

Capacity Value of Energy Storage in PJM

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TABLE OF CONTENTS

| EXECUTIVE SUMMARY | 2 |
|---|----|
| | |
| MODEL DEVELOPMENT | 5 |
| STUDY TOPOLOGY | 6 |
| LOAD MODELING | 7 |
| ECONOMIC LOAD FORECAST ERROR | 9 |
| RENEWABLE PROFILES | 9 |
| WIND PROFILES | 9 |
| SOLAR PROFILES | 11 |
| HYDRO PROFILES | 12 |
| CONVENTIONAL RESOURCES | 13 |
| UNIT OUTAGE DATA | 13 |
| DISPATCH ORDER AND EMERGENCY OPERATING PROCEDURES | 16 |
| ENERGY STORAGE RESOURCE CONFIGURATIONS | 17 |
| SIMULATION RESULTS | 17 |
| SINIOLATION RESULTS | 1/ |
| CONCLUSION | 20 |

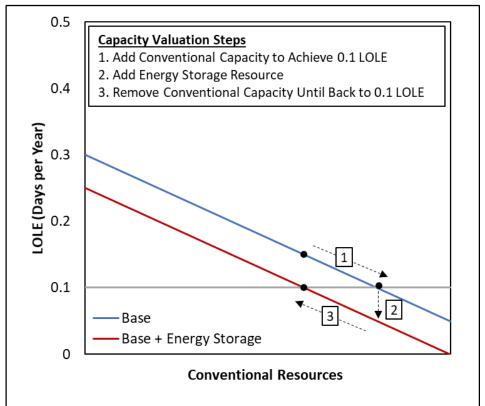
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EXECUTIVE SUMMARY

Astrapé Consulting performed a capacity valuation of energy-limited resources (ELRs) using the Strategic Energy and Risk Valuation Model (SERVM) for the PJM Interconnection, L.L.C. (PJM). The intent of this analysis was to determine the duration requirements for ELRs based on their ability to provide the same reliability benefits as conventional fully-dispatchable resources. This analysis was performed using the projected and potential resource mix in PJM over the planning horizon¹ which included aggressive energy storage deployments. Since reliability considerations are unique to the composition of the fleet in each electric system, it was critical that our analysis use an accurate representation of the current and projected PJM system.

Figure 1. Capacity Value Approach Using SERVM

The calculation of ELR capacity value in **SERVM** included several steps, as shown in Figure 1. First, reliability was calibrated in PJM and its neighbors to 0.1 Loss of Load Expectation (LOLE). This threshold is the generally accepted reliability criterion employed the United States and represents a single day of firm load shed in a 10 year period. Next, ELR capacity was added to the



system, improving reliability. Finally, perfectly available and fully dispatchable capacity was removed until reliability returned to 0.1 LOLE. The ratio of perfectly available capacity removed to ELR capacity added defines the ELR capacity value.

The results of our analysis demonstrate that with energy storage deployments up to 4,000 MW, 4 hours of duration allows those resources to provide full capacity value relative to a resource without duration limits. With energy storage deployments up to 8,000 MW, 6 hours of duration allows those resources to provide full capacity value. Within these limits, storage can replace traditional generation MW-for-MW with no reduction in system reliability.

The binding limit on providing reliability is generally either a capacity constraint or an energy constraint. This varies by system. In most of the United States, reliability is primarily constrained by

¹ The planning horizon as used in this report refers to a period of 10 years which is used to reflect ample opportunity to monitor load and technology trends and update resource requirements to protect reliability.

capacity. In these systems, reliability events occur when peak loads exceed the capacity of available resources. However, in the Pacific Northwest which serves a majority of its load with hydro resources, energy is the binding constraint. In these systems, the installed capacity is significantly higher than the most extreme peak demand, but limits on the availability of hydro energy can result in reliability events that can occur for extended durations over both peak and non-peak load hours. PJM is currently capacity constrained. In addition to assessing the capacity value of marginal additions of energy-limited resources, this study analyzed whether a shift to energy constrained reliability was possible in the PJM system with the incorporation of potential ELR deployments. With high enough penetrations of energy-limited resources, reliability events occur in shoulder load hours when ELRs exhaust their energy supply. However, the level of ELR deployments of typical durations between 4 and 6 hours that was required to shift PJM to energy-constrained reliability was unrealistic in the 10-year planning window. The findings from this analysis confirm our findings in other jurisdictions. Analysis performed in the New York Control Area showed that significant ELR capacity with 4-hour duration could be expected to provide full capacity value relative to a resource without duration constraints². While a number of factors including resource mix and load shape can influence the capacity value of energy limited resources in a particular region, Astrapé's experience of performing similar studies across the country for the last 20 years has consistently demonstrated that energy-limited resources can provide significant capacity value.

As part of this analysis, Astrapé also provided a qualitative review of the duration of historical reliability events. While our bottom-up analysis using SERVM demonstrates the value of 4-6 hour duration ELRs, a review of historical events can provide some level of calibration. In PJM, performance assessment periods are recorded when the confluence of generator availability and load conditions are such that reliability is of concern. Generally during these periods demand response resources are dispatched. In the period from June 2011 through the end of 2014, PJM recorded 9 system-wide performance assessment periods. These events ranged from less than one hour to 11.3 hours in duration, with almost all being 6 hours or less. The only event significantly longer than 6 hours was an event that declared in anticipation of tight conditions and was not due to energy constraints. The implications of this event will be discussed in more detail. Having performed reliability studies for nearly two decades, our experience demonstrates that reliability is actually improved by resource diversity even if resources being added have constraints. The survey of historical reliability-constrained periods is shown in Table 1. Of note, there have been no performance assessment periods in PJM since 2014.

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² "Load Shape Development and Energy Limited Resource Capacity Valuation". NY-BEST. 2019. ("NY-BEST NYISO Study").

Table 1. PJM System-Wide Performance Assessment Periods Since 2011

| Date | Emergency Procedure | Start Time (EPT) | Stop Time (EPT) | Duration of Event (Hours) |
|------------------|---------------------------|---------------------|--------------------|------------------------------|
| March 4, 2014 | Emergency Load Management | 5:30 AM | 8:30 AM | 3.00 |
| January 30, 2014 | Voltage Reduction Warning | 6:50 AM | 7:35 AM | 0.75 |
| January 8, 2014 | Emergency Load Management | 6:00 AM | 7:00 AM | 1.00 |
| January 7, 2014 | Emergency Load Management | 4:00 PM | 6:16 PM | 2.27 |
| January 7, 2014 | Primary Reserve Warning | 12:55 AM | 12:14 PM | 11.32 |
| January 6, 2014 | Voltage Reduction Warning | 7:27 PM | 9:23 PM | 1.93 |
| July 18, 2013 | Emergency Load Management | 2:40 PM | 6:00 PM | 3.33 |
| July 17, 2012 | Emergency Load Management | 3:08 PM | 7:05 PM | 3.95 |
| July 22, 2011 | Emergency Load Management | 1:30 PM | 7:37 PM | 6.12 |

The only performance assessment period with a duration significantly longer than 6 hours was on January 7, 2014 during the Polar Vortex. The load pattern on this day, as shown in Figure 2, was not suggestive of the need for long duration resources. Rather, as implied by the event being a "Primary Reserve Warning," the concern was that operators might not have been able to maintain adequate reserves over the course of the day. During a Primary Reserve Warning, generators are required to defer maintenance and take other steps to ensure they are available when called; the equivalent for storage would be to stand ready at full charge, which storage can do for an unlimited period of time. Energy limitations would not have affected storages' ability to provide reserves for the entire duration of this event.

Reliability was of concern for a long period this day because of correlated outages. Between a lack of access to firm fuel, cold weather related availability issues, and other forced outages, over 40 GW were unavailable³. The correlated issues that resulted in conventional generator outages generally would not apply to batteries. A system with more homogeneous resources is more susceptible to these coincident issues than one which contains more heterogeneous resources with different categories of constraints.

³ https://www.pjm.com/~/media/library/reports-notices/weather-related/20140509-analysis-of-operational-events-and-market-impacts-during-the-jan-2014-cold-weather-events.ashx

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145,000 140,000 135,000 130,000 Load (MW) 125,000 **Emergency Load** 120,000 Management Primary Reserve 115,000 Warning 110,000 105,000 100,000 8:00 AM 4:00 AM 2:00 PM 8:00 PM 4:00 PM 12:00 AM 2:00 AM 6:00 AM 12:00 PM 6:00 PM 10:00 AM 10:00 PM Time

Figure 2. Load on January 7, 2014

While caution is warranted in using historical data to justify duration requirements since the system will be evolving, the primary takeaway is that the duration of reliability concern does not necessarily match the shape of the load. PJM frequently refers to the load shape as being very high for 10 hours in a day to support the need for 10 hours of duration for capacity resources. However, this claim is not borne out in the historical data. This historical review is consistent with the findings from the SERVM-based simulations that demonstrate that 4-6 hour duration energy limited resources can provide full capacity value compared to conventional resources, even with a system with a load shape that is relatively flat during high load days. The following sections detail the input development for the SERVM simulations.

MODEL DEVELOPMENT

The SERVM model utilized for this study is the same as that used for resource adequacy evaluations performed by Astrapé for systems such as ERCOT, MISO, SPP, AESO, as well for electric utilities such as Tennessee Valley Authority, Southern Company, Duke Energy, and Pacific Gas and Electric. The data development and study framework used in those analyses are similar to those employed in this analysis as well. Both the process and the model have been vetted by state regulators for over three decades.

The high-level framework of the SERVM simulations included the construction of a large number of synthetic demand, weather, and generator outage profiles or scenarios against which to test system reliability. For each one of those scenarios, the reliability contributions of various energy storage portfolios with a range of configurations were quantified. The weighted average contributions across all scenarios was ultimately used to calculate the capacity value of each energy storage configuration. The following sections detail the efforts involved with creating the data for these scenarios and ensuring robust correlations of loads and resources across the wide geographical area simulated.

STUDY TOPOLOGY

Figure 3 shows the study topology that was used for the study. SERVM models the regions in Figure 1 with a transportation model representation⁴, allowing for regions to share capacity based on economics and subject to physical transmission constraints. The following is a list of regions included in the study:

- PJM MidAtlantic
- PJM West
- PJM South
- NYISO (Zones A-K)
- Wisconsin-Michigan (MISO)
- Indiana (MISO)
- Illinois (MISO)
- TVA
- Progress Carolinas
- Duke

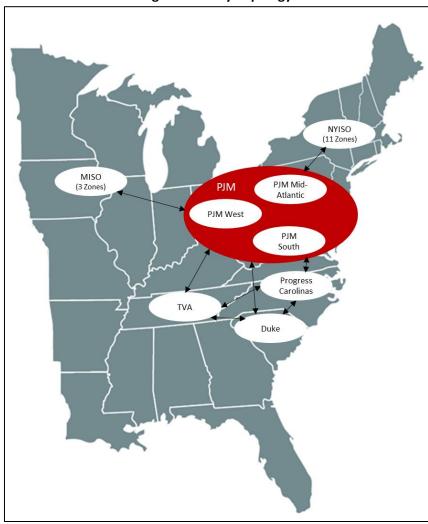


Figure 3. Study Topology

⁴ Static imports and export constraints are defined between zones or groups of zones rather than modeling the electric system with DC or AC network models. This is standard practice for resource adequacy analysis.

LOAD MODELING

To model the effects of weather uncertainty, 38 weather years were developed to reflect the impact of weather on load. Based on the 2011 to 2018 historical weather⁵ and load⁶, a neural network program⁷ was used to develop relationships between weather observations and load. Different relationships were built for each season and for each zone to ensure that proper weather diversity was captured. These trained relationships were then applied to the last 38 years of temperature profiles to develop 38 synthetic load shapes for the 2019 study year. This neural network process has also been used in resource adequacy analyses by MISO, SPP, ERCOT, AESO, CPUC, Southern Company, Duke Energy, and TVA which all use SERVM with similar input development methods to plan for reliability.

Equal probabilities were given to each of the 38 load shapes in the simulations. Figure 4 ranks all weather years by summer peak load and shows variance from normal weather. In the most severe weather conditions, the peak can be as much as 7.5% higher than under normal weather conditions.

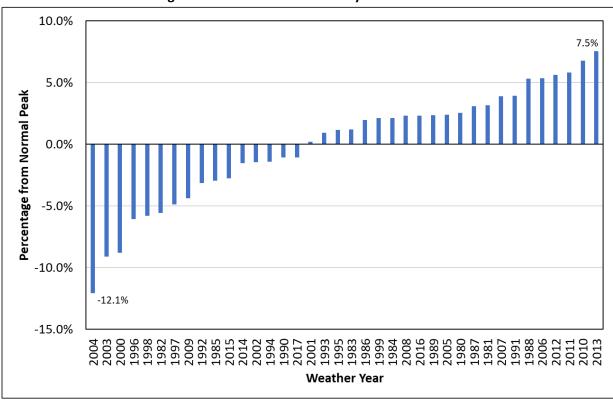


Figure 4. 2019 PJM Peak Loads by Weather Year

Since this study was designed to measure the need for duration, an important step in the calibration was ensuring the daily load shape matched historical profiles. Figure 5 shows a comparison of the average daily shape during the top 10 load days in the synthetic shapes versus the top 10 load days

https://dataminer2.pjm.com/feed/hrl_load_metered

⁵ Historical temperature data pulled for multiple cities in the PJM footprint from the following web location: https://www7.ncdc.noaa.gov/CDO/cdoselect.cmd

⁶ PJM historical load data pulled from the following website:

⁷ Astrapé Consulting uses the NeuroShell Predictor software produced by Ward Systems. The following input variables are fed into the program: temperature, 8 hour temperature, 24 hour temperature, 48 hour temperature, hour of week factor, and load. A network file is produced by the NeuroShell Predictor which defines a relationship for any possible combination of input variables and loads.

from recent history confirming that our modeled shapes are consistent with the load patterns expected in PJM.

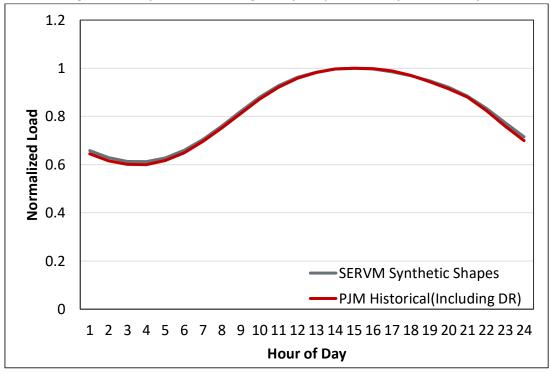


Figure 5. Comparison of Average Daily Shape of the Top 10 Load Days

Loads for each external region (Duke, MISO, PJM, Progress Carolinas, and TVA) were developed in a similar manner as the PJM loads. A relationship between hourly weather and publicly available hourly loads was developed based on recent history, and then this relationship was applied to 38 years of temperature data to develop 38 load shapes.

Table 2 summarizes the peak load for the PJM system and the load diversity relative to the interconnected regions.

| Table 2 | . Regional | Load | Diversity |
|---------|------------|------|-----------|
|---------|------------|------|-----------|

| | | , | | |
|----------|--------------------------|---|------------------------|--|
| | Peak Load | Load Diversity (% below non-coincident 50/50 peak) | | |
| Region | (MW) | | | |
| | Non-Coincident Peak Load | At System Coincident Peak | At PJM Coincident Peak | |
| Duke | 18,137 | -5.6% | -7.4% | |
| MISO | 57,665 | -5.2% | -7.7% | |
| NYISO | 33,254 | -5.8% | -6.6% | |
| PJM | 153,379 | -0.6% | 0.0% | |
| Progress | 14,011 | -10.5% | -11.6% | |
| TVA | 32,283 | -12.4% | -13.5% | |
| System | 295,435 | 0.0% | -0.8% | |

ECONOMIC LOAD FORECAST ERROR

The two uncertainties that are modeled in SERVM are uncertainties due to weather and uncertainties due to economic growth. These non-weather drivers of load forecast errors differ from weather-related forecast errors because they increase with the forward planning period, while weather uncertainties remain relatively constant and can be independent of the forward period.

The non-weather load forecast error multipliers were developed by reviewing the Congressional budget Office (CBO) GDP forecasts 3 years ahead and comparing those forecasts to actual data. A standard deviation was calculated, and a normal distribution was developed for economic load forecast error. Because electric load grows at a slower rate than GDP, a 40% multiplier was applied to the raw CBO forecast error.

Table 3 shows the economic load forecast multipliers and associated probabilities used in this study. The table shows that 6.1% of the time, it is expected that the load will be under-forecasted by 4% 3 years out. The load forecast multipliers were applied to all regions.

Table 3. Economic Load Forecast Multipliers Used in Modeling

| Load Forecast Error Multiplier | Probability (%) |
|--------------------------------|-----------------|
| 0.96 | 6.1 |
| 0.98 | 24.2 |
| 1.00 | 39.4 |
| 1.02 | 24.2 |
| 1.04 | 6.1 |

The SERVM Model utilized each of the 38 weather years and applied each of these 5 load forecast error points to create 190 different load scenarios. Each weather year was given equal probability of occurring.

RENEWABLE PROFILES

WIND PROFILES

Wind profiles were constructed based on hourly historical data for 2016 to 2018 for PJM, NYISO, MISO, and SPP. The raw data was found on the entities' respective websites. To construct wind shapes back to 1980, random days were selected from the 2016 to 2018 dataset based on the aggregate PJM load. To maintain correlation, as shown in Figure 6, between load and wind and between the wind output in different regions, the same day was used for each region being captured.

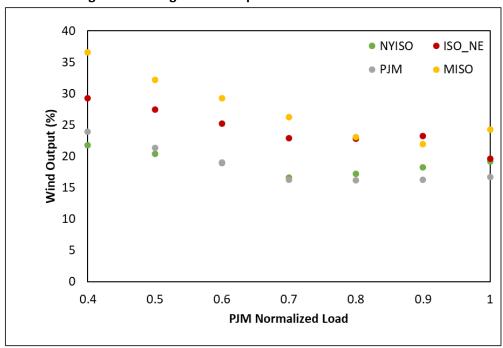


Figure 6. Average Wind Output as a Function of PJM Load

To smooth the transition between days (since days selected were not consecutive), the modeled output in hours 23 to 2 was averaged (hour 23 was the average of the profile in hour 22, 23, and 24; hour 24 was the average of hours 23, 24, and 1, etc.). The average final summer wind shapes are shown in Figure 7.

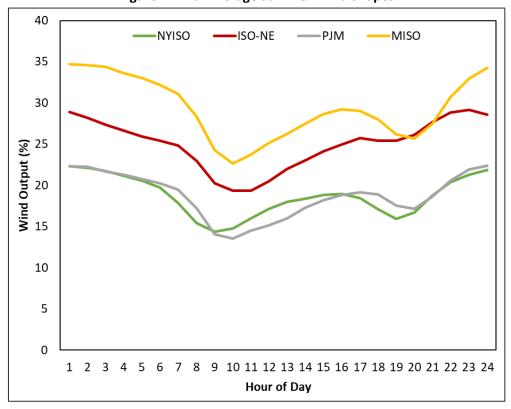


Figure 7. Final Average Summer Wind Shapes

SOLAR PROFILES

Five solar profiles (one for each of the following zones: PJM, NYISO, MISO, Duke/Progress, and TVA) were developed from data downloaded from the NREL National Solar Radiation Database (NSRDB) Data Viewer⁸. Data was downloaded for the 5 different locations for the available years, 1998 to 2017. Historical solar data from the NREL NSRDB Data Viewer included variables such as temperature, cloud cover, humidity, dew point, and global solar irradiance. The data obtained from the NSRDB Data Viewer was input into NREL's System Advisory Model (SAM)⁹ for each year and location to generate the hourly solar profiles based on the solar weather data for a fixed solar PV plant. Inputs in SAM included the DC to AC ratio of the inverter module and the tilt and azimuth angle of the PV array. Data was normalized by dividing each point by the input array size. Solar profiles for 1980 to 1997 were selected by using the daily solar profiles from the day that most closely matched the peak load out of all the days +/- 2 days of the source day for the 1998 to 2017 interval. The profiles for the remaining years 1998 to 2017 came directly from the normalized raw data. The previous steps for selecting a profile were completed for each of the 5 locations. Figure 8 shows the August average daily solar profiles for 1980 to 2017.

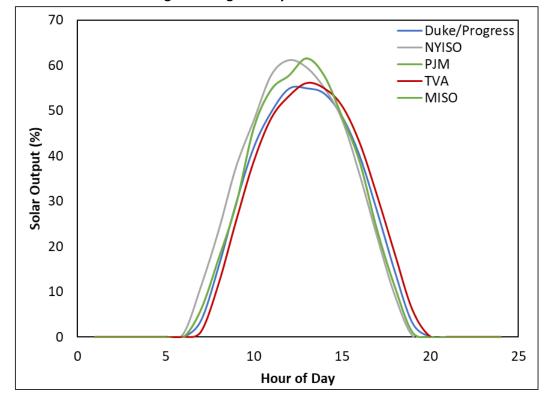


Figure 8. August Daily Fixed Solar Profile

⁸ https://nsrdb.nrel.gov/nsrdb-viewer

⁹ https://sam.nrel.gov/

HYDRO PROFILES

Available hydro data from 1980 to 2017 was collected from the U.S. Energy Information Administration Form 923. The projects in all of the zones modelled were assigned to their appropriate regions for all 38 weather years. Using the aggregate actual hourly data provided by PJM from 2016 to 2018, inputs were developed to be used by the proportional load following algorithm for the proper PJM zones.

The average daily minimum and maximum dispatch levels, the total monthly energy, as well as the monthly maximum dispatch levels were identified from the historical hourly data for PJM. Minimum and maximum daily dispatch levels and monthly maximum dispatch levels were defined as a function of monthly total energy as shown in Figure 9.

PJM did not supply hourly hydro data by resource type, so all projects are modeled together, including pumped storage hydro. The low minimum daily flows then reflect some pumping during low load periods. In the model, the entire hydro fleet was modeled as a single unit but dispatched consistent with the patterns described below.

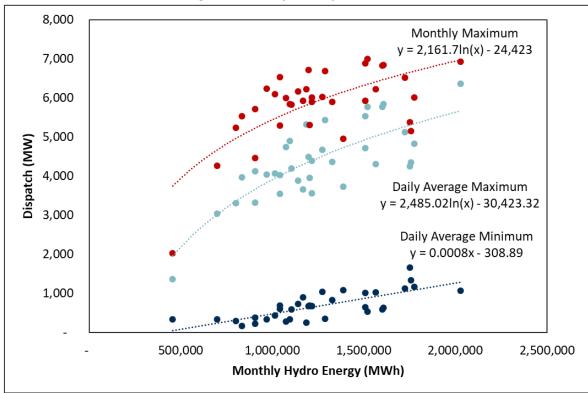


Figure 9. PJM Hydro Dispatch Levels

The curve fit equations were then used to apply to historical energy from the monthly energies calculated in the EIA form. SERVM optimally schedules the hourly hydro energy while respecting these constraints. The daily maximum and minimum dispatch and monthly maximum dispatch in conjunction with the total monthly energy are parameters that go into the determination of the hourly hydro schedule. The daily minimum hydro dispatch is scheduled at the minimum load hour of the day, and the daily maximum hydro is scheduled at the maximum load hour of the day. The monthly maximum hydro is scheduled at the max load hour of the month.

The above process was repeated for neighboring regions with hydro capacity. For regions where hourly generation was unavailable, the PJM hourly hydro generation was scaled by capacity and then applied to the monthly generation from the EIA form.

Scheduled hydro units are modeled with maximum capacity, total energy, daily average energy, and the schedule flow range. The total energy is the total amount of hydro that will be produced in a given month. This value cannot be greater than the total maximum hydro capacity multiplied by the number of hours in the month. The simulation logic will not allow the unit to simply run at the maximum hydro capacity for all hours because the monthly hydro energy constraint will be violated. After the minimum weekly flows are taken into account, the remainder of the month's energy is scheduled as peak shaving.

CONVENTIONAL RESOURCES

The conventional resources included in the 2019 study are the same resources listed on the PJM website as being included in their 2019-2020 RPM Resource Model¹⁰. To accurately reflect the flexibility of the PJM system, each resource was modeled with detailed unit variables and all constraints were respected by SERVM in the simulations. While fuel prices and other economic variables were not available publicly, Astrapé developed inputs that allowed for a reasonable commitment and dispatch schedule of the entire fleet; base load resources were modeled to operate at availability while peaking resources dispatched less than 1,000 hours per year. The installed reserve margin was calibrated in the analysis to achieve 0.1 LOLE for the base case¹¹.

The neighboring region resources were also modeled with publicly available unit data found in IRPs and on their respective websites.

UNIT OUTAGE DATA

Unlike typical production cost models, SERVM does not use an Equivalent Forced Outage Rate (EFOR) for each unit as an input. Instead, historical events are entered in for each unit, and SERVM randomly draws from these events to simulate the unit outages. The events are entered using the following variables:

Full Outage Modeling

Time-to-Repair Hours
Time-to-Fail Hours

Partial Outage Modeling

Partial Outage Time-to-Repair Hours Partial Outage Derate Percentage Partial Outage Time-to-Fail Hours

¹⁰ https://www.pjm.com/-/media/markets-ops/rpm/rpm-auction-info/2019-2020-rpm-resource-model.ashx?la=en

¹¹ This entailed retiring conventional capacity since the current level of reserves is expected to produce better reliability than the 0.1 LOLE standard. Simulating at 0.1 LOLE is a conservative approach when measuring the capacity value of energy limited resources, since at higher levels of reliability, resources are only needed for shorter duration.

Planned Outages

Planned outage rates are entered for each unit. SERVM schedules each planned outage event during shoulder seasons to minimize reliability impact for each zone.

Astrapé inserted generic outage distributions and scaled the data so the system average forced outage rate would be comparable to typical averages seen in that region. PJM publishes forced outage rate data used in their resource adequacy studies, but their data is based on must-run dispatch, so it is not directly comparable to the values shown here. The forced outage rate data used in analysis based on must-run dispatch is reduced for periods where units were forced offline but not needed to serve load. Since SERVM uses economic dispatch, raw higher EFOR values were used. Sensitivity analysis performed in the New York Control Area shows this doesn't have significant effect on the capacity value of energy limited resources¹². Table 4 shows the average EFOR values from all the distributions imported into SERVM for each PJM unit category.

Table 4. PJM EFOR Values by Unit Category

| ruble 4.13m El On values by Omit category | | |
|---|----------|--|
| Unit Category | EFOR (%) | |
| Nuclear | 5.47 | |
| Combined Cycle | 5.89 | |
| Gas Turbine | 12.10 | |

An important aspect of unit performance modeling is the cumulative MW offline distribution. Most service reliability problems are due to significant coincident outages. Figure 11 shows the distribution of outages for the PJM Balancing Area based on historical modeled outages. The figure demonstrates that in any given hour, the system can have between 0 and 20,000 MW of its generators offline due to forced outages. Each point on the curve demonstrates the probability that a specific MW quantity of capacity or less is forced offline. The figure shows that in approximately 90% of all hours throughout the year, the balancing area has less than 12,700 MW in a non-planned outage condition. The corollary is that in 10% of all hours in the year, more than 12,700 MW are in a forced outage state.

¹² "Load Shape Development and Energy Limited Resource Capacity Valuation". NY-BEST. 2019. ("NY-BEST NYISO Study"), at Page 10.

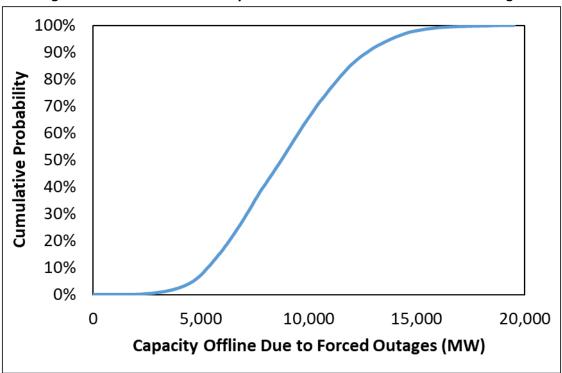


Figure 10. Cumulative Probability of Conventional Resources on Forced Outage

It is important to note that generator outages also have a shape. Outages do not remain static over a long period of time as generators are frequently failing or returning to service. The approach employed in prior PJM analysis¹³ essentially assumes a static shape to generator outages which will tend to overstate the need for duration as compared to the dynamic SERVM approach which as an hourly chronological model reflects variability in generator outages over time. The static shape in the PJM analysis is a function of using a capacity outage table to derive the likelihood of extended outages. A capacity outage table simply measures the probability of particular levels of outages on a system. Since a capacity outage table does not have the ability to capture duration or other chronological effects, it should not be used to measure the capacity value of energy limited resources. Figure 11 illustrates how a static representation of outages may overstate the need for duration relative to a dynamic outage draw process. In the static representation, load exceeds resources for a period of 6 hours versus a period of 2 hours in the dynamic representation.

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¹³ "Demand Resource Saturation Analysis". Page 4. Affidavit of Thomas A. Falin on Behalf of PJM Interconnection, L.L.C 2012. Docket No. ER11-000.

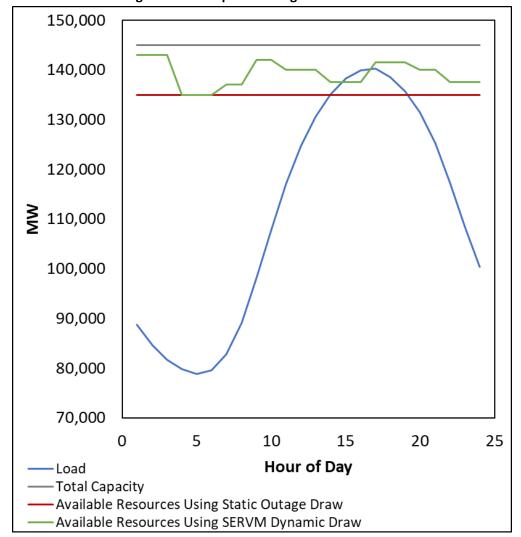


Figure 11. Example of Outage Draw Methods

DISPATCH ORDER AND EMERGENCY OPERATING PROCEDURES

The order in which energy storage resources are dispatched has an impact on their capacity value. The flexible and efficient characteristics of energy storage resources results in those resources typically serving ancillary service needs most of the time, being dispatched to serve energy only late in the dispatch stack. Given that some ancillary services are typically maintained even during emergency conditions, some quantity of energy storage resources are able to provide capacity value without ever being dispatched for energy by serving ancillary services. During non-emergency conditions, energy storage resources may be dispatched to arbitrage energy prices very early in the dispatch stack. However, for capacity value assessments such as this, the primary concern is how energy storage resources will be utilized during emergency conditions. The dispatch in SERVM attempts to mimic the approach that would be utilized in actual emergency conditions. This would be to use energy storage to serve ancillary services where appropriate and only dispatch energy storage when necessary. This would include preserving energy limited resources by dispatching high cost, but unconstrained resources first. In practice, this efficient dispatch occurs from ordinary economic scheduling, even without explicit optimization of energy-limited resources' schedules. Other emergency operating procedures such as voltage reduction are not modeled prior to firm load shed to be consistent with approaches employed by PJM in prior resource adequacy analysis.

ENERGY STORAGE RESOURCE CONFIGURATIONS

To identify potential thresholds of duration and penetration of energy storage resources that could affect reliability goals, the following matrix of energy storage portfolios was constructed.

Table 5. Energy Storage Portfolios Modeled in SERVM

| | | Storage Duration (HR) | | |
|------------------|--------|-----------------------|---|---|
| | | 2 | 4 | 6 |
| Penetration (MW) | 1,000 | Х | Х | Х |
| | 2,000 | Х | Х | Х |
| | 4,000 | | Х | Х |
| etrati | 8,000 | | Х | Х |
| Pene | 10,000 | | | Х |
| | 12,000 | | | Х |

SIMULATION RESULTS

The simulations determine how much generation can be replaced by a given amount of energy-limited resources while maintaining constant reliability.

Reliability for all zones included in the study was calibrated to 0.1 LOLE by removing conventional capacity. To identify whether the system met the 0.1 LOLE standard, thousands of SERVM simulations representing a wide range of weather-related load uncertainty, economic forecast uncertainty, and generator outage uncertainty were performed. After calibrating to 0.1 LOLE, energy-limited resource capacity was added to the system which improved reliability. Finally, capacity with perfect availability was removed from the system until reliability returned to 0.1 LOLE. These steps were replicated for various combinations of energy-limited resource duration and penetration. The capacity value of energy-limited resources is calculated as the ratio of perfectly available capacity removed to energy-limited capacity added. This reflects the amount of traditional capacity the storage can replace.

If 0.1 LOLE was achieved when 1,000 MW of energy storage resources were added and 1,000 MW of capacity with perfect availability were removed, the energy storage would provide 100% capacity value. The use of capacity with perfect availability in this process is consistent with PJM's practice of measuring resources by their Unforced Capacity (UCAP), so that differences in forced outage rates do not distort the comparison. The analysis is intended to identify what duration is required for energy storage to provide identical capacity value to that provided by conventional dispatchable resources before the impact of forced outage rates is considered. This process is illustrated in Figure 12.

¹⁴ In the terminology used by PJM, Unforced Capacity (UCAP) = Installed Capacity (ICAP) * (1 - EFORd). For this analysis, the comparison resources have EFORd = 0%, so the UCAP equals ICAP.

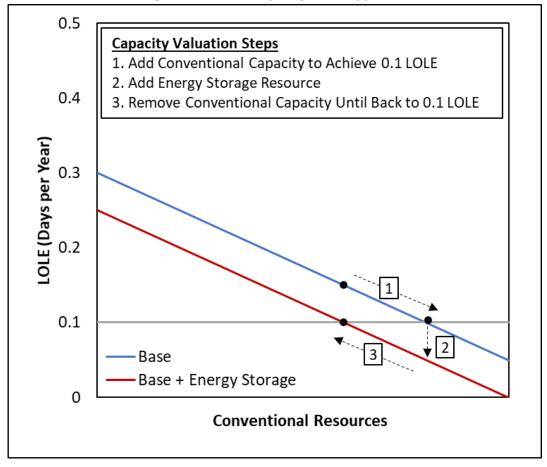
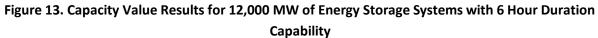


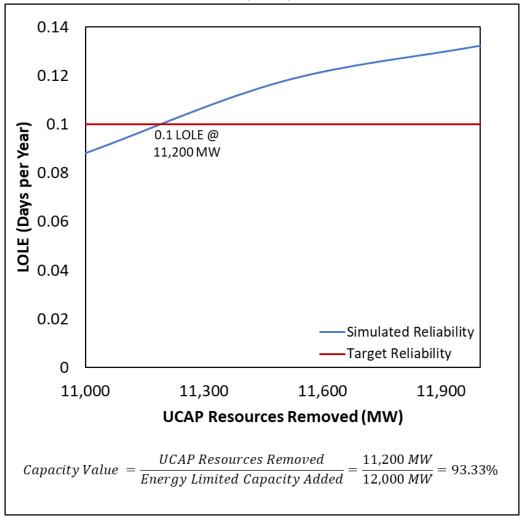
Figure 12. SERVM Capacity Value Approach

The capacity value was calculated using the following equation once the reliability met the 0.1 LOLE target.

$$Capacity\ Value = \frac{UCAP\ Capacity\ Removed}{Energy\ Limited\ Capacity\ Added}$$

For each portfolio analyzed, the full complement of synthetic weather years and load forecast error scenarios was simulated for a range of UCAP resources being removed until a value of 0.1 LOLE was achieved. As an example, when the 1,000 MW energy storage portfolio with 4 hours of duration was simulated, a range from 800 - 1,000 MW of conventional UCAP resources was removed. The LOLE in the 800 MW removed scenario was lower than 0.1 and in the 1,000 MW scenario was equal to 0.1, demonstrating a 100% capacity value. Figure 13 contains a visual example of how the capacity value was calculated with the simulated results for 12,000 MW of 6 hour resources.





The simulated results for each portfolio analyzed are shown in Table 6.

Table 6. Capacity Value Results for Simulated Studies

| Duration (Hours) | Penetration (MW) | Capacity Displaced (MW) | Capacity Value (%) |
|-------------------------|------------------|-------------------------|--------------------|
| 2 | 1,000 | 1,000 | 100.00 |
| 2 | 2,000 | 2,000 | 100.00 |
| 4 | 1,000 | 1,000 | 100.00 |
| 4 | 2,000 | 2,000 | 100.00 |
| 4 | 4,000 | 3,996 | 99.90 |
| 4 | 8,000 | 7,648 | 95.60 |
| 6 | 1,000 | 1,000 | 100.00 |
| 6 | 2,000 | 2,000 | 100.00 |
| 6 | 4,000 | 4,000 | 100.00 |
| 6 | 8,000 | 8,000 | 100.00 |
| 6 | 10,000 | 9,789 | 97.89 |
| 6 | 12,000 | 11,200 | 93.33 |

CONCLUSION

Simulating the entire PJM electric system plus those of its direct neighbors demonstrates that energy storage systems with duration capability of 4 hours can provide up to 4,000 MW of capacity of equivalent reliability value to that supplied by conventional resources. Storage systems with 6 hour duration can provide up to 8,000 MW of capacity of equivalent reliability value to conventional resources. For comparison, PJM's entire battery fleet combined would amount to less than 40 MW of 4-hour duration storage; the entire amount of non-hydro storage installed in the entire United States amounts to roughly 500 MW¹⁵ of 4 hour duration storage.

A 4-hour duration requirement would correctly represent the capacity value of storage under current market conditions and would remain accurate until the amount of installed storage in PJM increases by two orders of magnitude. Our study shows no justification for longer duration requirements, and that, at current levels of penetration, duration requirements longer than 4 hours reduce the capacity value of storage to well below the amount of traditional capacity it provides equivalent service as.

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¹⁵ Sum of energy capability of installed resources in MWh divided by 4