Impact of Dynamic Storage Capacity Valuation in Capacity Expansion Models

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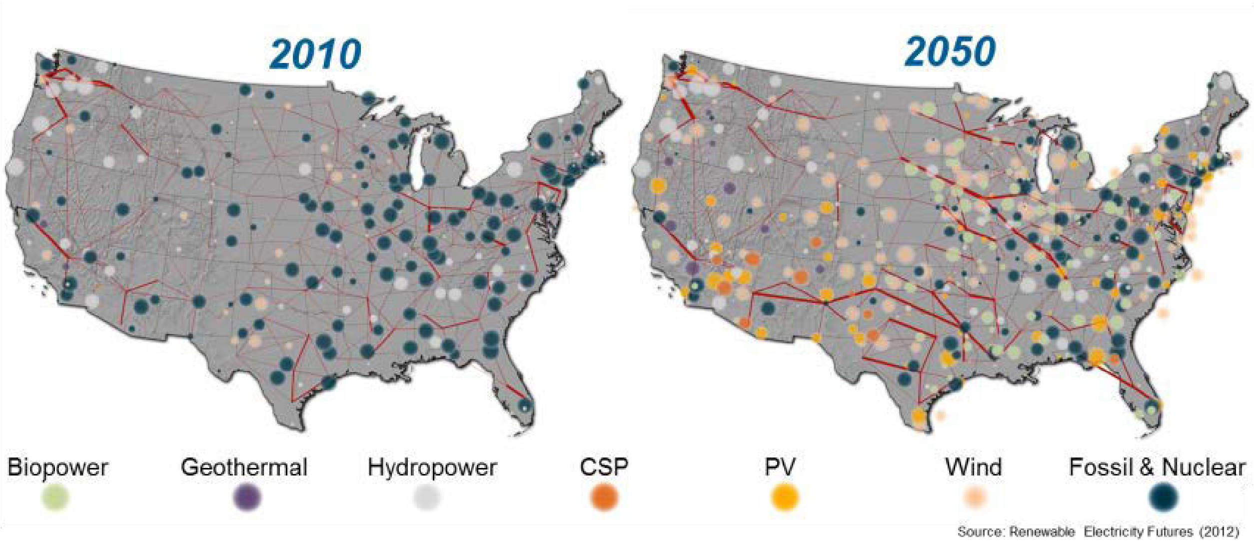
Who are we and what do we do?

Regional Energy Deployment System (**ReEDS**) is a capacity expansion model (CEM) that optimizes the buildout of the future U.S. power system



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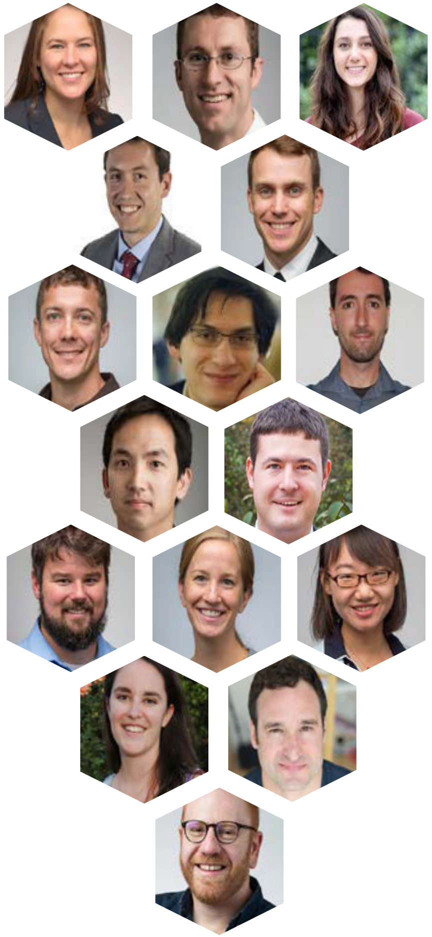
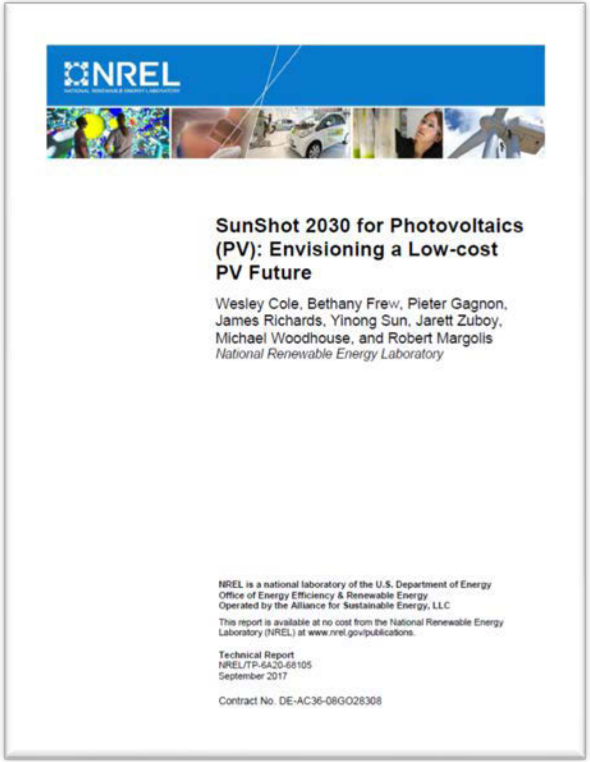


What have we been studying?


NREL
SunShot 2030 for Photovoltaics (PV): Envisioning a Low-cost PV Future
Wesley Cole, Bethany Frew, Pieter Gagnon, James Richards, Yinong Sun, Jarett Zuboy, Michael Woodhouse, and Robert Margolis
National Renewable Energy Laboratory

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Technical Report
NREL/TP-6A20-68105
September 2017

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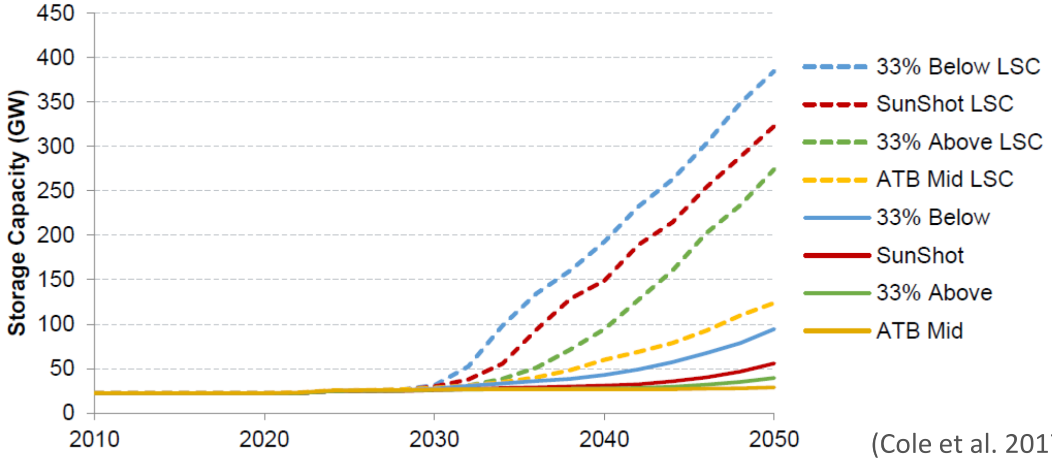
- U.S. Department of Energy "SunShot 2030" PV (3¢/kWh) and low-cost battery storage scenarios



(Cole et al. 2017b)

At high storage penetration levels, storage capacity valuation becomes important…

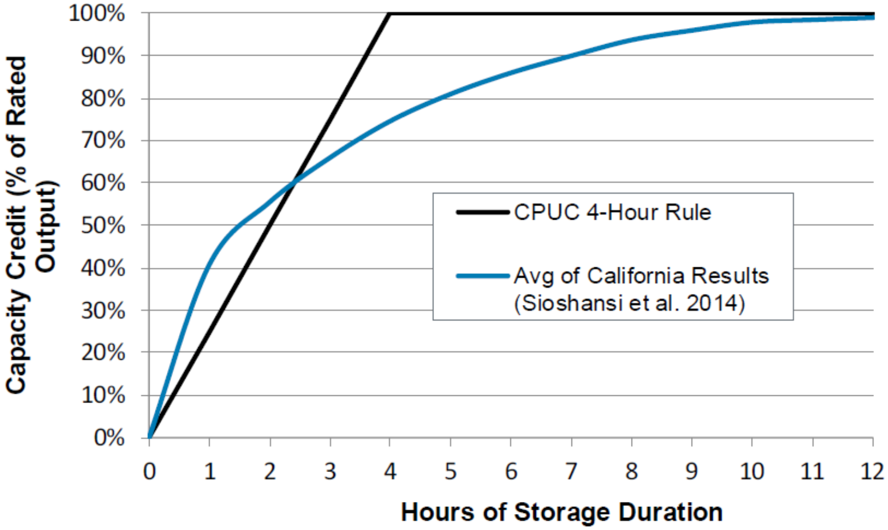
What is capacity value (CV)?

- Fraction of the installed capacity that reliably contributes to meeting load during times of highest system risk
  - Ideally calculated with probabilistic approach, but CEMs typically use approximation methods
  - Implemented in planning reserve margin constraints in CEMs
  - Widely applied to wind and solar, but less understood for storage (active area of research in CEMs, see Cole et al. 2017c)

- Storage CV=1 means device can discharge at rated capacity for full duration of "high risk" periods
  - Longer duration storage tends to have larger CVs because they are more likely to provide full discharge for full duration of high risk periods

CEM approaches to storage CV

- **Static CV**
  - Regardless of amount of storage deployed
  - May vary by duration (Sioshansi et al. 2014)
  - May vary by technology
- **Dynamic CV**
  - Simple dispatch simulation between sequential optimization periods (Hale et al. 2016)
  - Based on pre-determined functional fit (current ReEDS approach for batteries)

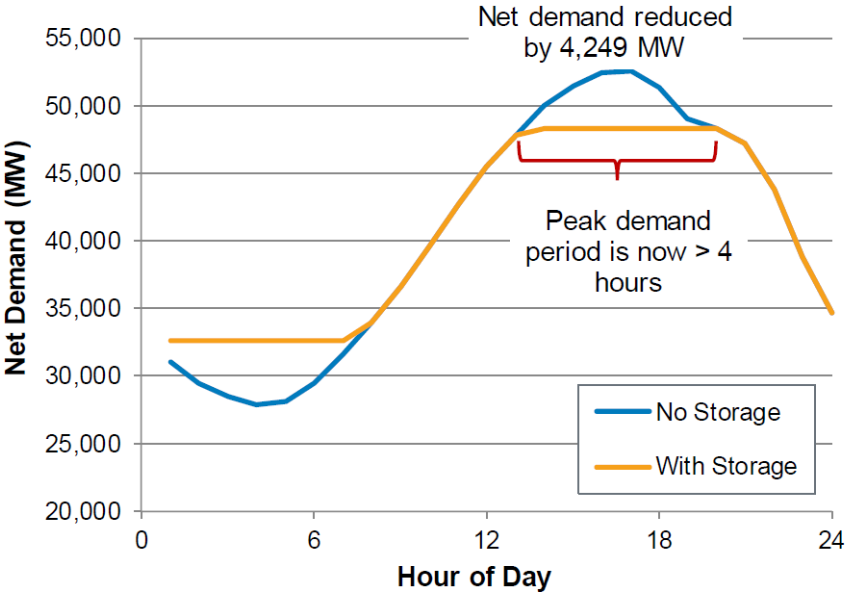


(Denholm and Margolis 2018)

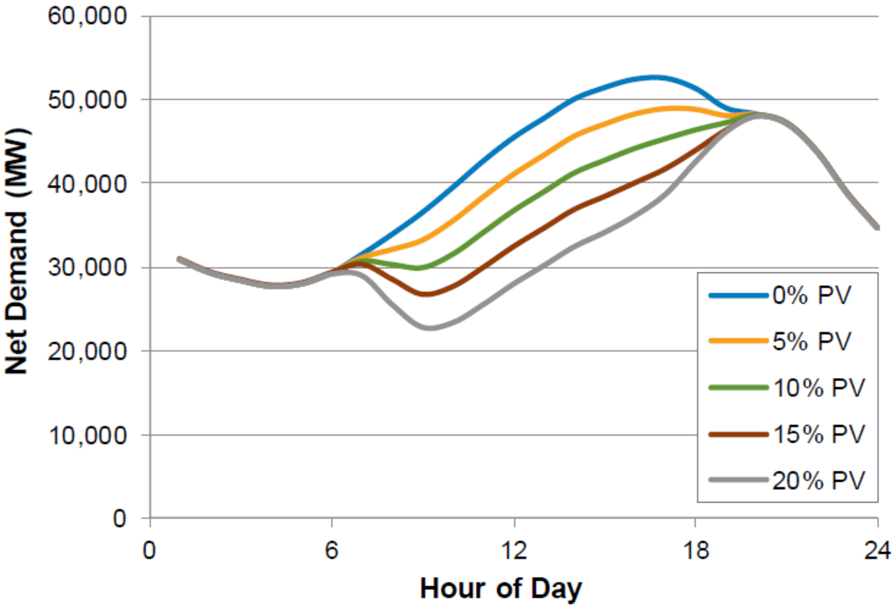
Sioshansi et al. (204) curve represents an analysis of two regions in California using multiple years of historic price and load data with storage dispatch based on electricity prices; “CPUC 4-hour rule” curve is based on resource adequacy rules for California’s investor-owned utilities

Our approach: peak net load reduction as a proxy for storage CV

The potential for storage to reduce peak net load depends on storage penetration and duration (left) and PV penetration (right)



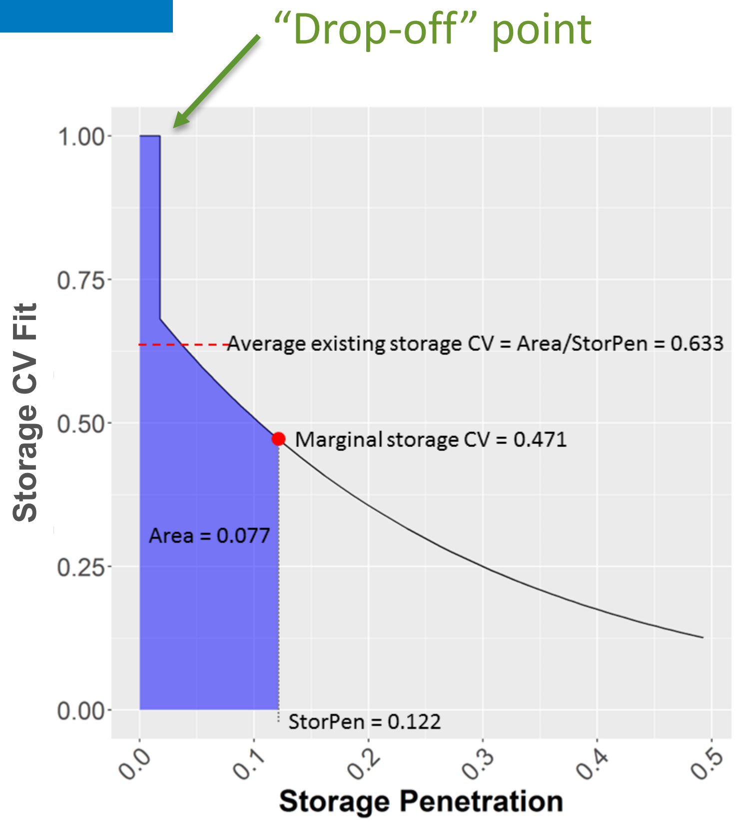
Impact of 4-hour storage dispatch on net load on the peak demand day in 2011 in California (Denholm and Margolis 2018)



Change in California net load shape due to PV (Denholm and Margolis 2018)

ReEDS dynamic storage CV method

- **3 key parameters** for battery storage CV:
  - Storage penetration (capacity-basis)
  - PV penetration (energy-basis)
  - Storage duration
- **Multiple regression fit** of peak net load reduction potential as a function of these 3 parameters
  - Based on results from NREL's REFlex model using California data for 2007-2015 (Denholm and Margolis 2018)



ReEDS “Functional Form” fit

$$MargStorCV(StorPen_{shifted}, PVPen) = \begin{cases} 1, & StorPen_{shifted} \leq drop\_fit \\ r^{StorPen_{shifted} + shape(PVPen)}, & StorPen_{shifted} > drop\_fit \end{cases}$$

Shifted to normalize across years

Piecewise logarithmic drop-off point fit, then a polynomial fit for the declining storage CV curve

Where:

“Drop-off” point

$$drop\_fit = \begin{cases} log_a(c * (PVPen - minPVPen) + 1) + minStorPen, & PVPen < minPVPen \\ log_b(d * (PVPen - minPVPen) + 1) + minStorPen, & PVPen \geq minPVPen \end{cases}$$

$$shape(PVPen) = i * PVPen^5 + j * PVPen^4 + k * PVPen^3 + l * PVPen^2 + m * PVPen + n$$

36 Scenarios
(all use low cost storage = LCS)

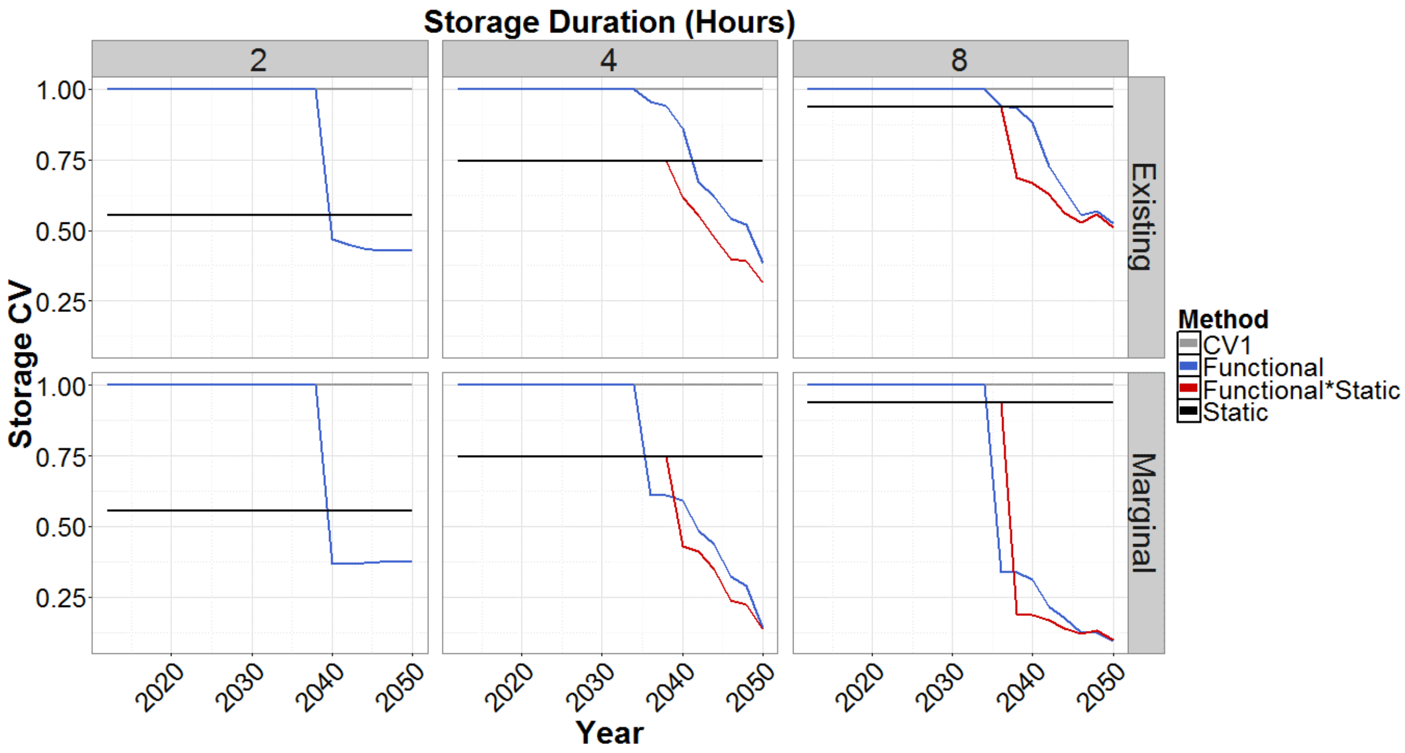
Scenario	Durations (hours)	Battery Storage CV Methods	Notes
Mid Case LCS	2, 4, 8	Static, Functional, Functional*Static, CV=1	ATB Mid Scenario with low cost storage
RPS 80 LCS	2, 4, 8	Static, Functional, Functional*Static, CV=1	RPS 80% target with low cost storage
High PV LCS	2, 4, 8	Static, Functional, Functional*Static, CV=1	Low cost PV and low cost storage

Static:
Battery CV =
- 0.555 for 2-hour
- 0.76 for 4-hour
- 0.937 for 8-hour (Sioshansi et al. 2014)

For all:
Pumped hydro and CAES CV = 1

All scenarios are derived from the 2017 NREL *Standard Scenarios* (Cole et al. 2017a), which use input cost values from the 2017 NREL Annual Technology Baseline (ATB) (NREL 2017)

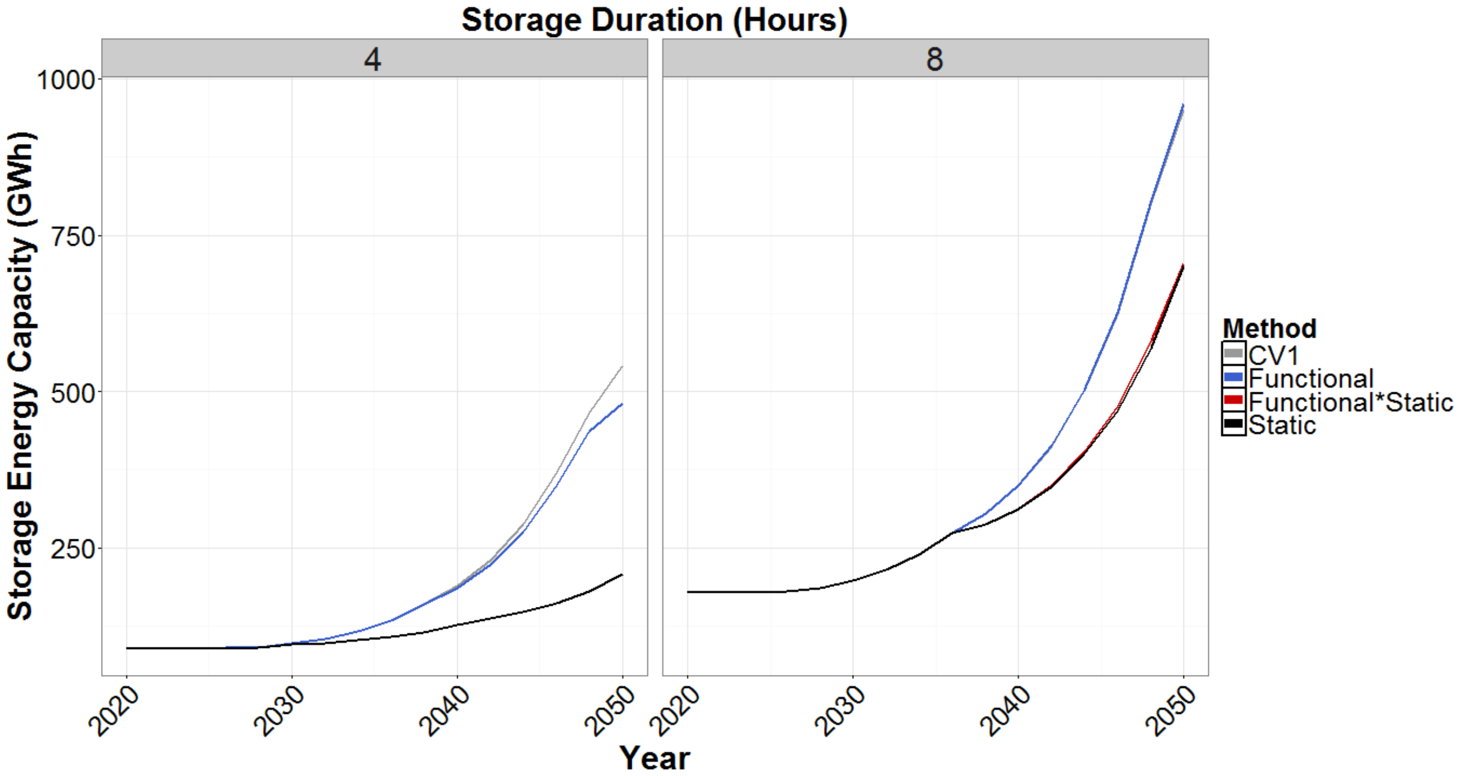
Storage CV method differences



RPS 80 LCS scenario

MISO-West RTO

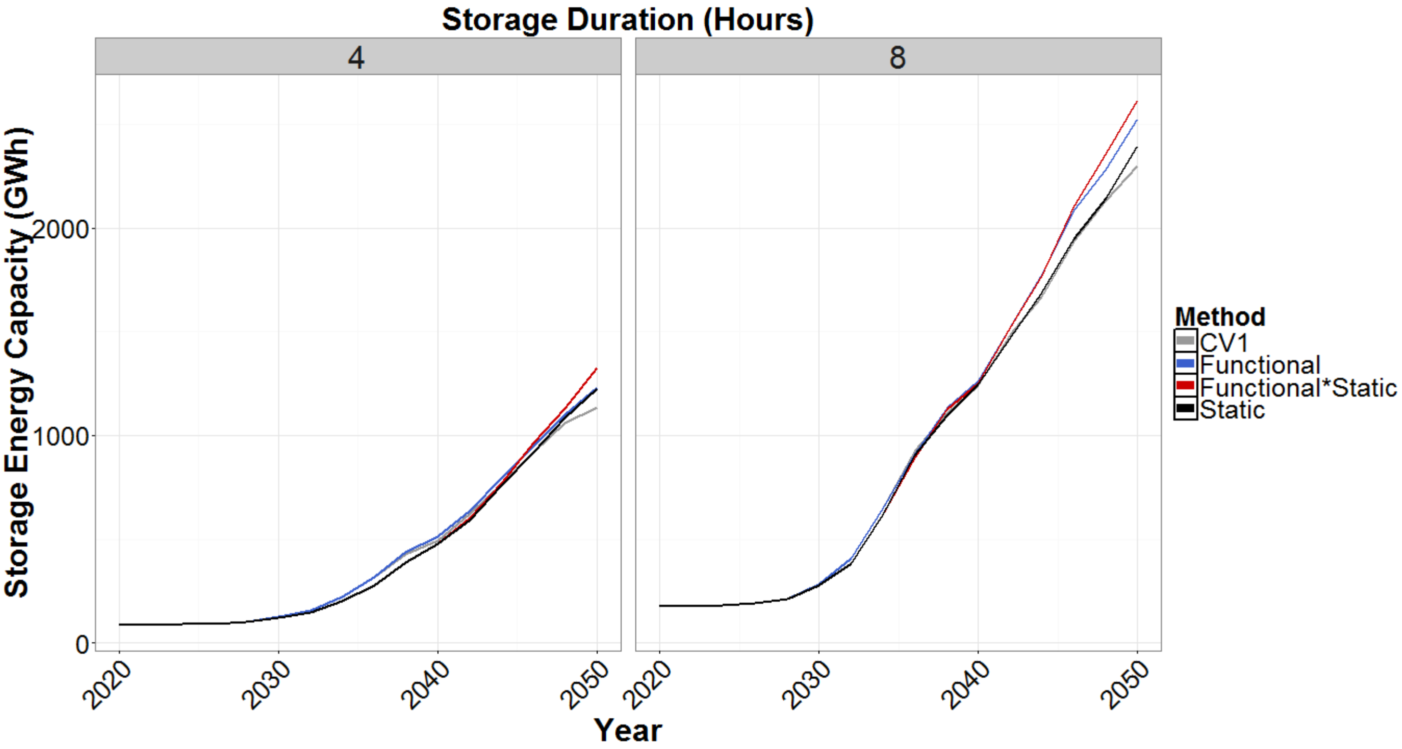
Storage deployment
(less favorable storage conditions)



ReEDS builds more storage with methods that give storage a CV of 1 for some portion of capacity

Cumulative storage deployment in ReEDS by year for each storage CV method for Mid Case LCS scenario with 4- and 8-hour durations

Storage deployment
(more favorable storage conditions)



Cumulative storage deployment in ReEDS by storage CV method for each storage CV method for RPS 80 LCS scenario with 4- and 8-hour durations

ReEDS builds more storage capacity with declining storage CVs because storage is the lowest-cost capacity resource even as the CV declines; cost of additional storage capacity is outweighed by the energy value (and other values) provided by that additional capacity

Key takeaways

- **Storage deployment is very nuanced**, driven by the value to cost tradeoff
  - Assumed cost inputs and value streams, including storage CV method
  - Relative economics of next-cheapest option (usually gas CTs)

- Larger storage deployment is seen in ReEDS (low cost storage) with:
  - Storage CV methods that assign larger CVs under less favorable storage conditions
  - Storage CV methods that assign smaller CVs under more favorable storage conditions

Next steps

- Continue to improve upon this simple dynamic storage CV method (Functional*Static)
  - Fit storage CV curves to region-specific data
  - Incorporate wind
  - Capture full set of storage value streams
  - Mixed portfolio of storage durations
  - Incorporate chronology- and forecast-error-related impacts

➢ End goal: fully endogenize

References and other resources

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Thank you

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Appendix

Functional Form fit coefficients

Functional Form fit coefficients by storage duration

	Nonlinear squares estimate											Calculated from data	
durationHr	i	j	k	l	m	n	r	a	b	c	d	minPVPen	minStorPen
2	7.29E-2	2.11	3.12E-1	-2.67E+2	-2.14E+3	1.43E+3	1.15E-1	2.09E+23	8.43E+35	1.20E+2	2.00E+1	0.09	1.961E-3
3	-2.36E+1	1.98	1.43E-1	9.78E+1	2.18E+2	-2.20E+2	5.55E-2	4.88E+7	7.29E+32	2.75E+1	5.44E+1	0.07	9.215E-3
4	-3.22E+1	1.55	6.83E-2	2.72E+2	1.29E+3	-1.01E+3	2.87E-2	1.03E+4	5.49E+20	2.01E+1	5.21E+1	0.07	1.779E-2
5	-1.47E+1	4.15E-1	2.17E-2	2.09E+2	1.22E+3	-9.12E+2	1.60E-2	2.93E+2	2.42E+16	1.49E+1	4.81E+1	0.07	3.789E-2
6	1.43E+1	-4.51E-1	-3.94E-2	-3.17E+1	6.21E+2	-2.23E+2	4.37E-3	8.47E+2	1.98E+22	2.16E+1	1.64E+2	0.07	6.010E-2
7	5.76E+1	-1.44	-8.11E-2	-5.35E+2	-2.32E+3	1.89E+3	6.17E-4	3.87E+3	1.65E+11	2.50E+1	5.06E+1	0.07	9.431E-2
8	5.83E+1	-1.97	2.30E-5	-4.95E+2	-1.95E+3	1.65E+3	2.34E-3	3.43E+2	2.57E+9	9.56	3.64E+1	0.07	1.357E-1