Analyzing Renewables in a Utility Energy Mix

Roy L. Nersesian

Renewables are a real challenge for utility operators, particularly solar and wind power. Renewables such as biomass, geothermal, and hydro are as controllable as fossil fuel plants. Hydro has its challenges if rainfall in the reservoir's watershed can't keep the reservoir full—but within reservoir depth restraints, output is controllable.

A Microsoft Excel spreadsheet modeling of solar and wind may be in terms of averages. Averages totally ignore inherent variability. Simulation provides a more dynamic picture to appreciate the extent of risk and be able to evaluate ways to mitigate risk.[1]

SOLAR POWER

Exhibit 1 shows the vagaries of sun power.

The following formula predicts how much sunlight reaches the ground for different degrees of cloud cover:

$P = 990 * (1–0.75F^3)$ watts/meter^2, where F is cloud cover.

When F equals 100 percent for total cloud cover, solar panels can still generate 25 percent of their capacity compared to a clear day. Peak sun power exists only for three to four hours per day and tapers off to zero at sunset and remains there until sunrise. Whereas a fossil fuel or nuclear plant can operate at 95 percent of its nameplate capacity, solar plant output averages about 25 percent of its nameplate capacity based on a 12-hour day.

A simulation of solar power output was performed for winter and summer resulting in different, but similar, probability distributions. One probability distribution models high solar power in summer from longer days and less cloud cover and another for low solar power in winter from shorter days with greater cloud cover. Moreover, the sun is much lower on the horizon in winter than in summer. Three normal curves were tailored to transform probability distributions covering two days of a year to probability distributions for every day of the year, as seen in **Exhibit 2**.[2]

Exhibit 2 reflects the output of a 1-megawatt solar plant located in northerly latitudes where the sun lies close to the horizon in winter.

WIND POWER

While it would be possible to create a probability distribution of wind power using a wind turbine and a probability distribution of wind speeds, the approach taken in **Exhibit 3** was based on the actual output of a wind farm.

Several observations can be made. Energy output is less during the summer than the winter, as seen by the more frequent occurrences of zero percent capacity output. The most common outputs in Exhibit 3 are full power or no power with some intermediate points. It appears that output has a greater probability of being less than 50 percent than above 50 percent. There were several occasions when zero output lasted as long as 10 days.

Roy L. Nersesian is a professor in the Department of Management and Decision Sciences at the Leon Hess School of Business at Monmouth University. He has published two books in the field, *Energy Economics* (Routledge, 2016) and *Energy Risk Modeling* (Palisade, 2013). He also has another, *Utility Risk Modeling*, awaiting publication.

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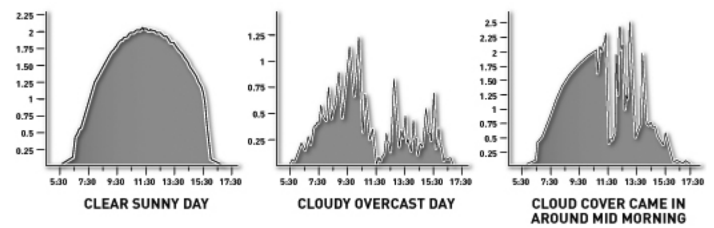
Exhibit 1. Vagaries of Sun Power



Suppose an analysis of actual data shows that winter output averages 35 percent and summer averages 25 percent of nameplate capacity. At full capacity, a 1-megawatt wind turbine generates 24 megawatt-hours or 8.3 megawatt-hours at 35 percent capacity output and 6.0 megawatt-hours at 25 percent capacity. **Exhibit 4** models Exhibit 3 with arbitrary probabilities for intermediary outputs and adjusts the probabilities for zero and 100-percent output to achieve the desired average energy output.

Exhibit 5 is the resulting wind pattern for a single iteration of a simulation.

Exhibit 2. Adjusted Daily Solar Output

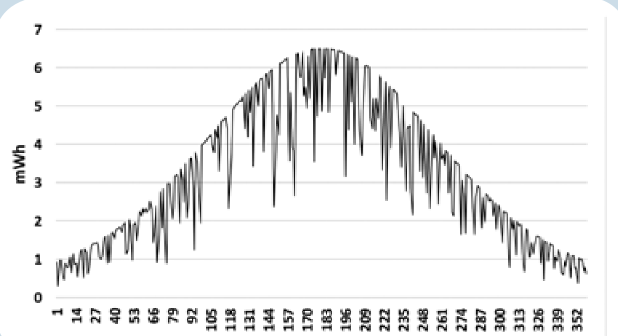
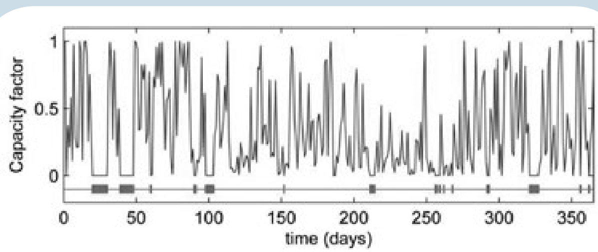


Exhibit 3. Wind Power Distribution



Visual inspection reveals that frequency of full output is less in summer than in winter.

Visual inspection reveals that frequency of full output is less in summer than in winter, share of outputs being lower than 50 percent is greater than being higher, and the presence of lengthy spans with zero output, all more or less in agreement with Exhibit 3.

COMBINING 1 MEGAWATT SOLAR WITH 1 MEGAWATT WIND

Exhibit 6 combines 1 megawatt of solar with 1 megawatt of wind on a daily basis over a year's time.

This chart may appear startling. The high values are for wind at full capacity for 24 hours (24 megawatt-hours), whereas high values for solar are about 6.5 megawatt-hours, taking into consideration that full power is only about four hours per day and no power for 10–14 hours per day. Peak winter power is essentially wind only because of the northerly location of the solar power facility, where peak winter solar power is only 20 percent that of summer.

Maximum summertime output of solar and wind is 30 megawatt-hours, but daily output may be less depending on cloud cover and wind speed.

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MODELING UNCERTAIN DEMAND

Eight beta probability distributions, a special case of a pert probability distribution, were arbitrarily assumed to be able to model annual electricity demand. **Exhibit 7** compares the derived probability distribution with actual day in terms of an index value of 100 for base load. Peak load is three times that of base load. The fit is quite good.

Each beta distribution, shaped like an inverted U, requires three assessments: minimum, maximum, and most likely or peak value, or in this context, start and end days and day of peak value. @RISK Evolver derived these assessments that created the generated probability distribution in Exhibit 7. A few of the individual beta distributions were almost identical, which means one or more could be removed while preserving the integrity of the fitted distribution.

In a typical simulation of demand, the general shape is fixed, with each day being about 10 percent, plus or minus. The use of several beta probability distributions allows for selected start and end times to vary randomly within limits on an annual basis. This allows for the profile of demand to change each year during a simulation while preserving its essential character. **Exhibit 8** shows a single annual iteration of the index, which is linked directly to base load.

ELECTRICITY STORAGE

Significant solar and wind power in the energy mix to fuel a utility creates surpluses or shortfalls in generated electricity.

The logical absorber/supplier of electricity is a battery—not just any battery, but a superbattery.

The logical absorber/supplier of electricity is a battery—not just any battery, but a superbattery, defined as five times larger in capacity than the largest existing storage battery at one-fifth the cost. Because the superbattery does not exist, the most common alternative for storing and supplying large quantities of electricity is a pumped storage plant. Surplus electricity is consumed pumping water from the lower to upper reservoir. Shortages of electricity are met by water flowing from the upper to lower reservoir

Exhibit 4. Desired Average Energy Output—Winter vs. Summer

	L	M	N	O	P	Q
5	Winter Output					
6						
7	Prob	54%	10%	5%	5%	26%
8	Output mW	0	0.25	0.5	0.75	1
9						
10		Average mW Output:		0.35		
11		Rated mWh Capacity:		24		
12						
13		Average mWh:		8.4		
	L	M	N	O	P	Q
17	Summer Output					
18						
19	Prob	64%	10%	5%	5%	16%
20	Output mW	0	0.25	0.5	0.75	1
21						
22		Average mW Output:		0.25		
23		Rated mWh Capacity:		24		
24						
25		Average mWh:		6		

Exhibit 5. Wind Output

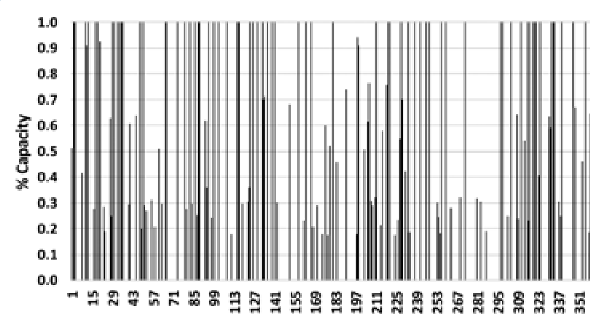

Exhibit 6. Total Solar and Wind 1 mW Plants

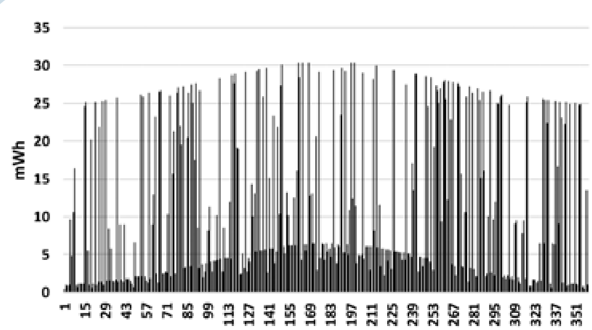

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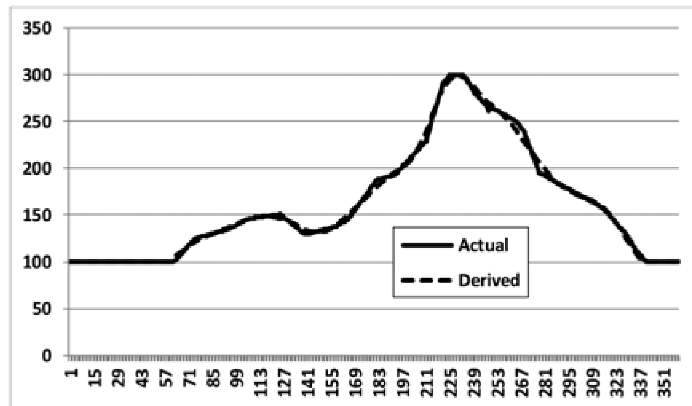
Exhibit 7. Derived Probability vs. Actual Day



powering generators that had previously been used as pumps.

Suppose for some shape of an upper reservoir, the equation linking energy content y of the upper reservoir to depth of water (x) is the following:

$$y = x^4 + x^3 + x^2 + x + 10$$

What is desired is not energy content as a function of depth, but depth as a function of energy content for measuring performance. While this equation cannot be solved algebraically, there is a substitute way measuring depth in terms of energy content using Excel trendlines. **Exhibit 9** lays out the worksheet where x is the depth of water and y is the energy content of the reservoir along with the derived best-fitting curve.

Depth of water is equal to 0.9511 * energy content in megawatt-hours raised to the 0.2529th power. The power trendline turns out to be a perfect fit. Now any change in the stored energy in the battery, which is known on a day-to-day (or hour-by-hour or minute-by-minute) basis by the magnitude of surplus or shortfall in

Exhibit 8. Derived Probability—One Iteration

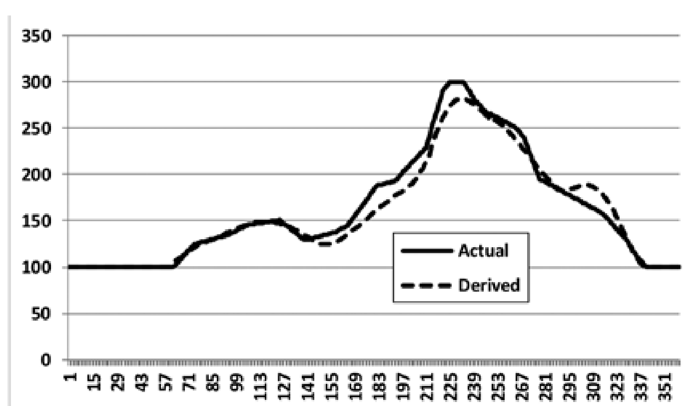
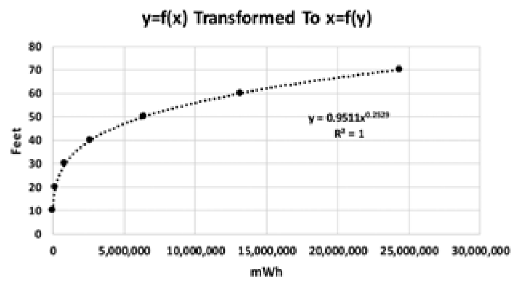


Exhibit 9. Energy vs. Reservoir Water Depth

y	x
11,120	10
168,430	20
837,940	30
2,625,650	40
6,377,560	50
13,179,670	60
24,357,980	70



generated electricity, can be translated straightforward to depth of water in the upper reservoir. This is akin to measuring a change of charge in a battery versus a change in the amount of stored electricity.

BUILDING THE MODEL

The logic behind the model is to first create the daily output of solar and wind and then bring into the picture fixed supply of electricity (coal/nuclear) and variable supply (natural gas).

> The model is to first create the daily output of solar and wind and then bring into the picture fixed supply of electricity.

Total supply is then compared to demand to obtain either a daily surplus or shortfall of electricity in megawatt-hours. Thirty percent of the electricity stored in the pumped storage facility is assumed lost in pumping water, generating electricity, and the loss of energy (gain in entropy) associated with the dissipation of the momentum of discharged water entering a reservoir. System performance was based on the water level in the pumped storage reservoir being neither too high to spill over the dam nor too low to threaten its capacity to generate electricity to cover shortfalls. The initial assessment of 1 megawatt-hour of energy content in the upper reservoir was proven to be too small.

The capacity was tripled to avoid draining the reservoir (and hence the battery) dry.

RUNNING THE MODEL

RISKOptimizer, another Palisade product within the Decision Tool Suite, was used to maximize the size of the solar and wind farms while minimizing the following:

1. The absolute difference between an ending energy content of 2 million megawatt-hours and the beginning energy content
2. The number of days when reservoir capacity exceeded design capacity of 490 feet representing 3 million megawatt-hours
3. The number of days when reservoir capacity was below 50 feet
4. The number of occurrences of battery exhaustion (negative energy content in the reservoir)

To increase the contribution of solar and wind power in the energy mix, it was necessary to reduce the initial 1,000 megawatts of fixed supply (coal/nuclear) to 400 megawatts to enlarge the role of variable supply (natural gas). The general conclusion of this and all previous efforts has been that fixed supply of energy that, by definition, cannot be quickly adjusted does not go well with the vagaries of renewable energy. But natural gas plants can respond rapidly to changes in renewable output. Solar and wind will continue to benefit from the current trend of transforming fixed to variable power supplies as low-cost natural gas plants replace retired coal and nuclear plants.

The RISKOptimizer solution maximizes the role of renewables for the given profile of electricity demand that peaks at about 3,500 megawatts. The

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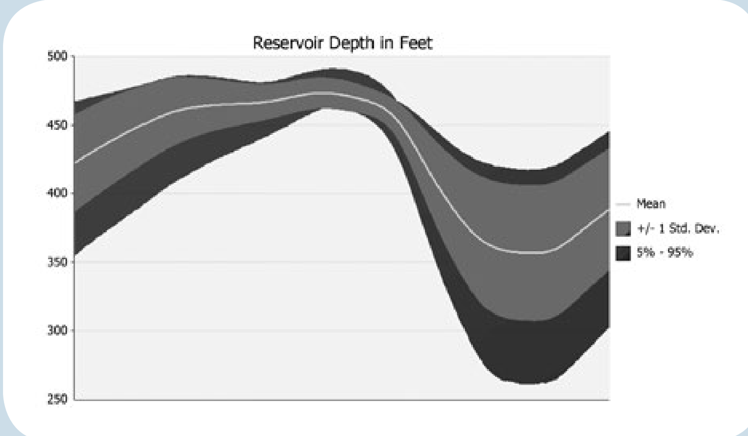
Exhibit 10. Probability of Water Required Over a Year



solution was 400 megawatts for fixed supply, eight natural gas plants of 100 megawatts each for 800 megawatts as variable supply, 3,000 megawatts nameplate capacity for solar, and 1,900 megawatts nameplate capacity for wind. If fossil fuel/nuclear were the sole sources, about 4,000 megawatts of nameplate capacity would be adequate. But in maximizing renewables, 6,100 megawatts of nameplate capacity is needed, plus a pumped storage unit of 3 million megawatt-hours.

From this, there can be no doubt that renewables will generate more costly electricity even if electricity from a solar panel or from a wind turbine is price-competitive with electricity from fossil fuels. However, there are many consumers willing to pay more in electricity rates to support phasing out coal and nuclear plants. **Exhibit 10** is the probability distribution of water depth in the reservoir.

There are many consumers willing to pay more in electricity rates to support phasing out coal and nuclear plants.

Water depth does not exceed 490 feet, the maximum depth of the reservoir, and the minimum depth during the time of peak demand is about 250 feet. This indicates that the assumed capacity of the pumped storage facility may be too large. A smaller size, such as 2 or 2.5 million megawatt-hours, could be incorporated in the model to get a better assessment of the required capacity of the pumped storage facility, or superbatteries when they become technologically and commercially available.

Reducing required battery capacity improves the economic analysis of renewables.

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ADAPTABLE TO SPREADSHEET MODELS

My book, *Utility Risk Modeling*, when published, is intended to provide ideas and approaches, described herein, that may be amenable to "real-life" situations in adopting renewables into a utility energy mix. It is hoped that these ideas and approaches can be adopted as changes to existing spreadsheet models of utility operations without requiring a massive effort to set up a new model.

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NOTES

1. Simulation software from @RISK Decision Tools Suite by Palisade Corporation.
2. Evolver, part of the @RISK Decision Tools Suite, aided in the tailoring.

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