



SPECs Early-Stage Decision Model

User's Manual

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SPECs
Solar-Plus for Electric Co-ops



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The SPECs ESD Model is presented as an open-access software tool, suited to user customization, and the authors welcome comments on the model or on this manual, which may contribute to subsequent versions of this publication.

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Further information posted at [Solar Plus for Electric Co-ops](#)

Disclaimer

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1 INTRODUCTION

The [Solar Energy Innovation Network](#) is a collaborative research effort led by the National Renewable Energy Laboratory (NREL) and supported by the U.S. DOE Solar Energy Technologies Office. The Innovation Network supports teams across the United States that are pursuing novel applications of solar and other distributed energy resources by providing critical technical expertise and facilitated stakeholder engagement. This support gives the teams a wide range of tools to realize their innovations in real-world contexts. Teams are composed of diverse stakeholders to ensure all perspectives are heard, key barriers are identified, and the resulting solutions are robust and ready for replication in other contexts.

Solar-Plus for Electric Co-ops (SPECs) is a project led by Cliburn and Associates, LLC, with the North Carolina Clean Energy Technology Center (NCCETC) and co-funded by the Solar Energy Innovation Network. SPECs aims to increase the pace and impact of front-of-the-meter (FTM), solar-plus-storage procurements for electric cooperative utilities (co-ops). Electric distribution co-ops are a primary target audience, but local public power utilities, wholesale power suppliers, and other entities sponsoring or co-sponsoring solar-plus-storage projects are also likely beneficiaries. Working in partnership with numerous co-ops and industry stakeholders, SPECs identified a combination of factors, including utility staff limitations, the fast-changing nature of the storage industry, the challenges of working with specialized vendors and grid partners, and the needs of utility decision-making boards, which often contribute to long project delays, and too often, suboptimal results.

The SPECs Early-Stage Decision (ESD) model is central to the SPECs procurement solutions toolkit. The ESD model is an Excel-based spreadsheet model, which provides information about the economic and strategic value of a proposed battery-storage project or solar-plus-storage (solar-plus) project. The model can be used to explore combinations of storage-related project value streams in order to define a potential project, while educating co-op decision-makers about project benefits and costs. A sensitivity analysis function speeds the development of “what-if” scenarios. A gap analysis function solves for top-priority metrics and supports the inclusion of hard-to-monetize strategic values, such as the value of storage to defer costly system upgrades in light of increasing distributed solar and other distributed energy resources (DERs). Model outputs include the utility data, assumptions, and use-case scenarios that are recommended content for the requests for proposals (RFPs). The model may also provide an initial “sanity check” for RFP responses, supporting further discussions among utility staff, vendors and stakeholders. *The ESD is not a “finance-grade” modeling tool, and users are cautioned to be mindful of its limitations*, but the model has been reviewed by users, who recommend it as a way to drive faster and better project design and planning, as well as to facilitate better communications with vendors, grid partners, and stakeholders.

The model focuses on the exploration of likely battery energy storage system value streams. In particular, the model helps characterize the savings and costs from demand charge reduction, energy arbitrage, ancillary services sales, distribution upgrade deferral, and increased resiliency.

The model assumes procurement using a solar power purchase agreement (PPA) and an energy storage service agreement (ESA). This approach is increasing in popularity and is suited to co-ops and public power utilities that cannot directly access tax-related benefits. However, this user's manual provides notes and references to ensure that the ESD model provides useful results, even if planners prefer to adapt results to a different project financing approach. Further, the ESD model is designed around a process that readily incorporates data and some value outputs from NREL's System Advisor Model (SAM), which is accessible at <https://sam.nrel.gov/>. SAM is a free software model that facilitates technical and economic decision-making for people in the renewable energy industry. The ESD model process flow, shown in Figure 1, includes scenario definition, data collection and running SAM, new data entry, and analysis of results.

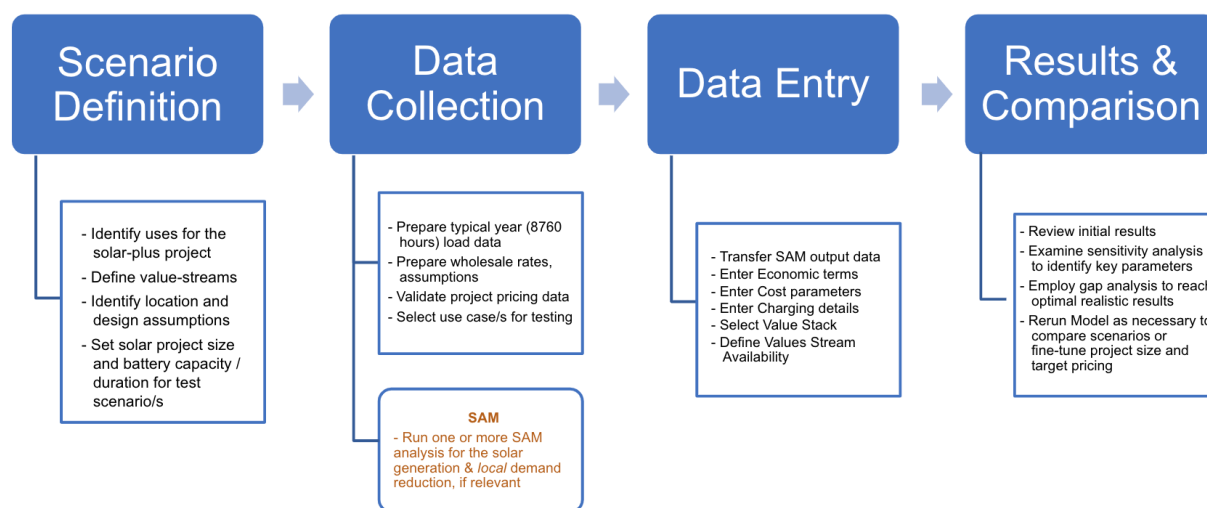


Figure 1: SPECS Early-Stage Decision Model Process Flow.

2 NREL'S SYSTEM ADVISOR MODEL (SAM)

Excel-based models are not ideal for running computationally intensive calculations. In order to keep the Excel-based ESD model user-friendly, it dovetails with specific functions of a more complex and details model, SAM. SAM is a robust technical and financial simulation tool that allows users to model location-specific solar photovoltaic (PV) system performance and specific aspects of solar-plus-storage system performance; however, it does not currently allow for the exploration of multiple value streams from solar-plus-storage systems, nor is it customized for electric co-op use. The ESD model taps SAM to simulate annual hourly values for a solar PV system and to simulate the hourly charging and discharging of the battery to reduce local system peak demand. This hourly time series data will then be imported into the ESD model to explore the costs and benefits of adding (or "stacking") additional value streams for the solar-plus-storage system. Details for downloading free SAM software, setting appropriate parameters, and importing the simulation outputs in the ESD model are detailed in an Appendix of this manual, Section 6.3, Using SAM to Prepare the ESD model. Figure 2, below, is also included in that Appendix.

Data Requirements to Run SAM and the ESD Model

SAM Parameters	Default Value
Battery Size (kWh-AC)	
Battery Power (kW-AC)	
Min Battery State of Charge	0.15
Max Battery State of Charge	0.95
PV Array Size (kW-DC)	
PV degradation rate	0.5 %/year

ESD Model Parameters	Default Value
PV PPA Price (\$/kWh)	
Battery ESA price (\$/kWh)	
Contract Price Escalator	0
Calendar-life degradation rate	1.0 %/year
Battery End of Life	80%
Battery turnovers to reach 90% of capacity	1300
Wholesale Energy Cost 1 (\$/kWh)	
Wholesale Energy Cost 2 (\$/kWh)	0 \$/kWh
Electricity cost escalation rate/year	0
Utility local demand charge (\$/kW)	
Utility demand escalation rate/year	0
Utility coincident peak charge (\$/kW)	
Freq regulation capacity payment	0.011 \$/kW-hr
Freq regulation nominal price decline	5 %/yr
Freq regulation hrs/day available	24 hrs
Inflation rate	0.025 /yr
Utility nominal discount rate	0.07 /yr

REC Price	0.002 \$/kWh
Infrastructure deferral capital cost (\$)*	
Infrastructure deferral years*	
Microgrid controller/additional infrastructure unit cost*	300,000 \$/MW
Anticipated Outage duration (hrs)*	
Peak of Lost Load (kW)*	
Ave lost load (kW)*	

Figure 2: Data Requirements to Run SAM and, subsequently, the ESD Model. Details are provided in the Appendix, Section 6. Data marked with an asterisk (*) represent optional parameters and are not required for basic use of the model.

3 DETERMINING INITIAL BATTERY/PV SIZES

Setting initial battery and PV system sizes is prerequisite to using the ESD model. Users may have various constraints, guiding them to PV size and battery capacity. For example, perhaps they already have a PV system and wish to add battery storage, or they are constrained by physical space, financing, or technical limits related to the point of interconnection. Such considerations can inform the project design; yet many users may be unsure of where to begin. Background information on battery operations and degradation is included in the Appendix. Users are also reminded to review the market landscape for battery system trends. Specification of an unusual battery size or system match may constrain vendor responses to the RFP. Additional suggestions regarding system scale are offered below.

For many utilities, local peak-shaving is a top value stream that can drive the storage acquisition. Here, the duration of a typical peak, which is related to customer load characteristics and existing load-management efforts, may impact project battery requirements. The broader the peak, the more battery energy will be required to reduce the peak by a given amount as shown in Figure 3 below.

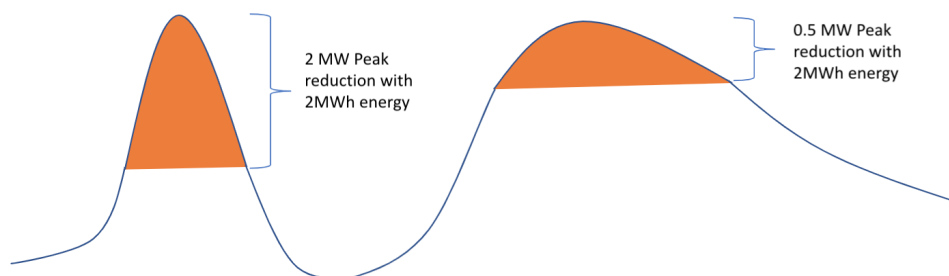
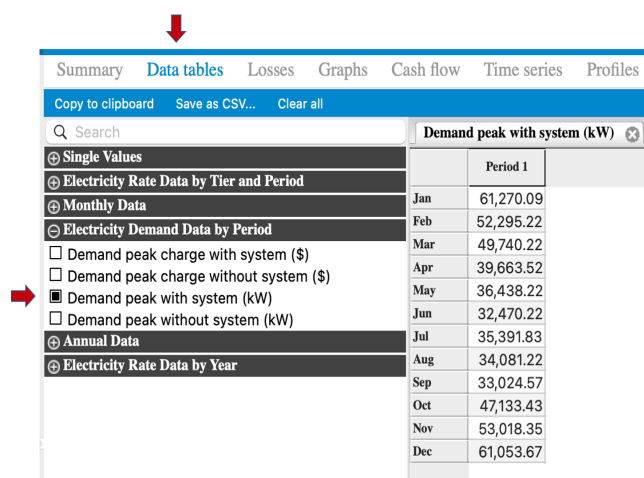


Figure 3: Illustrative Example of Peak Shaving Opportunities that can be achieved with a 2-MW battery at 1- to 4-hour durations (providing 2 MWh of energy) for different load shapes.

Depending on scale, the addition of local solar generation without battery energy storage would typically reduce a mid-day peak and narrow its duration on the load curve, but effectively shift the peak to the evening. (The resulting load shape is often referred to as a duck curve.) Planners should anticipate such impacts.

Because the impact of a given battery storage capacity on peak-shaving depends upon the nature of the peaks, the project modeler might use SAM to run a series of different battery and solar sizes and observe the output variable



Demand peak with system (kW)	
	Period 1
Jan	61,270.09
Feb	52,295.22
Mar	49,740.22
Apr	39,663.52
May	36,438.22
Jun	32,470.22
Jul	35,391.83
Aug	34,081.22
Sep	33,024.57
Oct	47,133.43
Nov	53,018.35
Dec	61,053.67

“Demand peak with system (kW),” as shown in Figure 4. If several runs are being made with the same battery energy capacity (MWh), and increasing the capacity shows little additional impact on the demand peak, then one could ascertain that the peak is relatively wide, and additional battery energy capacity would be required, in order to improve the likelihood of achieving peak demand reduction. Note that battery energy capacity is the primary cost driver for a battery system, so aiming for the lowest effective capacity is well-advised.

Figure 4: Data Table Outputs from SAM.

In practical terms, system planners may first ask whether lower cost strategies and technologies have been optimized to manage the system load, before they increase the scale of the battery system. For example, an adjustment to solar orientation or use of single-axis tracking (SAT) may facilitate more modest and cost-effective use of battery storage. In addition, customer load management (e.g., automated equipment cycling or variable price signals) may help to cost-effectively address the local system peak. These strategies can lead to significant savings on battery storage capacity.

Assuming here that the user’s focus is on addressing battery size, SAM has a useful capability, referred to as parametric runs, which allows the user to quickly make many changes to select variables, such as battery power and duration, and produces the impacts on select output, such as peak reduction. This capability is very useful in determining a good range of choices for battery energy capacity, when peak-shaving is a targeted value stream. [Here is a video](#) demonstrating the use of parametric runs in SAM. See also the Appendix of this manual for background information on battery system sizing and operations.

Figure 5, below, was produced in Excel using parametric runs in SAM to output annual peak-demand reduction cost savings for 2-MW battery power with 2-, 4-, 6-, and 8-MWh capacity, matched with 2-, 4-, and 6-MW PV system sizes. The annual peak demand reduction impacts for the battery were calculated after subtracting out the PV peak-reduction impacts. The resulting financial benefit for this scenario was estimated assuming a 15 \$/kW demand charge and a 10-

year battery life. (This level of demand charge is typical in some—though not all—regions of the country.) The y-axis is \$ saved per MWh of battery installed, so the higher the value the better. As shown in the graph, the benefits rise steeply at first, from increasing battery energy capacity from 2 MWh to 4 MWh. The impact of further incremental increases appears to level off, suggesting that the peak has been significantly reduced and increasing battery capacity is now having less per-unit impact. Based on the preliminary analysis for this scenario, the user might select a base case with a 2- or 4-MW PV system and a 2-MW battery of 2- to 3-hour duration (4 to 6 MWh).

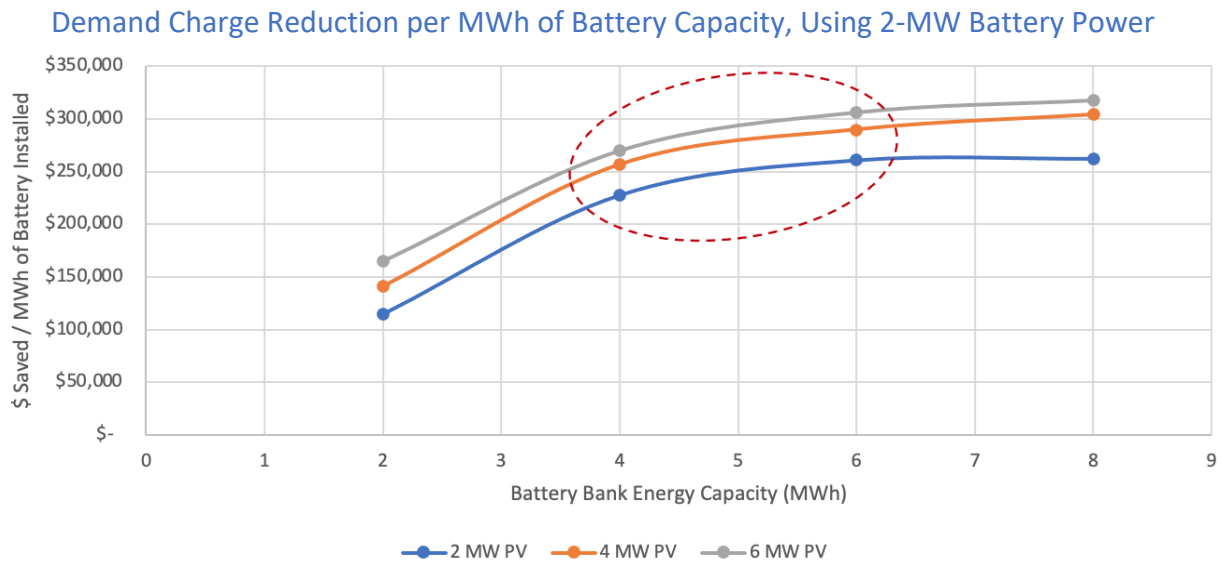


Figure 5: Example Illustrating the Economic Impact of Choosing an Optimal Range for Battery Capacity (MWh) in a solar-plus-storage system that has the objective to address a specified system peak, while using 2-MW PV and a 2-MW storage battery.

In order to integrate the economic impacts of additional value streams, such as energy arbitrage, one alternative to running SAM parametric with peak-shaving would be to use an iterative approach: making several runs in SAM with different PV and battery design configurations, and then exploring each run in the SPECS ESD model. In this approach one might simply keep increasing the battery and PV parameters until the economic gains begin to plateau.

4 SPECS EXCEL-BASED ESD MODEL

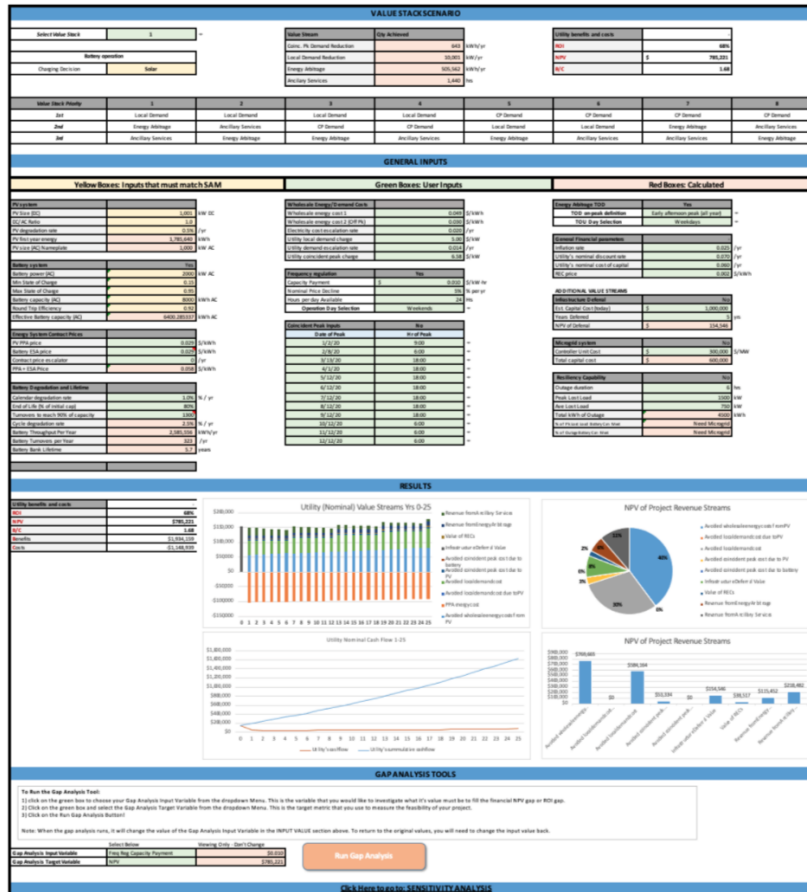
4.1 ESD Inputs Tab

Users are reminded to review Section 6.3 of this user's manual, Running SAM and Importing Simulation Outputs to SPECS to run the ESD model. It details data requirements and preparations to run the ESD. After importing data from SAM into the SAM Inputs tab, the user will primarily use the Inputs tab on the Excel workbook. The Inputs tab for the ESD model is divided into five sections:

- Value Stack Scenario
- General Inputs

- Results
- Gap Analysis Tool
- Sensitivity Analysis

Figure 6, below, is a reduced view of the Inputs tab, with each of these five sections highlighted. The use of each section is described below.



Value Stack Scenario

General Inputs

Results

Gap Analysis Tool

[Link to Sensitivity Analysis](#)

Figure 6: Overview of the ESD Model Spreadsheet, Inputs Tab.

4.2 Use Case and Battery-Charging Parameters

Batteries can be dispatched in ways that allow them to capture revenue from different value streams. However, there are opportunity costs for pursuing different value streams; for example, if a battery has been discharged to reduce a load peak, it may not be used for another value stream until it has been charged again. Note that the ESD is not an optimization model that can determine a battery dispatch schedule to optimize revenue across multiple value streams. Instead, the user is presented with different value stacks that estimate corresponding revenue streams, likely to be accessible for electric distribution utilities now or later, within the project lifetime. The four different values streams for this analysis are:

- Reducing the monthly demand peak on the local distribution system (i.e., local demand).
- Reducing the coincident demand peak on the regional transmission system (i.e., coincident peak demand). This is typically a charge passed through by the local co-op's wholesale power supplier.
- Shifting energy from a time of low value to a time of higher value (i.e., energy arbitrage). For example, this applies if the local co-op has a wholesale time-of-use rate.
- Using the battery to address ancillary service value, currently limited in this model to the value of frequency regulation.

Note that these value streams relate primarily to avoided costs at the wholesale or regional-services level. The local co-op may wish to explore other value streams, such as the ability to shift solar generation in order to increase solar-hosting capacity on the local distribution grid. Such value streams may be highly desirable; however, they are addressed separately, in the Gap Analysis section of the ESD model.

As shown in Figure 7, below, the model user is first asked to choose one of eight likely scenarios that estimate revenue from three prioritized value streams. Prioritization results in the battery first being dispatched to the top priority, then second priority, and finally the third.

Value Stack Priority	1	2	3	4	5	6	7	8
1st	Local Demand	Local Demand	Local Demand	Local Demand	CP Demand	CP Demand	CP Demand	CP Demand
2nd	Energy Arbitrage	Ancillary Services	CP Demand	CP Demand	Local Demand	Local Demand	Energy Arbitrage	Ancillary Services
3rd	Ancillary Services	Energy Arbitrage	Energy Arbitrage	Ancillary Services	Energy Arbitrage	Ancillary Services	Ancillary Services	Energy Arbitrage

Figure 7: Tab 1 of the ESD Allows Selection Among Eight Combinations of Solar-Plus-Storage Value Streams.

In summary, the methodology for assessing multiple value streams is based on a fair approximation of how batteries function in a solar-plus-storage, value-stacked application. The assumption that the battery system would be discharged for one purpose per day is generally conservative and is realistic for the purpose of this model. If the user requires charging only from the solar resource, then the profile for battery availability would be informed by the solar resource assessment function in SAM and the ESD model. In a case where the locally available solar resource does not support daily charging year-round, use of the SAM model would define such limitations. If the user would allow the battery to be charged from solar and/or from the grid, then the battery could be recharged daily as needed (i.e., there are no energy availability limitations).

Given these assumptions, the solar and battery is operated first to maximize the primary value stream. For example, in many cases, this would be local peak-demand reduction. The battery requirements for this task vary, but assuming operation to maximize the primary value stream, the model would then apply remaining energy in the battery and available days to fulfill requirements for the secondary value stream. If energy and days remain to address a tertiary value stream, then the battery would fill those requirements last. Subsequently, any remaining energy that is not used by the battery would go to the grid, and for remaining days, the battery would be left unused. In practice, if the battery is properly sized and the selection of value streams is relevant, the battery is likely to be fully utilized.

Benefits of a Streamlined Model for Early-Stage Decision-Making

As noted above, the ESD model is not intended to be a finance-grade planning model. At the outset of this project, the SPECs team confirmed that, while there are numerous proprietary and industry-provided project planning models, sophisticated solar-plus-storage modeling tools and consulting support are simply not accessible for many electric co-ops. This is especially true in the early stages, when projects face critical “go/no-go” decisions. Thus, the SPECs team designed the ESD model as a robust project screening and educational tool. It provides a baseline for comparing different storage use cases in an acceptably accurate and conservative manner. It screens out project use cases that are not economic, while it identifies project use cases that are economic, or for which further analysis, called a “gap analysis,” could help.

Specifically, using the ESD model’s gap analysis function, the user can define the value gap between initial economic results and the desired outcome (e.g., break-even or better results). The ESD model then supports development of strategies to fill the value gap by adjusting assumptions or calculating an estimated, additional strategic value, such as a grid-upgrade deferral or perhaps an estimated value for resilience enhancements.

There are limitations to using a streamlined, spreadsheet-based model like the ESD. Yet the SPECs team performed initial research on the impact of these overt simplifications—primarily through collaboration and a review process with battery research scientists and industry stakeholders. The team concluded that, while more field verification is needed, the benefits of this approach outweigh the costs. A key objective of the ESD model is to prepare co-op planners and decision-makers to dive deeper into solar-plus-storage operational capabilities and limitations if and when they are ready to take next steps toward project procurement. Furthermore, the ESD model helps users to organize project data and performance objectives for presentation to project bidders and for the subsequent procurement process.

An overview of **value-stream options** includes:

- **Local Demand.** Distribution utilities typically hold wholesale supply contracts from an electric generating and transmission cooperative (G&T) and/or other wholesale provider. Many distribution utilities have a local demand charge that is based upon the peak demand each month, often ranging between 10 and 20 \$/kW¹. A battery system can be discharged in order to reduce the monthly peak, thus reducing the monthly demand charge. A battery would typically need to be discharged across multiple days to make a meaningful reduction in monthly peak demand. For some utilities, the single largest peak in a month is only marginally higher than the next highest peak, meaning

¹ [Clamp, A. \(2017\). When It Comes to Battery Storage Systems, Co-ops Should Focus on a Primary Application \(Tech Surveillance\). National Rural Electric Cooperative Association.](#)

that multiple peaks on multiple days must be reduced in order to significantly reduce peak demand. Experience, co-optimization with load management, and increasingly, machine-learning artificial intelligence (AI) software, can be useful for successfully addressing the peak day and time.

- **Coincident Peak Demand.** The coincident peak demand charge is based on the peak power (kW) usage that is coincident with the demand peak of the energy supplier—likely a G&T. Many distribution utilities pay a fixed rate per kW-month for the entire year, or they pay a variable seasonal rate. If the coincident peak is forecasted accurately, then the battery system may only need to operate once per month, or to discharge 12 cycles per year, in order to offset coincident peak demand, leaving substantial opportunity to tap other value streams. The number of dispatches required is often influenced by the availability of accurate forecasting and real-time information that may be provided by the wholesale supplier.
- **Energy Arbitrage.** If the wholesale supplier offers time of use (TOU) or time of day rates, then the local utility can charge the battery during periods of cheaper energy and discharge it during times of more expensive energy, thus reducing the wholesale energy bill. In some regions, wholesale TOU rates may be imposed instead of demand charges. They also may complement demand charge reduction, since demand peaks often occur at times of more expensive TOU energy rates, where available. In some cases, users may wish to test a TOU rate, which may be introduced in the future. Note that the term “energy arbitrage” is sometimes also applied to the value of managing solar generation and dispatch locally—an operation that is also called “solar shifting.” While that value may be significant (as discussed in Section 5.1, Gap Analysis, of this user's manual), the choice of Energy Arbitrage from the value-stack options on the Inputs page of this model pertains *only* to wholesale cost savings.
- **Ancillary Services.** These comprise services that support reliable operation of the transmission and distribution grid. Typical ancillary services include frequency regulation, reactive power and voltage control, spinning and non-spinning reserves, and blackstart capabilities. Assuming that there is a functioning regional Independent System Operator (ISO) or Regional Transmission Operator (RTO) market or a balancing authority that is willing to offer ancillary services compensation, a local co-op may monetize ancillary services value from a solar-plus-storage project. In some cases, the co-op could work through its wholesale power supplier or another aggregator to value and market these services. Users also may test “what-if” scenarios, as they plan solar-plus projects in regions where such markets are emerging. The ESD model Ancillary Services value stream is currently designed to account only for the market value of frequency regulation.

An overview of **battery-charging options** is summarized below. The selection of battery-charging parameters is a decision that the user initially needs to make before running SAM; however, it should be checked again, as the user prepares to run the ESD model. The input should automatically set when data is imported from SAM to the ESD model.

- **Solar-Only Charging.** The battery may be set to charge only from solar generation. Users of the ESD model will find that if the battery is restricted to charge only from solar, this will limit the battery's availability for all value streams, especially second and third priority value streams, since the battery will need to wait for solar availability to recharge. Especially in locations with limited solar resources, that could require waiting at least until the following day before discharging the battery again. If the user chooses to run SAM with parameters set to allow charging from solar and the grid, they are likely to see greater revenue streams for the value stacks in the ESD model. Access to tax credits during the acquisition process could impact this decision². For a battery system to be eligible for the federal Investment Tax Credit (ITC), current to 2021, the battery would need to charge at least 75% of the time from solar. Check current Federal and state ITC policy, as Congress is reviewing favorable alternative proposals, and some states also have incentives³.
- **Solar or Grid Charging.** Alternatively, the battery may be set to charge from both solar and the grid. By comparing results from this option to the results of the solar-only charging option, the user can approximate the impact of the ITC on the project's economic results.

Note that the ESD model assumes a solar-plus-storage project is acquired through a PPA with an accompanying battery ESA. In using this acquisition model, the ITC credit would likely be received by a taxable project development partner, and savings would be passed through to the hosting non-taxable utility through lower pricing. Testing the impact of the ITC on solar-plus-storage economics is informative, but practically speaking, users can generally assume solar-only charging, incorporating the benefit of the ITC incentive, so long as they assume they will use the PPA/ESA acquisition model.

4.3 General Inputs

The section titled General Inputs allows the users to adjust a range of parameters that impact the financial outputs for the modelled battery and PV system. This section has various colored boxes:

- **green** (to be modified by the user)
- **yellow** (updated automatically with input/import from SAM)
- **red** (calculations - no user interaction).

² [Federal Tax Incentives for Energy Storage Systems, NREL.](#)

³ [Database of State Incentives for Renewables & Efficiency \(DSIRE\)](#)

4.3.1 Values That Must Match SAM

The values that are used to define the PV system capacity and battery system power rating and duration are automatically updated when new SAM data is pasted into the SAM Inputs tab. These values are incorporated within the ESD model calculations. However, because the model calculations are based upon the time series that comes from SAM (e.g., solar generation and battery charging and discharging quantities), these values should not be changed by the user, unless the changes are made in SAM and the SAM simulation is subsequently re-run.

PV system	
PV Size (DC)	2,000 kW DC
DC/AC Ratio	1.2
PV degradation rate	0.5% /yr
PV first year energy	2,686,681 kWh
PV size (AC) Nameplate	1,667 kW AC
Battery system	
	Yes
Battery power (AC)	2000 kW AC
Min State of Charge	0.15
Max State of Charge	0.95
Battery capacity (AC)	8000 kWh AC
Round Trip Efficiency	0.9
Effective Battery capacity (AC)	6400 kWh AC

Figure 8: Values Imported from SAM.

4.3.2 Energy System Contract Prices

The ESD model assumes that neither the battery nor the PV system will be purchased and owned by the utility; rather, their energy and energy services will be acquired through a PPA for the PV system, accompanied by a battery ESA. Utility PPA prices for PV-only systems, during the 2018-2020 timeframe, in the 5- to 20-MW size range (distribution utility FTM scale), were priced from 0.035 - 0.08 \$/kWh⁴. For reference, Berkeley Lab and other sources periodically provide solar and storage pricing updates, with the storage costs expressed as a “PPA adder.”

Energy System Contract Prices	
PV PPA price	0.045 \$/kWh
Battery ESA price	0.015 \$/kWh
Contract price escalator	0 /yr
PPA + ESA Price	0.060 \$/kWh

Figure 9: Energy System Contract Prices.

One novel approach to pricing for solar-plus-storage service contracts presents a single combined price for solar-plus-storage, based on assumptions (expressed in contract terms) regarding how the battery will be operated. Market data collected for utility solar-plus-storage projects in 2017-2019 suggests that the adder is a function of the percent of the ratio of battery capacity to PV capacity, rather than strictly a function of battery energy capacity. This makes sense, since the PPA price is paid for every unit of energy produced by the PV system. If the battery system can only store a small percentage of the PV energy, one would not expect that user to pay a large battery storage adder for the PV PPA price (i.e., the battery is only being utilized for a fraction of the solar production). If, however, the battery system is able to store a larger percentage of the solar PV production, one would expect the adder to increase, as the battery storage will likely be utilized with each unit of energy produced by the PV system. Note that the ESD model allows the user to explore such price changes and uncertainties with the sensitivity analysis tool, described in Section 5.2.

⁴ For reports on recent solar PPA pricing, see: <https://emp.lbl.gov/utility-scale-solar>

In Figure 10, below, the adder is seen as a function of battery system capacity as a percentage of total PV capacity in the system, from a 2018 study⁵. Note that all battery systems in the study are 4-hour duration, so increased battery power also coincides with a scaling of battery energy capacity. Figure 10 shows that for 2018 projects in which the battery capacity was 25% of the PV capacity, PPA adders ranged between 0.003-0.005 \$/kWh; whereas for a large project (300-MW PV) in which the battery capacity was 75% of the PV capacity, the PPA adder was about 0.015 \$/kWh.

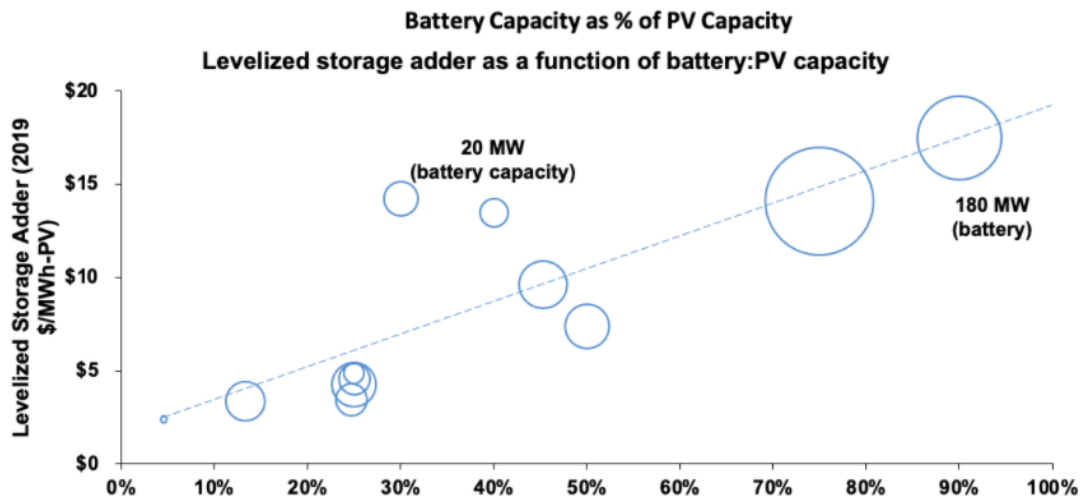


Figure 10: Levelized Storage Adder for Hybrid Solar-Plus-Storage Projects is shown as a function of battery to PV capacity. The storage adder ranges from 0.003 \$/MWh for battery capacity that is 25% of the PV capacity, increasing to 0.015 \$/MWh for battery capacity that is 75% of PV capacity. (Source: Bolinger et al, 2019)

For users of the ESD model that have limited access to market-specific pricing data, it is recommended that projects in the range of 5- to 10-MW PV initially use a PPA price in the range of 0.03 - 0.05 \$/kWh, with an ESA price of 0.02 - 0.03 \$/kWh for battery systems in the 2- to 4-MW range with 4-hour durations. Users may set ESA pricing on the higher end for battery systems that can store a larger fraction of energy produced by the PV system. SPECs recommends testing several combinations of PPA/ESA prices in preparation for a solar-plus-storage procurement, as a preparation for reviewing more updated and market-specific information, which the co-op is likely to obtain in a Request for Information (RFI) or early-round RFP process. SPECs research has indicated a great deal of variation in regional pricing, driven by developers' competitive positions and by their ability to access specified product/solutions. An informed negotiation process is part of any best-practice procurement.

For utilities that prefer to finance and purchase solar and storage assets, the ESD model currently does not provide a direct solution. The references and considerations described above shed some light on asset-purchase pricing, but currently, the impacts of market competition on

⁵ Bolinger, M., Seel, J., & Robson, D. (2019). Utility-scale solar: Empirical trends in project technology, cost, performance, and PPA pricing in the United States—2019 Edition.

pricing prevent development of a reliable rule of thumb to convert PPA/ESA pricing to a specific asset-purchase price. SPECs recommends using the PPA/ESA approach for the initial “early-stage” economic analysis. This will provide an internally consistent way to compare use cases and economic alternatives, informing the development of the RFP, which can subsequently request bids for the chosen financing strategy.

4.3.3 Wholesale Energy and Demand Charges

In the General Inputs section of the ESD Model spreadsheet, the user should specify wholesale energy costs, escalation rates, and demand charges, as applicable. Most utilities that purchase wholesale energy at a fixed rate from a supplier (as opposed to buying on a market) typically have a single rate. If this is the case, the user would simply enter zero for “Wholesale energy cost 2 (Off Pk).” If the co-op has or anticipates having on peak and off peak wholesale energy pricing, then the lower of those rates should be entered as the wholesale energy cost 2 (Off Pk). This supports the choice of a use case that includes energy arbitrage.

Further, the user should enter a value for the “Electricity cost escalation rate,” as the average annual increase that the utility anticipates, including anticipated rate increases for any reason, over the project lifetime (25 years). While solar and wind energy are becoming least-cost resources, certain resource integration and grid reliability costs, as well as other concerns, are expected to drive rate increases. As mentioned earlier in this manual, many distribution utilities have a local demand charge that is based upon their peak demand each month, often ranging between 10 to 20 \$/kW⁶.

Wholesale Energy/Demand Costs	
Wholesale energy cost 1	0.050 \$/kWh
Wholesale energy cost 2 (Off Pk)	0.030 \$/kWh
Electricity cost escalation rate	0.020 /yr
Utility local demand charge	5.00 \$/kW
Utility coincident peak charge	7.00 \$/kW
Electricity demand escalation rate	0.014 /yr

Figure 11: Inputs for Demand-Cost Reduction and Energy Arbitrage Use Cases.

This value should be entered in the model as the “Utility local demand charge.” The coincident peak (CP) demand charge is based on the peak power (kW) usage that is coincident with the demand peak of the energy supplier. The user can enter the date and hour of the expected coincident peak in a table in the General Inputs section. Users are encouraged to adapt these inputs to address their particular situations; for example, some utilities that have unconventional wholesale rates or multiple supply contracts can create a blended rate that reflects the impact of more complex wholesale agreements.

⁶ [Clamp, A. \(2017\). When It Comes to Battery Storage Systems, Co-ops Should Focus on a Primary Application \(Tech Surveillance\). National Rural Electric Cooperative Association.](#)

4.3.4 General Financial Parameters

The input parameters contain several variables that are used in the financial calculations. The default value for inflation is the average annual inflation rate in the U.S. over the last 30 years, i.e., 2.5%. The average nominal cost of capital for rural electric utilities, between 2008 and 2017, is estimated to be 6%⁷, and that is the current default value within the ESD model. The default for the utility's nominal discount rate is 7%⁸.

General Financial parameters	
Inflation rate	0.025
Utility's nominal discount rate	0.070
Utility's nominal cost of capital	0.060
REC price	0.002

Figure 12: General Financial Parameters provided as default options.

The average nominal cost of capital for rural electric utilities, between 2008 and 2017, is estimated to be 6%⁹, and that is the current default value within the ESD model. The default for the utility's nominal discount rate is 7%¹⁰.

The Renewable Energy Credit (REC) price pertains to co-ops or other utilities that can monetize REC values in compliance with regulatory mandates. REC prices vary greatly nationwide and should be verified. If REC prices are not applicable, enter zero. All financial assumptions, including REC prices, should be reviewed based on current and anticipated wholesale agreements and cost trends over the life of the project.

4.3.5 Energy Arbitrage

Energy arbitrage, at its most basic level, entails buying energy at one price and selling it at a higher price. The ESD model assumes that arbitrage is supported by wholesale time-of-use (TOU) rates or access to a wholesale power market, where prices change based upon supply and demand. Under any of these conditions, shifting solar-generated energy from one time of day to another could have monetary or strategic value. The ESD model compares the economics of battery-enabled shifting upon wholesale or market-imposed costs.

Some utilities that currently do not have TOU rates may wish to use the ESD model to test a use case that includes arbitrage value, in order to understand the impacts of a possible future rate change or of an emerging regional electricity market, where prices fluctuate with wholesale demand.

⁷ Royer, Jeffrey S. "Measuring the cost of capital in cooperative businesses." *Agribusiness* 35.2 (2019): 249-264.

⁸ See, for example, [this document](#) for the Sixth Northwest Conservation and Electric Power Plan

⁹ Royer, Jeffrey S. "Measuring the cost of capital in cooperative businesses." *Agribusiness* 35.2 (2019): 249-264.

¹⁰ See, for example, [this document](#) for the Sixth Northwest Conservation and Electric Power Plan

If the user is investigating a use case that applies wholesale TOU rates, they must enter these in the General Inputs section of the model as “Wholesale energy cost 1” and “Wholesale energy cost 2 (Off Pk).” Note that the second (Off Pk) value must be the cheaper rate.

Wholesale Energy/Demand Costs	
Wholesale energy cost 1	0.049 \$/kWh
Wholesale energy cost 2 (Off Pk)	0.030 \$/kWh

Figure 13: Wholesale Demand Cost Inputs required for the arbitrage case.

Next, the user may choose from among several options that define how and when the TOU rates apply. Under “Energy Arbitrage TOU,” the user can set the analysis to reflect how different rate options are applied on a daily or seasonal basis. Figure 14 shows one pre-loaded option. Other options that may be selected are listed below.

Energy Arbitrage TOU	Yes
TOU on-peak definition	Late afternoon peak (all year) ➡
TOU Day Selection	Weekdays ➡

Figure 14: Example Input Settings, regarding how TOU rates are applied.

In all, there are three pre-loaded options for defining TOU on peak rate periods, plus a manual input option:

- Early afternoon peak (all year) - on peak (2:00 - 5:59 pm)
- Late afternoon peak (all year) - on peak (4:00 - 8:59 pm)
- Seasonal (summer early afternoon peak & winter morning/evening peaks) - on peak (November to April: 6:00 - 9:59 am & 6:00 - 9:59 pm, and May to October: 2:00 - 5:59 pm)
- Manual input

To use the Manual Input option, the user must first open the Values tab of the ESD model, located to the far right of the Inputs tab. There, the user can create hour-by-hour and month-by-month rate-table parameters. Enter 1 for times when the off peak wholesale energy rate applies (identified as “Off Pk” under “Wholesale Energy/Demand Costs” on the Inputs page), and 0 for times when the more costly “Wholesale Energy Cost 1” applies.

In addition, the user must make a TOU day selection to indicate when the rate schedule would apply, either choosing “none,” or options for weekdays or weekends. For all other times, the rate indicated in “Wholesale energy cost 1” would apply. By incorporating these settings, the ESD model can approximate the benefits of battery-based energy arbitrage, as a secondary or tertiary value stream.

Remember, the option to set energy arbitrage as a secondary or tertiary value stream in this model pertains only to achieving wholesale power cost savings. A different interpretation of energy arbitrage is sometimes called “solar shifting.” This approach would time the charging and discharging of a strategically sited battery to improve the match between local resource

availability (e.g., local solar generation) and the local load curve. Solar shifting and related issues are addressed separately in this user's manual, in Section 4.3.7, Infrastructure Deferral, and Section 5.1, Gap Analysis.

4.3.6 Ancillary Services

As briefly defined above, ancillary services refers to a range of services that generators or energy storage systems provide in order to maintain grid stability and reliability in the face of imbalances between supply and demand, integration of intermittent resources, and power outages. Typical ancillary services include

- Frequency regulation
- Reactive power and voltage control
- Spinning reserves
- Non-spinning reserves, and
- Blackstart capabilities.

In service areas controlled by fully regulated utilities, these services are often provided by vertically integrated utilities that manage portions of the grid or by RTOs or ISOs. In areas with partially or fully deregulated markets, these services are traded on wholesale markets.

The figure below, from Balducci et al¹¹, shows compensation ranges for various ancillary services. Frequency regulation is the most profitable ancillary service for distribution utilities, where there are monetary mechanisms (either through an ISO/RTO or wholesale market) for compensation. Frequency regulation is the default focus for the ESD model's analysis of ancillary services value.

Several FERC orders, such as FERC Order 755, have helped ensure that energy storage systems receive fair compensation for frequency regulation. FERC Order 755 requires energy storage systems to be compensated based upon performance. Most entities will compensate frequency regulation based on a capacity payment, which rewards the provider of the service for the opportunity cost of making a given capacity available, and a mileage payment based upon the sum of the up and down deviations of the frequency signal being regulated. Some markets also compensate based on the accuracy of the regulation. Capacity payments for ancillary services represent the larger part of total available revenue¹².

¹¹ [Balducci, P., Alam, M., Hardi, T., & Wu, D. \(2018\). Assigning value to energy storage systems at multiple points in an electrical grid. *Energy & Environmental Science*, 11\(8\).](#)

¹² [Liu, K., Chen, Q., Kang, C., Su, W., & Zhong, G. \(2018\). Optimal operation strategy for distributed battery aggregator providing energy and ancillary services. *Journal of Modern Power Systems and Clean Energy*, 6\(4\), 722-732.](#)

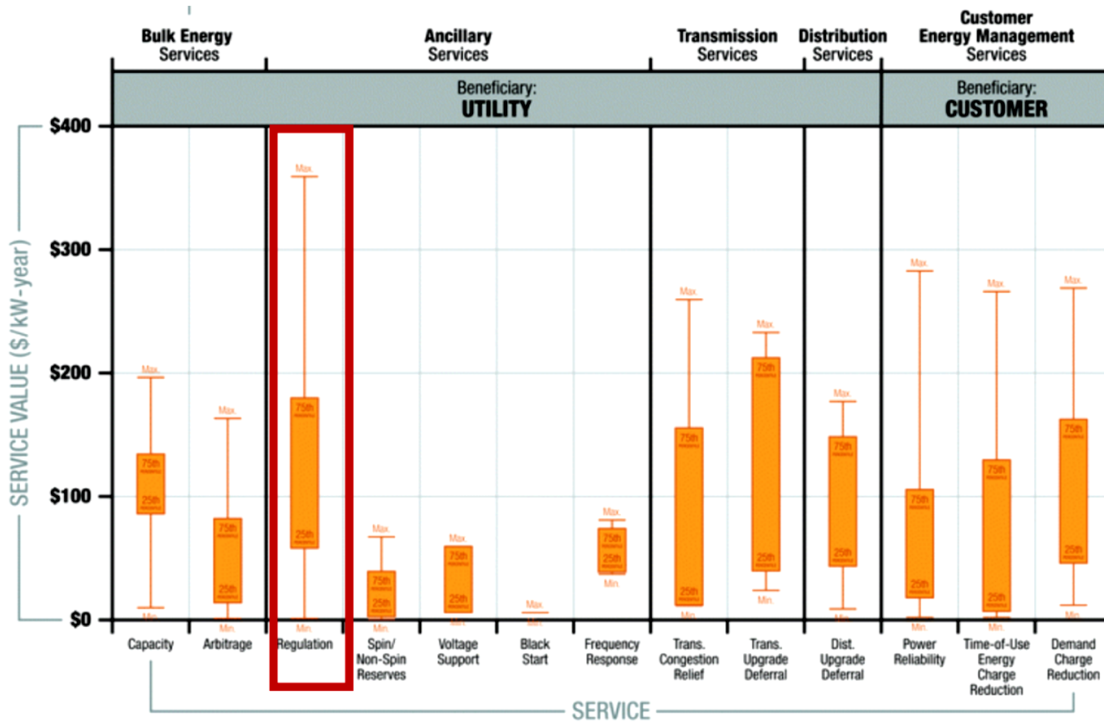


Figure 15: Ranges of Value for Various Services that Battery Storage Can Provide. Image from Balducci, P, Alam, M., Hardi, T., and Wu, D. (2018) in Energy and Environmental Science, 11 (8).

The figure below, also taken from Balducci et al, shows compensation structures in various regions and markets, current as of 2018. Though representative, this payment schedule may change with supply and demand for frequency regulation services.

Service	RTO/ISO					
	PJM	MISO	CAISO	NY ISO	ISO-NE	ERCOT
Capacity payment	Yes	Yes	Yes	Yes	Yes	No
Mileage payment	Yes	Yes	Yes	Yes	Yes	Yes
Accuracy payment	No	No	Yes	Yes	No	No
Basis of mileage payments	DA and real time	Real time	DA and real time			

Figure 16: Assigning Value to Energy Storage Systems at multiple points in an electrical grid. Table from Balducci, P, Alam, M., Hardi, T., and Wu, D. (2018) in Energy and Environmental Science, 11 (8).

The ESD model provides a very simple estimation of revenue that might be earned from providing frequency regulation services in a market, as described below.

$$Revenue(\$) = Market\ Price\left(\frac{\$}{MW\ per\ hr}\right) \times Capacity(MW) \times Availability(hr)$$

The market price for capacity payment is often in \$ per MW per hour of participation in the market. Capacity is the power rating for the battery system and is based upon a battery being able to provide the capacity commitment for the duration of the hour bid. For example, a 2-MW bid for one hour would require the battery to have at least 2 MWh of storage capacity. It would need this capacity to modulate the frequency with 2 MW, whether that is up or down, requiring the absorption or dispatch of energy. The default value for frequency regulation

payments in the model is 11 \$/MW-hr, based upon the average value of numerous markets from 2017.¹³

Availability is based upon the time that the battery meets bid requirements, in terms of energy capacity. For example, if the battery would not be delivering any other services on weekends, then the daily participation on weekends could be 24 hours. The user also must select the pattern of days that the battery would be available to participate in the market. The ESD model provides options simply defined as weekends or weekdays, assuming the user's choice would be set so it would not conflict with other selected value streams, e.g., energy arbitrage. This feature of the model is streamlined compared to actual market participation, but it approximates a conservative value of frequency regulation, where markets exist.

Frequency regulation	Yes	
Capacity Payment	\$	0.011 \$/kW-hr
Nominal Price Decline		5% % per yr
Hours per day Available		24 Hrs
Operation Day Selection	Weekends	

Figure 17: Input Table for Frequency Regulation.

Energy throughput (which will affect degradation for the battery) when delivering frequency regulation is estimated as 20%, similar to values used in other analytic models¹⁴. This means that if a 2-MW battery is bid into a frequency regulation market for one hour, it would only be utilizing about 20% of its full capabilities and only absorb or dispatch 0.4 MWh of energy to meet the market need. This default value of 20% can be changed in the Values tab of the ESD model, should the user have unique or new data to apply to the utility's specific scenario.

Users should be cautioned against basing long-term revenue estimates upon a high return from ancillary services, such as frequency regulation. As more energy storage systems come online, the market may become saturated, leading to steep declines in value for a number of ancillary services¹⁵. Under those conditions, they may fall to near-market or sub-market levels. As a safeguard, the ESD model includes a variable for an exponential rate of decline in the market price for the 25 years of the project, with a default of 5%. This means that each year, the revenue obtained from frequency regulation will be reduced by 5% of the previous year's value. If the user would like to negate such annual revenue degradation, the value may be set to 0%.

The ESD model is focused on ways to monetize frequency regulation as a relevant ancillary services value today. However, other values are emerging, and the model may be updated to include additional values. In addition, targeted local applications for storage-derived ancillary services may become highly valued in the future. Battery storage applications may solve local

¹³ Denholm, Paul, Yinong Sun, and Trieu Mai. 2019. [An Introduction to Grid Services: Concepts, Technical Requirements, and Provision from Wind](#). Golden, CO: NREL/TP-6A20-72578.

¹⁴ Concepcion, R. J., Wilches-Bernal, F., & Byrne, R. H. (2019, August). [Revenue opportunities for electric storage resources in the Southwest Power Pool Integrated Marketplace](#). In 2019 IEEE Power & Energy Society General Meeting (PESGM) (pp. 1-5). IEEE.

¹⁵ Mandel, J., Morris, J., & Touati, H. (2015). [The economics of battery energy storage](#). Rocky Mountain Institute. Technical Appendix A

grid reliability problems or resolve transmission-level issues, such as potential back-feeding on a high-renewables grid. The ESD model does not directly address these value streams, but they are reflected in infrastructure deferral savings discussion below.

4.3.7 Infrastructure Deferral

Increasingly, situations arise at the local level, where energy storage or solar-plus-storage can help to optimize the local solar resource. Infrastructure upgrade deferral represents one subset of such benefits that may be monetized, and which may be a strong local-project driver. A value stream from infrastructure deferral may support one or more of the ESD use cases, so this value is treated separately in the ESD model.

The model provides a simple, proxy valuation for the deferral of a distribution-grid investment, as the difference between the value of the capital investment at the time of the solar-plus-storage project and the net present value (NPV) of the project, if it were deferred several years into the future. The resulting value may underestimate the true, total value of a successful infrastructure deferral strategy; that value could be more fully explored through non-wires alternative (NWA) studies and more complex models. The ESD offers this streamlined approach to advance a more inclusive, strategic decision-making process.

In the ESD model, the primary deferral value arises due to the deferral of borrowing, as reflected in electric utility's cost of capital. The present value of the deferred investment can be represented as

$PresentValue = \frac{C_0}{(1+k_r)^T}$, where C_0 is the cost of a capital investment at a given time and T is the number of years into the future that the capital cost would be deferred. The term $1 + k_r = \frac{1+k_n}{1+i}$ represents the real cost of capital for the electric utility, with k_n being the nominal cost of capital and i the inflation rate.

As an example, imagine that a capital investment of \$1,000,000 for feeder-line reconductoring is planned, but the development of a solar-plus-storage project could cause the reconductoring to be delayed by 5 years.

The average nominal cost of capital for rural electric utilities, between 2008 – 2017, is estimated to be 6%¹⁶. The average annual inflation rate in the U.S. over the last 30 years was 2.5%. Using these values, the real cost of capital is:

$$1 + k_r = \frac{1 + 0.06}{1 + 0.025} = 1.034$$

Thus, the present value of the deferred investment would be: $PresentValue = \frac{\$1,000,000}{(1.034)^5} = \$154,546$.

¹⁶ Royer, Jeffrey S. "Measuring the cost of capital in cooperative businesses." *Agribusiness* 35.2 (2019): 249-264.

The value to the project would then be the difference between the capital cost and the present value of the deferred investment, or \$154,546. Because this value does not represent all related savings, which in reality would require much more (and hard to estimate) input data, it should be considered as a reference point in a broader discussion of strategic project value. SPECS has created a structure for that discussion, called a gap analysis process. That process, detailed in Section 5.1 below, asks the user to define the gap that needs to be filled between the initially calculated project economics (expressed as NPV, IRR, etc.) and acceptable minimum metrics. It then seeks to apply “just enough” additional value (in this case from the proxy distribution deferral value stream and possibly from other strategic value streams), in order to achieve threshold cost-effectiveness. In short, the gap analysis provides a decision-making tool to get promising projects beyond the initial go/no-go decision point.

4.3.8 Resilience and Reliability

A battery storage system may increase both resilience and reliability by reducing the frequency and impact of electricity outages on portions of the distribution grid. Reliability refers to the grid’s ability to minimize common outages. It can be characterized by the System Average Interruption Duration Index (SAIDI), which represents the average interruption duration for each customer served on a distribution grid. In contrast, resilience refers to the grid’s ability to respond to and recover from power outages that are greater in both geographic coverage and time.

Several methods may be used to quantify the value of avoided power interruptions, such as contingent valuation, damage cost, input-output modeling, and defensive behavior¹⁷. The primary cost of an outage is typically calculated as the productivity losses or damage costs to local customers. Damage cost and defensive behavior methodologies look at the revealed preferences of customers, related to what they pay to avoid an outage, such as the purchase of a back-up generator system or insurance-cost impacts upon either the local utility or the utility plus all affected customers.

The ESD model provides another streamlined proxy method, using data provided in the General Inputs section of the model, for utilities to begin to explore costs and benefits of resiliency, which could be incorporated into a solar-plus-storage solution. As another approximated value, ESD model assumes that resiliency capability will be considered as a strategic local project value, subject to the gap analysis process. The model asks users to specify the characteristics of the outages that they are looking to avoid, such as peak and average loads, outage duration, and outage frequency. The model can then estimate the additional costs that would be required for the solar-plus project to meet their outage criteria.

¹⁷ [Rickerson, W., Gillis, J., & Bulkeley, M. \(2019\). The value of resilience for distributed energy resources: An overview of current analytical practices. National Association of Regulatory Utility Commissioners.](#)

If the user wishes to run the ESD model to ensure grid resiliency, it would be important to include additional costs for microgrid infrastructure, such as switchgear and a microgrid controller, and to update the battery specifications, so they meet the user's resilience needs (i.e., the anticipated load requirement and duration for an outage). The model includes a default value of \$300,000 per MW for a microgrid controller and additional infrastructure¹⁸. The user must provide

- Outage duration they are seeking to cover
- Peak of lost load (kW)
- Average of lost load (kW)

Microgrid system		Yes
Controller Unit Cost	\$	300,000
Total capital cost	\$	600,000

\$/MW

Resiliency Capability		No
Outage duration		6
Peak Lost Load		1500
Ave Lost Load		750
Total kWh of Outage		4500
% of Pk Lost Load Battery Can Meet		133%
% of Outage Battery Can Meet		142%

hrs
kW
kW
kWh

Figure 18: Microgrid Inputs and Resiliency Calculations.

Using these inputs, the ESD model calculates the total kWh of the outage based upon duration and average lost load, and it provides the user a percent of peak lost load and overall outage that the solar-plus system could meet when it is fully charged. The user should be aware that if the grid outage occurs after the battery has been discharged for another purpose, the battery's availability will be limited, until it is fully or partially charged again by the solar resource. The user may then decide to adjust the battery size and run the prerequisite SAM model again in order to meet their desired reliability/resilience requirements.

The principles of the ESD gap analysis (discussed in Section 5.1) are useful for applying the results of this project-resilience analysis. Decision-makers would be asked to consider whether the additional cost (gap) created by adding resilience microgrid features could be offset by adjusting other project economic expectations or by considering non-monetary strategic values. Decision-makers might consider both this calculated resilience value plus other strategic values, such as achieving emergency-service goals or meeting utility insurance requirements. SPECS recommends that the ESD user provide both the analysis of solar-plus-storage *without and with* microgrid capabilities, in order to inform decision-makers fully. SPECS also notes that adding a resiliency function—especially in the context of a PPA/ESA acquisition—will affect the battery operating agreement or storage warranty. Anticipate a negotiation with prospective developers around resiliency requirements.

5 ESD MODEL RESULTS AND ANALYSIS

The ESD model provides a series of outputs under the Results section on the Inputs tab. The primary metrics that are calculated include the project NPV, Return on Investment (ROI), and Benefit/Cost Ratio. The NPV is the net present value of the summation of future costs and

¹⁸ [Giraldez Miner, J. I., Flores-Espino, F., MacAlpine, S., & Asmus, P. \(2018\). Phase I Microgrid Cost Study: Data Collection and Analysis of Microgrid Costs in the United States. National Renewable Energy Lab.\(NREL\), Golden, CO.](#)

benefits (i.e., income) over the project lifetime. A positive NPV indicates the benefits exceed the costs. The ROI is simply the ratio of benefits to costs, expressed as a percentage.

Project Metrics	
ROI	81%
NPV	\$1,490,392
B/C	1.81
Benefits	\$3,339,065
Costs	-\$1,848,673

Figure 19: Metrics for Project Evaluation.

The Results section also provides several graphics that enable the user to quickly review the primary cost and benefit drivers. Figure 20, below, shows on the left the stack of annual costs and benefits over the project lifetime. The pie chart on the right shows the NPVs for each value stream, as a percentage of the project’s total economic benefits.

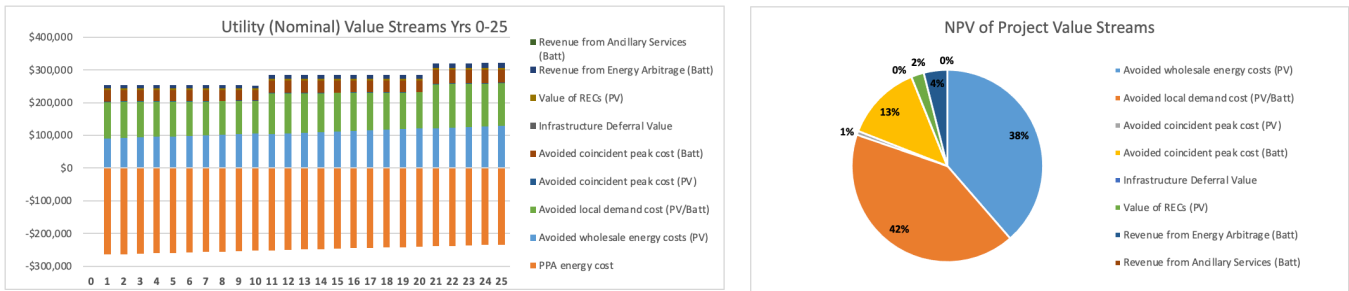


Figure 20: Graphic Illustrating Annual Value Streams of the Project Life and Overall Proportional Value Streams, as shown in the ESD Results section.

In Figure 21, below, the graph on the left side portrays results as nominal cash flow for the project life, showing utility’s annual cash flow in red, and cumulative cash flow in blue. On the right, the NPV of Project Revenue Streams provides more detail on the magnitude of specific value streams.

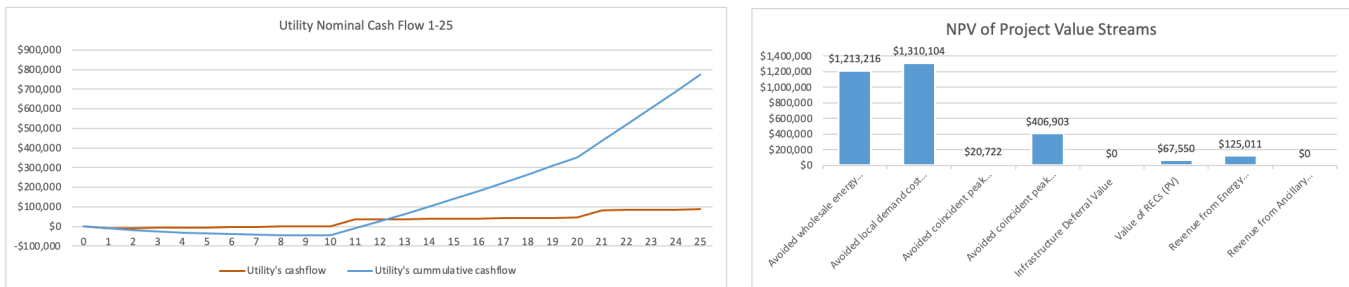


Figure 21: Graphic Illustrating Nominal Cash Flow and the NPV of Each Value Stream, as shown in the ESD Results section.

The ESD Input tab also provides access to two additional analytic tools, the Gap Analysis and (via a link) the Sensitivity Analysis. These tools allow the user to explore the sensitivity of specific economic metrics and to speed project fine-tuning, as well as to support the inclusion of strategic values, such as infrastructure deferral and resiliency. These tools are described in Sections 5.1 and 5.2, below.

5.1 Gap Analysis

In business management, the term “gap analysis” describes a comparison of actual performance with a desired, optimal level of performance. Gap analysis may be used to support an argument for a process change or investment that impacts future strategic performance, including values that are not primarily economic. For users of this model, the gap analysis applies both to an economic gap, using standard performance metrics to reach break-even or a specific goal, and to the fine-tuning of the strategic argument, to assign value to less conventional utility and community benefits. For example, the gap analysis process can help decision-makers to incorporate costs and benefits associated with risk-management, resiliency goals, infrastructure deferral, or local sustainability and renewable energy policies.

In short, the ESD gap analysis allows the user to explore the value gap that needs to be filled by one or more harder-to-quantify or negotiable value streams. In some cases, a policy-related or strategic value stream could be a key driver for a solar-plus project.

There may be cases where a user is exploring a project that falls short of one or more standard economic metrics, such as a desired internal rate of return (IRR) or net present value (NPV). It may be that the economics appear unfavorable because there is uncertainty in how to quantify some of the value streams, or because some of the value streams may be negotiable, such as project pricing or, in some cases, wholesale rate parameters.

The Gap Analysis section of the model provides the user with the option to run a simple numerical solver that will determine what a targeted input variable must be (e.g., PPA price or demand charge) in order to reach a desired NPV or IRR. The utility can then conservatively assign value to strategic benefits or seek bidders that can lower specific costs, seeking “just enough” value to meet minimum project requirements.

To run the gap analysis, the user should first save the existing spreadsheet, in order to reference the original analytic run and to be able to restore certain values after the gap analysis, if desired. Then the user must choose an *input metric* from the dropdown menu, as shown in Figure 22. This selected variable should be the one that the co-op might specify in the RFP or negotiate with the parties involved, in order to fill the project’s economic gap. For example, they might ask, “What if we could negotiate a slightly better battery system ESA price?” or “What if we could defer an infrastructure upgrade for a few more years, thanks to the strategic value of this project?”

The user then selects a *target metric*, such as NPV or IRR, from a second dropdown menu. This is the metric that will be used to measure the feasibility of the project. Once these two values are chosen, the user clicks on “Run Gap Analysis.” This will bring up a window, asking for the target metric value—in this example, “Enter desired Net Present Value.” **Note that when this**

Battery ESA Price

PV PPA Price
Wholesale energy cost 1
Wholesale energy cost 2 (Off Pk)
Utility local demand charge
Utility coincident peak charge
Freq Reg Capacity Payment
Infrastructure Years Deferred
Infrastructure Capital Cost

Figure 22: Input Metrics for Gap Analysis, here choosing the battery price metric.

function is run, it will change the actual input variable's value in the General Inputs section of the model. That is why the first step in the gap analysis should be to save previous work.

If the calculation returns a value that seems unrealistic, then the user should reduce the value for the input metric to a minimum acceptable value and then run the gap analysis again to see if the new input metric could drive a successful economic outcome. For example, if the initial run shows a Battery ESA price of 0.01 \$/kWh to achieve an IRR of 8%, then the user should reenter the lowest *reasonable* Battery ESA price that they think they can achieve, and then test to see if a minimum acceptable target metric can be achieved. If a project is close to cost-effective, co-op planners generally can apply their experience to match metrics that can “close the economic gap” without too many iterations.

The gap analysis also assumes that some less conventional, strategic project values may need to be counted, in order to close the gap. Utility decisionmakers are often motivated by strategic values that are currently hard to assess, and thus are often left out of the economic discussion. Project planners know that such values are seldom “equal to zero.” The gap analysis allows them to incorporate a minimum, supportable proxy value, in order to close an economic gap and achieve the project’s minimum target metrics. This strategic planning approach was first documented by Bourg, Cliburn, and Powers for application in local solar development, where many local utility decision-makers were responsive to it.¹⁹ The approach may be applied to the strategic value of regulatory or contract compliance, local grid reliability, fire or storm risk management, achievement of local sustainability goals and even customer retention values, when solar or solar-plus-storage can meet customers’ energy-service needs. One key to successfully applying the gap analysis is to seek minimum acceptable values, rather than to engage in a thorough, time-consuming, and potentially costly value-of-solar analysis. The gap analysis is a practical alternative, especially for co-ops and public power utilities that have leeway for local decision-making to serve the needs of their communities and member-owners. In short, the gap analysis provides a decision-making tool to get promising projects beyond the initial go/no-go decision point.

5.2 Sensitivity Analysis

Sensitivity analysis provides a tool for the user to look at how a desired target metric, such as project NPV or ROI, changes in response to a range of input variables. Sensitivity analysis is valuable for project development, because it may be inadvisable or impossible to define exactly what some input variables, such as PPA price, should be. In modeling without access to a sensitivity analysis, the user would have to run the model over and over, changing the PPA price or other variable and comparing runs side by side. Using the sensitivity analysis function, the user could see how sensitive the target metric is in relation to a range of PPA prices, all at once. The sensitivity analysis both saves time and supports easy comparisons.

¹⁹ Bourg, J., Cliburn, J., and Powers, J. (2017) [The GAP process: A streamlined economic analysis for the procurement and pricing of community solar](#). Community Solar Value Project for the U.S. Department of Energy, Solar Market Pathways.

The analysis is accessed by clicking a link on the General Inputs page of the model. Once the analysis is run, outputs are visualized in a two-dimensional grid that allows users to gauge NPV or ROI sensitivity to two independent input variables concurrently. For example, the figure below shows a heat map of the NPV changes with respect to solar PPA price (vertical axis) and battery ESA price (horizontal axis). The lighter the color, the higher the value of NPV.

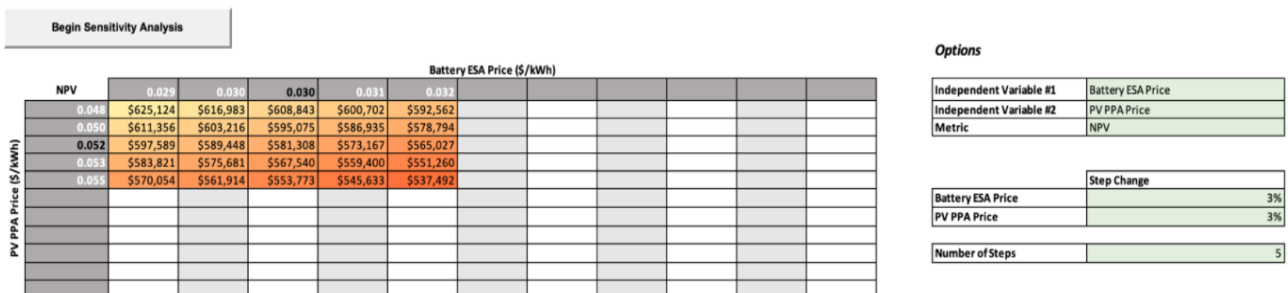


Figure 23: ESD Sensitivity Analysis Function shows the sensitivity of the project NPV to aspects of project pricing, using a 3% variation in each input variable with each step. This function effectively compresses the analytic process.

The user can determine the scale over which the sensitivity analysis will vary by setting the percent by which the values will vary with each step-change. The users may also set the number of steps applied. The model is preloaded for a 3% step-change, but users may customize this metric.

In addition, the sensitivity analysis provides line graphs to visualize the same data in two dimensions, as shown in Figure 24. The graph on the left shows NPV as a function of battery ESA price for the five different values of PPA price. This is the equivalent of plotting each row of the heat map. The graph on the right shows NPV as a function of PV PPA price for the five different values of battery ESA price. This is the equivalent of plotting each column of the heat map.

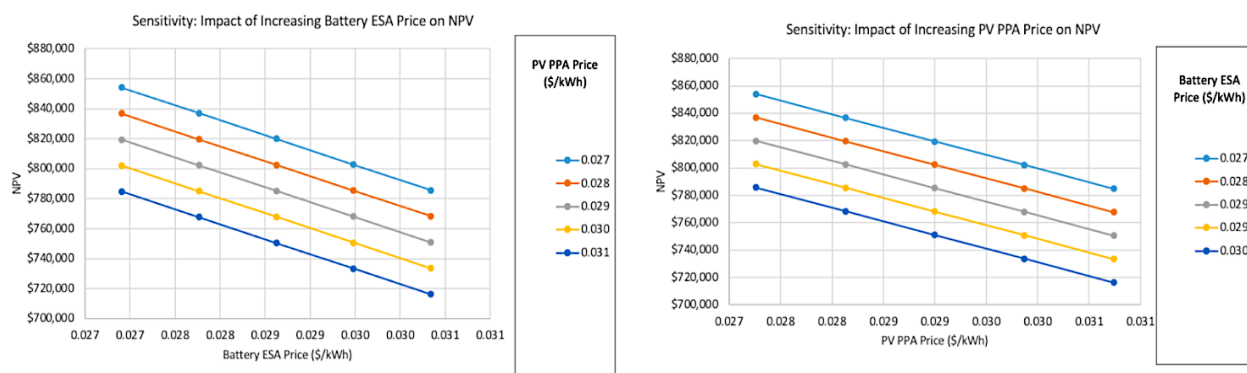


Figure 24. Graphic Results from the Sensitivity Analysis, showing the sensitivity of NPV to battery ESA (left), where each line is equivalent to a row of the heat map, and (right) showing NPV sensitivity to the solar PPA price.

6 Appendices

6.1 ESD Model Checklist

The following two tables show input values that are needed to run SAM and the ESD model. Parameters that are marked with an asterisk (*) are not required for a basic run of the model. Also, default values may be adjusted.

This checklist is also provided under the RFP Outputs tab of the ESD model. A utility that is using the ESD model to define project goals and broad specifications would be encouraged to share their assumptions, via a completed Model Checklist. For the RFI or a first-round RFP, the co-op might wish to provide only a summary of project goals and key assumptions. However, in later-round discussions with bidders, the full model spreadsheet could be shared, as way to see how each potential vendor would approach a more detailed analysis of the early-stage project concept and fine-tune the analytic results.

SAM Parameters	Default Value
Battery Size (kWh-AC)	
Battery Power (kW-AC)	
Min Battery State of Charge	0.15
Max Battery State of Charge	0.95
PV Array Size (kW-DC)	
PV degradation rate	0.5 %/year

ESD Model Parameters	Default Value
PV PPA Price (\$/kWh)	
Battery ESA price (\$/kWh)	
Contract Price Escalator	0
Calendar-life degradation rate	1.0 %/year
Battery End of Life	80%
Battery turnovers to reach 90% of capacity	1300
Wholesale Energy Cost 1 (\$/kWh)	

Wholesale Energy Cost 2 (\$/kWh)	0 \$/kWh
Electricity cost escalation rate/year	0
Utility local demand charge (\$/kW)	
Utility demand escalation rate/year	0
Utility coincident peak charge (\$/kW)	
Freq regulation capacity payment	0.011 \$/kW-hr
Freq regulation nominal price decline	5 %/yr
Freq regulation hrs/day available	24 hrs
Inflation rate	0.025 /yr
Utility nominal discount rate	0.07 /yr
REC Price	0.002 \$/kWh
Infrastructure deferral capital cost (\$)*	
Infrastructure deferral years*	
Microgrid controller/additional infrastructure unit cost*	300,000 \$/MW
Anticipated Outage duration (hrs)*	
Peak of Lost Load (kW)*	
Ave lost load (kW)*	

Figure 24. ESD Model Parameters and Defaults.

6.2 Battery Degradation

There are a wide variety of mechanisms that lead to capacity degradation in Li-ion batteries, which are dominant in the market today and the focus of the SPECS project work. Variables that impact battery capacity degradation include depth of discharge (DOD), state of charge (SOC) of the battery while resting, rate of charge/discharge, battery temperature, age, and energy throughput.²⁰ The ESD model takes a more streamlined approach, accounting for battery degradation or decay simply as a function of battery age, cycling, and throughput. Degradation that is increased at high temperatures can be partly mitigated by conditioning the containers; however, the energy cost to do so must be included in a final economic analysis. It is important to monitor market-wide improvements in battery operations and performance and to examine performance for a particular product and site when finalizing the battery storage warranty or

²⁰ See DNV GL's Battery Performance Scorecards: <https://www.dnvgl.com/power-renewables/index.html>

ESA. Yet this introduction to battery degradation principles, combined with experience applying these principles by running the ESD model, offers a useful place to start.

Notably, some battery ESAs are written so that the subscriber is guaranteed the full battery nameplate capacity for a given time frame. When using the ESD model, the user may set the degradation to zero if they expect to seek out an ESA with guaranteed battery capacity. However, in cases where degradation is not covered, considering its impact is essential. Furthermore, an ESA with a guaranteed capacity may prove more costly over time than one that assumes degradation and eventual replacement.

6.2.1 Calendar-Life Degradation

The ESD model assumes that calendar-life and cycle-life degradation are independent mechanisms within the battery, and thus their degradation rates can be summed to produce a net annual capacity degradation. Battery calendar-life degradation provides a simple empirical estimate of how the battery degrades over time. This battery degradation is caused by chemical reactions within the battery, and it is typically accelerated at higher states of charge and at high temperatures. While the calendar-life degradation rate for a resting battery is non-linear (faster initially and then slowing down), it may be approximated as linear. The figure below shows three lines from a model of calendar-life degradation²¹, for different resting SOC. The red dotted line shows the default calendar-life degradation rate used in the SPECs Early-Stage Decision Model (ESD), which is 1.0 % capacity loss per year. This approximation is a straight-line approximation for the calendar-life modeled degradation for a SOC of 0.9.

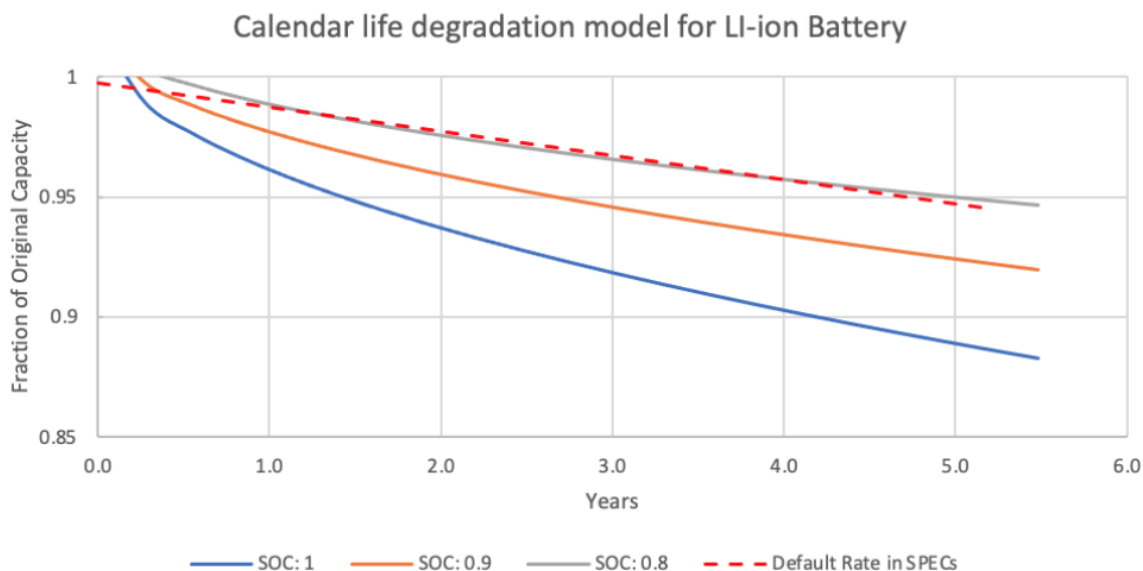


Figure 25: Default Calendar Life Capacity Degradation Rate in SPECs ESD (1%) compared to analytic models of calendar life degradation for batteries kept at various states of charge (SOC). The analytic model is from Smith et al (2017). *Life prediction model for grid connected Li-ion battery energy storage system*.

²¹ [Smith et al \(2017\). Life Prediction Model for Grid Connected Li-ion Battery Energy Storage System. NREL. Pg 3.](#)

Notably, a leading battery performance testing program at DNV GL recently observed calendar-life degradation in the range of 0.2 - 1% per year under test conditions.²²

6.2.2 Cycle-life Degradation

Cycle-life degradation occurs with all battery chemistries and results each time the battery is charged or discharged. Cycle-life degradation accelerates with high or low battery temperature, lower depth of discharge, and higher charge/discharge rates. Battery end-of-life (EOL) is usually defined as occurring when the battery degrades to 80% of its initial capacity.

The figure below, from DNV GL's *2020 Battery Performance Scorecard*, shows energy throughput to 90% remaining capacity for various Li-ion battery systems, identified by chemistry, with 50% of the systems being NMC (Nickel Manganese Cobalt Oxide). Throughput is seen as a more dependable metric for looking at battery decay, as opposed to cycles, which can vary over depth of discharge and resting state of charge. Total number of turnovers is defined as the total cumulative discharged energy, divided by the battery's nameplate capacity. Turnovers would align closely with the number of cycles for a new battery but would be less than total cycles as capacity degrades.

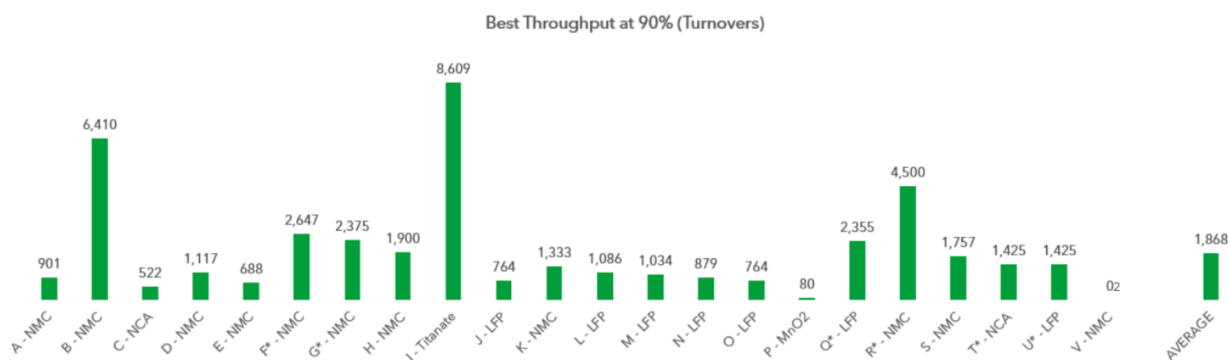


Figure 26: Throughput of Different Tested Batteries. Source: DNV GL (2020). *2020 Battery Performance Scorecard*. Page 29.

While the average throughput for all batteries was 1,868 turnovers, this is skewed by several outliers. Removing the high and low values in the example above (6410, 8609, 80, 4500), leaves an average of 1,325 turnovers to 90% throughput.

Cycle-life degradation in the ESD model is determined by users entering in a value on the model spreadsheet for "Turnovers to reach 90% of capacity," which should be based upon current and future results from DNV GL's Battery Performance Scorecards. The current default is 1,325, but it could be customized, if the user

Battery Degradation and Lifetime	
Calendar degradation rate	1.0% / yr
End of Life (% of initial cap)	80%
Turnovers to reach 90% of capacity	1300
Cycle degradation rate	2.5% / yr
Battery Throughput Per Year	2,585,556 kWh/yr
Battery Turnovers per Year	323 /yr
Battery Bank Lifetime	5.7 years

Figure 27: Battery degradation parameters and calculations.

²² DNV GL (2020). *2020 Battery Performance Scorecard*. Page 29.

knows what battery chemistry they would be using, based on an average value from current data reported by DNV GL, as shown in the previous figure.

The reason that the ESD model sums the values for cycle-life degradation and calendar-life degradation is because the cycle-life degradation rate results from batteries that are tested in a laboratory, with a high rate of cycling over a shortened time period. That alters the true mechanisms of calendar-life degradation. If the user were to have access to battery degradation field data, where capacity fade would include calendar-life and cycle-life degradation, the user could enter zero for calendar degradation rate and only use a value for “Turnovers to reach 90% of capacity.” For the general purposes of the ESD model, the user may simply use the defaults provided.

6.3 Running SAM and Importing Simulation Outputs to SPECS

The SPECS ESD model relies upon some inputs derived from running the U.S. DOE National Renewable Energy Laboratory (NREL) System Advisor Model (SAM). SAM is a widely trusted and user-friendly tool for the economic analysis of power systems, including functions to assess solar-plus-storage demand-reduction values. The SPECS ESD model dovetails with SAM, adding new features, so it can provide solar project assessment and review of demand-reduction values, integrated with an assessment of *multi-value* solar-plus-storage use cases, viewed from a utility project perspective. The integration of SAM with the SPECS ESD model offers a practical solution for utilities’ early-stage solar-plus-storage project decision-making.

The freely available SAM model can be downloaded and installed from: www.sam.nrel.gov. The ESD model was developed with SAM Version 2020.11.29.²³ After SAM is downloaded and installed, the user may follow the steps below to set it up, run it, and transfer the outputs to the ESD model. Note that with the SPECS Excel-based model, will also come a SAM project file called *SAM-generic-user-file.sam*.

Users are advised to refer to SAM support materials to run the overall model for solar-plus-storage system assessment. Online technical support for SAM includes several user-friendly videos and resources that can help project designers dive deeper into strategic solar design. The instructions below pertain specifically to the integration of SAM with the ESD model.

1. **In order to assess savings on demand charges, SAM must be run as if it were assessing a behind-the-meter (BTM), commercial system.** This is analogous to the situation of a distribution utility that pays wholesale demand charges. In SAM, the user will need to choose: Create new project > Choose Battery Storage > Detailed PV-Battery > Distributed > Commercial Owner, as shown in the image below:

²³ System Advisor Model Version 2020.11.29 (SAM 2020.11.29). National Renewable Energy Laboratory. Golden, CO. Accessed December 27, 2020. Updates to the SAM model are anticipated to be compatible with SPECS ESD model for the foreseeable future.

Choose a performance model, and then choose from the available financial models.

▶ Photovoltaic	▶ Power Purchase Agreement
▼ Battery Storage	▼ Distributed
Detailed PV-Battery	Residential Owner
PVWatts-Battery	Commercial Owner
Generic System-Battery	Third Party Owner - Host
▶ Concentrating Solar Power	Third Party - Host / Developer
▶ Marine Energy	Merchant Plant
Wind	

2. **Choose an appropriate location and solar resource file** under “location and resources”. Follow SAM instructions to choose or download a solar resource file to the model. The user may want to download a weather file for a specific year if load data is from a specific year, rather than the default typical meteorological year (TMY) file. On the Location and Resource page, type a location name or address and change the file option from the Default TMY File option to the Choose Year option. Then click Download and Add to Library and follow the prompts to choose a year. As of May 2021, the National Solar Radiation Database (NSRDB) has historical data from 1998 to 2019. The most recent year is updated periodically.
3. **Check the System Design (for PV) setting** under “System Design”. Select “Estimate Subarray 1 Config” Specify array size in kW DC and the DC to AC ratio (1.2 is the default in the SPECS model). See illustration below.

PV-Battery, Commercial	
Location and Resource	
Module	
Inverter	
System Design	
Shading and Layout	
Losses	
Battery Cell and System	

AC Sizing

Number of inverters

DC to AC ratio

Desired array size kWdc

Desired DC to AC Ratio

☒ Estimate Subarray 1 configuration

4. **Set battery storage parameters** under “Battery cell and system”.
 - Battery Bank Sizing. For example: 8,000 kWh, 2,000 kW, as illustrated below. Make sure that this setting is AC in order to be consistent with assumption in the ESD Excel model.
 - ☒ Set desired bank size
 - ☐ Specify cells
- Desired bank power kW ☐ DC units

Desired bank capacity kWh ☒ AC units
- Scroll down to **Power converters**
 - Set to DC for a case where the batteries would be charged by “Solar Only” in the ESD model. **Make sure the inverter power ratings are greater than the battery power.** Check “inverter clipping” in output variables to see if there is an issue.
5. **Set the battery degradation to zero** under “Battery Lifetime”.

- Under “Cycle Degradation” the battery capacity should be set to 100% regardless of the depth of discharge or the number of cycles so that the battery does not degrade.

–Cycle Degradation–

Import...	Depth-of-discharge (%)	Cycles Elapsed	Capacity (%)
Export...	20	0	100
Copy	20	5000	100
Paste	20	10000	100
Rows:	80	0	100
	80	1000	100
6	80	2000	100

- Under “Calendar Degradation” the circle with “none” should be selected.

–Calendar Degradation–

☒ None
 ☐ Lithium-ion model
 ☐ Custom

- Note: The battery degradation is all handled internal to the ESD model, so any degradation counted in SAM will lead to an overestimation of battery decay and a shorter battery life.

6. Select a Storage Dispatch Controller option > Dispatch Options > Peak Shaving One-day Look Ahead

Losses
 Battery Cell and System
Battery Dispatch
 Grid Limits
 Lifetime and Degradation
 System Costs
 Financial Parameters
 Incentives
 Electricity Rates
 Electric Load

Storage Dispatch Controller
 –Dispatch Options–
☒ Peak shaving one-day look ahead
☐ Peak shaving one-day look behind
☐ Input grid power targets
☐ Input battery power targets
☐ Manual dispatch
☐ Price signal forecast

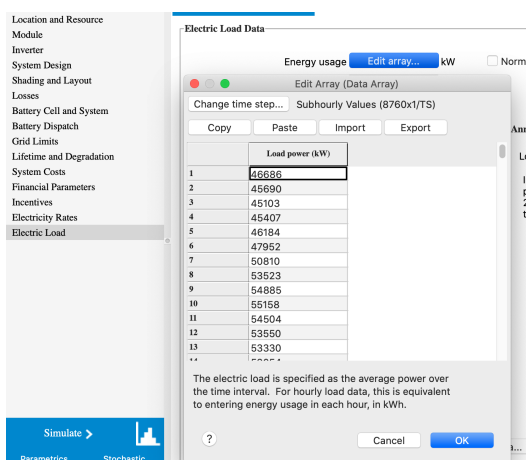
- Charge Options.** Select “Battery can charge from system,” if the user plans to run the “Solar Only” battery charging option in the ESD model. Make sure that the PV system is adequately sized to charge the battery, and that the inverter selected is large enough, so that it will not limit solar or battery operations. Select both “Battery can charge from system” and “Battery can charge from grid,” in order to assess both options. Note that if the latter option is chosen, the system may not benefit from the Federal solar-plus-storage tax credit (ITC).

–Charge Options–

For manual dispatch, charge options are defined below by dispatch period.

- ☐ Battery can charge from grid
☒ Battery can charge from system

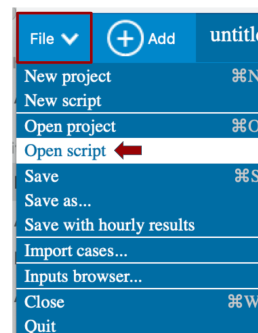
8. **Electric Load.** Click on “Edit Array” to import the utility’s hourly load profile for one year (8760 values) in units of kW. If the load data is for a particular year, download a weather file for that year as described in Step 2 above. This will help ensure that any correlation between the load and weather is represented in the analysis assumptions. If the data represents the average load over a historical period, then use a typical meteorological year (TMY) weather file. Many analysts would recommend reviewing results from multiple years of utility hourly data, due to the possibility of a one-year anomaly. For use with the ESD model, which aims to provide quick, estimated results, the utility may quickly review annual load data from several years, in order to choose the most representative data, or it may use another method to aggregate the data sets. As a supplement to the requirements of this model, the utility may be asked to provide multiple (typically 3 or more) years of hourly load data to share with short-listed bidders in the later stages of a project procurement.



9. **Run the simulation.** Press “Simulate” to run the SAM simulation function.

10. Importing SAM output into SPECS ESD model

- In order to facilitate importing SAM simulation outputs into SPECS, the SAM model comes with a script, named **sam-to-specs.lk**, which will run the model and create a CSV (spreadsheet) file, with all of the relevant SAM parameters and time series needed to run the ESD model.
 - To run the script, the user clicks on: File > Open script > sam-to-specs.lk
 - This will open a new window with the script. In the script window choose “run”, which will result in the creation of a file called **sam-inputs-for-specs.csv**
- The CSV file contains the following parameters, as illustrated in the figure below.
 - PV DC Nameplate capacity
 - DC-AC ratio
 - PV annual DC degradation rate



- Battery AC power (kW)
- Battery minimum state of charge
- Battery maximum state of charge
- Battery AC energy capacity (kWh)
- Battery round trip efficiency (%)
- Battery can charge from grid
- Battery can charge from system

	A	B	C	D	E	F	G
1	PV DC name	1001.16095					
2	DC-AC ratio	1.001161					
3	PV annual DK	0.5					
4	Battery AC p	2000					
5	Battery mini	0.15					
6	Battery maxi	0.95					
7	Battery AC e	8000.35667					
8	Battery round	92.356308					
9	Battery can c	0					
10	Battery can c	1					
11	Electricity lo	Electricity to	Electricity to	Electricity to	Electricity to	Battery state	of charge (%)
12	46686	0	0	0	0	50	
13	45690	0	0	0	0	50	
14	45103	0	0	0	0	50	
15	45407	0	0	0	0	50	
16	46184	0	0	0	0	50	
17	47952	0	0	0	0	50	
18	50810	0	0	0	0	50	
19	53523	0	18.599685	0	0	50.196219	
20	54885	0	317.280156	0	0	53.534805	
21	55158	0	522.518503	0	0	59.01351	
22	54504	0	663.142892	0	0	65.941518	
23	53550	0	645.363183	0	0	72.664697	
24	53330	0	579.780677	0	0	78.691882	
25	53054	0	525.794971	0	0	84.148828	
26	53039	0	552.688682	0	0	89.876151	
27	54225	0	356.488283	0	0	93.567147	
28	59121	0	102.724124	0	0	94.630502	
29	60491	0	0	1000	0	82.934928	
30	59801	0	0	353.115535	0	79.006261	
31	59091	0	0	0	0	79.006261	
32	57360	0	0	0	0	79.006261	

And time series:

- Electricity load (kW)
 - Electricity to battery from grid (kW)
 - Electricity to battery from system (kW)
 - Electricity to load from battery (kW)
 - Electricity to load from system (kW)
 - Battery state of charge (%)
- The final step requires the user to select the first 7 columns (A-H) in the CSV file, copy them, and then paste them in the same first 7 columns in the SPECS ESD Excel Model's tab called SAM Inputs. The data will then automatically update throughout the ESD model.

6.4 Model Assumptions & Logic

This section will illuminate the logic behind the battery operation and solar dispatch based upon each scenario. There are numerous assumptions that are made regarding battery availability and operation in order to simplify the model and make it operationally quicker and user- friendly, while maintaining technical integrity. The logic can be changed by modifying the embedded calculations if the user has a scenario where the existing model is not adequate. However, this comes with the warning: The authors cannot assure the effectiveness of the

model's performance, once modifications are made, because many calculations and cells are interconnected and inform multiple further calculations.

6.4.1 Logic Basics

Scenarios for the use cases that may be tested with the ESD model are introduced in Section 4.2, Value Stack Selection. Scenarios 1 through 4 all utilize local demand reduction as the primary value stream and scenarios 5 through 8 use CP demand reduction as the primary. Scenarios 5 and 6 both prioritize local demand reduction as the secondary value stream. For scenarios 1 through 4, the primary value stream is calculated using SAM's output while scenarios 5 and 6 use a modified set of SAM outputs adjusted to account for the primary CP demand value stream. CP demand, energy arbitrage, and frequency regulation (ancillary services) are all calculated internally to the ESD model and use the SAM model results were applicable (i.e., the solar array generation).

Value Stack Priority	1	2	3	4	5	6	7	8
1st	Local Demand	Local Demand	Local Demand	Local Demand	CP Demand	CP Demand	CP Demand	CP Demand
2nd	Energy Arbitrage	Ancillary Services	CP Demand	CP Demand	Local Demand	Local Demand	Energy Arbitrage	Ancillary Services
3rd	Ancillary Services	Energy Arbitrage	Energy Arbitrage	Ancillary Services	Energy Arbitrage	Ancillary Services	Ancillary Services	Energy Arbitrage

Figure 28. Illustration of Use-Case Scenarios for the ESD Model.

As stated previously, the ESD model assumes that the battery can only be used once a day to serve one of the three selected value streams. The solar energy is used by the battery where applicable each day, and the remaining energy is sent to the grid in order to offset otherwise purchased electricity.

The model also delineates two different logics between the different battery charging options, solar only and solar and/or grid. When the battery may only be charged by solar the battery's modeling is more complicated because there is a necessity to check the availability of solar energy to charge the battery, which limits its ability to be as readily available. Under a dual charging scenario, the battery is more easily deployed since it may be charged at any point by solar or the grid. Under ideal and real-world circumstances, the battery would be charged from the cheapest energy source likely. The ESD model makes some assumptions about the charging energy source in the dual charging scenarios to limit complications, as discussed below.

The four major use case value streams considered include local demand reduction, coincident peak demand reduction, energy arbitrage, and ancillary services in the form of frequency response. Local demand reduction logic is largely handled by SAM with some modifications for specific scenarios. Coincident peak (CP) demand reduction is calculated based upon the actual CP day and hour from historical data. It assumes that the storage will be dispatched only once to meet the need. This assumption may be adjusted by a proxy method discussed below if the user has only partial wholesale market information and forecasting. (If the utility has no ability to access such information, it may not be appropriate to target this value stream.) Energy arbitrage is calculated by determining the amount of energy available during off peak hours that can charge the battery and then be sold in the on peak hours. Frequency regulation

(ancillary services) are calculated simply by determining the number of hours that storage is expected to bid into the market and multiplying the number of hours by the storage nameplate capacity (MW). For ancillary services, the amount of energy in the battery is not considered as the system would have to charge and discharge to and from the grid in order to supply ancillary services. Ancillary services are an option for the solar only scenarios, however it should be noted that the need to interact bidirectionally with the grid for ancillary services could void the solar only charging limitations in order to obtain the ITC.

6.4.2 Solar Only Charging Logic

For all the scenarios where the storage is limited to solar only charging, the battery's availability and its operation are determined by the amount of energy generated and available to the battery prior to its operational need.

Scenario 1 [Local Demand, Energy Arbitrage, Ancillary Services]

1. The solar and battery operations are imported from SAM in order to determine demand reduction, solar generation to the grid, and battery throughput
2. On each day where energy arbitrage is dictated to be available for compensation, the amount of solar energy below the battery energy capacity that is off peak is summed. On days where the battery is available (not already in use for local demand) the energy summed is "shifted" to on peak.
3. For all the remaining days that the battery has not been used for the two above value streams and that ancillary services are dictated to be available for compensation, the battery nameplate capacity is multiplied by the number of hours the battery can bid into the ancillary services market.

Scenario 2 [Local Demand, Ancillary Services, Energy Arbitrage]

1. Same as Scenario 1
2. On each day where ancillary services are dictated to be available for compensation and the battery has not been used for local demand reduction already, the battery nameplate capacity is multiplied by the number of hours the battery can bid into the ancillary services market.
3. For all the remaining days that the battery has not been used for the two above value streams, the amount of solar energy below the battery energy capacity that is off peak is summed and assumed to be "shifted" to on peak hours.

Scenario 3 [Local Demand, Coincident Peak, Energy Arbitrage]

1. Same as Scenario 1
2. On coincident peak days where the battery is being used for local demand reduction, the battery output during the CP hour is used for CP calculations. On days where the battery is available, the amount of energy available to charge the battery for two hours prior to the CP hour is summed. The energy summed is then used to calculate a fraction of the total battery energy capacity. This fraction is then multiplied by the battery's energy capacity to determine the fraction of the total energy capacity that the coincident peak hour demand reduction achieved is expected. As noted above, if the utility has a lower level of confidence in CP forecasting and real-time information, but

still wishes to apply the battery to reduce CP demand costs, then the CP demand rate may be adjusted to roughly approximate the percentage of total annual value in this value stream that is likely to be captured.

3. Same as scenario 2

Scenario 4 [Local Demand, Coincident Peak, Ancillary Services]

1. Same as Scenario 1
2. Same as Scenario 3
3. Same as Scenario 1

Scenario 5 [Coincident Peak, Local Demand, Energy Arbitrage]

1. As the primary value stream, the battery is assumed to be fully charged and therefore the battery reduces the coincident peak by the full battery capacity.
2. The local demand reduction is calculated based upon the SAM model similar to scenarios 1-4, with two modifications. To ensure the battery is charged and able to produce the full CP reduction, the battery's state of charge at midnight prior to the CP day as dictated by SAM is observed. If the state of charge is below 80% full then the SAM battery operation the local demand operation for the day before is voided to ensure the battery is 100% full for CP. Similarly, if the total amount of energy after the CP hour for that day is less than 80% of the battery state of charge that SAM shows at midnight at the end of the day, then the day after local demand battery operation is also voided. See further notes above on the wholesale-level forecasting and real-time information that may be needed to pursue fully access the CP value stream.
3. Same as Scenario 2

Scenario 6 [Coincident Peak, Local Demand, Ancillary Services]

1. Same as Scenario 5
2. Same as Scenario 5
3. Same as Scenario 1

Scenario 7 [Coincident Peak, Energy Arbitrage, Ancillary Services]

1. Same as Scenario 5
2. Since there is no local demand reduction the SAM battery operation is ignored. Rather, the total amount of PV solar generation is calculated for non-coincident peak days and all of the off peak energy below the battery's energy capacity is summed and shifted to off peak.
3. Same as Scenario 1

Scenario 8 [Coincident Peak, Ancillary Services, Energy Arbitrage]

1. Same as Scenario 5
2. On each day where ancillary services are dictated to be available for compensation and the battery has not been used for coincident peak reduction already, the battery nameplate capacity is multiplied by the number of hours the battery can bid into the ancillary services market.
3. Same as Scenario 2 with the note that the amount of solar energy available is from the total PV solar generation (as opposed to the solar generation left after the battery is used for local demand reduction as dictated by SAM).

6.4.3 Solar-Plus Grid Charging Logic

For all coincident peak and energy arbitrage battery charging, the battery will be charged by the grid exclusively unless the solar PPA costs less than the off peak grid rate on a \$/kWh basis. If the PPA is cheaper, then the battery will be charged by solar in proportion to the amount of solar energy available and the amount of energy needed.

Scenario 1 [Local Demand, Energy Arbitrage, Ancillary Services]

1. The solar and battery operations are imported from SAM in order to determine demand reduction, solar generation to the grid, and battery throughput
2. Since the battery is not limited from solar charging only, it is assumed that the battery shifts its full energy capacity from off peak to on peak on all days that energy arbitrage is dictated and that the battery is not already being used for local demand reduction.
3. For all the remaining days that the battery has not been used for the 2 above value streams and that ancillary services are dictated to be available for compensation, the battery nameplate capacity is multiplied by the number of hours the battery can bid into the ancillary services market.

Scenario 2 [Local Demand, Ancillary Services, Energy Arbitrage]

1. Same as Scenario 1
2. On each day where ancillary services are dictated to be available for compensation and the battery has not been used for local demand reduction already, the battery nameplate capacity is multiplied by the number of hours the battery can bid into the ancillary services market.
3. For all the remaining days that the battery has not been used for the 2 above value streams, the full battery energy capacity is shifted from off peak to on peak.

Scenario 3 [Local Demand, Coincident Peak, Energy Arbitrage]

1. Same as Scenario 1
2. Since the battery is not limited from solar charging only, the battery reduces the coincident peak by full battery capacity on each day that the battery is not being used for local demand reduction. On days set for local demand reduction battery operation, the battery output during the CP hour is used, the same as in the solar only charging scenarios. See further notes above on the wholesale-level forecasting and real-time information that may be needed to pursue fully access the CP value stream.
3. Same as Scenario 2

Scenario 4 [Local Demand, Coincident Peak, Ancillary Services]

1. Same as Scenario 1
2. Same as Scenario 3
3. Same as Scenario 1

Scenario 5 [Coincident Peak, Local Demand, Energy Arbitrage]

1. The battery is assumed to reduce the coincident peak by full battery capacity on each CP day. See further notes above on the wholesale-level forecasting and real-time information that may be needed to pursue fully access the CP value stream.

2. The local demand reduction battery operation is completed as SAM dictates it with the exception of the days when the battery is being utilized for the coincident peak. This is similar to the solar only scenarios except day before and after considerations are not important since the battery can be recharged at any point from the grid.
3. Same as Scenario 2

Scenario 6 [Coincident Peak, Local Demand, Ancillary Services]

1. Same as Scenario 5
2. Same as Scenario 5
3. Same as Scenario 1

Scenario 7 [Coincident Peak, Energy Arbitrage, Ancillary Services]

1. Same as Scenario 5
2. Since the battery is not limited from solar charging only, it is assumed that the battery shifts its full energy capacity on all days that energy arbitrage is dictated and that the battery is not already being used for coincident demand reduction
3. Same as Scenario 1

Scenario 8 [Coincident Peak, Ancillary Services, Energy Arbitrage]

1. Same as Scenario 5
2. On each day where ancillary services are dictated to be available for compensation and the battery has not been used for coincident peak demand reduction already, the battery nameplate capacity is multiplied by the number of hours the battery can bid into the ancillary services market.
3. Same as Scenario 2