Impact of Dynamic Storage Capacity Valuation in Capacity Expansion Models

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Tables of Contents

List of Figures

List of Tables

1 Introduction

Capacity expansion models (CEMs) are tools commonly used by power system planners, policymakers, and other stakeholders to inform decisions regarding the buildout of the electric grid. These models range in scope from a single utility or region (WECC 2013; Mai et al. 2015) to national tools (Eurek et al. 2016; EIA 2014; EPRI 2017). In addition, a reduced form capacity expansion representation is often included in global tools called integrated assessment models (IAMs), which account for broader climate, emissions, and/or economic dynamics (Pietzcker et al. 2014; Pietzcker et al. 2017; Intergovernmental Panel on Climate Change (IPCC) 2015; Edelenbosch et al. 2017). CEMs typically solve for the least-cost portfolio of generators, transmission, storage, and other resources that are needed to reliably serve load while meeting a suite of policy and/or economic constraints. Contrary to operational models that often look at a single year of least-cost dispatch at subhourly resolution, CEMs look out years or decades into the future with a coarser temporal resolution for the system dispatch (Cole et al. 2017).

Capacity value (CV), sometimes referred to as capacity credit, is the fraction of the installed capacity that reliably contributes to meeting load during times when the system has the highest probability of not meeting load.[1] In practice, this is enforced through a load serving entity's pre-determined resource adequacy requirement, which could be a probabilistic-based target such as loss of load expectation (LOLE) or a planning reserve margin.[2] In CEMs, the capacity contribution of all resources is commonly enforced through a planning reserve requirement. The concept of CV has been widely applied to variable renewable energy (VRE) resources, namely wind and solar, e.g., (Milligan et al. 2017; Mills and Wiser 2012; Keane et al. 2011; Duignan et al. 2012; Madaeni et al. 2013), but less literature exists on how to value the capacity contribution of storage resources, e.g., (Denholm and Margolis 2018; Madaeni et al. 2011; Sioshansi et al. 2014). This is in part because the CV of storage depends on multiple system parameters, which makes the computational representation within CEMs a challenge.

For storage to achieve full CV (i.e., CV = 1), it must be able to discharge at its rated capacity for the full duration of any peak periods. Peak load and net load periods are often correlated with the times of highest probability of dropping load, and these events can span multiple consecutive hours. A longer duration storage device is more likely to fulfill this requirement, thus leading to larger CVs for longer duration storage (Sioshansi et al. 2014; EPRI 2017). However, at what point—and to what degree—storage CV declines with shorter durations is unclear.

Several jurisdictions are actively determining how to value the capacity of storage for planning purposes, generally producing duration-based CV curves or binned values. For example, the California Public Utility Commission (CPUC) has established the so called "four-hour" rule for

[1] The term "capacity credit" is sometimes used to refer to physical capacity, while "capacity value" is the economic value of that capacity (Mills and Wiser 2012). We use the term capacity value to refer to physical capacity in this paper. One true definition for this physical capacity is the Effective Load Carrying Capability (ELCC), which is the is the contribution (units of MW which can then be reported as a fraction of the installed capacity to represent CV) that an additional resource provides to meeting the system's load while maintaining a fixed system-wide reliability level.

[2] Each planning area selects its desired resource adequacy target, which is largely a political decision. For more details on resource adequacy, see (Milligan et al. 2016; Milligan, Frew, Clark, et al. 2017; Pfeifenberger et al. 2013).

the investor owned utilities in California. This requires storage resources to be capable of providing maximum power output for four consecutive hours over three consecutive days in order to be eligible to contribute to resource adequacy requirement (CPUC 2014, 2017).[3] Under this framework, resources with a duration of less than four hours will always have a CV less than one. The New York Independent System Operator (NYSIO) uses a similar four-hour rule for storage resources to be eligible to participate in the capacity market (Johal, Tome, and Collison 2016).[4] Portland General Electric (PGE) is evaluating the best way to determine the capacity contribution from storage for their IRP process, including an ELCC-based approach to better account for uncertainties (Portland General Electric 2016). In another example, an ELCC-based analysis of an ERCOT-like system concluded that storage resources with four or more hours of duration could obtain a full CV of 100%, or very close to it (Johal et al. 2016).

However, recent work reveals that the CV of storage is not just a static value based only on storage duration hours, but rather, it also varies based on the penetration levels of PV and storage (Denholm and Margolis 2018). These inter-related factors are driven by energy capacity constraints, as well as the underlying load and VRE profile shapes that define the period of peak net load (load minus VRE). For example, PV tends to reduce peak net load magnitudes, and at high enough penetration levels, PV can shorten the duration of the net peak load. The CV of storage can be further impacted by suboptimal storage dispatch decisions resulting from uncertainty, limited foresight, or price taker behavior (Sioshansi et al. 2014). In this study, we include sensitivity cases that evaluate the impact of this availability limitation by applying a derating factor to our calculated CVs.

The objective of this paper is to demonstrate the impact with a CEM of moving from a static storage CV to a curve-fitted approximation that captures the interactions between storage duration, PV penetrations, and storage penetration. We fit and then use those curves to calculate the battery storage CV as a function of the storage duration, storage penetration, and PV penetration. We use the Regional Energy Deployment System (ReEDS) model developed at the National Renewable Energy Laboratory (NREL) to show the impact of this improved storage capacity valuation on deployment. We also provide a curve fit equation for use by other modeling teams. This exogenous, but dynamic, approach is meant to be a first step in improving the representation of storage in CEMs. This simplified method is similar, but different, to other dynamic approaches that aim to improve the estimation of storage CV within CEMs (Hale et al. 2016). Additional work is needed to fully endogenize the system interactions that best characterize the capacity contribution from storage; this necessarily involves increasing model temporal resolution and allowing the interaction of multiple storage durations.

[3] The 2018 Resource Adequacy Guide (CPUC 2017) refers to "Appendix B of D.14-06-050" (CPUC 2014) to determine qualifying capacity for energy storage.
[4] We note that many system operators in the United States are currently assessing new market eligibility requirements for storage, particularly in light of the recent Federal Energy Regulatory Commission (FERC) Order 841 (see: https://www.ferc.gov/whats-new/comm-meet/2018/021518/E-1.pdf)

2 Storage CV Curves

Storage CV curves were fit to results for California from NREL's REFlex model (Denholm and Margolis 2018) as a function of storage penetration, PV penetration, and storage duration. To be consistent with the method used in REFlex, we calculate storage penetration as the battery power *capacity* divided by the instantaneous peak load, and PV penetration as the total annual PV generation *energy* divided by the total annual system load. Thus, a storage penetration of .05 means the total storage power capacity is 5% of the peak load, and a PV penetration of 0.3 means the annual generation from PV that serves load is 30% of the total annual load. Numerous curve fits were explored. We chose to implement a relatively simplistic multiple regression fit, which can be applied to other CEMs.

2.1 Curve Fit

The storage CV curves were fit to results from NREL's REFlex model using multiple years of input load and solar data for California. REFlex is a reduced-form dispatch model that calculates the supply/demand balance of an electricity system (Denholm and Hand 2011; Denholm and Margolis 2016; Denholm, Kuss, and Margolis 2013; Denholm and Margolis 2018). It performs a chronological dispatch of aggregated thermal and hydro units assuming generator flexibility limits, including ramp rates and minimum generation levels (Denholm and Hand 2011). It can also perform chronological dispatch of demand response, energy storage, and vehicle charging to evaluate methods to improve utilization of VG resources (Denholm et al. 2013). For the data used in this study, REFlex optimally dispatched storage to reduce peak net load, assuming an 80% round-trip efficiency and no storage outage rates (Denholm and Margolis 2018). This approach approximates the CV of storage as the potential of storage to reduce the peak net load.

We implemented a multiple, nonlinear regression fit, which we call the Functional Form. We selected a piecewise nonlinear curve fit because it was able to closely approximate the data we were fitting (see R-squared values in Table 1), and it provided a more simplistic representation that can be more easily applied to other models and analyses.[5]

Table 1. R-squared Values for Functional Form Fit

Duration (Hours)	Functional R-squared
2	0.9120
3	0.9599
4	0.9606
5	0.9732
6	0.9751
7	0.9733
8	0.9847

[5] We also fit the data to a gamma curve, sigmoid curve, and variations of an exponential function, but none of these other functions fit the data as well

For this work we model storage CV as a function of three parameters: PV penetration level, storage penetration level, and storage duration hours. The relationship between storage CV and two of these dimensions—PV penetration and storage penetration—is captured in Figure 1 for a storage duration of four hours.

Along the storage penetration dimension (horizonal axis in Figure 1), storage CV starts at 1 and then drops off after a certain storage penetration level, which varies by duration. This relationship between storage CV and storage penetration is further shown in Figure 2 with example of curves for the Functional Form fit for durations of two, four, and eight hours. Figure 2 illustrates the "drop-off" point, which occurs at higher storage penetration levels for larger storage durations. This drop-off point is the threshold beyond which a given storage duration can no longer discharge at its full rated capacity to reduce peak net load; in other words, the width of the peak net load period exceeds the hours of storage duration. Because a storage device would have to reduce its discharge to some fraction of its rated capacity, which declines rapidly as the peak net load width increases, storage CV similarly sees a sharp decline past the drop-off point.[6] We apply our multiple regression technique to capture this drop-off point using multiple years of data from Denholm and Margolis (2018), as well as to capture the declining storage CV curves.

The relationship between PV penetration and storage penetration at the location of each drop-off point for various storage durations is shown in Figure 3. These curves define the maximum storage penetration providing a full CV of 1. The shape of these curves is driven by the impact of PV generation on the net load shape. At lower PV penetration levels (below about 8% here), storage has a declining potential to provide a full CV of 1 because the PV flattens the net load shape. However, above this PV penetration threshold (i.e., the inflexion point or "dip" in Figure 3), storage has an increasing potential to provide a full CV of 1 because PV creates a "peakier" net load shape (Denholm and Margolis 2018).

[6] See Denholm and Margolis (2018) for further explanation of the interaction between storage duration and peak net load reduction potential. The point at which storage can no longer provide full CV is typically where the width is significantly wider than the storage device as the first units of storage reduce the shoulders.

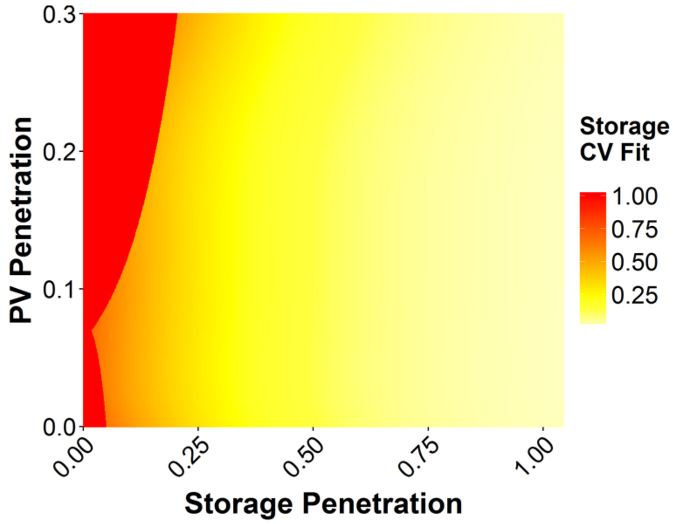
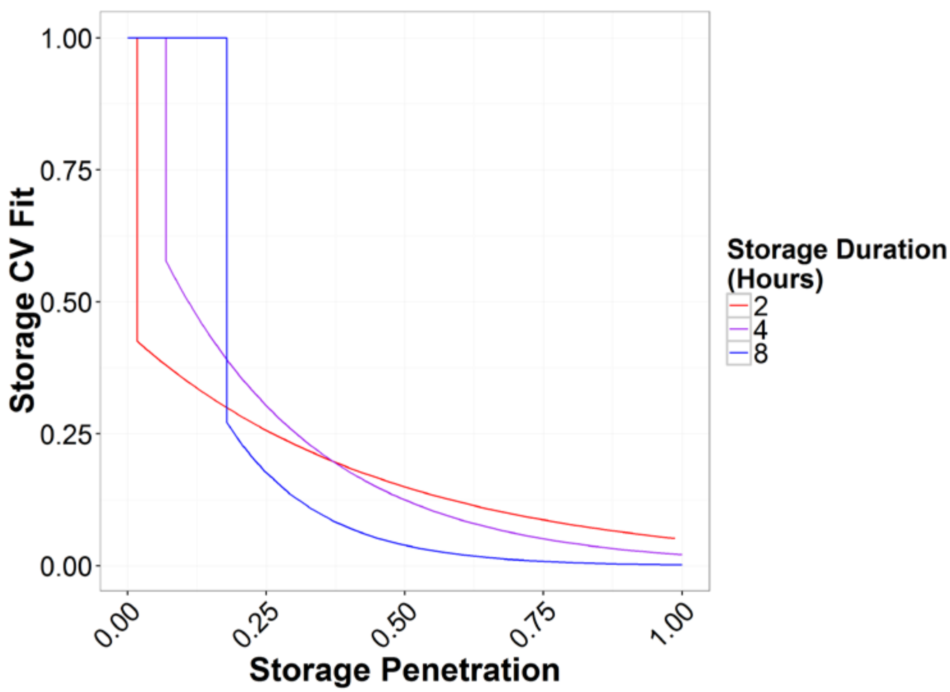


Figure 1. Marginal Storage CV as a function of PV and storage penetration with four-hour storage-duration



The “drop-off” point is where the storage CV drops below a value of 1.

Figure 2. Storage CV curves for Functional Form fit with storage durations of two, four, and eight hours and PV penetration of 10%

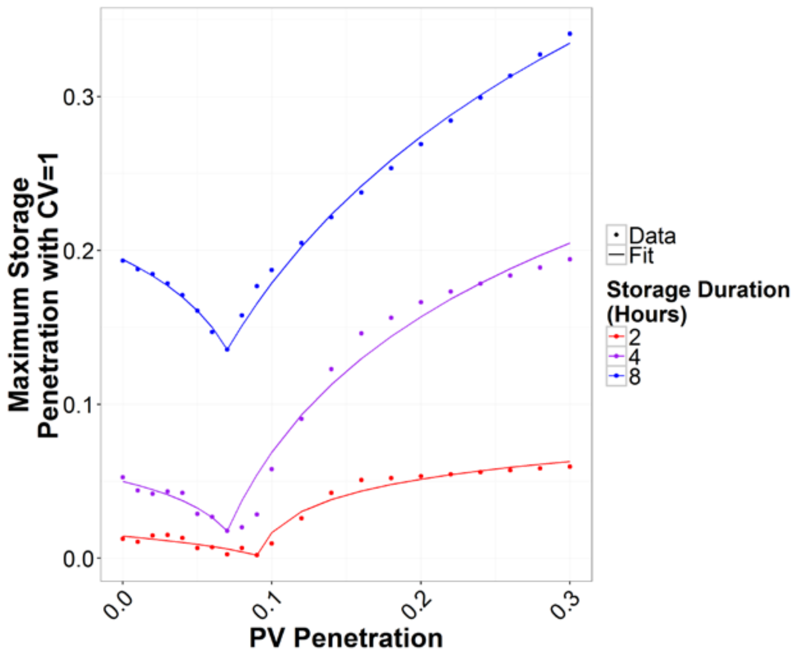


Figure 3. Functional Form fit and underlying data of the "drop-off" point where storage CV drops below 1, as a function of storage penetration and PV penetration with storage durations of two, four, and eight hours

The Functional Form fit was created for each storage duration using the following functions, which include both a function to determine the point at which storage CV is no longer one (drop_fit) and a polynomial fit for how the CV declines:

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

Where:

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

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

To normalize the storage CV curves for each year of data to a consistent drop-off point, each raw data drop-off point was shifted along the storage penetration dimension, as reflected by the $StorPen_{shifted}$ value, based on the piecewise logarithmic fit. Nonlinear least-squares estimates were determined for the parameters of the drop-off point and polynomial curve using the Levenberg-Marquardt algorithm (Elzhov et al. 2016); these parameters are summarized in Table 2.

Table 2. 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

For each storage duration, the *minPVPen* and *minStorPen* values correspond to the drop-off point with the lowest storage penetration for each storage duration. These values occur at the inflexion point (i.e., the "dip") for each storage duration in the Functional Form piecewise logarithmic curves in Figure 3. Figure 4 shows parity plots of the storage CV Functional Form fit against raw data by storage duration for all storage penetration levels (indicated by color) and all PV penetration levels (embedded). Though the fit is far from perfect, our objective is to capture the behavior of declining CV. A more precise fit of the data would not necessarily be superior given that we are considering peak not load reductions and not ELCC estimates.

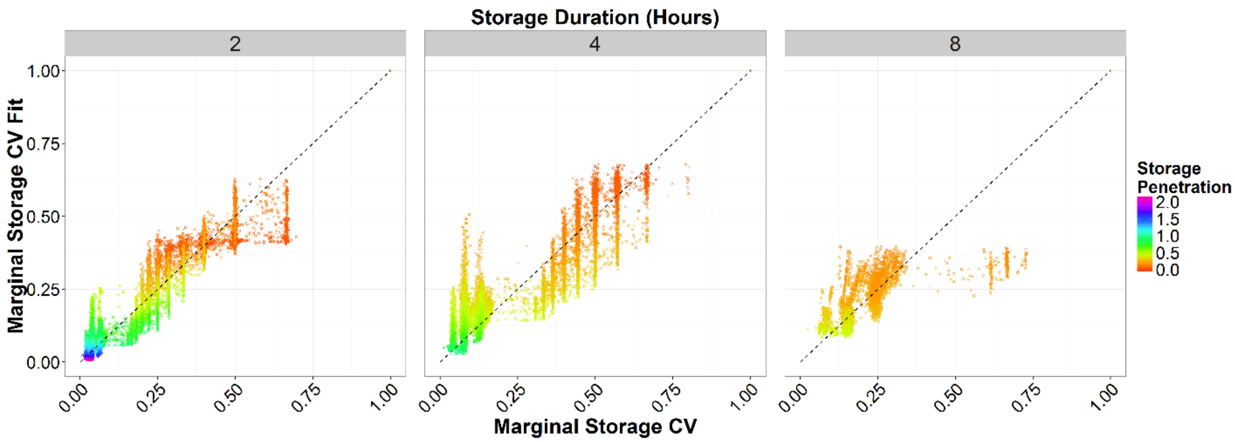


Figure 4. Parity plots of Functional Form curve fit of storage CV for all PV penetration levels, demarcated by storage penetration and storage duration hours

2.2 Existing versus New Storage CV

The improved storage CV method described here uses the existing battery storage penetration, existing PV penetration, and assumed battery storage duration outputs from a sequentially-optimized CEM. These values are then fed into the Functional Form curve fit described in Section 2.1 to calculate storage CV for battery storage capacity that is already deployed and marginal battery storage CV for new deployment in the subsequent CEM solve period.

With the Functional Form fit, existing storage CV is calculated by integrating along the given PV penetration curve from 0 to the current storage penetration (purple area in Figure 5).[7] This integration value is then divided by the storage penetration to return an average existing storage CV that is then applied to all existing storage (dashed red line in Figure 5). The marginal storage CV is the rightmost value along the storage CV curve where the curve intersects the storage penetration area, as shown by the red point in Figure 5.

[7] For a more exact fit to the PV penetration level, a linear interpolation is conducted between resulting integration values between individual discrete PV penetration curves.

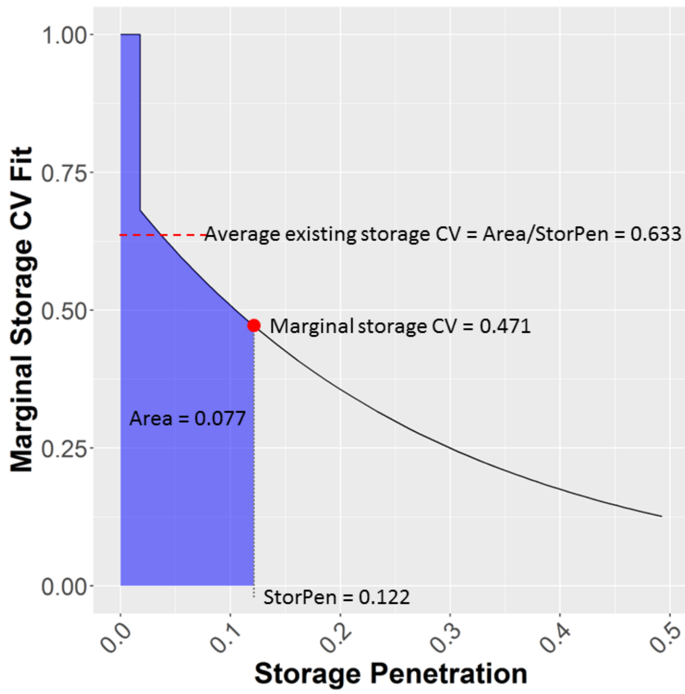


Figure 5. Illustration of the calculation of marginal and existing storage CV with the Functional Form curve fit for PV penetration of 7% and storage duration of four hours

3 Overview of Tools and Scenarios

We use the ReEDS CEM to examine the impact of an improved capacity valuation of storage. ReEDS is a CEM of the contiguous United States developed in the General Algebraic Modeling System (GAMS) (Eurek et al. 2016). ReEDS optimizes the regional mix of technologies that meets physical and policy requirements of the electric sector at least cost. The model is spatially resolved into 134 load balancing regions. Load balancing, planning reserve requirements, and most policy and operational constraints are applied at these 134 regions. These regions are also aggregated into 18 Regional Transmission Operators (RTOs) that very roughly represent regional cooperation areas. ReEDS is temporally resolved into 17 "timeslices" to capture seasonal and diurnal variations in load and resources. ReEDS optimizes investment decisions within two-year solve periods, sequentially solving from the present-day system out to the model horizon of 2050.

For determining how much firm capacity is needed, ReEDS employs a planning reserve margin that ensures total firm capacity is at least the peak demand plus the reserve margin. Storage can contribute to the firm capacity requirement, where firm capacity from storage is equal to the storage capacity times its CV. ReEDS previously approximated storage CV as a static value across all penetration levels (i.e., the storage CV did not change as a function of the grid mix or the amount of storage on the system), using preset duration-based values from Sioshansi et al. (2014) for battery storage (see "Static" entry in Table 4 for a summary of all previously assumed storage CVs in ReEDS). In our improved storage CV approach, we update the storage CV between each of the two-year solve periods to allow for the declining value of storage capacity with greater storage deployment, as well as the dynamic interaction with PV deployment and storage duration. These updated values are based on the Functional Form curve fit defined in Section 2.1 using the given storage duration value and the previous solve period's PV and storage penetration levels. Storage CVs are calculated for both the storage capacity that has already been deployed in the model and for the marginal next unit of new storage capacity.[8]

Within ReEDS, the calculated storage CV parameters feed into a planning reserve constraint, which typically ensures sufficient capacity is available during the annual peak demand period. This approach is consistent with many other CEMs and IAMs (IRENA 2017). Thus, these CV metrics inform the investment decision of new storage (as well as VRE resources, which have a separate capacity valuation treatment, see Frew et al. (2017)) by impacting the *capacity*-based value of those new additions. Both the existing and marginal battery storage CV are calculated at the ReEDS RTO level and then mapped to the BA level for implementation within the planning reserve constraint.

To evaluate the impact of implementing a multi-dimensional function to approximate storage CV in ReEDS, we ran three scenario settings for three different storage durations, each across four different storage CV methods: ReEDS former static value, Functional Form fit, Functional Form fit derated by ReEDS former static value to account for storage availability limitations, and CV set to 1. These 36 scenarios are summarized in Table 3, and the CV methods are further described in Table 4.

[8] For our application in ReEDS, we apply this dynamic storage CV approach only to battery storage. ReEDS applies a static CV for all other storage technologies.

Table 3. Scenario Matrix to Evaluate Storage CV Method in ReEDS

LCS=low cost storage; RPS = renewable portfolio standard

Scenario	Durations (hours)	Storage CV Methods	Notes[9]
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

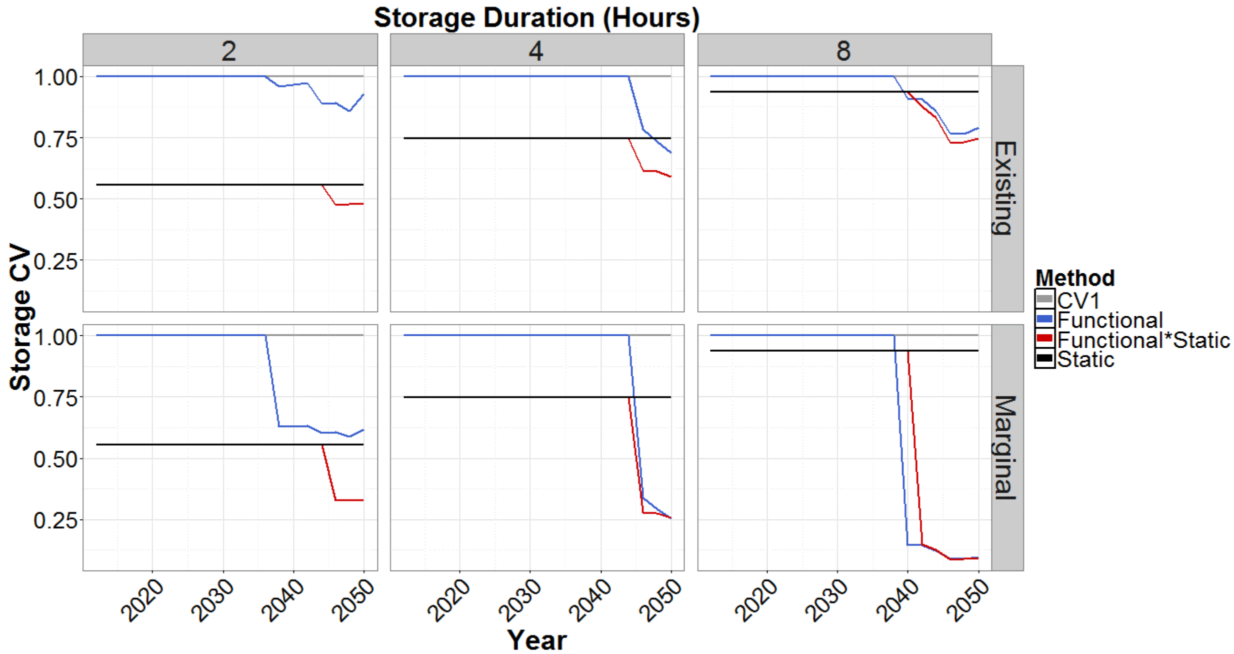
Table 4. Summary of CV Methods Evaluated

CV method	Summary of Values	Notes
Static	Battery = 0.555 for two-hour duration 0.76 for four-hour duration 0.937 for eight-hour duration Pumped hydro and CAES =1	Battery values from (Sioshansi, Madaeni, and Denholm 2014)
Functional	See Section 2.1	
Functional*Static	Battery values from "Static" multiplied by "Functional" values	
CV=1	CV=1 for battery, pumped hydro, and CAES	

4 Results

The results from various static and dynamic storage CV formulations are shown in Figure 6 for two ReEDS RTO regions: the Virginia-Carolinas (VACAR) and the western portion of the Midcontinent Independent System Operator (MISO-West). Both set of results are from the RPS 80 LCS scenario. Because the longer duration storage cases result in more storage deployment (not shown here), the two- and eight-hour duration cases see a sharper overall decline in CV in Figure 6, while two-hour duration storage remains closer to the initial CV for much of the time horizon. In Figure 6, the declining storage CVs are not always perfectly smooth due to year-to-year changes in PV penetration and growth in the peak load. Note that in all cases, the "CV1" and "Functional" storage CVs overlap in early years, and the "Functional*Static" and "Static" values overlap until storage CV begins to decline. Also note that all storage CVs presented in this Results section are only for battery storage, while all storage deployment results include all storage technologies.

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



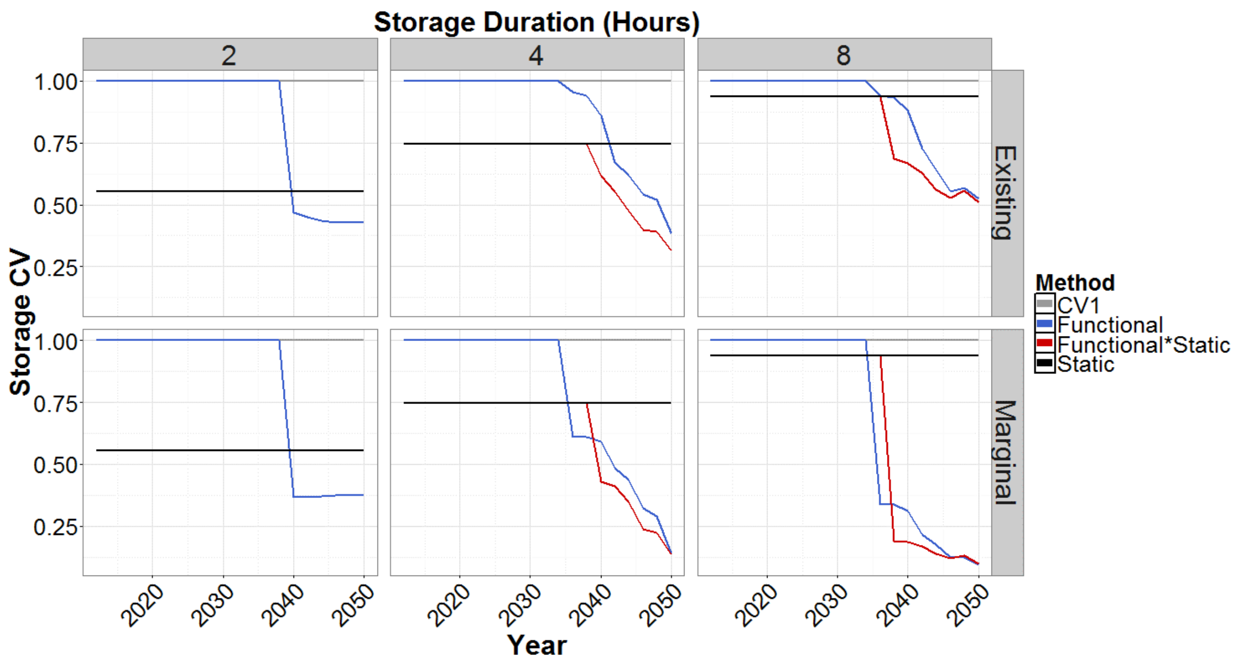


Figure 6. Battery storage CV for existing and new capacity by duration and CV method for VACAR (top) and MISO-West (bottom) for RPS 80 LCS scenario

4.1 Storage Deployment Magnitude and Timing are Sensitive to all Cost and Value Components

Storage deployment is driven by the value to cost tradeoff of storage. We assume low storage costs for all scenarios evaluated here. The value streams for storage include energy, capacity, and ancillary services. While the focus here is on the capacity value stream, as impacted by the chosen storage CV method, we find that storage deployment is sensitive to all of the above costs and values, including the relative economics of competing resources. Due to high reserve margins in the near-term (most regions in today's system are long on capacity) coupled with the assumed storage cost reductions, ReEDS does not build new storage capacity until the 2020s. Nearly all new storage deployment is battery storage. We observe two opposing trends in this deployment, depending on the relative tradeoff of cost and value. First, when conditions are less economically favorable for storage, storage deployment is greater with methods that assign larger relative CVs. However, in scenarios with more favorable economic conditions for storage, such as the RPS 80 LCS,[10] larger storage deployment is observed with declining storage CV.

For the first trend, there is a noticeable and sometimes persistent benefit to storage deployment with methods that employ a storage CV of 1 for even just a small amount of deployment (i.e., "CV1" and "Functional"). In these cases, we tend to see earlier and/or larger storage deployment. This is demonstrated in Figure 7 for the Mid Case LCS scenario where the methods that give storage a CV of 1 for some portion of capacity have delineation from methods that always assign storage a CV less than 1 (i.e., the ReEDS former "Static" method and "Functional*Static"); refer back to Figure 6 for an example of how these methods differ.

The left panel in Figure 7 with four-hour duration shows earlier and larger deployment of storage capacity with the methods that give storage a CV of 1 for some portion of capacity. This trend is driven by battery deployment that begins in the late-2020s. As we later discuss in Section 4.2, the divergence between larger versus smaller storage deployment is driven in part by the relative economic competitiveness of storage capacity with alternative new generation capacity from natural gas CTs.

In the right panel of Figure 7, the eight-hour duration case sees less divergence in deployment in early years, as all storage CV methods with this duration begin with similarly high CVs at or closer to 1. However, deployment delineates in later years between the methods which maintain a storage CV of 1 (i.e., "CV1" and "Functional") and methods with lower storage CVs (i.e., "Functional*Static" and "Static"). In this eight-hour case, the high CV methods again yield both earlier and larger buildout of storage.

[10] Storage is more favorable in this high RPS target scenario because it provides greater overall value with higher shares of wind and/or solar deployment. And because the RPS target is defined on a generation basis, the ability of storage to recover curtailed renewable energy becomes especially valuable.

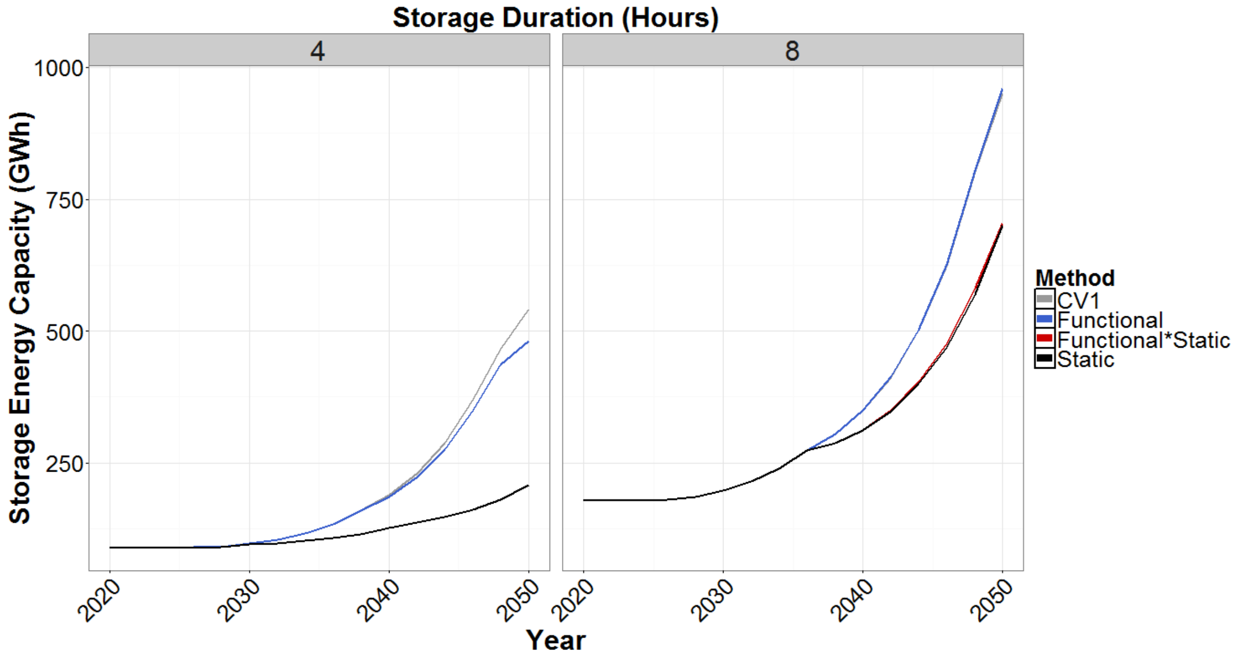


Figure 7. Cumulative nationwide storage deployment in ReEDS by year for each storage CV method for Mid Case LCS scenario with four- and eight-hour durations

The second key trend is contrary to the results presented thus far. We find that in some cases—particularly in scenarios with more favorable conditions for storage deployment, such as the RPS 80 LCS scenario (Figure 8)—ReEDS builds more storage capacity with declining storage CVs because storage is the lowest-cost/highest-value capacity resource even as the CV declines. In other words, the cost of additional storage capacity is outweighed by the energy value (and other values) provided by that additional capacity. This can be seen in Figure 8, where the greatest cumulative storage capacity in 2050 is realized with storage CV methods that eventually reach the smallest storage CVs after passing the "drop off" point in the underlying storage CV curves (i.e., "Functional" blue line and "Functional*Static" red line). This is reflected by the marginal storage CVs observed in the bottom rows for each region in Figure 6 for four- and eight-hour durations, where the drop-off points occur roughly around 2040, corresponding to the delineation observed in Figure 8.

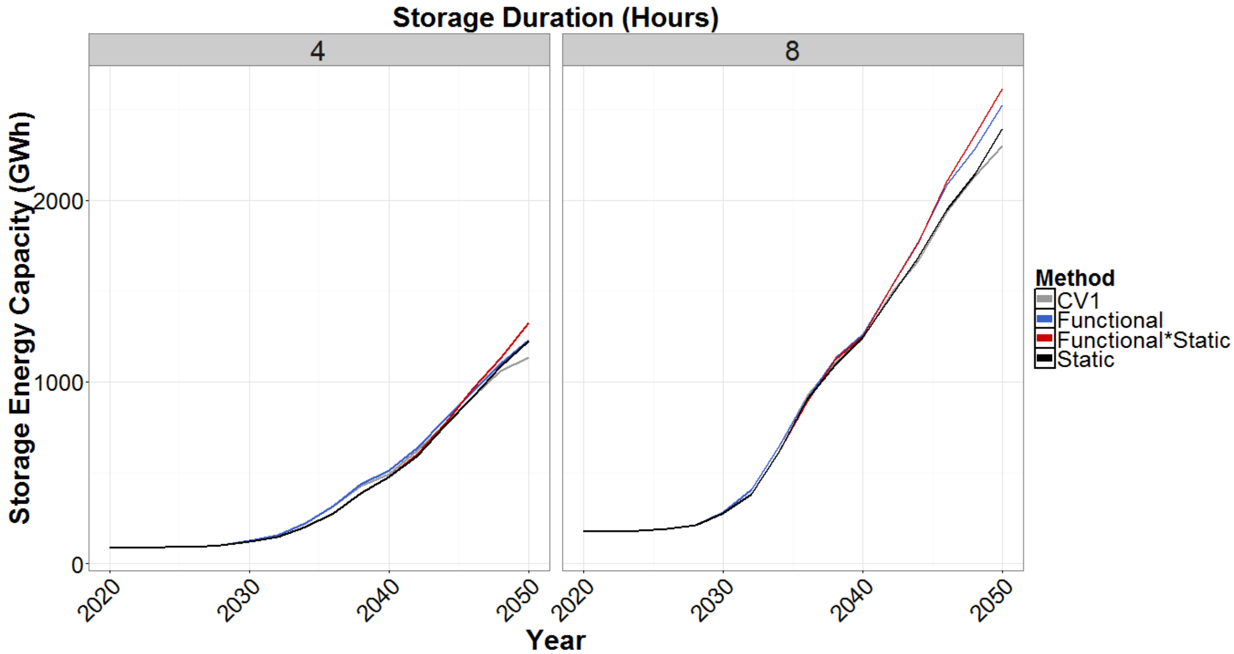


Figure 8. Cumulative nationwide storage deployment in ReEDS by storage CV method for RPS 80 LCS scenario with hour- and eight-hour durations

Storage deployment results like those shown in Figure 7 and Figure 8 are included in Appendix A for all scenarios, storage CV methods, and battery storage durations. Trends are similar between the High PV LCS and Mid LSC scenarios, with noticeably more storage deployed in the High PV LSC scenario because of the synergistic relationship with greater PV deployment realized in this low-cost PV case. The RPS 80 LCS scenario sees the highest overall storage deployment of the three scenarios because of the high deployment of both wind and solar.

4.2 Storage Deployment is Strongly Dependent on Relative Cost with New Capacity

Section 4.1 showed that storage deployment is a function of the tradeoff in capacity cost with all value streams. This tradeoff can be further explained by the relative economic value of alternative new capacity. Storage and natural gas CTs are typically the least-expensive new capacity in these scenarios.[11] Thus, ReEDS will build more storage capacity at lower storage CVs if the resulting capacity cost, minus all value streams, is less expensive for storage than natural gas CTs; otherwise, natural gas CTs are built.

An illustration of this tradeoff is conceptualized in Figure 9. The vertical axis is the storage CV by duration that would result in storage capital costs equivalent to natural gas CT capital costs, using the same capital costs as those implemented in ReEDS for the scenarios in Table 3.[12] For reference, these capital costs are summarized in Appendix B. The horizontal axis reflects different storage durations. When the storage CV is larger than the resulting tradeoff line, i.e., the pink up arrow, new storage capacity is more cost competitive than natural gas CT capacity on a

[11] Note that all scenarios considered here assume low storage costs.

[12] This assumes that natural gas CTs receive a CV of 1.

purely capacity basis (i.e., ignoring any other value streams of storage). When the storage CV is less than this line, i.e., the brown down arrow, ReEDS will choose to build natural gas CTs instead. Note that this illustration only accounts for one dimension—capital costs—of the feasible space for storage. Other costs and value streams can change the value proposition for storage. For example, the energy value of storage increases with larger durations, making the tradeoff point with natural gas CTs lower than the storage CV indicated by this figure. Furthermore, the storage CVs greater than 1 in this figure illustrate the storage CV mathematically required to be economically competitive with gas CTs at the assumed prices; a battery storage CV greater than 1 is not physically possible.

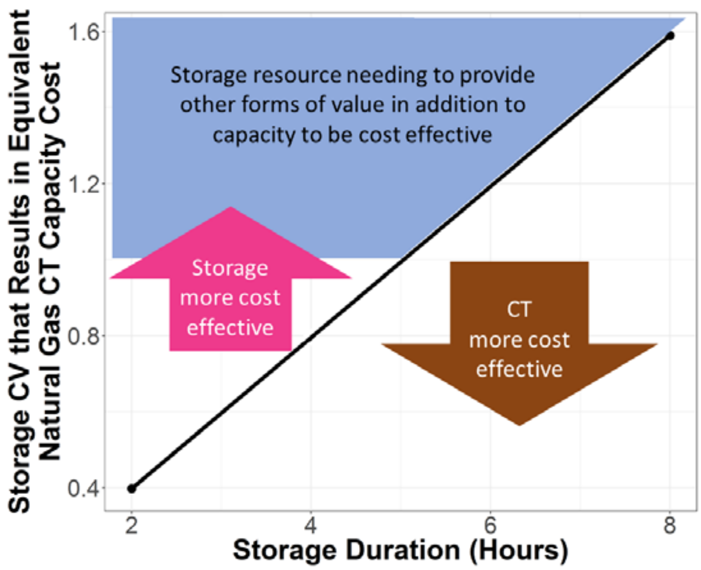


Figure 9. Storage CV (vertical axis) by duration (horizontal axis) that results in equivalent capacity cost for natural gas CT generator using 2030 capital costs and assuming all other value streams of storage are zero

An example of the storage and natural gas CT tradeoff is shown in Figure 10 and Figure 11 for the Mid Case LCS scenario with two hours of duration. Figure 10 shows the storage deployment, while Figure 11 is the difference in capacity for all resources relative to the former ReEDS "Static" storage CV method in 2050. In Figure 10, more storage is deployed for methods with a larger storage CV ("CV1" and "Functional") In these cases, the storage CV is above the threshold line in Figure 9, making storage more cost effective than natural gas CTs, as seen by the tradeoff between battery storage and natural gas CTs in Figure 11.

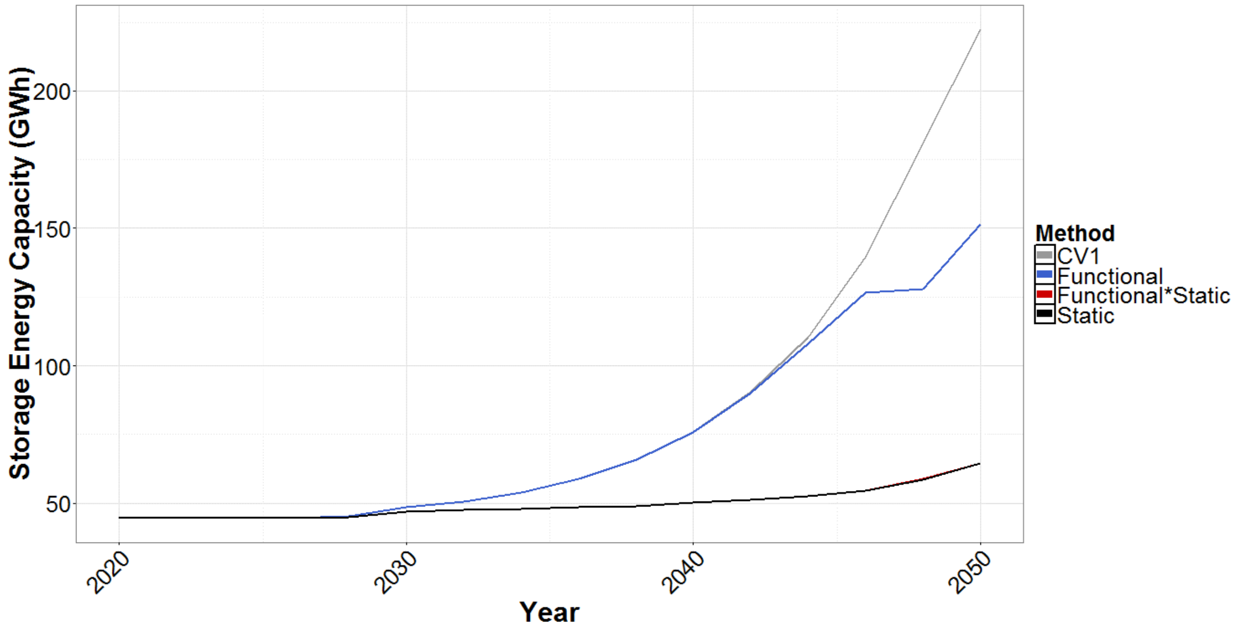
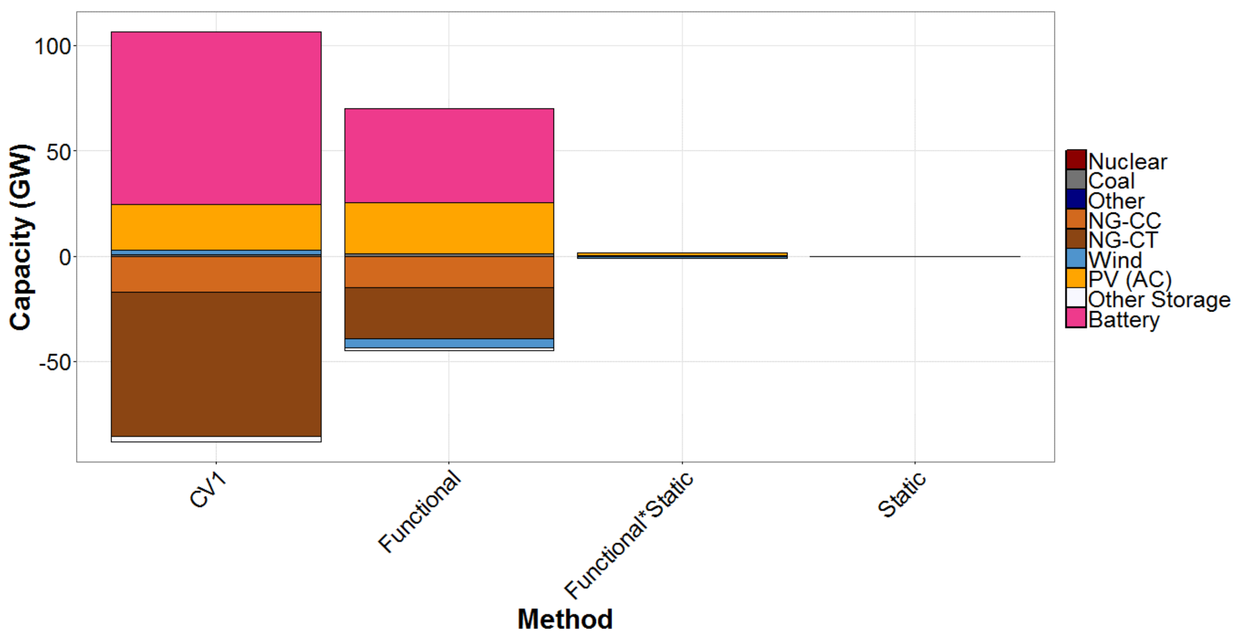


Figure 10. Cumulative nationwide storage deployment in ReEDS by storage CV method for Mid Case LCS scenario with two-hour duration



Differences are storage CV method minus "Static."

"Other Storage" includes CAES and pumped hydro; "PV (AC)" includes utility-scale PV and distributed PV; "Wind" includes land-based and offshore wind; "Coal" includes multiple coal technology types; and "Other" includes CSP, Biomass, Geothermal, Hydropower, and Oil-Gas-Steam.

Figure 11. Cumulative nationwide capacity difference in 2050 by technology type for each storage CV method relative to former ReEDS "Static" method for Mid Case LCS scenario with two-hour duration

5 Summary and Next Steps

Storage is a complicated, multi-faceted grid resource that presents many opportunities and challenges within a modeling framework. This paper set out to show the impact of more accurately representing the capacity value of storage in the ReEDS capacity expansion model. We specifically focused on an improved storage CV method capturing the interaction between PV penetration levels, storage penetration levels, and storage duration. This method fits data with a series of functional form curves to characterize the peak load reduction potential from storage at various PV penetrations, storage penetrations, and storage durations; we use this as a proxy for battery storage capacity value and update the resulting battery storage CVs in ReEDS between each solve period based on these fitted curves. We compare this approach against the former ReEDS method, which assumes static battery storage CVs, as well as a static CV of 1 case. We also include an availability-constrained case, which derates the functional form by the former ReEDS static value to account for uncertainty in electricity demand, storage dispatch, and generator outages, which could lead to times when these factors result in supply scarcity.

In attempting to show how our new CV method impacted storage deployment, our analysis revealed a more nuanced picture for storage deployment. A key piece to this puzzle is the tradeoff between the value of storage capacity and the value of storage energy, as well as the relative capacity-value-adjusted costs for storage versus those for alternative new capacity, namely natural gas CTs.

Moving forward, we recommend using our most conservative method, the derated "Functional*Static" method, for characterizing storage CV, due to our findings and the uncertainty in our fitted curves. However, future work should continue to build upon the methods and results presented here to improve the representation of storage in planning models. Some considerations for modeling storage include the following:

- **PV and storage penetration levels:** PV and storage resources have a synergistic relationship; PV deployment—after a certain penetration level—can result in a net load profile that enables storage to provide more peak net load reduction, and the energy value of storage can help PV become more economic. The exact relationship between PV and storage depends on the penetration level of both resources and the load shapes in each region. Future modeling efforts should continue to develop methods that captures these dynamics, eventually in a fully endogenized approach.
- **Storage duration:** Storage CV depends on storage duration, and different battery storage durations have different cost and value profiles. Future modeling efforts should continue to represent these various storage CV relationships and economic tradeoffs.
- **Full set of value streams:** This analysis focused on the capacity value and, at least in part, the energy value of storage. A primary driver in the deployment results was the relative cost for alternative new capacity (CTs) versus the value of storage. To more accurately capture this tradeoff, future work should consider the full set of value streams of storage (e.g., energy value and ancillary service value).
- **Portfolio of multiple storage durations:** The methods used in this analysis considered the CV and deployment of a single duration level of battery storage. Future work will extend the curve fitting method to evaluate the peak load reduction potential from a portfolio of multiple

storage duration battery options. More work is needed to determine an appropriate order of priority or other assumptions for operating such a portfolio.

- **Storage costs:** All ReEDS results presented here assumed low storage cost projections, which resulted in relatively high storage deployment levels. Future work should update these cost projections and ensure they are reasonable.
- **Chronology considerations:** Because storage is energy constrained, the chronology-related assumptions for how to operate storage can play a significant role in the reliable capacity contribution of storage. For example, if a contingency occurs immediately after storage discharges to reduce peak demand, storage has no available capacity to contribute during that critical period. Similarly, a lack of perfect knowledge of when peak demand will occur can lead to suboptimal discharging of storage that lends it unavailable during times of high need. Future work should account for these chronology- and forecast error-related impacts, potentially with probability-based or other robust methods that capture a wider set of possible system states.
- **Wind penetration level:** The impact of other VRE resources, namely wind, on the CV of storage was not considered in this analysis. Future work will extend the underlying data sets used to fit the storage CV curves to include wind penetration levels.
- **Regional differences:** The work here applied storage CV curves fitted to California data to all regions across the contiguous United States. Future work will fit storage CV curves to region-specific data sets to more accurately capture the interactions between load, VRE resources, and storage. For instance, regional differences in load and VRE profile shapes could affect the contributions that various storage durations have on reducing peak load.

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Appendix A: Storage Deployment Results from All Scenarios and Storage Durations

Total cumulative nationwide storage deployment from ReEDS for all years for the three scenarios with all storage CV methods and battery storage durations are shown in Figures A-1 to A-3.

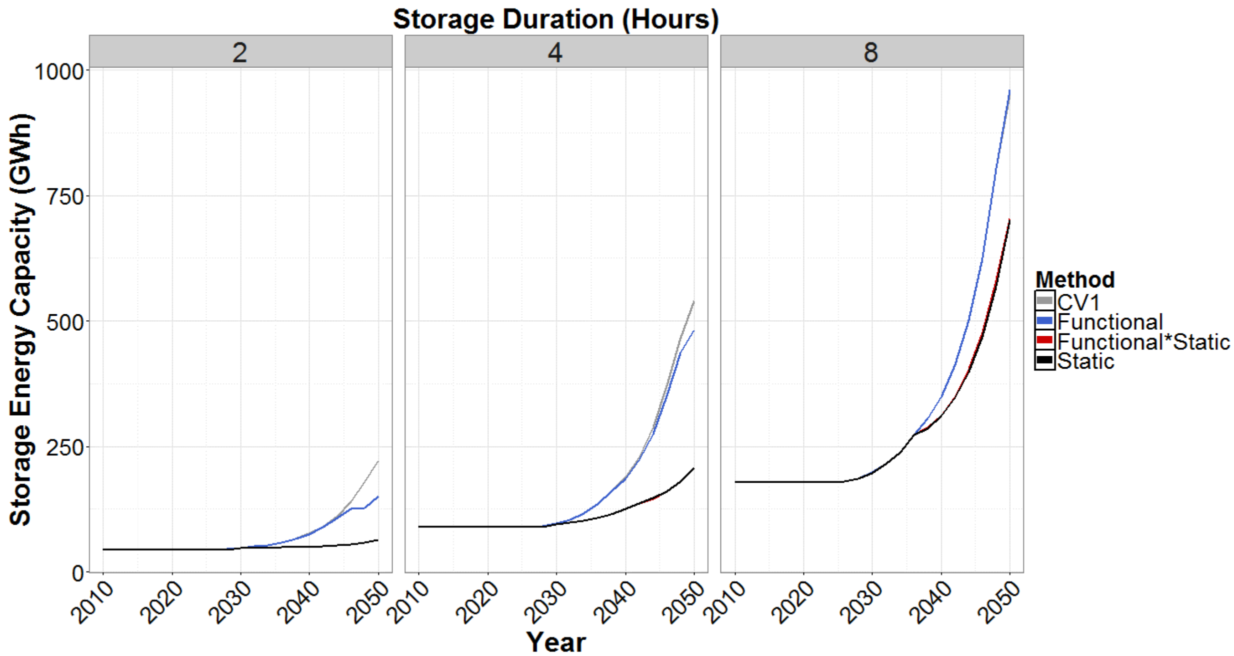

Figure A-1. Cumulative nationwide storage deployment in ReEDS by year for each storage CV method and battery duration for Mid Case LCS scenario.

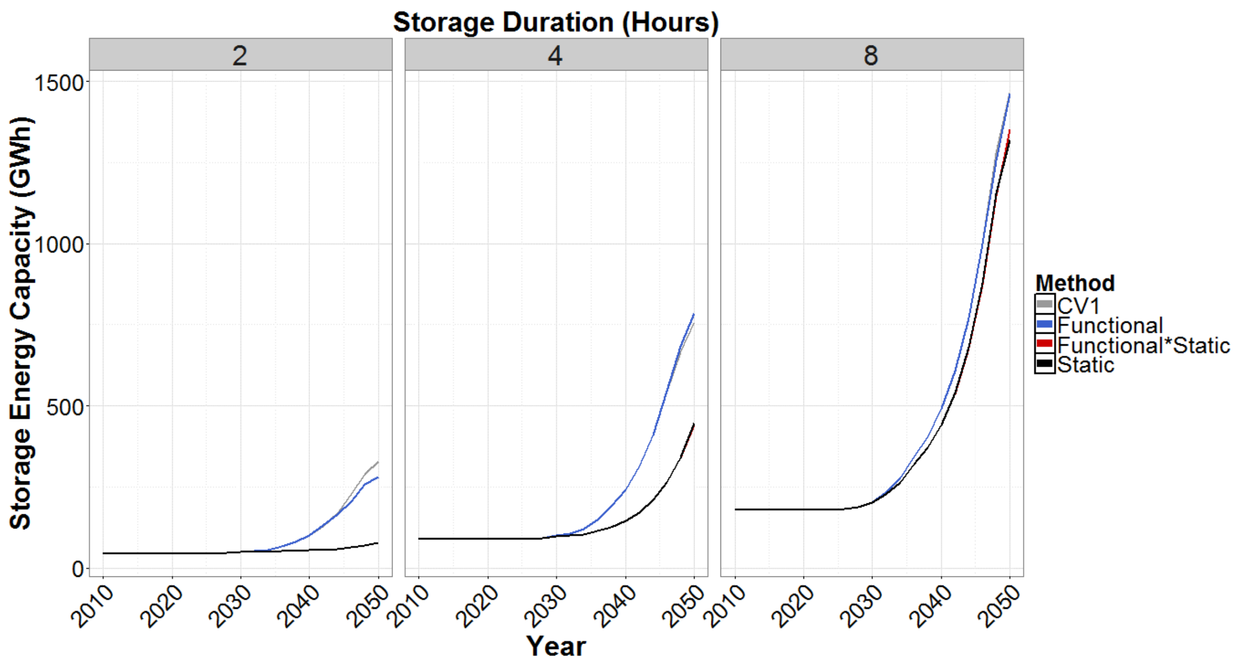

Figure A-2. Cumulative nationwide storage deployment in ReEDS by year for each storage CV method and battery duration for High PV LCS scenario.

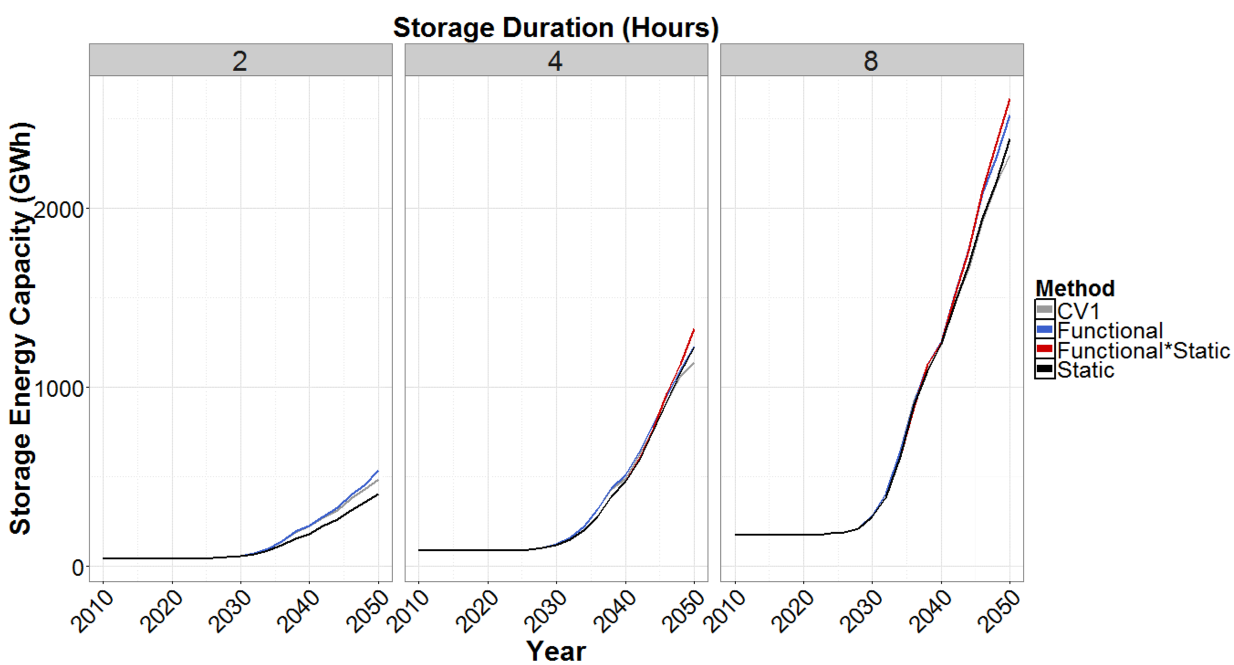

Figure A-3. Cumulative nationwide storage deployment in ReEDS by year for each storage CV method and battery duration for RPS 80 LCS scenario.

Appendix B: Battery and Natural Gas Combustion Turbine Costs

The capital cost assumptions used in this study for battery storage and natural gas combustion turbines are summarized in Table B-1.

Table B-1. Battery Storage and Natural Gas Combustion Turbine (NG-CT) Capital Costs ($/kW in 2016$)

Year	Battery			NG-CT
	Eight-Hour	Four-Hour	Two-Hour	
2016	3,752	2,207	1,435	864
2018	3,010	1,820	1,225	862
2020	2,267	1,432	1,014	857
2022	1,949	1,256	910	856
2024	1,631	1,081	806	852
2026	1,389	944	721	845
2028	1,224	845	655	831
2030	1,060	746	589	819
2032	1,012	706	553	810
2034	963	665	516	803
2036	918	626	480	796
2038	875	588	445	789
2040	832	551	410	782
2042	823	546	407	777
2044	813	541	405	772
2046	804	536	403	769
2048	795	532	400	765
2050	786	527	398	757