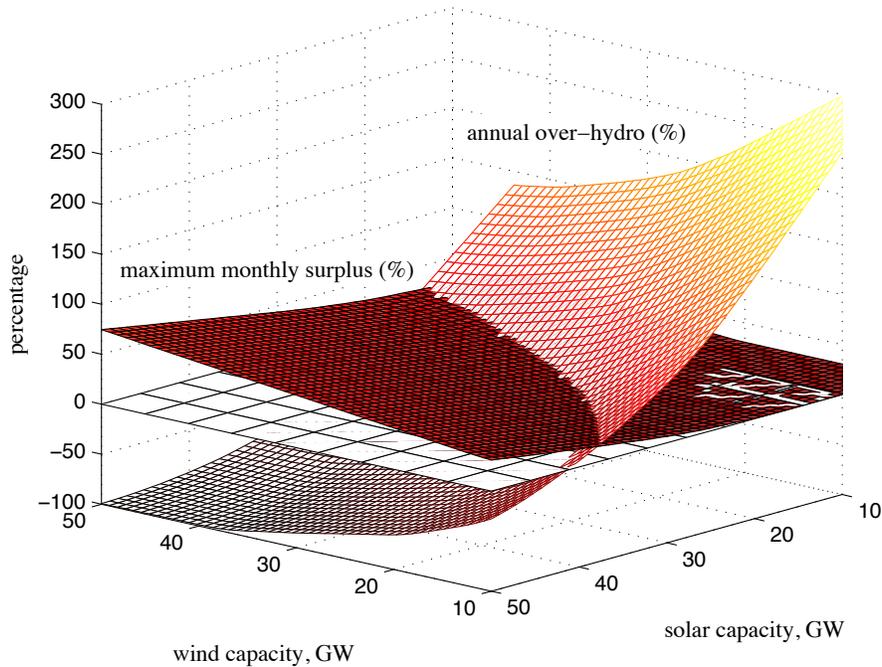


Figure 13: Over-hydro and maximum monthly surplus percentage surfaces in wind-solar capacity space. The figure demonstrates clearly that many choices of parameters (for example negative over-hydro percentage and less than 5% maximum monthly surplus) are simply not possible for any wind-solar capacity pair.

Several clear trends stand out in the figure. Over-hydro percentage increases with smaller solar capacities; there is less solar energy to fill the peak, and thus more hydro is required, often well beyond what is available. At the same time, the amount of surplus energy increases with larger solar capacities. Much of this surplus is typically in April, when solar and wind power output are both high, but demand is low and reasonably flat, causing the solar power peak to push above demand. Both over-hydro and max surplus percentages seem more sensitive to changes in solar capacity than wind capacity, but similar trends are seen as wind capacity changes. These surfaces show what is possible with various renewable packages, and allow us to select an optimal solution.

5.4. Feasible Limits on Over-Hydro and Surplus

Examining the optimization parameters in more detail, there are several interesting observations. Different choices of what is important in a resource mix, and at what level, will pull out other trends—these are only a few brief comments from our wind/solar capacity sweep.

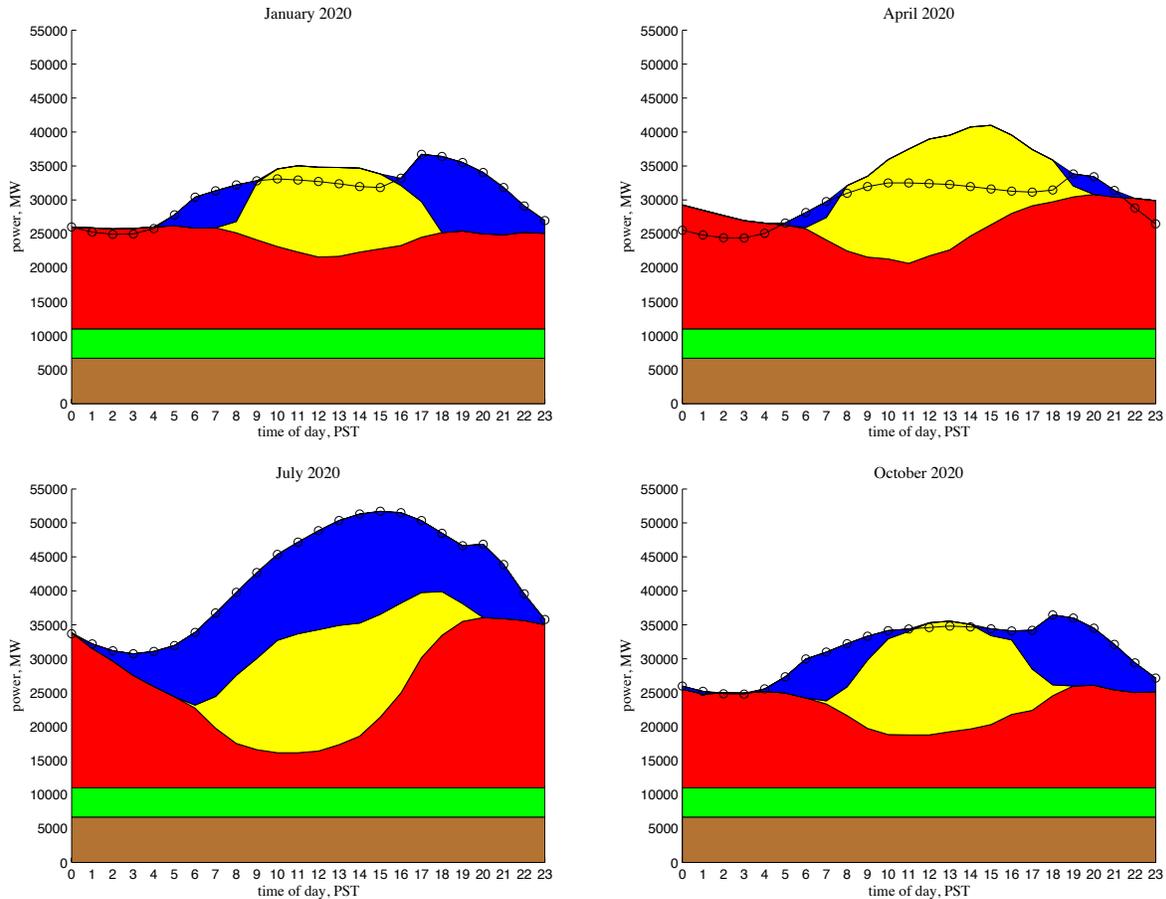
To be consistent with our goal of eliminating 80% of carbon-emitting electricity generation, it is important to restrict the annual over-hydro percentage to zero; a positive over-hydro percentage would require additional conventional peakers (gas turbines, for example) to meet demand. With this restriction, the lowest achievable maximum monthly surplus is 9.8%, for a pair of 31,224 MW wind power, 16,429 MW solar. The max monthly surplus is in April, with the surplus in other months well below 2%. This seems like a good solution, with the exception that the required hydro capacity exceeds nameplate in 13 hours out of these four days.

Another possible goal is to keep the April hydro usage within 5% of what is available, given that many small reservoirs are often forced to release a lot of water during and following the snowmelt rather than let their reservoirs spillover. However, we find that for all wind/solar pairs that satisfy this condition, hydro usage in other months is unreasonable. Most notably, the average January over-hydro percentage for these pairings is 153%. While shedded hydro in April is undesirable, we simply cannot expect 2.5x the usual amount of hydropower to be available in January, and for this reason we throw out the condition of being within 5% of April available hydro.

Considering our final condition—not exceeding 13,500 MW of hydropower in any hour of the day, restricts our portfolio options even further. In fact, if we enforce this condition for all hours of the year, and keep annual over-hydro percentage at or below zero, the lowest possible max monthly surplus is 13.8%; this is for a mix of 27,959 MW wind and 26,020 MW solar.

In meeting 80% of electric demand with solely renewable generation, this is our optimal case. The required hydropower stays fully within its limits, both by never exceeding nameplate capacity and by not exceeding gross MWh availability over the year. But the first of these two conditions is quite restrictive. By allowing the nameplate capacity to be exceeded in five hours of the four-day representative year (which end up all in July), we find an optimal solution is 28,776 MW wind, 22,184 MW solar. A renewable portfolio generated with this wind/solar pair along with geothermal and hydro exceeds hydro nameplate capacity in *only four hours* of these four representative days, but reduces needed solar capacity by nearly 4,000 MW, or 1.3 million rooftop systems! This is an enormous cost and material savings, and demonstrates the importance of peak shaving. One of the challenges in packaging a renewable peaking supply arises because of the huge swings in demand over the day, particularly in July. If truly no conventional peaking power is to be used, reducing the summer peak demand through any means—such as time-of-use pricing, rations, etc.—can reap huge savings by reducing the gross renewable capacities required.

The figures that follow show a peaking renewable supply for our optimal wind/solar pair (28,776 MW / 22,184 MW) in all four months. A flat year-round baseload of 6,678 MW meets the 20% of total demand not met by renewables.

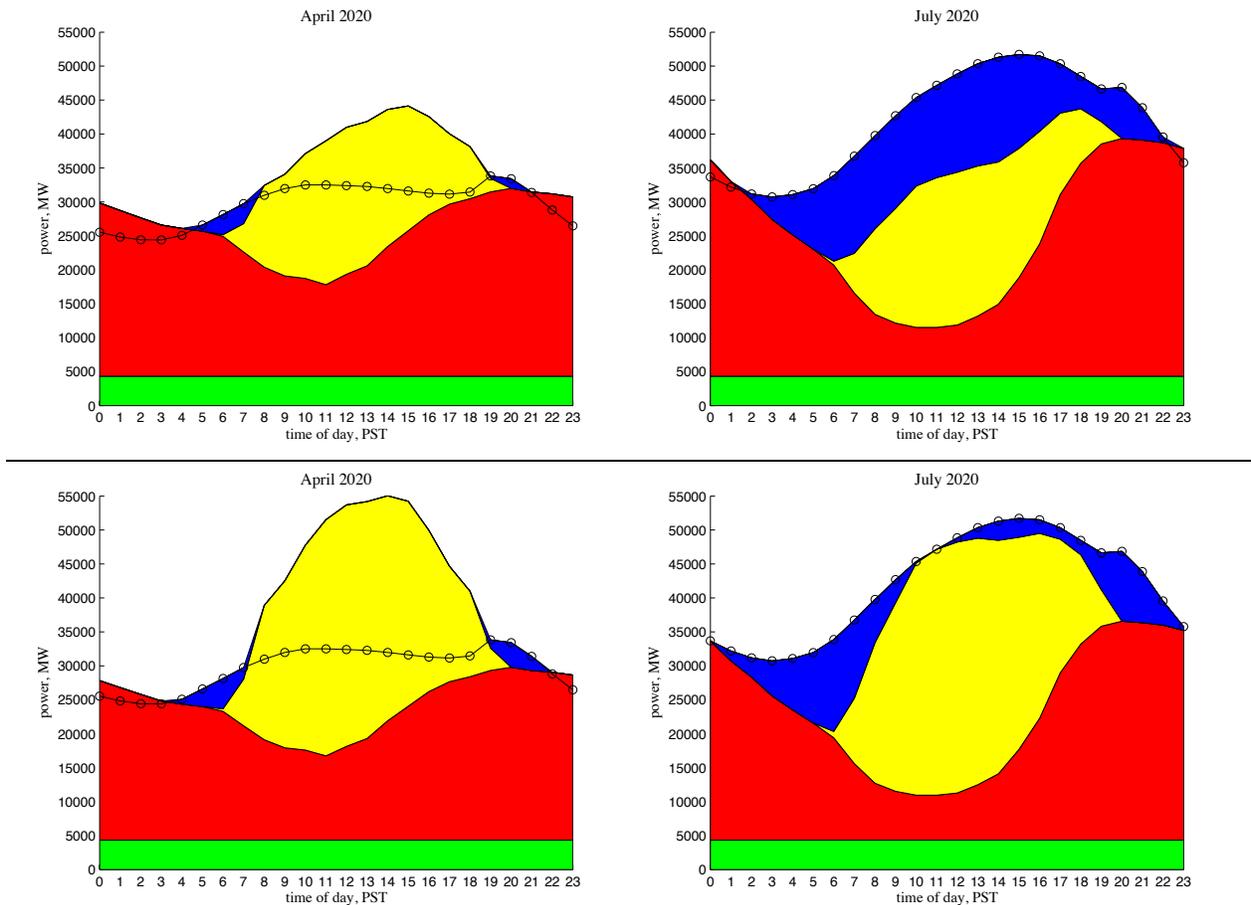


Figures 14-17: Peaking supplies in 2020 from our optimized renewable portfolio: 4,700 MW geothermal, 28,776 MW wind, 22,184 MW solar, and 13,500 MW (existing) hydro. The brown wedge is a conventional baseload of 6,678 MW year-round. For comparison, California has a current nuclear capacity around 4,100 MW (EIA, 2009). The over-hydro percentages for this portfolio in January, April, July, and October are: -12%, -91%, 74%, 9.6% (-3.9% annually). The monthly surpluses as a percentage of total renewable generation are: 2.1%, 11%, 0%, 0.3% (3.1% annually).

6. One Hundred Percent Renewable Supply

As an extension of our model, we consider what renewable capacity would be needed to supply 100% of California's electricity demand in 2020. Following the same method as above, we find an optimized resource pair of 40,204 MW wind and 27,939 MW solar. A renewable supply from this package exceeds nameplate hydro capacity for eight hours in the four days we use representing seasons (all in July), uses 2% less hydro over the year than average, and has monthly renewable energy surpluses of 2.6% in January, 14.8% in April, and 0.5% in both July and October. This surplus energy must be shed, and to some extent represents wasted cost and infrastructure. In light of this, this particular 100% renewable portfolio is optimized for the minimum monthly surplus of all wind/solar pairs in our swept range (10-50 GW of each) that also meet our annual limit on hydropower. The renewable supplies for April and July 2020 are shown in Figures 18 and 19.

An alternative method for selecting wind and solar capacities—though less rigorous—is to optimize the entire portfolio around July, the most demanding month for load-matching. We first select a wind capacity such that the geothermal and wind generation together exactly meet demand at midnight (when wind generation is near maximum and demand is near minimum). Given our estimated July 2020 demand, this wind capacity is 37,013 MW. The solar capacity is then scaled up until it also just meets demand, which occurs just before noon because of the shapes of demand and solar supply curves. The needed solar capacity, when calculated in this manner, is 45,889 MW. As seen in Figure 20, these capacities meet July demand very well, though the enormous solar capacity leads to huge surpluses in the rest of the year (27% in April (Figure 21), 11% annually), and the slightly lower wind capacity requires more hydro in January (25% over available) than our previous 100% portfolio. Both portfolios present interesting options, however, each with its own tradeoffs.



Figures 18-21: 100% renewable supplies in July 2020. The upper figures are for a portfolio selected using the same optimization parameters described in the 80% scenario, above. This leads to a package of 4,700 MW geothermal, 40,204 MW wind, 27,939 MW solar, and existing hydro. Monthly over-hydro percentages of: 0.3%, -92%, 60%, 33% (-2.1% annually); monthly surplus percentages are: 2.6%, 15%, 0.5%, 0.5% (4.2% annually). The lower figures are for a portfolio selected to optimize load-matching in July. Monthly over-hydro percentages are: 25%, -86%, 17%, 43% (-18% annually); monthly surplus percentages are: 11%, 27%, 0%, 11% (11% annually). While both portfolios adequately meet July demand, the enormous solar capacity in the second case leads to huge renewable energy surpluses in other months.

7. Summary and Discussion

This analysis presents one method of estimating renewable capacities required to meet a certain percentage of California electricity demand. Additionally, we show that the complementary intermittencies of wind and solar power, when packaged with the flexibility of hydro and a baseload of geothermal, serve to sufficiently smooth the delivered supply from a renewable portfolio to allow it to follow demand throughout the day. Our optimized portfolio meets or exceeds demand in every hour of the year with existing hydro capacity and minimized surplus renewable generation—3.1% annually for the 80% renewable supply. Our model, however, is only a first step. It relies on several simplifying assumptions and does not reflect many issues that would be faced in real-world design of an 80% or 100% renewable electricity supply. Three assumptions are briefly discussed below.

Assumption 1: The statewide distribution of wind and solar farms will remain the same as total capacity scales up. With the huge capacities arrived at in our resource portfolios, this heavy concentration of wind turbines in a handful of locations is unlikely. A more complete model could place smaller wind or solar thermal capacities at hundreds or thousands of locations across the state (and use several different wind turbine types). This would serve to reduce the variability in delivered supply even more, further easing grid integration of these resources.

Assumption 2: Hydropower has ultimate flexibility over a day as long as the nameplate capacity is never exceeded, and good seasonal flexibility as well. While our assumption of good hour-to-hour flexibility is reasonable, our model does not fully consider seasonal restrictions on hydro usage. Our optimized cases, for example, are far under average hydro usage in April due to the relatively low demand and high solar power output. To be under April hydro usage is fine, but it is not the case that all of the unused hydro can be shifted to the summer and fall, as is done in our model. This could only work with large reservoirs, while the April hydro capacity from small reservoirs should be used in April or discarded. A more complete model could build in better rules about seasonal shuffling of hydropower.

Assumption 3: Our analysis is performed only for the *average* day in each month. By averaging demands, wind speeds, and insulations over the month, we are removing much of the fine variability in output that worries grid operators the most. Our model shows that the complementary intermittencies of wind and solar and the balancing power of hydro can deliver a relatively smooth, peaking supply despite seasonal and perhaps even day to day variations in supply. But our model does not address the issue of hour to hour or sub-hour fluctuations in wind or solar output. To a large extent these will be dampened due to the combination of huge, widely distributed capacities over the state, but they will not be removed entirely. A good follow-up to this model would be to use modeled or measured wind speeds and insulations on several specific days, with as good temporal resolution as possible, to calculate the statewide power supply from this same resource mix. This could reveal the utility of the average as a forecasting tool, as well as the range of variability present in a real system.

There are several other points that could be flushed out in a more rigorous model, such as a different shape of statewide demand in 2020 (due to TOU pricing, heavy EV adoption, efficiency improvements, etc.), a more detailed method for estimating solar thermal power output from insolation, and the adoption of long-term storage in some solar thermal facilities. For the purpose

of demonstrating smoothing of delivered supply by packaging renewables with complementary intermittencies, our exclusion of these points is fine.

While the required wind and solar capacities to meet 80% or 100% of California's electricity from renewables may seem enormous, they are still dwarfed by estimates of the total statewide potential. A 2005 CEC report estimated nearly 100,000 MW of developable wind potential at 70m, filtering out offshore, urban or forested areas, protected lands, and land with grade > 20% (Yen-Nakafuji). A separate estimate quotes California's offshore wind potential at 100-300 GW (Musial and Butterfield, 2004). And a 2008 NREL study estimated a California potential of 803,000 MW of concentrating solar power, not counting lands with a current primary use, sensitive and protected lands, and areas with slope > 1% (Mehos, 2008). Our 100% renewable capacity estimates are much larger than current capacities, but still well within potential limits.

The main purpose of this analysis is to show that despite the inherent variability in many renewable resources—specifically wind and solar power—a true portfolio of renewables can supply a significant fraction of statewide electricity demand, meeting or exceeding demand in all hours of the year. The complementary intermittencies of wind and solar, as well as the smoothing effect of integrating supplies from dispersed resources across the state, help to reduce variability and increase predictability of delivered supply. While renewable resources still face numerous barriers to adoption, the issue of integration into the grid is one that can be at least partially overcome through careful resource assessment and planning. This case study for California in 2020 suggests one possible means of assessing an area's renewable resources and determining an optimal renewable portfolio. Other portfolios are possible, many perhaps better, but this is our choice for an optimal portfolio for California in 2020 given our assumptions and goals.

Sources Cited

- American Wind Energy Association. (2007). *U.S. wind energy projects: California*. Retrieved June, 2007, from <http://www.awea.org/projects/projects.aspx?s=California>
- Archer, C. L., and M. Z. Jacobson, Spatial and temporal distributions of U.S. winds and wind power at 80 m derived from measurements, *J. Geophys. Res.*, 108 (D9) 4289, doi:10.1029/2002JD002076, 2003.
- Archer, C.L., and M.Z. Jacobson, Supplying baseload power and reducing transmission requirements by interconnecting wind farms, *J. Applied Meteorol. and Climatology*, 46, 1701-1717, doi:10.1175/2007JAMC1538.1, 2007.
- Betz, A. (1920). Das Maximum der Theoretisch Möglichen Ausnützung des Windes durch Windmotoren. *Zeitschrift für das gesamte Turbinewesen*, September 1920, 307-309.
- California Energy Commission. (2001a). *California monthly hydro generation: Utility-owned*. Retrieved November 2007, from http://www.energy.ca.gov/electricity/monthly_average_hydro_gen.html
- California Energy Commission. (2001b). *Peak electricity demand forecasts*. Retrieved July 2007, from http://www.energy.ca.gov/electricity/commission_demand_forecast.html
- California Energy Commission. (2002). *Overview of geothermal energy in California*. Retrieved July 2007, from <http://www.energy.ca.gov/geothermal/overview.html>
- California Energy Commission. (2004) *Integrated energy policy report: 2004 update*. Sacramento, CA: Office of State Publishing.
- California Energy Commission. (2005). *California geothermal resources*. Sacramento, CA: Office of State Publishing.
- California Energy Commission. (2007). *California electrical energy generation, 1996 to 2006 total production, by resource type* [Data file]. Retrieved July 2008, from http://energyalmanac.ca.gov/electricity/electricity_generation.html
- California Energy Commission. (2008a). *Hydroelectric power in California*. Retrieved July 2008, from <http://www.energy.ca.gov/hydroelectric/index.html>
- California Energy Commission. (2008b). *Large solar energy projects*. Retrieved July 2008, from <http://www.energy.ca.gov/siting/solar/index.html>
- California Independent System Operator. (2007). *Oasis: system load reports* [Data file]. Retrieved June 2007, from <http://oasis.caiso.com/>
- California Public Utilities Commission. (2007a). *California solar initiative*. Sacramento, CA: Office of State Publishing.
- California Public Utilities Commission. (2007b). *California transmission information and projects*. Retrieved June 2007, from <http://www.cpuc.ca.gov/puc/Energy/transmission.htm>
- California State Association of Counties. (2007). *California county population estimates*. Retrieved July 2007, from <http://www.csac.counties.org/images/users/1/population.pdf>
- California Senate. (2002). *California renewables portfolio standard program* (SB 1078). Sacramento, CA: Office of State Publishing.
- California Wind Energy Association. (2007). *Our goal: 20% of California's electricity from wind by 2020*. Retrieved July 2007, from <http://www.calwea.org/bigPicture.html#calwea5>
- Carrizo Energy, LLC. (2007). *Application for certification: Carrizo solar energy farm*. Retrieved July 2008, from http://www.energy.ca.gov/sitingcases/carrizo/documents/applicant/afc/AFC_Volume_1/AFC_Volume_1.pdf
- Dvorak, M. J., Jacobson, M. Z., & Archer, C. L. (2007). California offshore wind energy potential. *In review*.
- Energy Information Administration. (2009). *California nuclear industry*. Retrieved June 2009, from http://www.eia.doe.gov/cneaf/nuclear/page/at_a_glance/states/statesca.html
- Geothermal Energy Association. (2007). *All about geothermal energy*. Retrieved July 2007, from <http://www.geo-energy.org/aboutGE/basics.asp>
- Marion, W., & Wilcox, S. (1994). *Solar radiation data manual for flat-panel and concentrating collectors*. Golden, CO: National Renewable Energy Laboratory.
- Kahn, E., 1979: The reliability of distributed wind generators. *Electric Power Syst. Res.*, 2, 1–14.
- Masters, G. (2004). *Renewable and efficient electric power systems: Appendix C: Hourly clear-sky insolation tables*. Stanford, CA: John Wiley & Sons.
- Mehos, M. (2008). *Utility-scale solar power: opportunities and obstacles*. National Renewable Energy Laboratory.
- Musial, W.S., & Butterfield. (2004). Future for offshore wind energy in the United States. *Proc. Energy Ocean*, 2004.
- National Renewable Energy Laboratory. (date unknown). *PV watts: A performance calculator for grid-connected PV systems*. Retrieved August 2008, from http://rredc.nrel.gov/solar/codes_algs/PVWATTS/version1/
- Quaschnig, V., & Muriel, M. (2001). *Solar power—photovoltaics or solar thermal power plants?* VGB Congress Power Plants 2001. Retrieved August 2007, from <http://www.volker-quaschnig.de/downloads/VGB2001.pdf>
- REPower. (2007). *MM92: The 2-megawatt power plant with 92 metre rotor diameter*. Retrieved July 2007, from http://www.repower.de/fileadmin/download/produkte/PP_MM92_uk.pdf
- Yen-Nakafuji, D. (2005). *California wind resources*. Retrieved October 2008, from <http://energy.ca.gov/2005publications/CEC-500-2005-071/CEC-500-2005-071-D.PDF>