Intermittency and the Value of Renewable Energy

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Views on solar energy

Like just about everyone who has looked at the numbers on renewable energy, solar power in particular, I was wowed by the progress. Something really good is in reach.

-Paul Krugman, The New York Times, Apr. 21, 2014

For weeks now, the 1.1 million solar power systems in Germany have generated almost no electricity.... As is so often the case in winter, all solar panels more or less stopped generating electricity at the same time. To avert power shortages, Germany currently has to import large amount of electricity [including by] powering up an old oil-fired plant in the Austrian city of Graz.

-Der Spiegel (German newsmagazine), Jan. 16, 2012

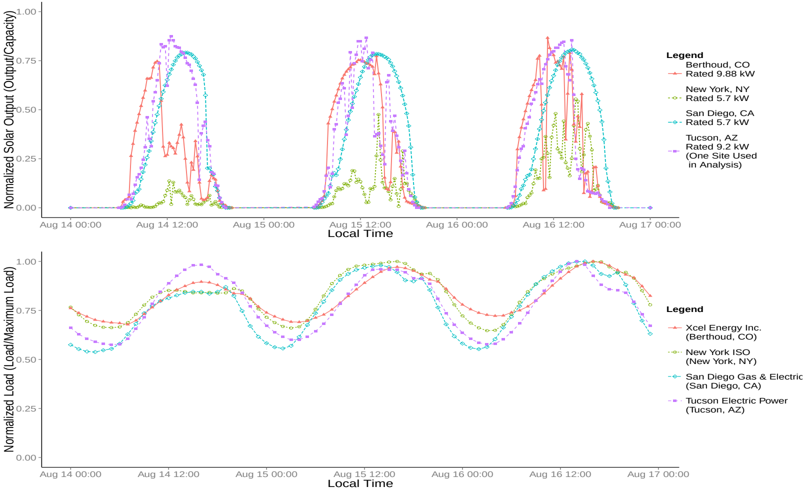
Renewable energy

- Renewable energy capacity has increased dramatically
  - Caused by huge drops in costs
  - Also, policies to mitigate greenhouse gas emissions
- A key problem is intermittency
  - Solar generators only produce when the sun is shining
- Intermittency might hugely affect economic value, or equivalently social costs, of renewables
  - *Der Speigel* quote suggests that electricity system operators use costly backup generation to manage intermittency of large-scale solar
- Large-scale solar may require significant changes
  - Different investment, operations, and demand-side management policies
  - These changes may be necessary to mitigate social costs

Intermittency

- We develop an empirical method to quantify social costs and CO_2 emissions from large-scale renewables
- Idea: solve for decisions that maximize total surplus given different renewable energy capacity levels
- Social costs depend crucially on:
  1. Variability of energy source including how it correlates with demand
  2. Forecastability of source
  3. Costs of building backup generation for system reliability
- We develop formal model of *reserve operations*
- Method can be used to examine social costs of different renewable energy sources and in different contexts

Intermittency: example from Aug. 15, 2011



Relation to literature

- Economic theory literature on reserve operations
  - Joskow and Tirole (2007) developed economic model
  - We take their model to data
- Systems engineering literature
  - One strand focuses on output variability
    - E.g., Fabbri et al. (2005), Mills and Wiser (2010)
    - No optimization
  - Another uses power systems optimization models
    - E.g., Madaeni and Sioshansi (2013), Mills et al. (2013)
    - Optimization over scheduling
    - Reserve operations and investment use rules of thumb
- Empirical economics literature
  - Some studies deal with time-varying generation profile
    - E.g., Denholm and Margolis (2007), Borenstein (2008)
    - Use of price not ideal for out-of-sample forecasting
  - Others deal with fossil fuel capacity adjustment
    - E.g., Lamont (2008), Skea et al. (2008)

What does our economic analysis bring to the table?

- Systems engineering literature already evaluates costs of renewable energy
  - No optimization of welfare maximization problem
- Our economic analysis is fundamentally different
  - We reoptimize operator decisions as a function of renewable energy penetration
  - Requires balancing consumer welfare lost from system outages against costs of backup capacity
  - Model both long- and short-run decisions and consistent with large-scale penetration
- Without reoptimization, output fluctuations from large-scale solar could lead to suboptimal decisions
  - E.g., high probabilities of system outage, or excess investment in backup capacity
- To our knowledge, first paper to use weather forecast data to identify forecastable component of renewable variability

Remainder of talk

Electricity industry in the Tucson area

- Vertically integrated electricity service provider: Tucson Electric Power (TEP)
  - We model planner's problem and don't model market power
- TEP owned 2,275 MW of capacity in 2011
  - Almost all coal or natural gas
  - 91% of *planned* fossil fuel capacity in Arizona is from natural gas combined cycle generators
  - Our base analysis only allows new fossil fuel investment in this one generator type
- Tucson is situated within the Western Interconnection which allows for import or export of power
  - Base model treats Tucson in isolation but we consider imports/exports in a robustness check

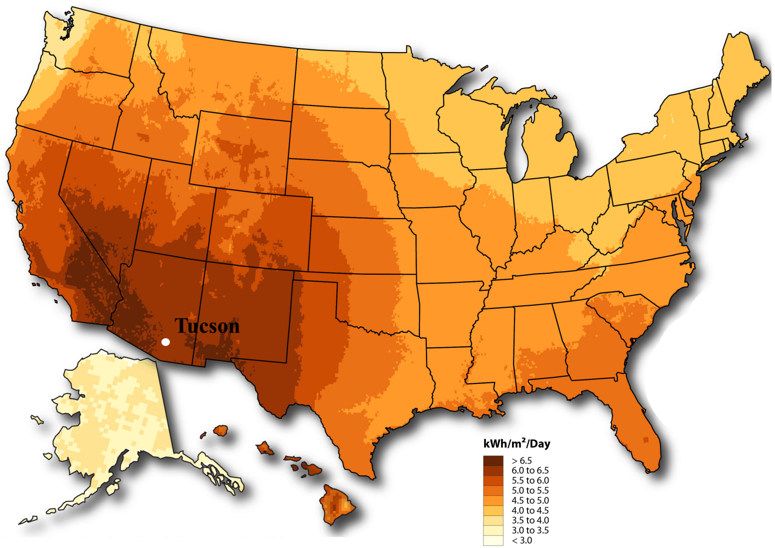
System operations

- System operations involve:
  - Control of generators
  - Decisions about rationing power to customers
  - Control of backup systems
- System operator ensures reliability in part by having generators available on a stand-by basis
- Without system operations, each supplier imposes an externality
- NERC standards specify contingency reserves:
  - Must be sufficient in case of failure of largest generator
  - Utilities also hold balancing reserves of 1-1.5% of peak load
  - Provides benchmark against which we can compare predictions of model

Solar photovoltaic (PV) energy

- Solar PV systems use panels of material (such as silicon) to convert solar radiation into DC electricity
- Inverters convert DC current to AC
- Technology has been improving rapidly
- Interconnection costs are not huge
  - Utility-scale solar typically located near transmission lines
  - Reported interconnection costs are $<$ \$1 per MWh
  - Different than wind power
  - We don't model them
- Arizona's Renewable Portfolio Standard mandates 30% distributed generation for renewables, e.g. rooftop solar
  - We model reduction in transmission costs and different installation costs of rooftop solar
- Entire Southwest U.S. has high solar potential
  - See figure

Photovoltaic solar resources



Overview of model

- System operator is faced with:
  - Fixed solar capacity level
  - Fixed retail price of electricity
  - Existing generators
- In Stage 1:
  - Operator chooses new capacity investment
  - Price for *interruptible power contracts*
- In Stage 2:
  - For each hour of each year operator observes:
    - Next day weather forecast
    - Generators under maintenance
  - Operator then chooses:
    - Generators to schedule for production/reserves
    - Quantity to curtail from interruptible contract customers

Overview of model (continued)

- In each hour, following scheduling and curtailment decisions, solar output and load (demand) are realized and some generators may fail
- Two possible outcomes:
  1. Load is less than output plus operating reserves (adjusting for line losses)
     - Operator adjusts generation to balance output with load
  2. Load is greater than output plus operating reserves
     - System outage: loss of load for large fraction of customers
     - Hopefully rare event!

Demand and welfare

- Assume retail price is a constant $\overline{p}$
- Constant elasticity demand up to reservation value v

$$Q^D(p, \overline{D}) = \begin{cases} 0, & p > v \\ \overline{D}p^{-\eta}, & p \leq v \end{cases}$$

- Scale of demand $\overline{D}$ is time varying and depends on weather forecast $F^D(\cdot|w)$
- Define "value of lost load" as average per-unit value of electricity
- VOLL and v have a monotonic relation
  - => Studies measure VOLL, which we can use to obtain v

Demand curtailment

- In first stage, operator offers interruptible power contracts at price p_c
- Users who sign up agree to have power curtailed as necessary (with one day notice) and be compensated a per-unit price of $p_c - \overline{p}$
- All users with valuation below p_c will sign up
  - Assume that mass of known consumers is based on minimum of $F^D(\cdot|w)$ distribution
- In second stage, observing the forecasted state, the operator *randomly* selects customers to curtail
- Higher p_c implies:
  - More curtailment possible
  - But, higher per unit welfare loss from curtailment

▸ Welfare Loss from Curtailment

Generation and reserves

- All generators last till year T
- Generators can either be scheduled at 0 or full capacity
- Each generator has:
  - a fixed production capacity
  - constant marginal cost of operation
  - per-period probability of maintenance
  - per-period probability of failure
  - ratio of reserve costs to operating costs, c^s
- There exists a set of current generators (from data)
- New fossil fuel plants:
  - The operator can choose n^{FF} new plants
  - All natural gas combined cycle or gas turbine
- Solar production:
  - System operator faced with a level of listed solar capacity
  - Produced from sites dispersed in metropolitan area

Transmission

- Distributed solar output does not incur transmission costs
- This reduces costs of solar in two ways:
  1. Reduces line losses
     - Line loss is quadratic in non-distributed generation
     - Let Q be load net of distributed solar and curtailed demand
     - Then:
       $$LL(Q) = \alpha(Q + LL(Q))^2$$
       where $Q + LL(Q)$ is non-distributed generation
     - Smaller root of quadratic implicitly defines $LL(Q)$
     - α can be estimated from line loss data
  2. Reduces fixed costs of transmission
     - We assume FC proportional to maximum expected non-distributed load

System operator's problem: second stage

1. Observes weather forecast and maintenance status
2. Schedules generators and chooses demand curtailment
3. Observes generator failures, demand and solar
4. Possibly a system outage occurs
   - Loss is $VOLL \times$ quantity$\times$ d^{outage}, where d^{outage} is number of periods times fraction of people affected
5. Otherwise, operator adjusts actual generation to be exactly equal to demand
   - This will occur by using highest cost plants for reserves

- Operator trades off system outage against reserve costs

▸ See production costs & system outage probability ▸ See hourly optimization problem

System operator's problem: first stage

- Operator chooses the best curtailment price and the number of new fossil fuel generators
- Operator takes the expected value of the surplus over all periods in one year and then discounting over the life of the generation units
- Building generators is costly, but it avoids system outage in peak periods

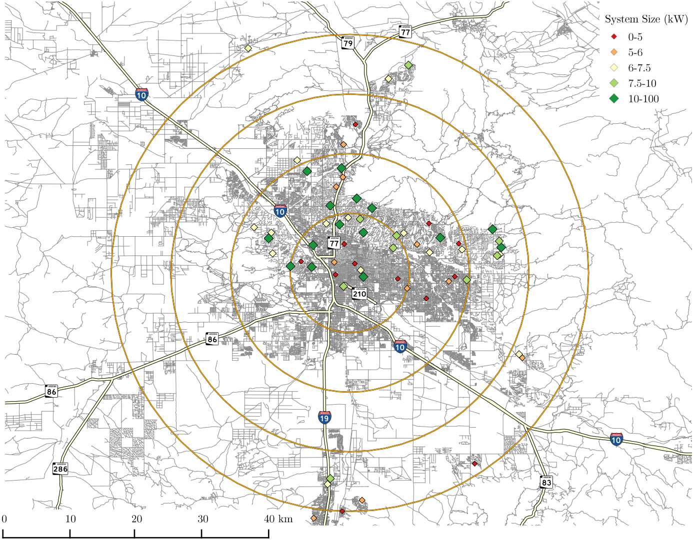
See expected welfare & total surplus

Data overview

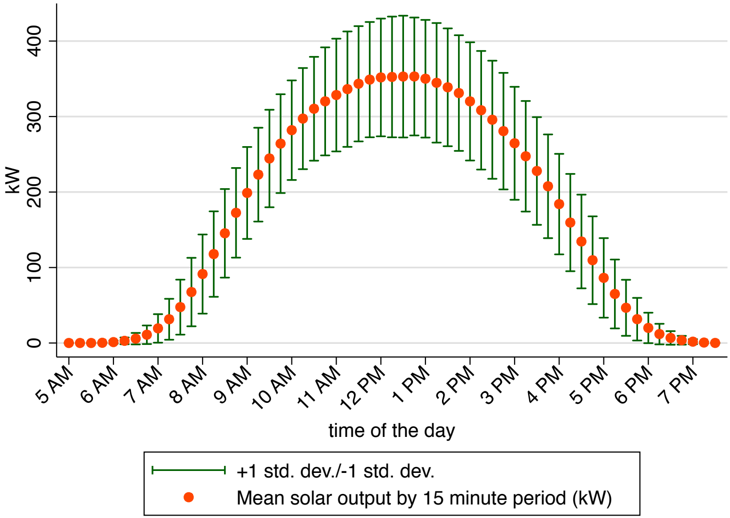
We obtain data from several sources:

- Energy Information Administration (EIA) and EPA data on generator characteristics, and fuel and electricity prices
- Solar data from UA Photovoltaics Research Lab:
    - 58 geographically dispersed installations
    - Keep installations within 40 kilometers of center of Tucson
    - Total rated capacity 517 KW
    - Observe at 15 minute level
    - Data for one year from May, 2011 - April, 2012
- ERCOT data from Texas for spinning reserve costs
- Load and “system λ” data from the Federal Energy Regulatory Commission (FERC)
- For robustness exercises:
    - Import/export quantities from EPA
    - Startup costs from NREL

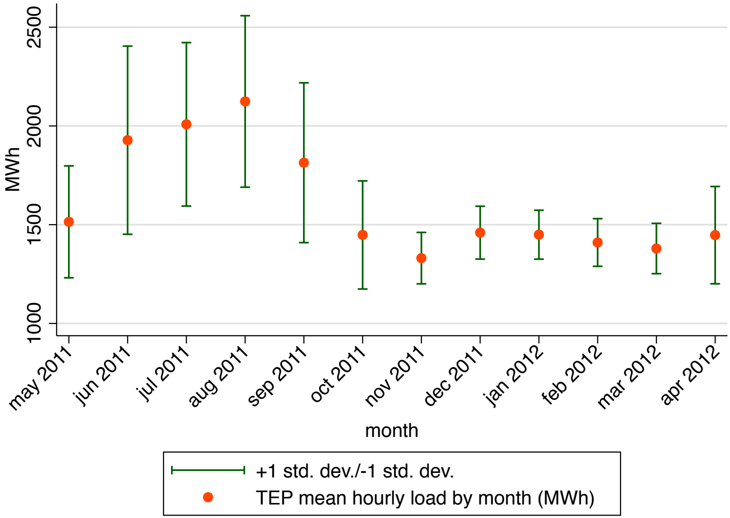
Map of Tucson solar sites in our data



Solar output summary statistics



Load summary statistics



Data overview (continued)

- Weather forecast data from National Oceanic and Atmospheric Administration (NOAA)
  - Forecast generally occurs around 3 AM for the next day
  - Forecast is given for windows of 3 hours
  - We interpolate to hourly level

Calculating generator marginal costs

- Following Wolfram (1999) and Borenstein et al. (2002) we calculate MC by multiplying heat rate by fuel cost
- Obtain heat rates from EPA eGRID2007 report
- Fuel costs:
  - For coal plants: EIA Form 423 multi-year fuel contracts
  - For gas plants: NYMEX 2010 future prices for delivery 2011-15 at Henry Hub in Louisiana
- Add SO_2 cap-and-trade permit fees from EPA
  - Multiply fees by emissions rates from EPA
- No NOx fees in western states
- New generator MC and capacity from EIA

Summary statistics on generator marginal costs

Unit type	# Units	Mean size MW	Mean MC \$/MWh	Mean NO_x Lbs./MWh	Mean SO_2 Lbs./MWh	Mean CO_2 Tons/MWh
Solar PV	2	6.5	0	0	0	0
		(0.5)	(0)	(0)	(0)	(0)
Coal	6	263	23	3.0	1.6	1.0
		(133)	(10)	(1.7)	(1.3)	(0.06)
Natural gas combined cycle	1	185	35	.09	.01	0.4
		(0)	(0)	(0)	(0)	(0)
Natural gas steam turbine	3	89	54	1.5	.03	0.5
		(13)	(0)	(0)	(0)	(0)
Natural gas turbine	6	39	71	3.5	.05	0.8
		(20)	(13)	(2.0)	(0.01)	(0.2)
Potential new natural gas combined cycle	–	191	32.6	0.05	0.01	0.4
Potential new natural gas turbine	–	91	47.6	0.31	0.01	0.5

Note: Standard deviations in parentheses. MC figures include emissions permits.

Demand parameters

- Use demand elasticity of $\eta = 0.1$ from the literature
- Use VOLL estimates of $8,000/MWh from literature
- Use demand growth of $g = 20\%$ from historical load growth
- Use retail price of electricity $\overline{p} = \$98.1$ from EIA numbers for Tucson
- Estimate load and solar via a joint regression model during the daytime
    - Regressors include:
        - Splines of forecast variables
        - Hours till sunset and from sunrise
        - Day-of-week and month-of-year indicators
        - Hour dummies
    - Precision of load and solar similar to forecasting studies and values used by utilities
        - R^2 of 0.959, 0.945, and 0.878 for daytime load, nighttime load, and solar output

Supply parameters

We estimate c^s as the ratio of ERCOT reserve auction prices to balancing market prices

- Balancing market price mean: \$65.41 / MWh
- Responsive reserve (10 minute) mean: \$27.05
- Up regulation (5 second) mean: \$22.71
- Mean of the ratios: 0.42 and 0.40
- Use $c^s = 0.41$

Table : Mean hourly maintenance and failure probabilities

	Failure probability, P^{fail}	Maintenance probability, P^{maint}	Mean number of units over period
Natural gas generator	0.0492% (0.01%)	0.0382% (0.008%)	342
Coal generator	0.099% (0.027%)	0.047% (0.010%)	859

Remaining supply parameters

Param.	Interpretation	Value	Source
d^{outage}	Mean hours $\times$ fraction affected for system outage	0.98	EIA
α	Line loss constant	0.000035	Computed from TEP reported 6.5% line loss
AFC^T	Average transmission fixed costs per MWh	\$1.259M	Borenstein and Holland (2005), Baughman and Bottaro (1976), TEP line loss cost
FC^{solar}	Solar capital cost per rated MW	\$4.41M	EIA
FC^{FF}	New gas generator capital cost per rated MW	\$1.10M	EIA
β	Discount factor	0.94	
T	Lifetime of generators (years)	25	

See details on computation of operator problem

The social costs of large-scale solar

Fraction of generation from solar	0%	10%	15%	20%
Foregone new gas generators	0	2	2	3
Mean system outage probability	4.76e-5	5.82e-5	5.81e-5	8.4e-5
Reserves (% of energy)	30.5	32.1	33.6	35.2
Curtailment quantity (% of load)	0.11	0.19	0.14	0.24
Curtailment price p_c ($/MWh)	661	469	431	804
Production costs	437.2	380.0	355.2	332.2
Reserve costs	78.1	81.5	82.8	84.8
Gas generator investment costs	2,090	1,672	1,672	1,463
Solar capacity investment costs	0	4,148	6,221	8,295
Transmission fixed costs	331.4	319.4	317.4	316.2
Loss in $ surplus per MWh solar	–	126.7	133.7	138.4
Loss in $ surplus per ton CO_2	–	293.1	283.5	279.1

Note: cost variables are measured in millions of dollars per year. Loss in $ surplus per MWh solar does not account for environmental benefits except for SO_2 permits.

Comparison of results

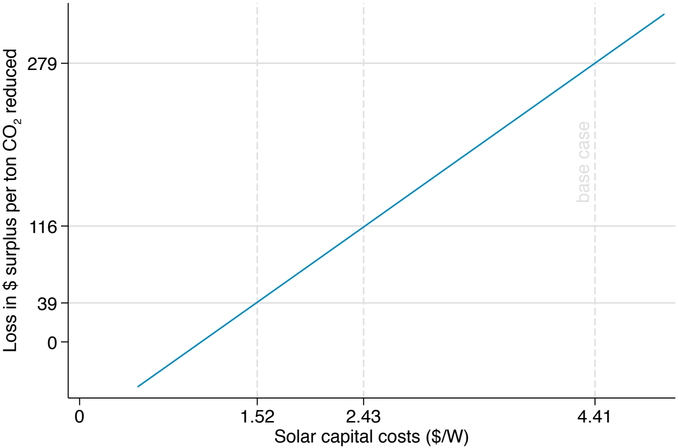
- Levelized cost difference value of solar
  - Average cost of solar PV: \$181.2/MWh
  - Average cost of gas generation: \$66.3 / MWh (EIA, 2011)
  - Difference: \$114.9 / MWh
  - Compare to social cost of \$138.4 for 20% solar
- System outage probability of 0.0048% similar to NERC "one day in ten year" standard
  - Depends on whether one day is "24 hours of system outage" of "one event"
  - Interpretation varies across utilities (Cramton et al., 2013)
- Reserve ratio of 30.5% is higher than used
  - NERC standards (mentioned earlier) imply 23% ratio
- Curtailment prices similar to range reported in literature
  - Baldick et al. (2006) report $[\$150, \$600] + \overline{p}$

Decomposition of social costs of 20% solar

Experiment	Loss in $ surplus per MWh solar	New gas generators	Curtailment price p_c ($/MWh)
Base case – feasible solar	138.4	7	804
No unforecastable intermittency	132.3	7	792
Fully dispatchable	92.4	1	300
Equal generation profile	133.8	7	783
Eliminate distributed generation	118.7	7	834
Fixed costs drop from $4.41/W to $2/W	39.4	7	804
Same policies as without solar	281.6	10	661
Rule-of-thumb policy, 10% cap. credit	154.8	10	661
Rule-of-thumb policy, 12.5% cap. credit	153.2	9	661

Note: “no unforecastable variance” produces at the forecastable mean. “Fully dispatchable” solar can be dispatched based on the demand forecast. “Equal generation profile” produces equally at every hour with the same total capacity as the baseline. “Rule-of-thumb" policies reduce fossil fuel capacity by the capacity credit of installed solar capacity and increase daytime reserves until the mean system outage probability is the same as in the base case.

Solar capital costs versus social costs for 20% solar



Note: $4.41 is our baseline solar capital costs. $39 is the EPA mean social cost of carbon and $116 is the 95-percentile social cost of carbon, both using a 3% discount rate.

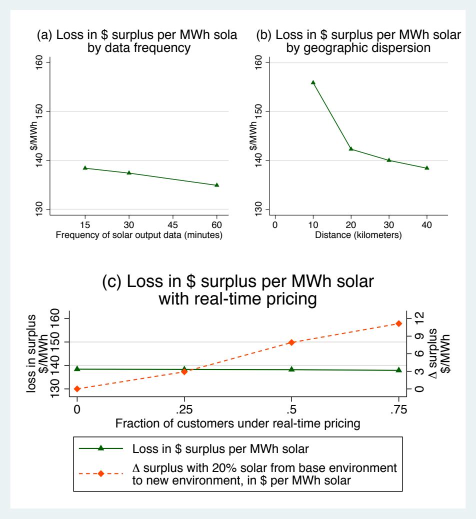
Robustness to functional form

- Real-time pricing
  - A fraction γ of customers on real-time pricing contracts
  - The system operator sets the real-time prices at the same time as scheduling generators, one day in advance (Borenstein and Holland, 2005)
- Imports and exports
  - We specify a net import supply curve of $q_t^I = \alpha_t^I + \beta^I \log p_t^I$
  - We estimate the net supply curve with an IV regression (Bushnell et al., 2008)
  - We use TEP's "system λ" as a proxy for market price
  - Estimates:
    - Operator would pay \$32.7 per MWh to import 300 MW
    - Operator would receive \$30.6 per MWh to export 300 MW in an hour

Social costs of 20% solar given different environments

Environment	Base surplus (million $/year)	Loss per MWh solar	New gas generators		Curtailment price	
			No solar	20% solar	No solar	20% solar
Base environment	134,481	138.4	10	7	661	804
No interruptible power contracts	134,453	137.8	12	10	–	–
Imports and exports allowed	134,508	139.2	10	8	–	–
Investment in additional generator type	134,482	138.4	8 / 3 (GT/CC)	6 / 3 (GT/CC)	677	696
Later (2PM) forecasts	134,482	139.3	10	8	701	488
Forecasts with 24-hour lagged demand	134,485	138.5	10	7	600	1,020
VOLL ↑ to $12,000	202,225	138.9	10	8	661	469

Costs from unforecastable intermittency, geographic dispersion, and real-time pricing



Conclusions

- We analyze the value of renewable energy with a three-part approach that accounts for intermittency
  1. Theoretical model based on Joskow and Tirole (2007)
  2. Process to estimate and calibrate parameters
  3. Computational approach for counterfactual policies
- Biggest limitations: no dynamics and no market power
- Costs of unforecastable intermittency are less than most utilities and forecasters believe to be true
  - Optimizing approach is important
  - Given large renewable penetration, utilities may need to obtain knowledge about how to change decisions
  - Social costs likely similar for southwestern U.S.
- Immediate investment in large-scale solar would reduce welfare
  - Welfare neutral at capacity costs of $1.52 per watt

- Curtailment quantity z:

$$0 \leq z \leq \overline{D}^{min}(w)\left[\overline{p}^{-\eta} - p_c^{-\eta}\right]$$

where $\overline{D}^{min}$ is the minimum demand for a given $F^D(\cdot|w)$

- Welfare Loss from Curtailment:

$$WLC(z, p_c) = \frac{\eta(\overline{p}^{1-\eta} - p_c^{1-\eta})z}{(\eta - 1)(\overline{p}^{-\eta} - p_c^{-\eta})}$$

Return

- Define actual production costs as $PC(D, x)$
- Example, two generators, capacity 1, $c_2 > c_1$, $D = 1.6$:

$$PC(1.6, (1, 1)) = c_1 + 0.6 \times c_2 + 0.4 \times c_2 \times c^s$$

- Individual generator output

$$x_j(on_j^t) = \begin{cases} k_j, & \text{with prob } (1 - P_j^{Fail})on_j^t \\ 0, & \text{otherwise} \end{cases}$$

- System outage probability

$$outage(\vec{on}, z, \vec{w}) =$$

$$\mathbf{1}\{\sum_{j=1}^{J+n^{FF}} x_j(on_j) + n^{SL}\overline{S} < \overline{D}\overline{p}^{-\eta} - z + LL(\overline{D}\overline{p}^{-\eta} - z - d^{SL}n^{SL}\overline{S})\}$$

Return

- Let m_j denote $0-1$ maintenance status
- Operator's hourly optimization problem:

$$W(\vec{w},\vec{m}|n^{FF},p_c) = \max_{\vec{on},z}$$

$$E\Big[\left(1-d^{outage}outage(\vec{on},z,\vec{w})\right)\left(\overline{D}\overline{p}^{-\eta}VOLL - WLC(z,p_c)\right)$$

$$-PC\left(\overline{D}\overline{p}^{-\eta} - z - n^{SL}\overline{S} + LL(\cdot), \vec{x}(\vec{on})\right) \mid \vec{w},\vec{m}\Big]$$

$$\text{such that } m_j = 1 \implies on_j = 0$$

- $LL(\cdot)$ has same argument as in system outage probability equation
- Actual computation includes 15 minute solar data
  - 4 solar observations per decision-making periods
  - Complicates notation, see Appendix B

Return

- Welfare per year from curtailment price decision:

$$V(n^{FF}) = \max_{p_c} E[H \cdot W(\vec{w}, \vec{m} \mid n^{FF}, p_c)]$$

- Value from investment decision:

$$V^* =$$

$$\max_{n^{FF}} \{ \tfrac{1-\beta^T}{1-\beta} V(n^{FF}) - n^{SL} FC^{SL} - n^{FF} FC^{FF} - TFC(n^{SL}) \}$$

Return

Computation of system operator problem

- We make some relatively small simplifying assumptions:
  - Operator will schedule plants in ascending order of MC
  - Operator will only curtail demand if all plants operating OR MC of last plant > $dWLC(z)/dz$
- System operator problem involves simulation of very small probability events
- We integrate over six dimensions:
  - Number of coal plants down for maintenance and failure (2)
  - Number of gas plants down for maintenance and failure (2)
  - All hours in sample period, which gives w^t
  - Variation in demand and solar output given w^t
- For each point in these six dimensions, we randomly select which generators are down

Return