PJM ELCC / RRS Model Evaluation

Prepared for PJM

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Executive Summary

E3 was retained by PJM to independently assess PJM's Effective Load Carrying Capability / Reserve Requirement Study Model (ELCC/RRS Model) for alignment with industry best practices in loss-of-load-probability (LOLP) modeling. The outputs of the ELCC/RRS model are used directly in PJM's capacity market (i.e., Reliability Pricing Model), determining both the system-wide capacity requirement (i.e., Reserve Requirement) and the capacity accreditation of individual resources (i.e., Effective Load Carrying Capability).

E3 is an independent consulting firm with extensive experience developing LOLP models and conducting LOLP studies across the North American continent.[1] To conduct this review, E3 developed a list of industry best practices for LOLP modeling and evaluated PJM's ELCC/RRS model against these best practices. Additionally, E3 provided a list of potential improvements for PJM to consider for the ELCC/RRS model.

Overview of Loss-of-Load-Probability Modeling and Best Practices

Ensuring resource adequacy requires accurate analysis to evaluate whether sufficient generating resources will be available when needed to meet demand. Among electricity system planners, there is a broad and growing consensus that **chronological probabilistic** methods are essential to accurately capturing the full suite of potential resource adequacy risks that electricity systems face. The consensus behind the importance of probabilistic methods is underscored by their increasingly prevalent use within the industry, from RTOs & ISOs charged with managing resource adequacy to utilities that manage their own portfolios.

The call for a probabilistic approach to resource adequacy implicates the need for a type of analysis known as **"Loss-of-Load-Probability" (LOLP)** modeling. LOLP models employ a variety of statistical and simulation techniques to compare forecast electricity demand with available generation resources under a broad range of conditions that account for variability of weather, loads, renewable generation, forced outages, and a number of other constraints and stressors that could impact the ability of a portfolio of generators to meet load.[2] Best practices for LOLP modeling include:

1. **Capture a diverse range of load conditions that account for potential extreme weather**
2. **Simulate generator outages stochastically and include correlated outages if historical data suggests this as a possible risk**

[1] https://www.ethree.com/tools/recap-renewable-energy-capacity-planning-model/
[2] https://msites.epri.com/resource-adequacy/tools/tool-capability-guidelines

3. **Incorporate realistic profiles for renewable generation that capture correlation with load**
4. **Simulate dispatch of energy-limited resources on a time-sequential basis**
5. **Reflect actual expected system operations**
6. **Ensure statistical significance of results**
7. **Balance model accuracy with tractability**
8. **Promote transparency**

Evaluation of PJM ELCC/RRS Model

E3 evaluated PJM's model and concluded that it is methodologically sound and consistent with industry best practices. In particular, PJM's transparency of methods, inputs, and outputs sets a standard for other markets and LOLP models. At the same time, E3's review found a few areas where the model could be improved. A summary of E3's assessment of key model features is provided below, where "pros" reflect how the current model is consistent with industry best practices for modeling resource adequacy risk, and "cons" reflect potential areas of improvement. The "pros" and "cons" in the table below are not necessarily equal in importance or significance but rather are presented to provide a comprehensive assessment of all aspects of PJM's model.

Model Aspect	E3 Evaluation
Load Modeling	**Pros:** Use of 31 weather years with 13 load rotations ensures the model captures a wide range of load conditions and corresponding reliability risks. **Cons:** Uneven day-of-week representation.
Forced Outages	**Pros:** Thermal and renewable outages are modeled stochastically using actual historical data, capturing correlated outage events such as Polar Vortex and Winter Storm Elliot. **Cons:** Battery outages are represented using static de-rates that do not vary by hour.
Planned Maintenance	**Pros:** Reasonably mimics actual system operations by intelligently scheduling maintenance during low-risk periods, while also capturing a minimum amount of "forced-in" maintenance during high-risk weeks that aligns with historical observation. **Cons:** Scheduling maintenance based on gross load does not account for variation in availability of renewables, although it is also important to accurately mimic system operations.
Thermal Resource Capability	**Pros:** Model incorporates ambient derates for thermal resources when temperatures rise. Model incorporates transmission network constraints through deliverability limitations. **Cons:** Generator capability is limited to capacity output in ambient summer peak conditions.
Variable Resource Representation	**Pros:** Twelve years of historical generation data captures wide range of potential availability conditions. Time-matched individual profiles to

	develop resource-class profiles appropriately represent geographic diversity and correlations between variable resources. **Cons:** Methodology to assign deliverability constraints to hours in PJM Model does not dynamically reflect transmission system conditions, although more complexity reduces tractability.
Load and Resource Scrambling	**Pros:** Introduces new plausible conditions while preserving correlation between load and resource performance by linking through temperature. Joint sampling of all resource classes preserves correlation between resource classes. Bin sizes ensure sufficient performance observations in each bin. Sufficient sampling ensures statistical significance. **Cons:** Weather for resource performance bins is not fully aligned with weather for load in "load rotations," which fails to preserve load and resource correlations. Does not capture multi-day resource performance events, although the near-term impact of this is likely to be limited. Assigning equal likelihood of recent and far-in-the-past resource performance may not reflect the system "as is" if resources have undertaken enhancements.
Dispatch of Energy-Limited Resources	**Pros:** Hourly time-sequential dispatch of energy limited resources and demand response enable realistic dispatch. **Cons:** Use of heuristic dispatch is not fully optimal, although it is very complex to implement optimization.
Resource Accreditation (ELCC)	**Pros:** Accreditation founded on marginal ELCC accurately and fairly accredits resource classes. Individual performance adjustment approach yields sufficiently accurate values.

Considerations for Improvement

E3's review also identified several aspects of the model where PJM may consider making future improvements. Each consideration for improvement has pros and cons along the following criteria: accuracy, objectivity, stability, transparency, tractability, impact, and ease of implementation. A summary of E3's considerations for improvement is provided here, with the body of the report outlining how each consideration scores along the evaluation criteria.

1. **Improve identification of critical hours**
2. **Publish critical-hour data** to increase transparency
3. **Draw load and resource profiles from the same weather conditions**
4. **Adopt seasonal/daily capability ratings** for unlimited resources to improve representation of temperature-dependent performance

5. **Schedule maintenance using net load** instead of gross load
6. **Gradually de-weight outdated performance data** as new events occur to more quickly capture changes in resource performance over time and maintain incentives for resource improvement
7. **Increase weather rotations to balance day-of-week representation**
8. **Calibrate solved load by adding "flat" load instead of scaling load**
9. **Extend and stochastically model hydro generation records** to capture wider hydrologic variability
10. **Stochastically model storage outages** to capture correlated failures
11. **Refine deliverability mapping** to link transmission constraints to system conditions rather than fixed calendar periods
12. **Represent capacity benefit of ties (CBOT)** dynamically by time and season
13. **Capture multi-day persistence in resource performance** to reflect extended low-output periods
14. **Optimize dispatch algorithms** for energy-limited resources, balancing realism and computational tractability

Summary

E3 concludes that PJM's ELCC/RRS model is fit for purpose, sophisticated, and aligned with industry best practices. It supports the efficient implementation of PJM's capacity market through accurate determination of both the Reserve Requirement and Effective Load Carrying Capability values. However, as with any existing LOLP model, there are opportunities for PJM to consider making improvements to ensure the model remains industry-leading and adaptable to future system dynamics.

Introduction

The PJM regional transmission organization is responsible for maintaining resource adequacy within the PJM footprint through the administration of a capacity market (the "Reliability Pricing Model").[3] This market is designed to allow loads and generators to transact "capacity" through a centrally cleared auction such that, under equilibrium conditions, the quantity of capacity transacted is sufficient to meet resource adequacy needs.[4] The price at which the market settles provides an economic signal to support investment in and retention of the resources needed to supply that capacity.

Two core functions of properly implementing the capacity market are to appropriately calculate 1) the total capacity requirements of the system and 2) the individual capacity accreditation values assigned to each resource. These determinations are essential to ensuring that the system achieves the "one day in ten year" target reliability standard and that resources are fairly compensated for the services they provide to the grid.

PJM performs these calculations with the "Effective Load Carrying Capability / Reserve Requirement Study Model" (also referred to as the **"PJM ELCC/RRS Model"** or "PJM Model"). This model falls within a class of models referred to as "loss-of-load-probability" models ("LOLP models"), which are industry standard to perform capacity market calculations. The PJM model is used to perform two related functions: 1) a "Reserve Requirement" calculation to determine the total capacity requirement for the system and 2) "Effective Load Carrying Capability" calculations to accredit the capacity value of individual resources.

At the direction of the PJM Board,[5] PJM retained E3 to perform a comprehensive review of the PJM ELCC/RRS Model for alignment with industry best practices and to identify potential areas for improvement.

E3's evaluation of the PJM ELCC/RRS Model is based on significant experience with loss-of-load-probability modeling. E3 has developed and maintains the RECAP LOLP model, which it has used to conduct reserve requirement and ELCC analyses for utilities across North America and to analyze evolving resource adequacy challenges facing the industry on behalf of a wide range of clients. Additionally, E3 has worked extensively with electric system operators – including PJM, NYISO, MISO, and ERCOT – on other LOLP models. Finally, E3's review leverages publicly available materials on LOLP modeling from both industry and academic sources.

An overview of this report is provided below:

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[3] https://learn.pjm.com/three-priorities/buying-and-selling-energy/capacity-markets.aspx

[4] The technical specification of this resource adequacy need is a loss-of-load-expectation (LOLE) standard of 0.1 days/year

[5] https://www.pjm.com/-/media/DotCom/about-pjm/who-we-are/public-disclosures/2025/20250804-board-correspondence-re-irm-and-fpr.pdf

- **Section 2: Overview of Loss-of-Load-Probability Modeling and Best Practices**
  - This section provides an overview of the importance and role of loss-of-load-probability modeling. It provides an overview of modeling best practices and how LOLP models are used to calculate values such as the total capacity requirement and individual capacity accreditation values.
- **Section 3: Evaluation of PJM Model Design**
  - This section provides E3's evaluation of the PJM ELCC/RRS model for alignment with industry best practices.
- **Section 4: Validation of PJM Model Performance**
  - This section tests inputs, methods, and outputs of the PJM ELCC/RRS to ensure that the model is working as intended.
- **Section 5: Considerations for Improvement**
  - This section provides a list of considerations for model improvement. E3 evaluates each consideration for improvement against the criteria of accuracy, objectivity, stability, transparency, tractability, impact, and ease of implementation.

Overview of Loss-of-Load-Probability Modeling and Best Practices

Industry Best Practices

Ensuring resource adequacy requires accurately understanding whether sufficient generating resources will be available when needed to meet demand. Among electricity system planners, there is a broad and growing consensus that **chronological probabilistic** methods are essential to accurately capturing the full suite of potential resource adequacy risks that electricity systems face. The importance of a probabilistic approach has been emphasized by a number of notable groups, including:

+ **NERC**, which has published technical reports on best practices in modeling approaches and data collection and has hosted a biannual Probabilistic Analysis Forum;
+ **The Western Electricity Coordinating Council (WECC)**, which recommends that "[p]lanning entities and their regulatory authorities should consider moving away from a fixed planning reserve margin to a probabilistically determined margin"[6];
+ **The IEEE Resource Adequacy Working Group**, wherein industry experts meet annually to share learnings and findings related to probabilistic analysis of resource adequacy; and
+ **The Energy Systems Integrations Group (ESIG)**, whose whitepaper *Redefining Resource Adequacy for Modern Power Systems* introduced six philosophically grounded principles for resource adequacy analysis that emphasize the importance of probabilistic methods. Among its six guiding principles for resource adequacy, ESIG's Redefining Resource Adequacy Task Force includes a direct endorsement that "[c]hronological operations must be modeled across many weather years" elaborating:

  > "Modeling sequential grid operations is critical to capture the whole picture: the variability of wind and solar resources along with the energy limitations of storage and load flexibility. Chronological stochastic analysis is thus increasingly important, simulating a full hour-to-hour dispatch of the system's resources for an entire year of operation across many different weather patterns, load profiles, and random outage draws."[7]

The consensus belief in the importance of probabilistic methods is further underscored by the increasingly prevalent use within the industry, from RTOs & ISOs charged with managing resource adequacy in the context of organized markets to utilities that manage their own portfolios to ensure reliability for their customers. The table below provides an overview of

[6] WECC. *The Western Assessment of Resource Adequacy Report*. Dec. 2020. https://www.wecc.org/Administrative/Western%20Assessment%20of%20Resource%20Adequacy%20Report%2020201218.pdf

[7] Energy Systems Integration Group (ESIG). *Redefining Resource Adequacy for Modern Power Systems*. 2021. https://www.esig.energy/wp-content/uploads/2021/08/ESIG-Redefining-Resource-Adequacy-2021.pdf

probabilistic models used across the industry for resource adequacy calculations. This table demonstrates the prevalence of probabilistic models for these purposes.

Table 1. Probabilistic models used for resource adequacy[8]

	Utility/Jurisdiction	Software Provider	Software
Canadian Utilities	Nova Scotia Power, Inc.	Energy Exemplar	PLEXOS
	Newfoundland Hydro	Energy Exemplar	PLEXOS
Southwest Utilities	Arizona Public Service Co	PowerGEM	SERVM
	El Paso Electric Co	E3	RECAP
	Public Service Co of New Mexico	PowerGEM	SERVM
	Salt River Project	PowerGEM	SERVM
	Tucson Electric Power	E3	RECAP
Other Western Utilities	Avista Corporation	Avista Corporation	AVAM (Excel-based)
	Black Hills Energy - Colorado	E3	RECAP
	NV Energy	E3	RECAP
	Portland General Electric	Portland General Electric	Sequoia
	Public Service Co of Colorado	E3	RECAP
	Puget Sound Energy	E3	RECAP
Eastern Utilities	Dominion Energy South Carolina	PowerGEM	SERVM
	Duke Energy Carolinas	PowerGEM	SERVM
	Florida Power and Light	E3	RECAP
RTOs	ISO New England	General Electric	GE-MARS
	New York ISO	General Electric	GE-MARS
	Midcontinent ISO	PowerGEM	SERVM
	ERCOT	PowerGEM	SERVM
	PJM	PJM	ELCC/RRS Model

The call for a probabilistic approach to resource adequacy implicates the need for a type of analysis known as **"Loss-of-Load-Probability" (LOLP)** modeling. LOLP models employ a variety of statistical and simulation techniques to compare forecast electricity demand with available generation resources under a very broad range of conditions that account for variability of weather, loads, renewable generation, forced outages, and other constraints and stressors that could impact the ability of a portfolio of generators to meet load.[9]

Modern LOLP models typically simulate the performance of the electricity system on an hourly basis over the course of the entire year. Within an LOLP analysis, these annual simulations are repeated hundreds or thousands of times – each iteration stochastically

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[8] Summary based on E3's work from: https://www.ethree.com/wp-content/uploads/2025/11/E3_New-Brunswick-Power_Resource-Adequacy-Framework.pdf

[9] https://msites.epri.com/resource-adequacy/tools/tool-capability-guidelines

capturing a different combination of weather conditions and outages – to provide a robust assessment of the probability of tail events that drive resource adequacy challenges.

The simulation of electricity supply and demand across a broad range of conditions allows LOLP models to calculate a variety of statistical measures of resource adequacy. These metrics quantify the expected frequency, size, and duration of loss of load events. Table 2 lists the typical metrics produced by LOLP models; among these, the most commonly used is **Loss of Load Expectation (LOLE)**, defined by NERC as "the expected number of days per time period (usually a year) for which the available generation capacity is insufficient to serve the demand at least once per day."[10] However, best practices also increasingly recognize that calculating multiple metrics provides additional insight into system reliability. Several common reliability metrics produced by LOLP models is provided in the table below.

Table 2. Typical metrics produced by LOLP models

Metric	Type (Units)	Definition
Loss of Load Expectation (LOLE)	**Frequency** (days per year)	Average number of days per year in which unserved energy occurs due to system demand exceeding available generating capacity
Loss of Load Events (LOLEV)	**Frequency** (events per year)	Average number of loss of load events per year, of any duration or magnitude, due to system demand exceeding available generating capacity
Expected Unserved Energy (EUE)	**Magnitude** (MWh per year)	Average total quantity of unserved energy (MWh) over a year due to system demand exceeding available generating capacity
Normalized EUE (nEUE)	**Magnitude** (parts per million)	Expected unserved energy normalized by total expected annual demand
Loss of Load Hours (LOLH)	**Duration** (hours per year)	Average number of hours per year with loss of load due to system demand exceeding available generating capacity

LOLP modeling has advanced significantly from its origins in the mid-1900s, and today resource adequacy program administrators (such as PJM) use both commercial and in-house software solutions to perform this analysis. Most LOLP models in use in the industry today use a Monte Carlo approach to simulate load and resource availability on an hourly, chronological basis to capture the inherent complexities of today's systems. While each model has unique qualities and idiosyncrasies, it is nonetheless useful to define a minimum standard of best practices for functionality needed to address the complex issues discussed above. In 2024, the Electric Power Research Institute ("EPRI") conducted a comprehensive review of LOLP models in use across the industry to "understand where the

[10] NERC. *Probabilistic Adequacy and Measures: Technical Reference Report.* https://www.nerc.com/comm/PC/Probabilistic%20Assessment%20Working%20Group%20PAWG%20%20Relat/Probabilistic%20Adequacy%20and%20Measures%20Report.pdf

industry stands as a whole" on the capabilities of these models.[11] This report, coupled with E3's judgement and experience, elucidates several best practices for LOLP modeling, including:

1. **Capture a diverse range of load conditions that account for potential extreme weather.** Electricity demand should reflect the expected range of possible weather variability across many years (including mild, average, and extreme).
2. **Simulate generator outages stochastically.** Generator outages should be modeled stochastically for all resources. If historical data suggests a possible risk of correlated outages among generators, this information should be included in simulation of outages.
3. **Incorporate realistic profiles for renewable generation that capture correlation with load.** Production patterns for variable resources (e.g. solar and wind) should incorporate multiple years of meteorological data and reflect underlying correlations with electricity demand.
4. **Simulate dispatch of energy-limited resources on a time-sequential basis.** A chronological approach to simulation of loads and resources should be used to incorporate constraints of energy-limited resources (e.g. energy storage, demand response, and hydro).
5. **Reflect actual expected system operations.** The model should use resources consistently with how system operators would be expected to use resources during times of system stress. The model should avoid perfect foresight that does not exist in practice and should mimic actual operator protocols during loss-of-load events.
6. **Ensure statistical significance of results.** The model should run sufficient replications in order to ensure statistical significance of LOLE or other reliability results. Because loss-of-load events only occur once every ten years on average, the model should simulate the system across hundreds or thousands of years of potential conditions to ensure statistical significance.
7. **Balance accuracy with tractability.** Simulating an electricity system across hundreds or thousands of years of potential conditions requires large computing horsepower. In order to ensure this process is tractable, the model may need to make simplifications in how accurately it models certain characteristics of the electricity system.
8. **Promote transparency.** The model should make inputs, methods, and outputs available and transparent for stakeholders to improve understanding and facilitate acceptance of model results.

Like most technical analyses, curating a robust, quality-controlled set of inputs, assumptions, and methods is critical to meaningful analysis of resource adequacy; at the same time, because LOLP models seek to capture exceptionally rare events in a probabilistic manner, developing datasets and methods that appropriately represent the magnitude and frequency of rarely observed "tail" events (and correlations among them) is a marked challenge. In *Reliability Evaluation of Power Systems*, author Roy Billinton

[11] https://www.epri.com/research/products/000000003002027832

recognizes this challenge: “Meaningful reliability data are not always easy to obtain, and there is often a marked degree of uncertainty associated with the required input.”

The challenges in gathering data and the corresponding uncertainties have compounded since this observation was written several decades ago. Practitioners of LOLP modeling must be cogently aware of the inherent limitations in their datasets and the implications they may have upon their evaluations. Among the most significant data challenges facing planners today:

+ **Distributions of extreme weather events:** forecasting future climatic conditions is increasingly challenging. While planners have long relied on extended samples of historical weather data to inform probability distributions of tail weather events; the assumption that historical conditions provide an accurate representation is an ongoing area of research within the field. Therefore, planners must be cautious to consider a broad plausible range of conditions that may extend beyond historical distributions.
+ **Renewable production data:** the adequacy of a system will depend, in part, on how renewables perform during rare extreme load events. For many renewable facilities, little to no historical data is available that can be used directly for this purpose if the resources are new or in development. For this reason, the use of simulated renewable profiles, which rely on historical meteorological data as inputs into simulations of wind and solar plant performance, is common practice. However, modelers must understand that this introduces a risk of simulated profiles deviating from actual performance due to simulation error and a variety of real-world factors that may not be captured in the simulation.
+ **Performance assumptions for emerging technologies:** generation technologies are quickly advancing, and electricity systems are presented with new resource options to meet their needs that would not have been available a decade ago. This trend is likely to continue, as research, development, and deployment will continue to bring new technologies into the market. While these advances offer long-term promise, planners should also take caution in assumptions made regarding the performance of new resources with limited operational history at commercial scale. Especially during early years of commercialization, new technologies may not perform as expected.
+ **Correlations among unit outages:** the assumption that forced outages of generators can be modeled as independent, uncorrelated events is a historically traditional practice in LOLP modeling; to the extent that underlying factors like weather patterns and fuel supply issues may affect outages at multiple plants simultaneously, it is important to capture this correlated risk. How to use the limited availability of robust data sets that inform this factor is an emerging area of research within the field.
+ **Representation of unit improvements:** some types of generators are capable of making enhancements or improvements over time such as improved weatherization or improved access to fuel. These changes mean that the historical performance of these units may not accurately reflect their expected future performance. At the

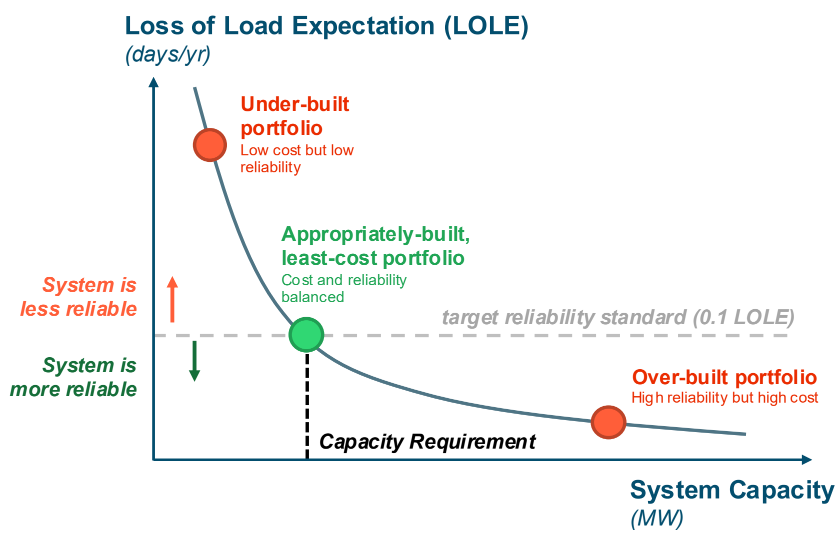
same time, *assuming* improved performance in certain extreme conditions that are rare by definition can introduce subjectivity into the model. Balancing these tradeoffs requires sound modeling judgment.

+ **Model tractability:** because LOLP models must simulate the system over hundreds or thousands of years to ensure statistical significance of rare events, they must maintain tractability, often by making key simplifications in areas such as generator dispatch and geographic granularity relative to a more detailed "production cost model" used in other areas of electricity system modeling. Determining where to add detail and granularity in the model requires sound judgment on the impacts of each decision.

Using LOLP Models in the Capacity Market

The first step in administering a capacity market is determining a total capacity requirement. PJM calculates a capacity requirement that will achieve a 1-day-in-10-year loss of load expectation reliability standard (e.g. 0.1 days/year LOLE), the most common resource adequacy standard used across North America. This process is illustrated in the figure below.

Figure 1: Illustration of Capacity Requirement Calculation



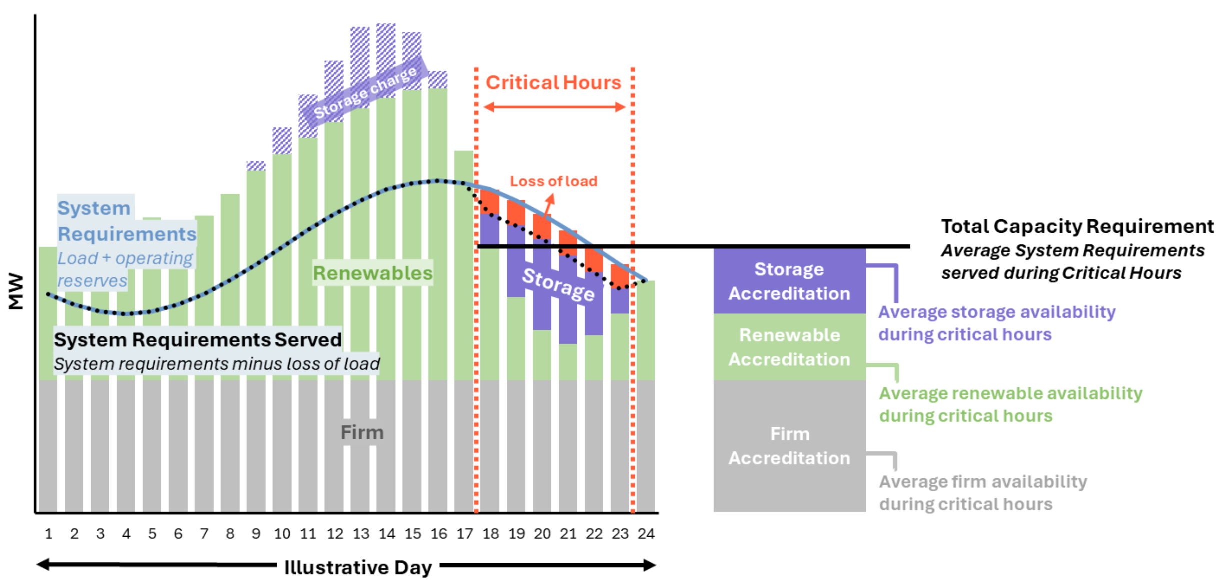
The result of this calculation is a total capacity requirement (expressed in megawatts) that represents the needs of the system during the times of highest loss-of-load risk. Historically, these periods of loss-of-load risk have occurred during peak load hours, but increasingly they occur outside of peak load hours when resource availability of renewables, thermal, or storage is low. To the extent that the hours that drive system capacity needs are outside of gross peak load hours, the total capacity requirement may be lower than the peak electricity demand. This very phenomenon has been observed in PJM's most recent analysis: PJM's recommended capacity requirement (what they term the "Forecast Pool Requirement" or

FPR) for the 2027/2028 Delivery Year is 0.9260.[12] This means that the total procured quantity of effective capacity is equal to 92.6% of the 50/50 system peak load.

Calculating the capacity accreditation value of resources using LOLP models is becoming increasingly common among utilities and RTOs throughout North America.[13] Specifically, the marginal effective load carrying capability ("marginal ELCC") metric is an application of LOLP modeling that represents the quantity of "perfect" capacity that could be replaced or avoided by a resource *while providing equivalent system reliability*. Another (mathematically identical) conceptualization of marginal ELCC is availability of a resource during "critical hours," defined as hours where additional energy will improve system reliability. For example, if a 100 MW resource has an ELCC of 50 MW, that means that 100 MW of this resource could displace the need for 50 MW of perfect capacity with no impact on system reliability. ELCC values are often expressed in percentage terms by dividing by the nameplate capacity; in this example, the ELCC of the resource would be 50%. Because ELCCs rely on the identification of critical hours that impact reliability, LOLP modeling is inherently necessary.

The figure below illustrates how LOLP models calculate both the capacity requirement and ELCC values. Specifically, LOLP models identify which hours are "critical" to system reliability. The total capacity requirement is equal to the average system need (load + required operating reserves) during those hours. Capacity accreditation (i.e., marginal ELCC) is equal to average resource availability during those hours.

Figure 2: Stylized Illustration of Capacity Requirement and Capacity Accreditation Calculations in LOLP Modeling



[12] https://www.pjm.com/-/media/DotCom/committees-groups/committees/mrc/2025/20250723/20250723-item-04---1-2027-2028-bra-fpr-and-irm---presentation.pdf

[13] For example, see slide 12 of "ELCC Concepts and Considerations for Implementation" https://www.nyiso.com/documents/20142/24172725/NYISO%20ELCC_210820_August%2030%20Presentation.pdf

One strength of an ELCC-based approach lies in the use of a common benchmark ("perfect capacity") against which the impacts of all resources can be measured. In "Redefining Resource Adequacy for Modern Power Systems," the authors espouse the principle that "there is no such thing as perfect capacity," elaborating: "Future resource adequacy analysis should explicitly recognize that all resources have limitations based on weather-dependence, potential for outages, flexibility constraints, and common points of failure."[14] By measuring each resource's impact on system reliability relative to this common benchmark, an ELCC-based approach is well-suited to achieve an aspirational level of technological agnosticism, placing all resources on a level playing field that accounts for the various constraints and limits on their availability.

PJM ELCC/RRS Model Overview

The PJM Effective Load Carrying Capability / Reserve Requirement Study Model (the "PJM ELCC/RRS Model" or "PJM Model") is the LOLP model that PJM has developed and maintains for the express purpose of use in the capacity market. PJM uses this model to determine the total capacity requirement (i.e. the "Reserve Requirement") that is necessary to achieve the reliability target as well as the capacity accreditation (i.e. "Effective Load Carrying Capability" values for resources) assigned to each resource for use in the capacity market.

PJM has provided documentation on the model methodology and functionality that this report does not reproduce.[15] The 70+ pages of documentation that PJM has released on the ELCC/RRS model exceed any publicly available documentation that E3 is aware of for any other LOLP model. Several features that are distinctive or notable about PJM's approach as of November 2025 include:

+ 31 historical weather years, 13 load rotations, and 100 resource availability draws for a total of 40,300 simulated years
+ Resource availability draws are taken from 12 years of historical data (2012 – 2024)
+ The model draws resource availability for all resource classes (e.g., solar, wind, thermal) from the same historical day to preserve correlation between resource classes
+ The model "scrambles" resource availability and loads through a temperature-based binning approach. Each day is assigned to a specific "bin" based on a PJM-calculated temperature-humidity index ("THI"). The THI metric represents system-wide weather conditions and is calculated as the load-weighted combination of temperature and humidity across the PJM footprint. The model then stochastically pairs historical resource performance days with historical load days that occur within the same THI bin. In this way, the model scrambles load and resource profiles that occurred on days with similar temperature

[14] Energy Systems Integration Group (ESIG). *Redefining Resource Adequacy for Modern Power Systems*. 2021. https://www.esig.energy/wp-content/uploads/2021/08/ESIG-Redefining-Resource-Adequacy-2021.pdf
[15] https://www.pjm.com/-/media/DotCom/planning/res-adeq/elcc/2025-pjm-elcc-rrs.pdf

- The model chronologically dispatches energy-limited resources such as energy storage and demand response to meet the residual needs of the system that other resource classes (including thermal and renewables) could not meet. Any unserved energy is classified as loss-of-load

PJM uses outputs of the ELCC/RRS model to directly inform two critical applications: (1) the *Forecast Pool Requirement*, which determines the capacity market procurement target to maintain the 0.1 LOLE standard, and (2) *resource accreditation*, which calculates Effective Load Carrying Capability values for resource classes and adjusts them to individual units via performance factors.

Evaluation of PJM Model Design

In this section, E3 evaluated the design of the PJM ELCC/RRS model to assess whether its methodological framework aligns with industry best practices for loss-of-load-probability modeling. This section focuses on the conceptual foundations of the PJM model to assess how the model represents the relationship between weather, load, and resource availability, and how those design choices influence the system's risk profile and resulting capacity accreditation values.

E3 identified the following aspects of PJM's model for evaluation:

+ **Representation of Load**
+ **Resource Forced Outages**
+ **Resource Planned and Maintenance Outages**
+ **Unlimited Resources Capability and Deliverability**
+ **Variable Resource Availability and Deliverability**
+ **Load and Resource Scrambling**
+ **Dispatch of Energy Limited Resources and Demand Response**
+ **Resource Accreditation**

For each model aspect, E3 provided the following:

1. **Best Practice:** What is industry best practice for this aspect of LOLP modeling?
2. **PJM Approach:** What is the current approach used in the PJM ELCC/RRS model?
3. **E3 Evaluation:** Is PJM's approach consistent with industry best practices? Does PJM's approach appropriately capture key reliability risks?

Representation of Load

Industry Best Practice

LOLP modeling should include a diverse range of potential load conditions (mild, average, and extreme). Because weather is the single biggest factor that drives load, best practice requires incorporating as many potential weather conditions as practicable, while recognizing that weather conditions too far in the past may not be reflective of current weather conditions. Such an approach not only ensures that the model includes extreme peak loads that drive reliability risk but also that the model contextualizes the appropriate expected frequency that these extreme loads are expected to occur. To achieve this, most LOLP models include a minimum of 20 years of load under different potential weather conditions with some using upwards of 80 years of weather conditions.

To capture potential future weather conditions, most LOLP models use historical weather data. Given that future weather conditions may not match historical conditions, it is an emerging area of research on how to adjust historical weather data to match future expectations.[16] However, climate adjustments are not standard in LOLP modeling today given the uncertainty in how weather patterns will change. Moreover, omitting climate adjustments to the historical weather record does not necessarily mean ignoring climate change altogether if the absolute level of load forecast in the LOLP model is based on future weather.[17]

Finally, LOLP modeling should use load profiles that accurately reflect the level and shape of expected loads during given weather and calendar conditions (e.g., month, day of week, holiday, etc.). Industry best practice achieves accurate load profiles through regression analysis or artificial neural networks.

PJM Approach

Loads in the PJM ELCC/RRS Model are developed by the *2025 PJM Long-Term Load Forecast Model*.[18] This model uses regression analysis to simulate hourly loads for 31 historical weather years (June 1993- May 2024). This approach yields an hourly load profile where each historical weather day occurs on a specific date. What this approach does not capture is the fact that an extreme weather day that occurred on a Sunday *could* have occurred on a Monday when loads are typically much higher due to commercial building occupancy. To reflect that historical weather patterns from a given day could reasonably have occurred on nearby dates, each weather year pattern is rotated +/- 6 calendar days, creating a total of 13 “load rotations” for each weather year. The result is 403 years of hourly load profiles (31 * 30) for a studied future delivery year.[19]

E3 Evaluation

PJM’s simulated loads accurately reflect the level of expected loads during given weather conditions when compared to historical loads. The figures below illustrate the strong alignment between historical and simulated load data for different temperature conditions. Additionally, the simulated loads used in the model do not introduce peak loads that are significantly higher than historical levels, indicating that the load conditions represented in the model are based on risks that have been observed historically and do not introduce undue or unfounded risk into the model.

[16] https://www.utilitydive.com/news/e3-new-york-nyserda-climate-change-decarbonized-energy-systems/721391/

[17] For example, the 50/50 peak load forecast could be based on future weather conditions, but historical weather variability could be used to estimate the variability of load around this 50/50 forecast

[18] https://www.pjm.com/-/media/DotCom/library/reports-notices/load-forecast/2025-load-report.pdf

[19] *See PJM’s 2025 Long-Term Load Forecast Supplement:* https://www.pjm.com/-/media/DotCom/planning/res-adeq/load-forecast/2025-long-term-load-forecast-supplement.pdf

Figure 3: Daily Peaks of Simulated & Historical Load in Summer

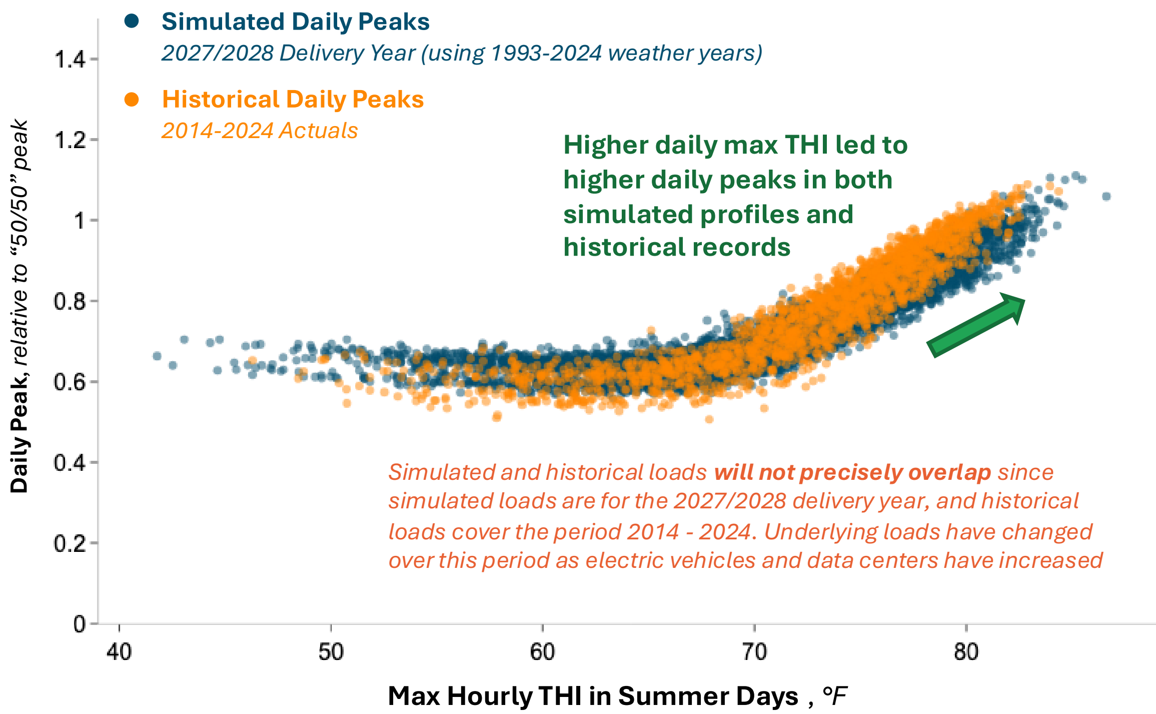
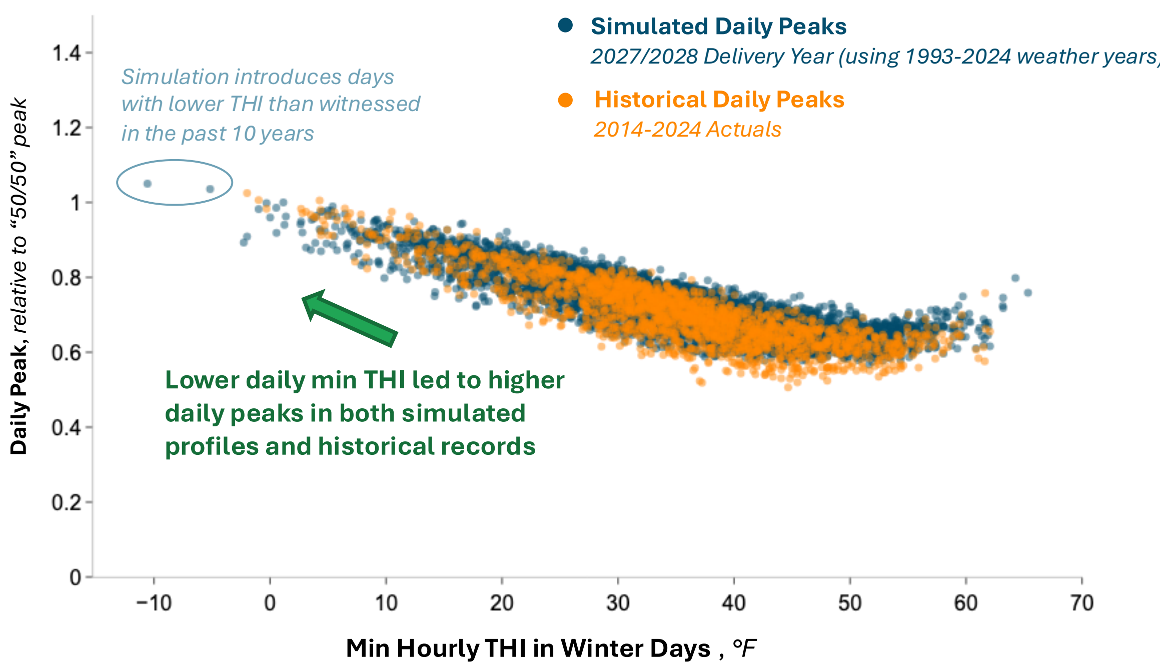
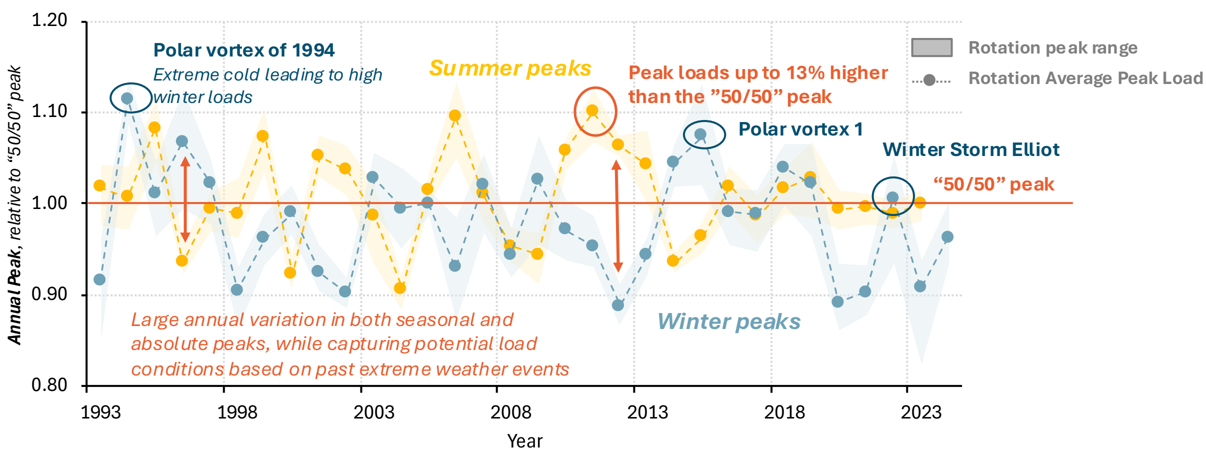


Figure 4: Daily Peaks of Simulated & Historical Load in Winter



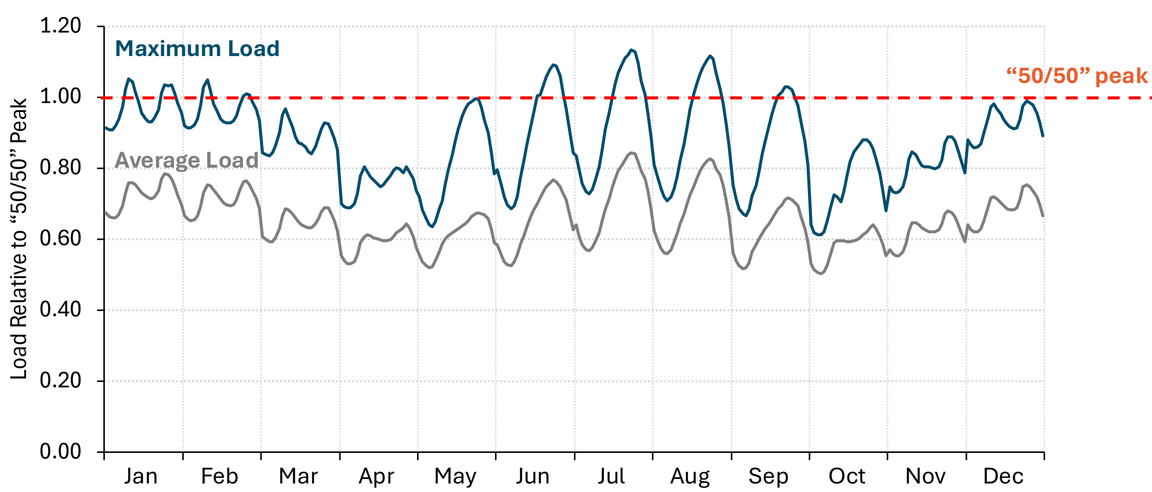
PJM's hourly load simulation process across 31 years of historical weather data provides a rich distribution of potential load conditions, is comparable with other industry models, and is consistent with LOLP modeling best practices. The figure below shows summer and winter peak loads for each simulated weather year. Summer peaks generally exceed winter peaks except during extreme winter conditions. This chart highlights that PJM's model does not contain a single static peak load value but rather a large range of potential peak loads across different weather conditions.

Figure 5: Summer and Winter Peak loads by Historical Weather Year



PJM's simulated load profiles also contain daily "shapes" that must accurately reflect how loads change throughout the day in order to accurately model how variable and energy-limited resources can help serve these loads. The figure below demonstrates how the load shapes reflect seasonal and diurnal load patterns, with the morning/evening double peak in winter (driven by morning and evening heating loads) and the single afternoon peak in summer driven by cooling loads. Additionally, this chart highlights the difference between load on an "average" day and the "maximum" loads simulated in the model. This once again highlights the rich set of loads that are used in the PJM model, consistent with best practice.

Figure 6: Average and Maximum Loads by Month-Hour



PJM's approach that rotates weather +/- 6 days for a total of 13 "load rotations" appropriately ensures that peak-producing extreme weather is applied to peak-producing calendar variables, with the most important calendar variable being day-of-week. However, this approach introduces an inconsistency where the day of the week for the initial simulated date is only represented *once*, whereas all other days of the week are represented *twice* through forward and backward rotations.

The table below summarizes E3's evaluation of how PJM's representation of load aligns with industry best practice.

Representation of Load: E3 Evaluation Summary	
Pros	**Cons**
+ Appropriately wide range of potential weather conditions and load levels + Simulated loads levels in different weather conditions match historical observations + Simulated load shapes match expected seasonal and diurnal load shapes	+ 13 load rotations may result in six of the seven days of the week being simulated twice for a given historical weather day, and one day of the week simulated once

Resource Forced Outages

Industry Best Practice

Accurately representing forced outages for dispatchable thermal resources (or what PJM terms "unlimited" resources) is critical to accurately characterizing the reliability of the system. This includes capturing periods where larger quantities of dispatchable thermal resources are on outage either due to random variability or external factors such as cold weather.

Best practices for modeling forced outages include:

+ Simulate a diverse range of aggregate dispatchable thermal outage performance that reflects observed and expected performance, including periods of higher than normal outage conditions. This is often accomplished through stochastic outage modeling
+ If historical data suggests a possible risk of correlated outages among generators due to common mode issues, such as extreme weather or fuel supply availability, incorporate factors in the model to reflect these risks

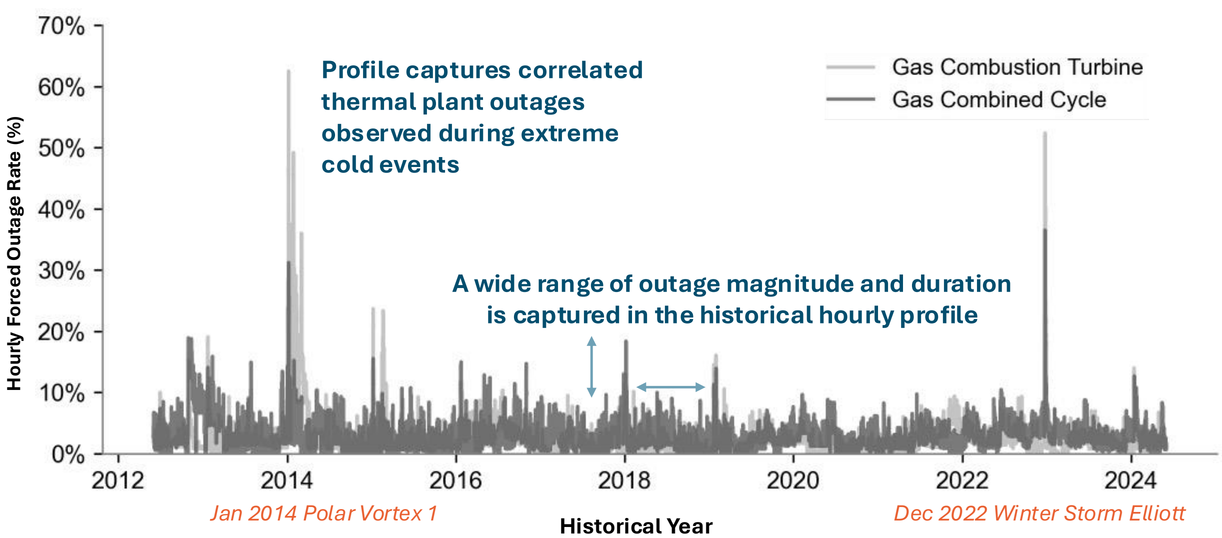
Application of these best practices varies widely across different LOLP models. Some approaches model forced outages individually for each unit while incorporating factors that increase the likelihood of failure for each individual unit during conditions that drive common mode failures. Other approaches model thermal performance in aggregate in ways that capture higher than average aggregate historical outage events.

PJM Approach

PJM incorporates forced outages differently by resource class:

- **Unlimited resources:** PJM models forced outages of unlimited resources by collecting historical daily forced outage profiles from NERC Generating Availability Data System ("GADS") and aggregating across all unlimited resources. By using these aggregated profiles across all unlimited resources, the model implicitly captures periods where aggregate forced outages are greater (or less than) average forced outages. Because daily forced outages are based on historical data, the model also captures the impact of historical extreme events where significant quantities of unlimited resources were unavailable (such as Polar Vortex 1 in January 2014 or Winter Storm Elliot in December 2022). The model stochastically pairs these forced outage profiles with load through a stochastic scrambling process that this report evaluates in a later section. The figure below shows PJM's historical hourly forced-outage timeseries, aggregated across the "Gas Combustion Turbine" and "Gas Combined Cycle" resource classes from 2012-2024. The timeseries shows significant variability in the timing, duration, and magnitude of unlimited resource forced outages.

Figure 7: Historical Forced Outage Record of Unlimited Resources



- **Variable resources:** PJM's modeling implicitly captures forced outages for variable resources (wind and solar) through historical availability profiles for these resources. Forced outages are embedded within these historical availability profiles and provide a reasonable representation of the probability and impact of forced outages for modeling purposes.

- **Battery storage:** PJM models battery storage resources by statically de-rating both the maximum discharge and charge rate in all hours by the historical average Equivalent Forced Outage Rate on Demand ("EFORd") from NERC GADS. PJM's approach therefore does not model periods where battery forced outages are higher or lower than average. The table below shows the static EFORd derates PJM applies to each battery storage resource class in the ELCC/RRS Model.

Table 3: Battery Storage Forced Outage Rate Assumption in PJM ELCC/RRS Model

Resource Class	Equivalent Forced Outage Rate on Demand (EFORd)
4-hour Storage	5.1%
6-hour Storage	2.3%
8-hour Storage	6.7%
10-hour Storage	2.8%

E3 Evaluation

For unlimited resources, PJM's use of forced outage profiles that are both 1) aggregated across all unlimited resources and 2) cover a 10+ year timeframe ensures that PJM achieves the best practice of simulating a diverse range of aggregate dispatchable performance, including periods of higher-than-normal outage conditions. Additionally, PJM's approach captures correlated outage events that are driven by common mode issues to the extent that these events are present in historical data. For these reasons, PJM's approach appropriately maintains the stochasticity of forced outages and correlation in thermal outages among unlimited resources. However, PJM's approach assumes future resource performance is identical to historical performance, limiting the model's ability to reflect unit enhancement measures such as improved winterization or fuel supply.

For variable resources, because PJM's historical availability profiles include forced outages, PJM's approach also captures periods of higher (and lower) variable resource outage conditions. For this reason, PJM's approach aligns with industry best practice.

For storage resources, while PJM's approach correctly approximates average forced outages over time, it does not capture periods where battery storage forced outages are higher than average. This approach understates a potentially important system risk. The impact of understating this risk will increase as battery storage penetration increases.

The table below summarizes E3's evaluation of how PJM's representation of load aligns with industry best practice.

Resource Forced Outages: E3 Evaluation Summary	
Pros	**Cons**
+ Simulates a diverse range of aggregate dispatchable performance, including periods of higher-than-normal outage conditions for unlimited and variable resources + Captures correlated outage events for unlimited and variable resources that are driven by common mode issues to the extent that these events are included in historical data	+ Static assumption of battery storage forced outages does not capture periods of higher-than-average forced outages and is inconsistent representation of unlimited and variable resources

Resource Planned and Maintenance Outages

Industry Best Practice

Planned and maintenance outages for unlimited resources temporarily reduce availability of these resources for scheduled inspections or maintenance activities.[20] Planned and maintenance outages are similar to forced outages, but their timing is more controllable by PJM and individual plant operators. Planned and maintenance outages are generally scheduled during the periods of low system reliability risk such as shoulder months in the spring or fall.

LOLP modeling best practice should incorporate planned and maintenance outages by scheduling these outages during periods of lowest system reliability risk while ensuring consistency with real-world operations. In other words, best practices limit the scheduling of maintenance during high-risk periods; however, to the extent that maintenance schedules are inflexible or imperfect foresight limits operators' abilities to avoid scheduling maintenance during high-risk periods altogether, some maintenance outages may reasonably be included during high risk periods.

PJM Approach

PJM models planned and maintenance outages for unlimited resources using two components: *scheduled* outages and *forced-in* outages:

- **Scheduled outages** are scheduled dynamically within the system to minimize overlap with high-risk periods. This is intended to reflect coordinated scheduling of planned and maintenance outages to minimize system risk. The required total

[20] Generators report planned outages and maintenance outages separately to NERC GADS. Outages are registered as "planned" if specifically listed within annually filed operation plans and typically scheduled only once or twice a year. Outages are registered as "maintenance" if it can be at least deferred to the following calendar week but is required before the next planned outage. For information on NERC outage categories, see: https://www.nerc.com/pa/RAPA/gads/DataReportingInstructions/2025_GADS_DRI.pdf

scheduled outage requirement for each resource is based on its registered planned and maintenance outages reported in GADS from June 1, 2012 to May 31, 2024. When GADS data is unavailable for individual units (such as new units), PJM uses class-averages. PJM's ELCC/RRS model schedules planned and maintenance outages into periods of lowest *gross* load, employing a valley-filling technique to spread these outages across the year.

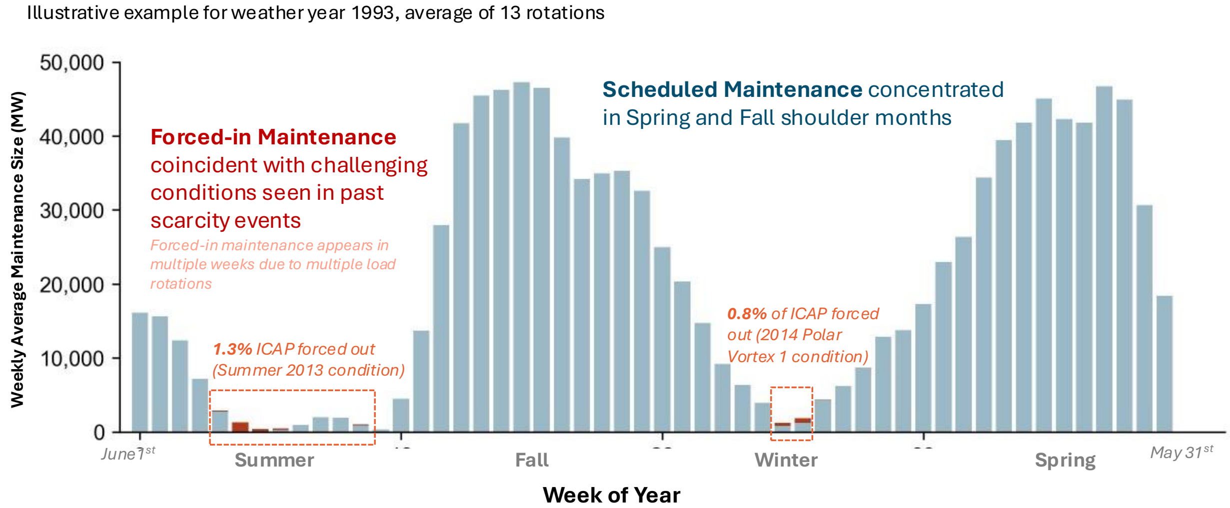
- **Forced in outages** are used to represent maintenance that occurs in spite of its coincidence with high risk. PJM has observed that some resources have experienced planned and maintenance outages during historical scarcity events, likely due to the fact that those scarcity events are not perfectly forecastable. To ensure the model reflects this real-world dynamic, PJM uses historical data to determine a minimum quantity of resources to represent as offline during future scarcity events. Specifically, PJM assigns observed maintenance outages from historical scarcity events to the seasonal peak-load week of each weather year as demonstrated in the table below.

Table 4: Forced-in Maintenance Rates from Historical Scarcity Events

Historical Scarcity Event	Maintenance Outage *% of Unlimited ICAP*	Weather Years Applied
Summer 2012	0.7%	1999, 2001,2006, 2010, 2011, 2012
Summer 2013	1.3%	1993, 1995, 2002, 2013
Polar Vortex 1 (2014, Winter)	0.8%	1993, 1995, 2002, 2013
Polar Vortex 2 (2019, Winter)	5.0%	1996, 2004, 2014
Winter Storm Elliot (2022, Winter)	2.4%	2022

The figure below illustrates the outcome of PJM's approach for both "scheduled" and "forced-in" planned and maintenance outages for unlimited resources for the 1993 weather year. Scheduled outages are concentrated in the spring and fall, the periods of lowest gross load. Forced-in maintenance introduces outages during the highest seasonal gross-load weeks.

Figure 8: Weekly Average Maintenance and Planned Outages for 1993 Weather



E3 Evaluation

PJM's approach to modeling both "scheduled" and "forced-in" maintenance and planned outages for unlimited resources reasonably reflects expected real-world operations.

The "scheduled outage" methodology resembles the intelligent scheduling of maintenance and planned outages that PJM uses in real-world operations. However, as variable and storage resources increase in penetration, gross peak load will not most accurately predict system risk. This is because risk periods are shifting to periods of extended low resource availability which may fall outside of gross peak periods.

The "forced-in outage" methodology ensures the model does not overstate scheduling flexibility for planned or maintenance and is aligned with observed outages during historical scarcity events. This feature therefore improves alignment with real-world operational constraints, recognizing that some maintenance cannot be deferred indefinitely and that operators have imperfect foresight of upcoming reliability events.

The table below summarizes E3's evaluation of how PJM's representation of load aligns with industry best practice.

Resource Planned and Maintenance Outages: E3 Evaluation Summary	
Pros	**Cons**
+ Reflects expected real-world planned and maintenance outages by 1) smartly scheduling outages into periods of lowest risk and 2) recognizing that imperfect foresight will yield some minimum level of resources on maintenance during scarcity events	+ Use of gross load to define risk periods does not fully align with evolving risk patterns as variable and energy storage resource penetrations increase (although gross load is used to some degree in PJM operational practices)

Unlimited Resource Capability and Deliverability

Industry Best Practice

Capability and deliverability ratings determine the potential generation capacity of unlimited resources when these resources are not experiencing forced, maintenance, or planned outages. "Capability" is the physical ability of a plant to generate power. "Deliverability" reflects the physical ability of the transmission network to deliver energy from the point of generation to load. Industry best practices for incorporating unlimited resources into LOLP modeling should:

- Represent changes to maximum potential generation capability (e.g., outages, ambient derates) based on real-time system conditions
- Represent key system network constraints, for example through resource deliverability constraints or zonal modeling

Application of these best practices varies widely across different LOLP models.

PJM Approach

PJM currently limits the maximum availability of unlimited resources to their "ICAP" rating in all hours. The ICAP rating of an unlimited resource is the lesser of its 1) Summer Net Capability rating and 2) Capacity Interconnection Rights (CIRs).[21] Summer Net Capability is the measured generation capability of a resource during the last 15 years of summer peak load conditions. Resources report updates to Summer Net Capability to PJM annually. CIRs is the quantity of deliverable generating capacity during summer peak conditions as assigned by PJM to individual resources in their interconnection agreements. Currently, PJM uses ICAP to represent maximum available capacity of unlimited resource in all hours of the year. However, PJM is in the process of introducing "Winter" deliverability constraints from RTEP for unlimited resource classes in future versions of the PJM Model.[22]

On an hourly basis, resources are derated below their ICAP rating when the temperature exceeds the level used to develop a resource's Summer Net Capability rating. This reflects the fact that under more extreme temperature conditions the ability of a plant to produce power decreases due to reduced thermodynamic efficiency. PJM refers to this as "ambient derating." PJM develops ambient derate profiles from historical derates submitted by individual resources in eDART (electronic Dispatcher Application and Reporting Tool) and aggregated by resource class. The model stochastically pairs both ambient derate profiles and forced outages with load through a scrambling process. This scrambling process is evaluated in a later section of this report.

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[21] For more information on ICAP, see page 25 of PJM Manual 21b: https://www.pjm.com/-/media/DotCom/documents/manuals/m21b.pdf

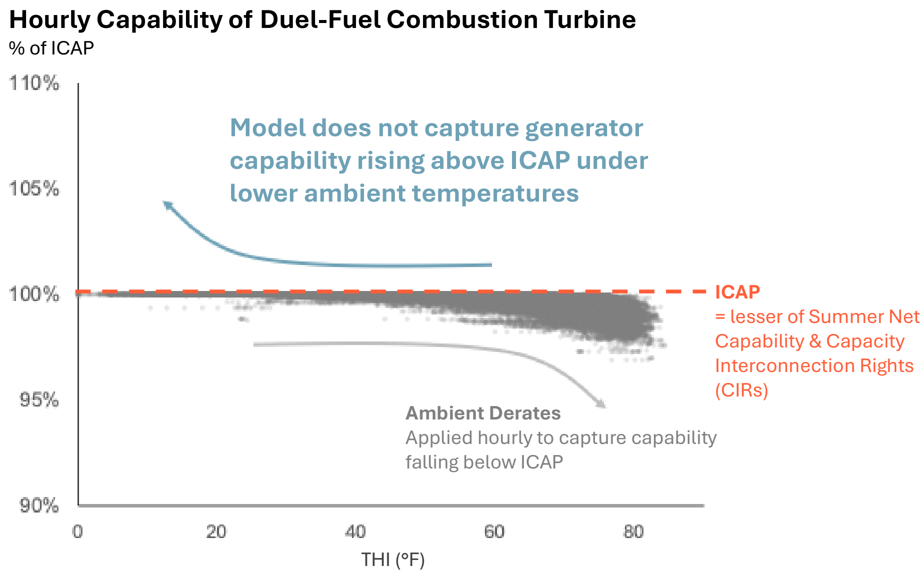
[22] For more information on the introduction Winter Deliverability for non-variable resources, see: https://www.pjm.com/-/media/DotCom/committees-groups/task-forces/elccstf/2025/20250403/20250403-item-05---reflecting-winter-capability-in-accreditation-education--design-considerations---pjm-presentation.pdf

E3 Evaluation

The PJM Model simulates resource performance in all hours of the year, but limits the potential generation capacity of unlimited resources based on generator capability and deliverability in summer peak load conditions. Thermal resources generally have higher potential generation capacity outside of summer peak conditions due to colder ambient temperatures. Additionally, resource deliverability is generally higher outside of summer peak conditions due to less network congestion in hours of lower load. Limiting the availability of unlimited resources at ICAP, which is the lesser of Summer Net Capability and CIR, under-represents availability in non-summer periods.

PJM's ambient derate methodology captures the relationship between temperature and thermal resource capability at high temperatures but does not capture generator capability rising above ICAP under lower ambient temperatures. The figure below illustrates how PJM asymmetrically applies ambient derates to the ICAP of unlimited resource classes when temperatures rise but does not apply ambient uprates when temperatures fall. PJM's approach limits the potential generation capability during cold temperatures.

Figure 9: Thermal Resource Capability Limited at ICAP



Because the majority of system risk occurs in the winter, this methodological decision does impact model results. PJM studied a modification that introduced a newly termed "winter ICAP" rating, defined as Winter Net Capability with all deliverability constraints removed.[23] The aggregate Winter ICAP of unlimited resource fleet was 8,561 MW higher than the total

[23] Winter Net Capability is the expected generation capability during the last 15 years of winter peak load conditions. The removal of all deliverability constraints in this study was a simplifying assumption that presented a bookend of how much winter ICAP could possibly increase. PJM has stated that they would apply winter deliverability ratings developed if directed to implement seasonal ICAP ratings.

Summer Net Capability due to colder ambient temperatures. Implementing this into the model resulted in 33% less unserved energy in winter months and a 1.1% lower IRM relative to the 2025/26 BRA model results.[24]

The table below summarizes E3's evaluation of how PJM's representation of load aligns with industry best practice.

Unlimited Resource Availability and Deliverability: E3 Evaluation Summary	
Pros	**Cons**
+ Ambient derates are applied to adjust resource capability when temperatures rise + Network constraints are incorporated through deliverability limitations	+ Generator capability is limited to potential capacity output in ambient summer peak conditions

Variable Resource Availability and Deliverability

Industry Best Practice

Variable resources (wind, solar, run-of-river hydro) have availability that varies on an hour-by-hour basis due to fluctuating meteorological and hydrological conditions. Industry best practices for incorporating variable resources into LOLP modeling include:

+ Representing the full spectrum of potential variable resource availability on an hourly basis across both low, average, and high resource availability periods. The LOLP model should use at least 5 but ideally 10+ years of historical availability data[25]
+ Incorporating resource availability profiles in a manner that preserves underlying correlations with electricity demand and other supply resources
+ Representing key system network constraints, for example through resource deliverability constraints or zonal modeling

When historical variable resource generation data is available, this can serve as a robust starting point for modeling future generation availability. However, given that many variable resource projects are new or in development, historical data may not exist for many projects. In its place, industry best practice uses simulated generation profiles using historical meteorological data (e.g., insolation) and the characteristics of the variable resource (e.g., inverter loading ratio). Best practices should also reflect the geographic diversity of variable resources within the modeled resource portfolio.

[24] For more information on the seasonal capability assessment in ELCCSTF Package C, see: https://www.pjm.com/-/media/DotCom/committees-groups/task-forces/elccstf/2025/20250522/20250522-item-02---elcc-accreditation-methodology-update-on-sensitivity-analyses---pjm-presentation.pdf

[25] https://iea-wind.org/wp-content/uploads/2021/08/2016_WIW16_Capacity-value_paper_final_web.pdf

PJM Approach

PJM variable resources include wind, utility-scale solar, intermittent hydro, and intermittent landfill gas. PJM develops generation profiles for individual variable resources on an hourly basis across 12 years from 2012 to 2024. PJM derives individual resource availability from settlement data where possible, adjusted for historical curtailment. Where settlement data is unavailable, PJM mostly uses a simulated profile derived from historical weather data and individual site characteristics.

The variable resource hourly profiles in the PJM Model are derived by using the lesser of resource availability (described in prior paragraph) and resource deliverability. PJM's Regional Transmission Expansion Plan (RTEP) process develops generator deliverability constraints under three snapshots of system conditions: "Summer", "Winter", and "Light-Load".[26]

PJM assigns each deliverability constraint a "time of year" window: "Summer Deliverability" applies to all hours from May through October. "Winter Deliverability" applies from 6pm-9am from November through April. "Light-Load Deliverability" applies from 9am-6pm from November through April. Each deliverability constraint is expressed as a percentage of Effective Nameplate Capacity for Solar and Wind variable resource classes. Deliverability of intermittent hydro and intermittent landfill gas is represented with ICAP.

E3 Evaluation

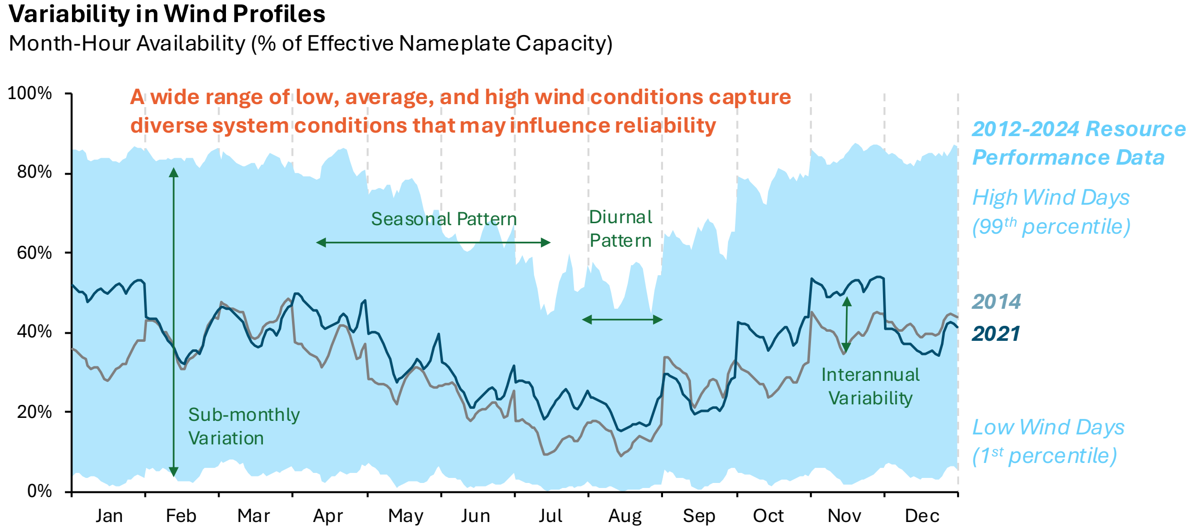
PJM's representation of variable resources using 12 years of historical data captures sufficient conditions to align with industry best practices. PJM's use of historical data where available objectively captures weather conditions and other outage factors. Weather-derived simulated profiles is an appropriate alternative where historical settlement data is unavailable. The development of resource-class profiles by aggregating time-matched individual site profiles appropriately captures geographic diversity and preserves correlations within the variable resource class.[27]

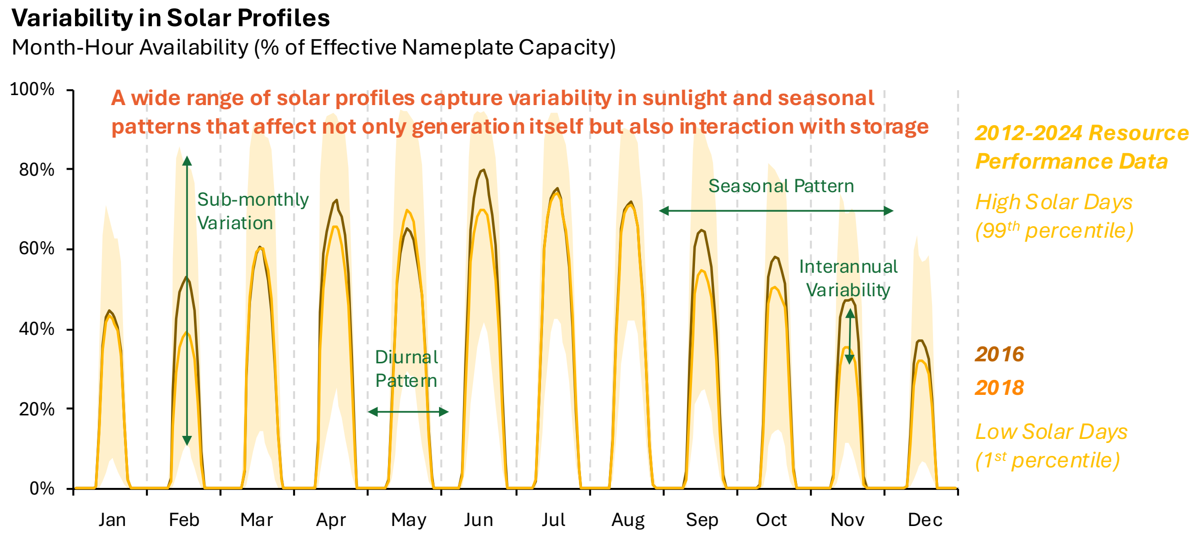
Variable resource availability profiles (or "shapes") must accurately reflect how availability changes between hours, seasons, and years to accurately model how variable resources can serve load. The figure below shows the average, 99th, and 1st percentile availability profiles for onshore wind and solar-tracking resource class by month/hour that are used in the PJM model. This chart shows how PJM's resource performance data captures a broad spectrum of potential wind and solar conditions, shown by the wide ranges shaded in blue and yellow.

[26] For more information on tests on Deliverability of Generation, see Attachment C.3 "Deliverability of Generation" on page 92 of PJM Manual 14b: https://www.pjm.com/-/media/DotCom/documents/manuals/m14b.pdf

[27] Capturing correlation between variable resources and load is addressed in the "Load and Resource Scrambling" section later in this report.

Figure 10: Variable Resource Availability Reflected in 2012-2024 Weather Year Profiles

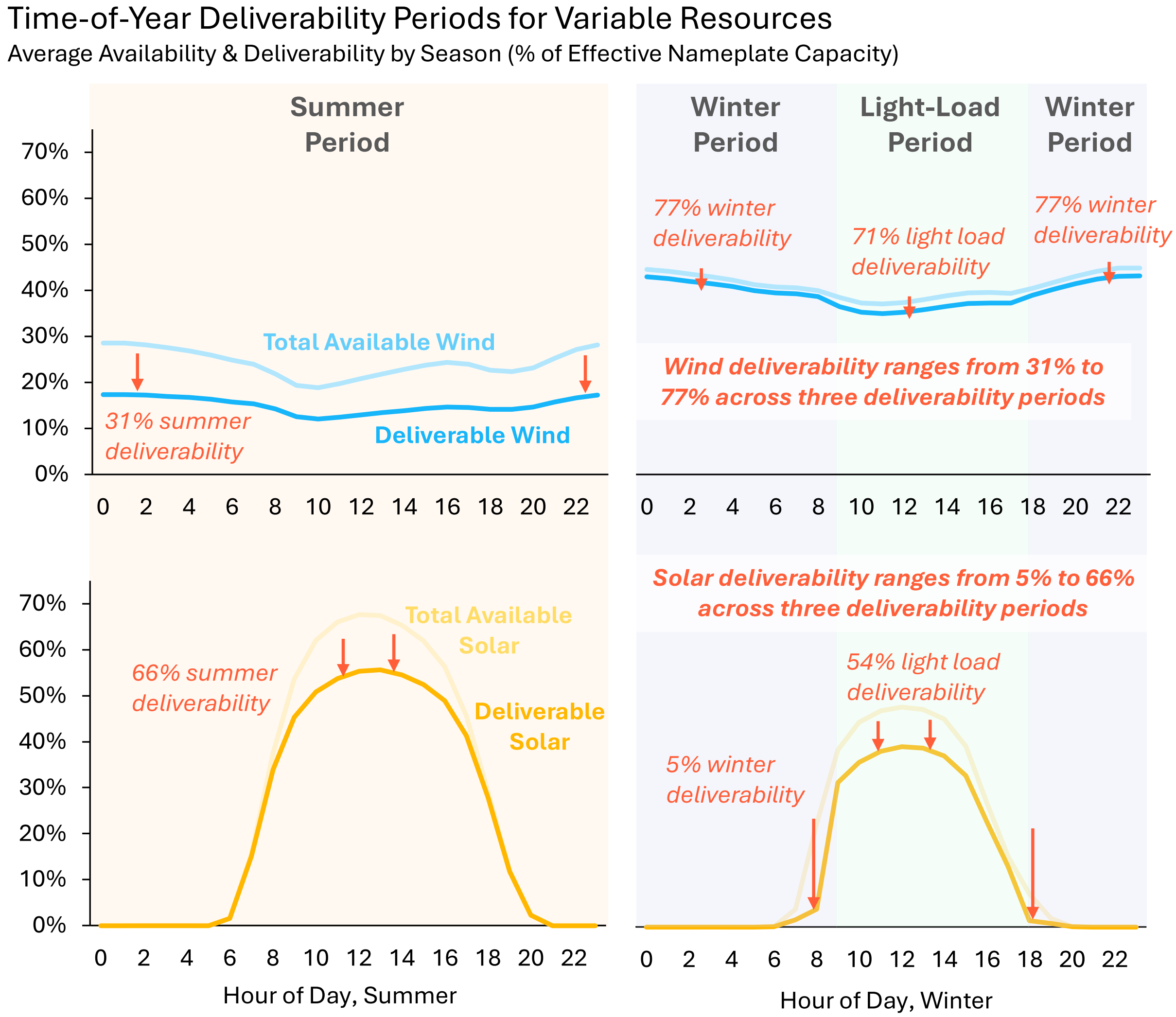




PJM applies deliverability constraints developed within PJM's Regional Transmission Expansion Plan (RTEP) to variable resource profiles, which aligns with industry best practice of representing key network constraints. Actual network congestion changes from hour-to-hour, but the complexity of network congestion makes temporally granular modeling of deliverability intractable. PJM therefore sets deliverability constraints based on a "time of year" methodology for "Summer", "Winter", and "Light-Load" periods.[28] Given the limited temporal granularity of deliverability constraints, best practice is to prioritize accuracy in during critical-hour periods. The figure below illustrates how deliverability constraints in PJM reduce the deliverable energy of variable resources.

[28] For more information on tests on Deliverability of Generation, see Attachment C.3 "Deliverability of Generation" on page 92 of PJM Manual 14b: https://www.pjm.com/-/media/DotCom/documents/manuals/m14b.pdf

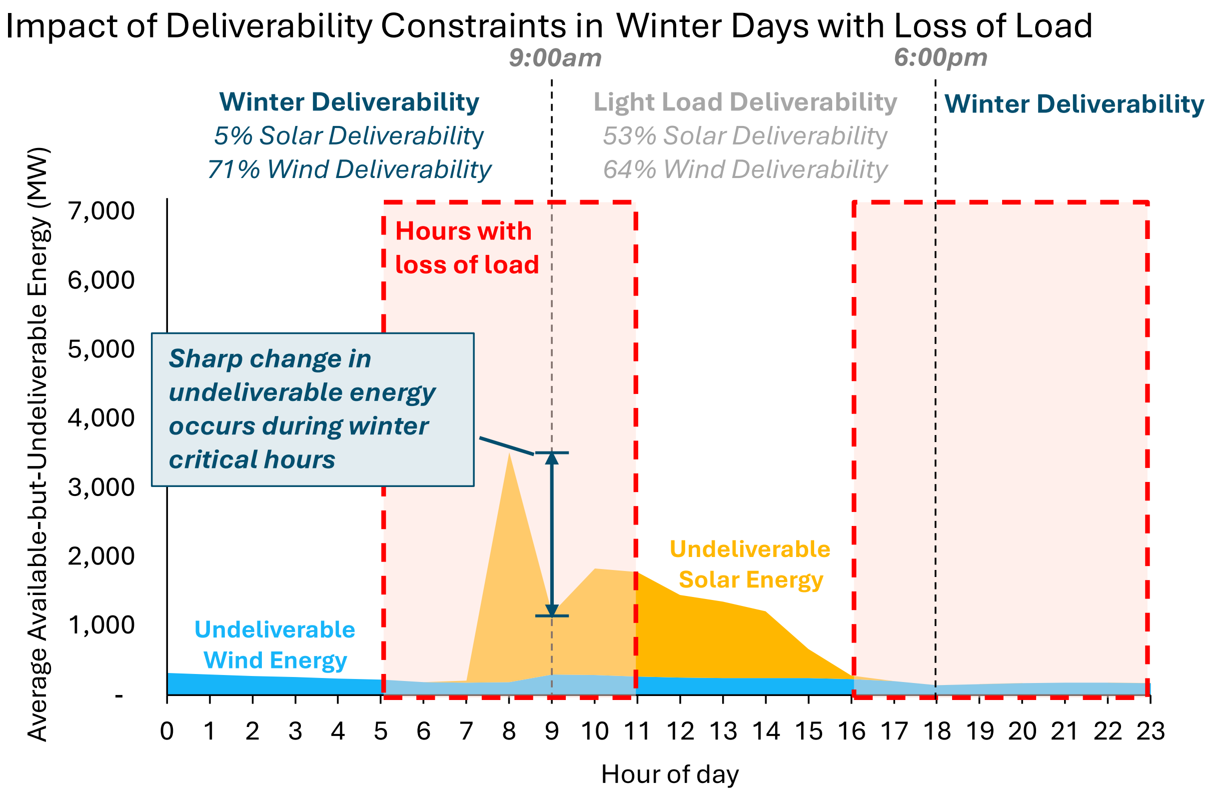
Figure 11: Deliverability of Variable Resources



Reductions in deliverability only impact model results to the extent that they impact resource performance during critical hours. The figure below illustrates reductions in wind and solar deliverability during winter days with loss of load. This figure shows that “Light-Load” deliverability constraints are being applied in hours with loss of load (when load is over 150 GW). While the “time of year” methodology to map deliverability constraints to hours in the PJM Model can reflect changes in network constraints on average winter days, it less accurately represents network constraints on peak winter days.

The figure below also highlights that transitioning from “Winter” to “Light-Load” deliverability constraints at 9 AM on winter days with loss of load has, on average, a 2 GW impact on available-but-undeliverable energy. This is illustrated through the sharp reduction in undeliverable solar at 9 AM when deliverability constraints relax to “Light-Load” levels.

Figure 12: Average Undeliverable Energy in Winter Days with Loss of Load



The table below summarizes E3's evaluation of how PJM's representation of load aligns with industry best practice.

Variable Resource Availability & Deliverability: E3 Evaluation Summary	
Pros	**Cons**
+ Sufficient number of years of historical variable resource availability data (12 years) to capture full spectrum of potential conditions + Aggregating time-matched individual profiles to develop resource-class profiles appropriately represents geographic diversity and correlations between variable resources + Deliverability constraints are applied to reflect network limits in a tractable (3 time-of-year periods) manner	+ Limited temporal granularity of deliverability constraints (summer deliverability, winter deliverability, light-load deliverability) limits overall granularity of variable resource representation. However, too much temporal granularity is intractable + "Time-of-year" methodology to assign deliverability constraints to hours in PJM Model does not directly reflect system conditions

Load and Resource Scrambling

Industry Best Practice

"Scrambling" is a practice used in nearly all LOLP models to expand the range of system conditions captured by historical data. This practice mixes and matches observed combinations of load and resource performance to construct plausible conditions that may have not been observed historically. The goal of scrambling is to ensure the model sees potential risk events that are important to the reliability of the system.

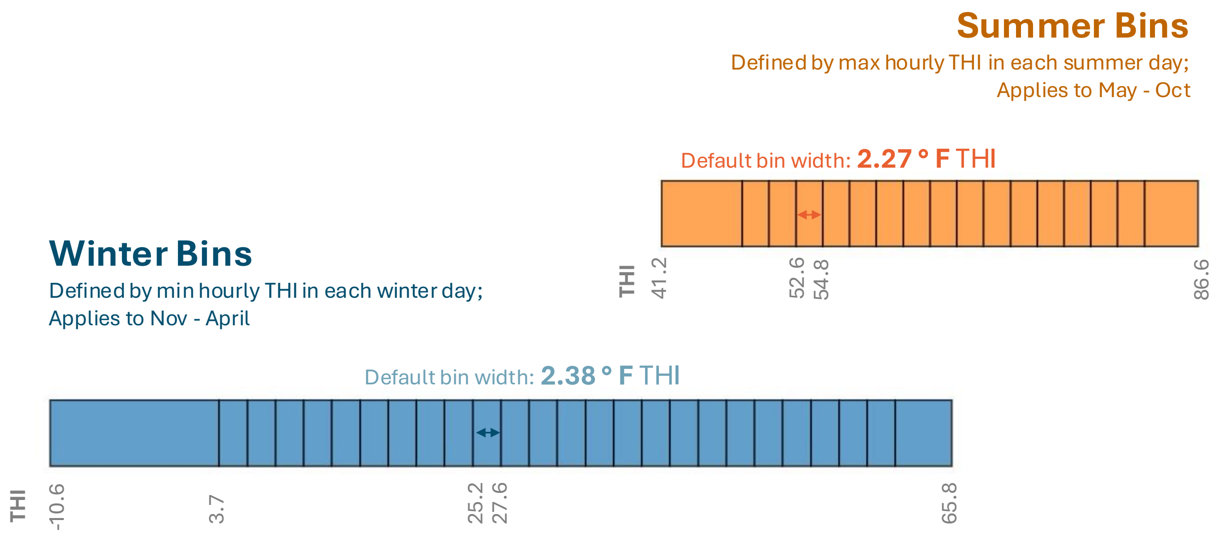
Implementing scrambling into an LOLP model nonetheless raises an important challenge – how to introduce plausible combinations of load and resource availability without introducing implausible combinations. Best practices within scrambling:

+ Limit scrambling based on underlying factors that drive correlation between loads and resources such as weather, load, and date. These model-imposed limitations preserve realistic correlation between loads and resources. For example, it would not make sense to pair the load profile from a hot summer day with a solar profile from a cold winter day
+ Ensure that plausible high-risk events (such as high load paired with low variable generation) are represented
+ Ensure sufficient scrambling replications so that model results are statistically significant

PJM Approach

PJM implements a scrambling methodology by limiting scrambling to within a set of PJM-defined bins based on temperature-humidity index ("THI") for both the summer and winter seasons. PJM's approach scrambles, with equal probability, daily load profiles and daily resource availability profiles within each THI bin. An overview of PJM's THI bins is provided in the figure below.

Figure 13: Seasonal THI Bins Used in PJM Model



The "size" of each bin is determined by the range of temperatures that define it, as illustrated above. A smaller bin will create fewer opportunities to scramble plausible load and resource conditions that were not observed historically, while a larger bin may introduce potential erroneous conditions into the model. This is particularly important for extreme temperature bins; because extreme events occur infrequently, there are only a handful of historical observations available to represent how the system behaves under those conditions, making it challenging to size bins that are both statistically robust and representative of physical system behavior.

PJM's approach differs slightly from other LOLP models where the probability of pairing days is based on how "similar" the days are along certain dimensions such as temperature, load levels, month, or other variables. In this sense, other models do not assign a strict boundary where the probability of pairing a resource performance day with a load day becomes zero but rather gradually reduces the likelihood of such a pairing as an underlying condition (such as temperature) becomes more different between the load and resource performance days in question. Despite the differences between these two methodological approaches, they both rely on the same principle of limiting scrambling based on underlying factors that drive correlations between loads and resources.

To decide the default width of bins, PJM applies the Freedman–Diaconis rule, a statistical method for choosing the optimal bin width for a histogram, balancing bias and variance to best approximate the true underlying data distribution. PJM bins weather data from 1993-2024 separately for the summer and winter seasons[29]. When there are too few observations in a bin, adjacent bins are merged to increase observations (e.g., the two rightmost hottest bins in summer are merged, and the six leftmost coldest bins are merged[30]). Once bins are

[29] Summer bins apply to modeled days from May 1 to October 31, winter bins apply to model days from November 1 to April 30.

[30] Note that this is sperate from the discussion of merging Winter Storm Elliot bin and Polar Vortex bin.

established, each day between 1993-2024 is assigned to a bin based on that day's temperature profile. The model scrambles daily load and resource profiles from the same temperature bin.

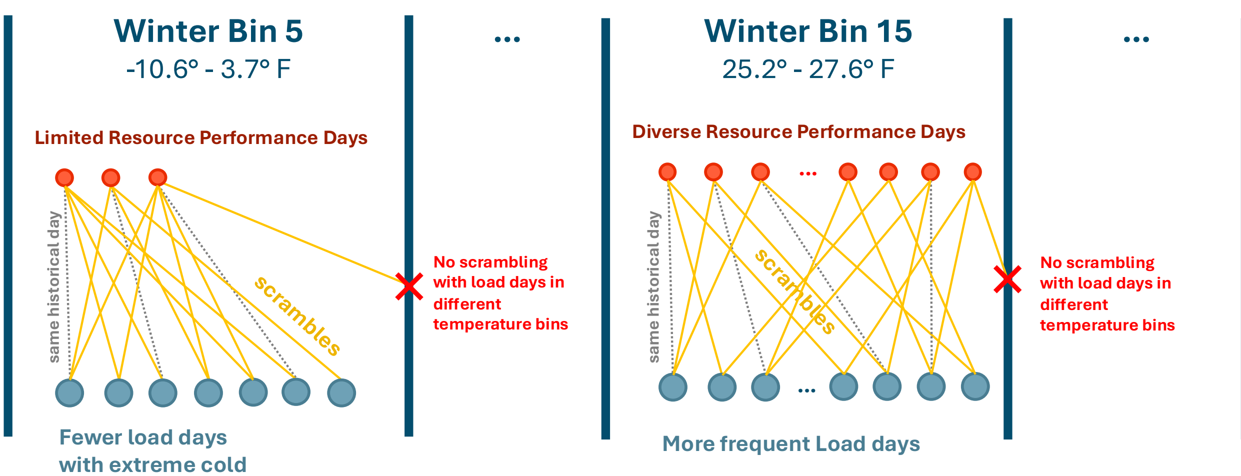
To ensure sufficient scrambling, PJM derives 100 unique resource generation profiles for each day within the 13 load rotations. These profiles are developed through random draws from historical performance days within the THI bin assigned to that day. For example, when scrambling generation for a load day that falls into winter Bin 15, 100 random draws are taken from historical observations in winter Bin 15. When the load day is "rotated" forward and backward by 6 calendar days in the remaining 12 load rotations, 100 random draws will be performed from the same bin (Winter Bin 15) for each rotation.

Another feature of PJM's current approach is that it does *not* scramble resource performance profiles for different resource classes. For example, while PJM may scramble generation from July 1st with load from July 6th (if they are in the same temperature bin), all generation (unlimited and variable resources) is pulled from July 1st.

Among all resource classes, intermittent hydro generation is not subject to this scrambling methodology. For hydro resources, each load year (1993 – 2024) is mapped to a specific hydro year (2012 – 2024) based on similarity of the peaks in the load years. These pairings are then used across all simulations. This means that while other resource classes are scrambled by day and vary across 100 resource performance scenarios, annual availability profiles for intermittent hydro generation are fixed for each weather year.

The figure below provides an illustration of PJM's scrambling approach.

Figure 14: Illustration of Scrambling Process in ELCC/RRS Model

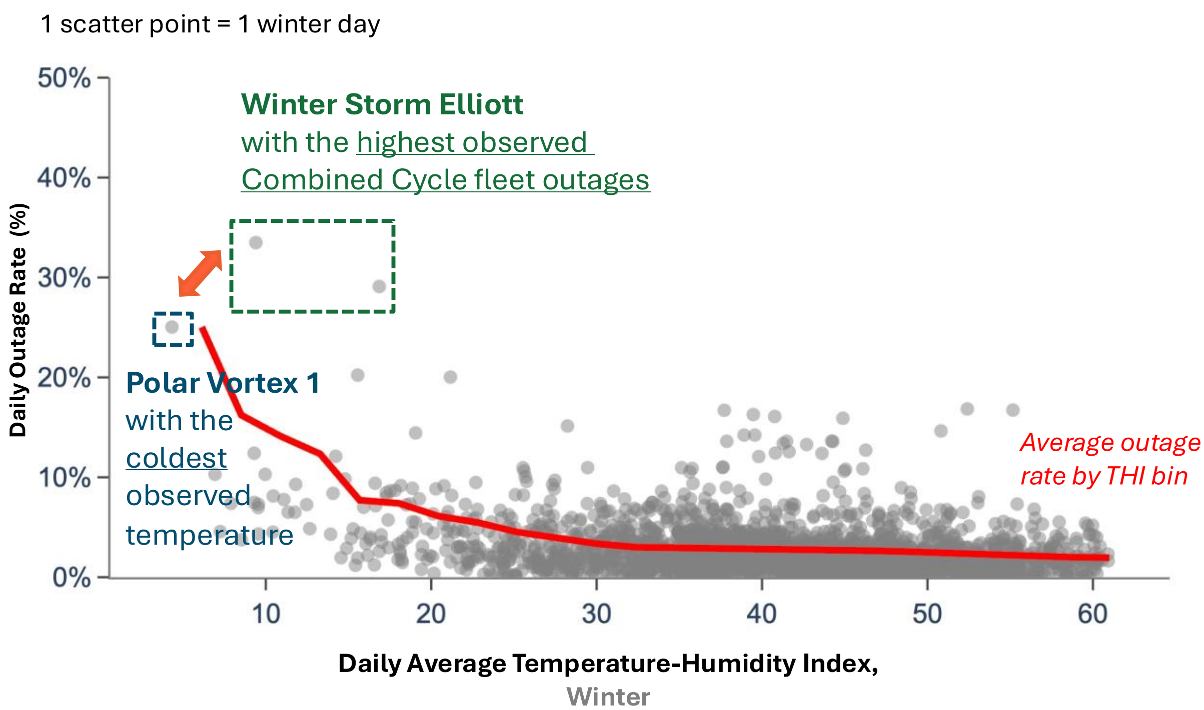


E3 Evaluation

PJM's approach of using a temperature proxy (in this case, "temperature-humidity index") to preserve correlation between load and resource availability is common practice in LOLP modeling and aligns with industry best practice.[31] This approach is common because temperature and humidity directly and indirectly impact both load and renewable resource production. For example, high temperatures and humidity drive high load levels due to air conditioning. At the same time, high temperatures are also caused by sunny conditions. It therefore is less likely that high temperature/load days would occur on days with low solar output. PJM's approach captures this effect.

Another factor that PJM's binning approach captures well is the correlation between low temperatures and unlimited resource performance. Low temperatures in PJM drive both high loads (due to electric heating) and higher forced outage rates for unlimited resources due to units freezing and reduced access to fuel. The figure below highlights how forced outage rates for combined cycle resources increase as temperature decreases.

Figure 15: Correlation Between Combined Cycle Fleet Daily Outage Rate (%) and Temperature-Humidity Index



Bin Size and Membership

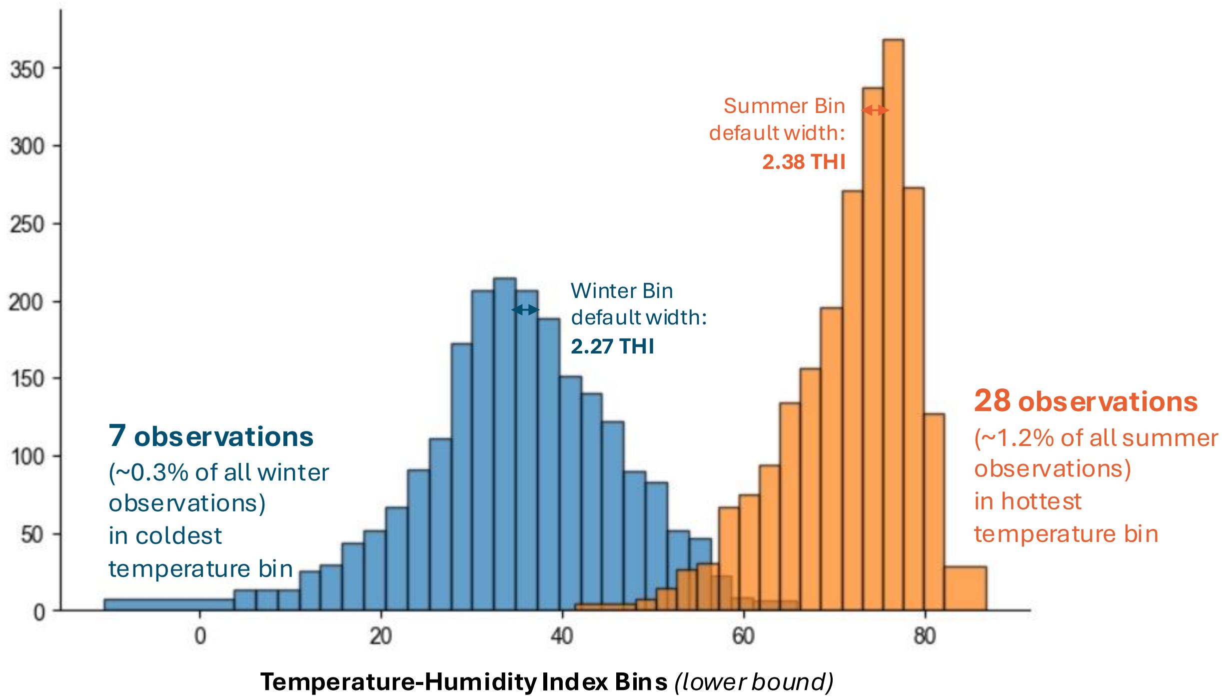
In PJM's binning methodology, one key assumption is defining the size of the bins. Larger bin sizes mean the model scrambles more load and resource pairings, resulting in a larger sample of potential system conditions. However, larger bin sizes also diminish correlation between load and resource days by scrambling days with underlying weather conditions that are more different. Ultimately, defining bin sizes (or in other LOLP models,

[31] Because temperature and load are so tightly correlated, some models use load levels itself as a proxy for temperature in the scrambling process

mathematically defining how "similar" days are to each other) is subjective to a degree and requires the modeler's judgement.

One important factor in determining bin definitions is ensuring there are sufficient number of load and resource performance days in each bin in order to ensure there is enough data to scramble. PJM's dataset relies on loads that are simulated using weather across 31 years (1993 – 2024) and resource performance across 12 years (2012 – 2024). As a result, there are many more load days than resource performance days in PJM's model. It is thus important that PJM defines large enough bins that there are a sufficient number of resource performance days in each bin. Otherwise, a bin with a single poor resource performance day could assume this level of performance across many load days, improperly increasing the impact of this day. The figure below shows the number of resource performance days that fall in each THI bin. The coldest bin contains 7 resource performance days, while the hottest bin contains 28 resource performance days. In E3's assessment, this is a sufficient number of days in the bins that contribute significantly to loss of load risk.

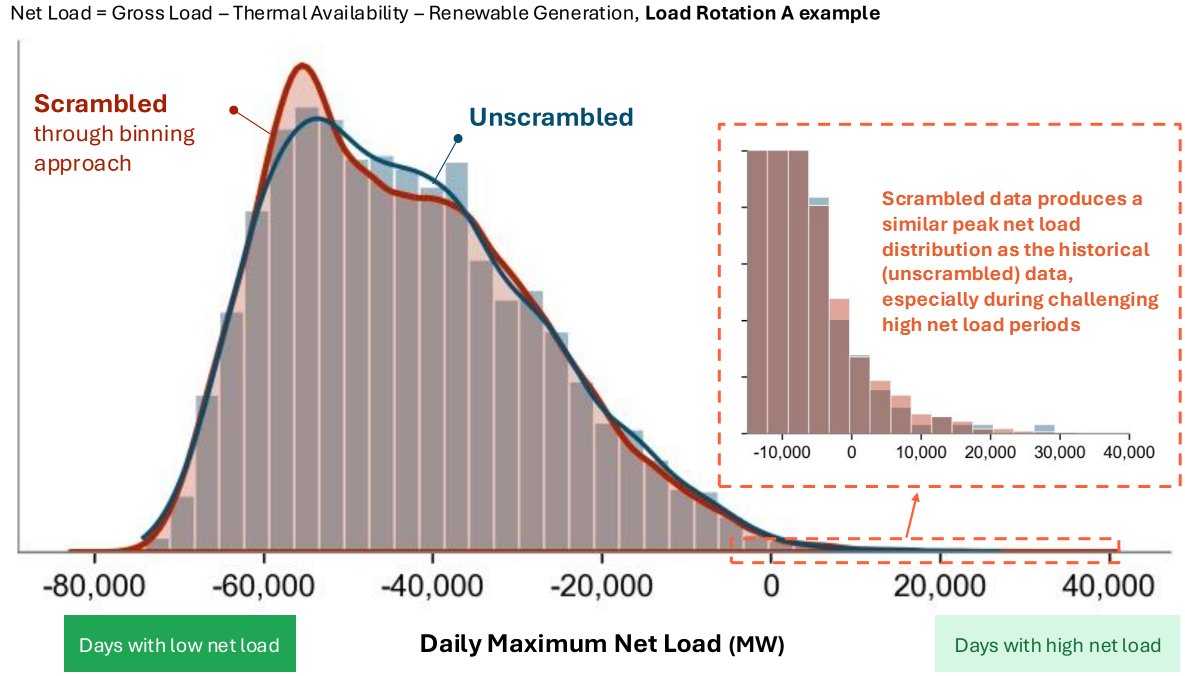
Figure 16: Number of Unique Historical Resource Performance Days in Each THI Bin



Load vs. Resource Performance Scrambling

After bins are defined, the model scrambles load and resource days within each bin. One way to measure how well this scrambling approach performs (and whether 100 resource performance draws are sufficient) is by comparing the distribution of net loads for historical data and scrambled model outputs. The figure below shows how these two distributions are very similar for the "unrotated" load scenario (i.e. Load Rotation A), indicating that the model's design performs well along this dimension.

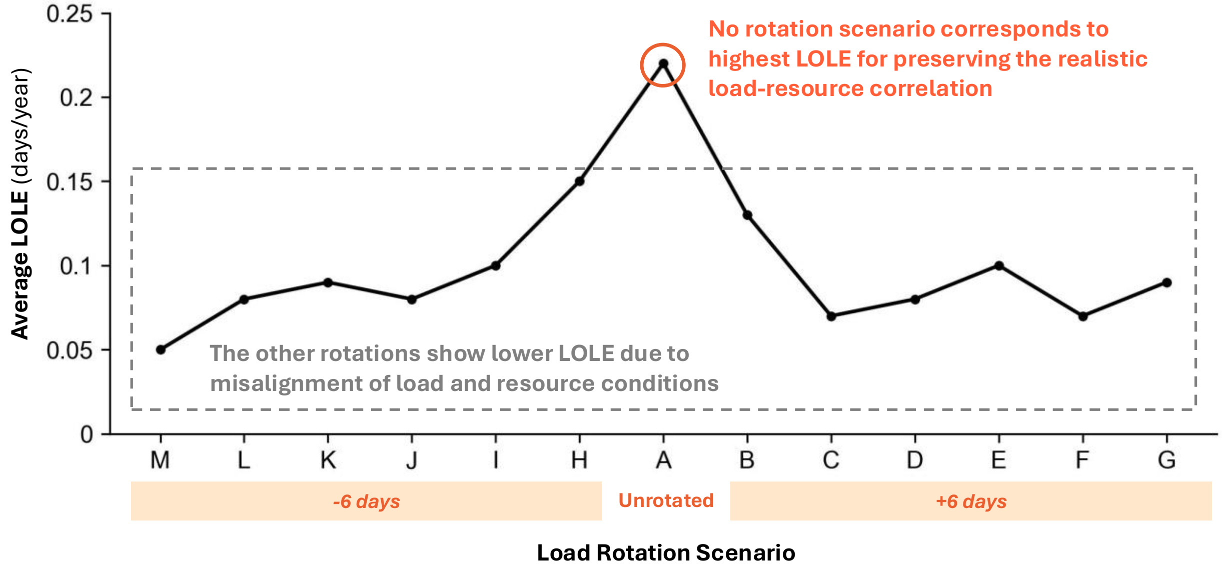
Figure 17: Daily Peak Load Net of Availability Resources Before and After Scrambling



However, the current PJM modeling approach does not just scramble loads and resource performance values for an "unrotated" day but rather uses 13 different load rotations. A concern with PJM's current implementation of load rotations is that while it rotates weather for the purpose of determining loads, it does not rotate weather for the purpose of drawing resource performance profiles. This leads to misalignment between the weather conditions reflected in the load profile and the weather conditions reflected in the resource performance assumptions for certain load scenarios. For example, resource performance conditions from non-extreme weather conditions might be paired with load profiles from extreme weather conditions when rotation introduces a more severe weather pattern.

How this over-scrambling impacts model results is an empirical question. If extreme weather (and its associated high loads) is correlated with poor resource performance, then over-scrambling will overstate the reliability of the system. Conversely, if extreme weather is correlated with good resource performance, then over-scrambling will understate the reliability of the system. Given that the majority of PJM's reliability risk is in the winter when resource performance is poor, over-scrambling overstates the reliability of the system. This finding is illustrated in the chart below. The "unrotated" load day (Load Rotation A) has over twice as many reliability events as the average across all load rotations. Rectifying this issue would appropriately reflect that PJM's system is less reliable than currently modeled.

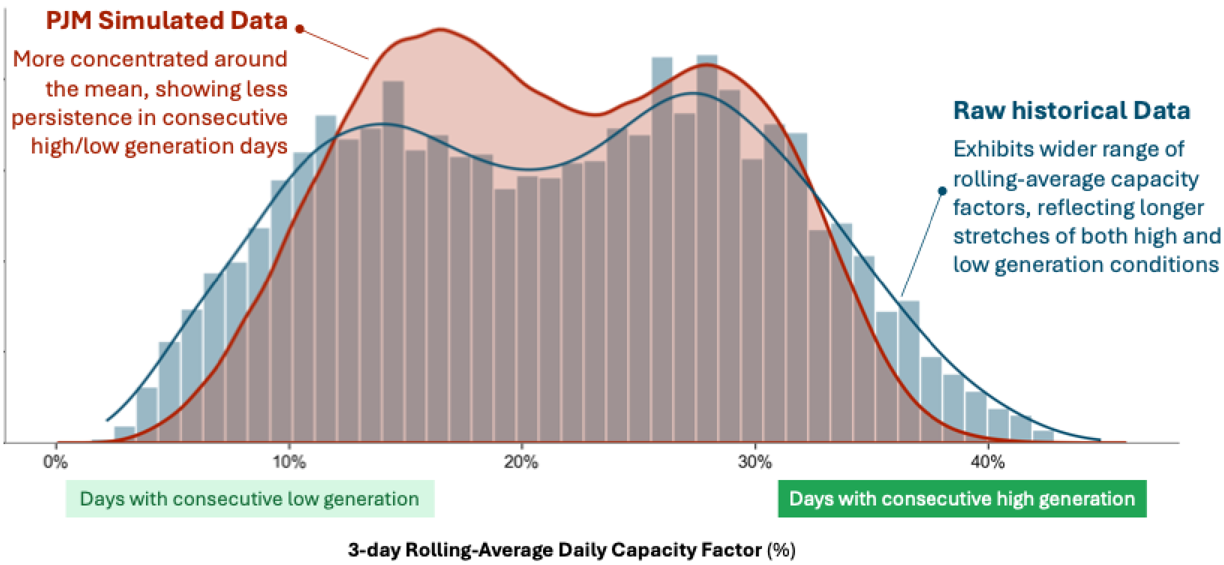
Figure 18: PJM 2027/28 BRA Simulated LOLE results by Load Rotation Scenario



Multi-day Scrambling Considerations

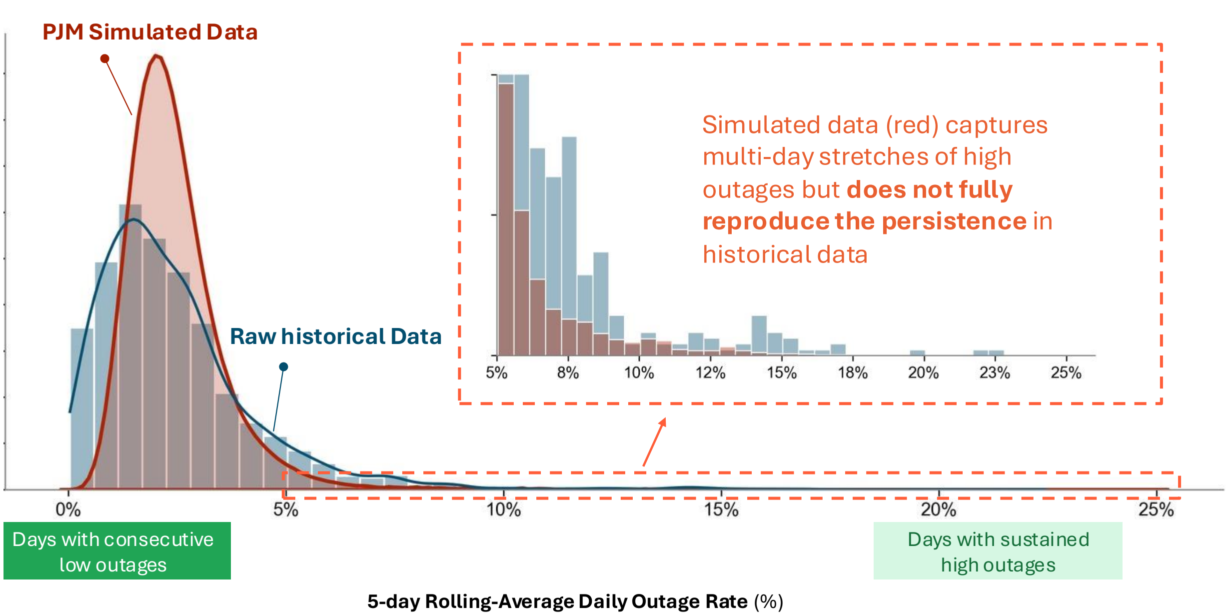
Another important feature of PJM's approach is that it draws resource performance days solely based on temperature of that day without consideration of the prior day's resource performance. This approach does not capture the fact that high and low resource performance days tend to cluster together due to multi-day weather patterns that pass through the PJM region. For example, cloudy (or sunny) days are more likely to be followed by cloudy (or sunny) days. The impact of this design element is shown in the figure below. The figure shows that for the 3-day rolling average capacity factor for tracking solar has both more high generation periods and more low generation periods than PJM's scrambled simulations.

Figure 19: Consecutive-Day Average Solar Performance Before and After Scrambling



This effect is also not just limited to variable resources. E3 observes the same phenomenon for combined cycle plants as shown in the figure below. This is likely due to the fact that when an unlimited resource fails, it can take multiple days to repair the unit.

Figure 20: Consecutive-Day Average Forced Outage Rates Before and After Scrambling



Whether or not the impact of multi-day resource availability impacts model results (either the LOLE of the system or resulting resource-class ELCCs) depends on the resources in the portfolio. As energy storage penetrations increase, the underrepresentation of multi-day periods of low resource availability risks overstating the reliability of the system and the ELCC of energy storage resources. This is because energy storage is likely to run out of charge in these (underrepresented) multi-day events. In a system without large quantities of energy storage, PJM's current approach is unlikely to significantly impact model results.

Resource Performance Scrambling across ELCC Classes

Another design choice of PJM's model is to *not* scramble resource performance across resource classes from different historical days. In other words, wind, solar, and unlimited resource performance is always drawn from the same historical day. While this limits the potential set of conditions available to the model, it also prioritizes preserving correlations of performance between resource classes. PJM's approach is reasonable and ensures the model does not introduce implausible combinations of wind, solar, and unlimited resource performance.

Resource Performance Scrambling Sampling Probability

Finally, in the current PJM framework, any resource performance day within each THI bin has equal likelihood of being stochastically selected by the model for pairing with a load day. One drawback of this approach is that resource performance days that occurred far back in the past may not accurately represent the system "as is" if units have undergone improvements or enhancements such as weatherization or improved fuel supply modifications. This is not only a concern for ensuring the model accurately estimates the reliability of the system and the ELCCs of resource classes, but also for sending economic signals to individual resources to undertake improvements and enhancements. If individual resources do not perceive that improvements will be recognized and rewarded through improved accreditation, they may be less likely to undertake these improvements to the detriment of the reliability of the system.

The table below summarizes E3's evaluation of how PJM's representation of load aligns with industry best practice.

Load and Resource Scrambling: E3 Evaluation Summary	
Pros	**Cons**
+ Aligns with industry best practice by scrambling load profiles and resource availability profiles in a way that introduces new plausible conditions while preserving correlation between load and resource performance by linking them through temperature + By not scrambling resource classes from different historical days, PJM's approach preserves performance correlations between different resource classes	+ Weather for resource performance bins is not aligned with weather for load in "load rotations", which fails to preserve realistic correlation between loads and resources + Does not capture high or low multi-day resource performance events in ways that aligns with historical observations (unlikely to significantly impact model results until larger quantities of storage are present) + By assigning equal likelihood to recent resource performance days and those

- Bin sizes ensure sufficient quantity of resource performance observations in each bin
- Number of resource performance draws ensure statistically significant model results

far in the past, PJM's approach may not reflect the system "as is" if resources have undertaken improvements or enhancements

Dispatch of Energy Limited Resources and Demand Response

Industry Best Practice

Unlike production cost models, LOLP models generally do not "dispatch" thermal resources in order to avoid unnecessary computation. Instead, LOLP models evaluate the *availability* of resources and how much the system could dispatch if needed. This approach works well for thermal resources. However, this approach does not work for energy-limited resources such as storage and demand response because their use in one hour directly reduces their availability in other hours. Therefore, it is industry best practice to time-sequentially dispatch energy-limited resources in LOLP models.

Best practice for dispatching energy-limited resources in LOLP models should 1) approximate how these resources would be used by system operators for the maximization of system reliability while accounting for limitations such as imperfect foresight and 2) be tractable in order to enable hundreds or thousands of years of dispatch as is standard in LOLP modeling. To balance these factors, industry best practice often approximates an "optimal" dispatch of energy-limited resources (where optimal is defined as one that maximizes system reliability) using a heuristic that is more computationally tractable than pure optimization.

Industry best practice of energy-limited storage dispatch also uses time-sequential simulation to track energy-limited resource state of charge, round-trip charging/discharging efficiency losses, and demand response call limits.

PJM Approach

PJM models the dispatch of energy-limited resources for battery storage (standalone and in hybrids), dispatchable hydro (i.e., "Hydro Non-Pumped Storage"), and demand response. The model tracks the state of charge for battery storage and dispatchable hydro resources on a time-sequential basis, allowing the model to capture how use of energy-limited resources can deplete their charge. This approach also tracks the time required to recharge these resources.

In lieu of pure optimization for the dispatch of energy-limited resources, PJM uses a more tractable heuristic that is best described as a "more available resources are dispatched first" methodology.[32] PJM defines more available resources as those with longer durations. Because demand response is available 24 hours a day in PJM, this is considered to be the most available resource and is therefore dispatched first.[33] The result of this approach is that PJM dispatches demand response in all hours where load exceeds unlimited and variable resources availability, before energy limited resources are dispatched. The energy-limited dispatch order in PJM's model is:

+ **Demand Response**
+ **10-hour storage**
+ **8-hour storage**
+ **6-hour storage**
+ **Hydropower with non-pumped storage**
+ **Solar-Storage (4-hour) Hybrids Open-Loop**
+ **Solar-Storage (4-hour) Hybrids Closed-Loop**
+ **4-hour storage**

PJM does not allow storage resources to charge during hours in which demand response is being dispatched. In other words, the model will not call demand response in order to free up generation resources to charge energy storage.

PJM charges energy-limited resources simultaneously at equal rates using available energy from unlimited and variable resources in excess of load. Hybrid resources can charge using co-located generation when available.

E3 Evaluation

PJM's use of time-sequential dispatch for energy-limited resources aligns with industry best practice.

PJM's heuristic dispatch using a "more available resources are dispatched first" methodology reasonably approximates how energy-limited resources would be used by system operators for the maximization of system reliability. This is because dispatching longer duration resources first preserves the maximum amount of instantaneous capacity for use by the system in later time periods. Additionally, PJM's heuristic is tractable and facilitates the dispatch of energy-limited resources across thousands of years of simulations.

Even though PJM's dispatch heuristic reasonably approximates optimal use of energy-limited resources, there are several plausible conditions where this approach is not optimal. For example, if the system is "energy short" as opposed to "capacity short" during a particular reliability event, it may be optimal to discharge resources with the highest roundtrip efficiency (which tend to be short-duration batteries) since they can recharge faster with less energy.

[32] Slide 15, https://www.pjm.com/-/media/DotCom/committees-groups/committees/pc/2024/20240216-special/elcc-education.pdf

[33] The approach to demand response modeling is described in recent revisions to PJM Manual 18.

Another aspect of PJM's dispatch that does not maximize reliability of the system is the limitations on using demand response to facilitate charging of energy-storage resources. There are not sufficient levels of energy storage on PJM's system today to observe how system operators would act in such a situation, making it difficult to align the model with the principle of reflecting real-world operations. Nonetheless, if PJM perceived a high risk of loss-of-load later in the day unless storage is able to charge earlier in the day, it is likely that PJM would consider enacting demand response to facilitate storage charging.

A fully optimized dispatch approach can account for other factors beyond just duration, including roundtrip efficiency. Incorporating such factors would be more accurate but also more complex and would reduce model tractability.

The table below summarizes E3's evaluation of how PJM's representation of load aligns with industry best practice.

Dispatch of Energy Limited Resources and Demand Response: E3 Evaluation Summary	
Pros	**Cons**
+ Hourly time-sequential dispatch of energy limited resources and demand response aligned with industry best practices in LOLP modeling + Tractable dispatch heuristic reasonably approximates system operations and facilitates thousands of model simulations	+ Dispatch of energy limited resources could be more optimal through an improved dispatch order. However, this would increase complexity and decrease tractability + Dispatch of energy limited resources could be more optimal by allowing energy storage to charge in hours where demand response is dispatched

Resource Accreditation

Industry Best Practice

Using LOLP models to accredit the effective capacity of resources is increasingly standard practice throughout North America. Markets such as PJM, MISO, NYISO have all implemented a marginal ELCC framework that accredits resources based on their availability during critical hours, and ISO-NE is actively exploring implementing this framework.

A strength of a marginal ELCC approach lies in the use of a common benchmark ("perfect capacity") against which the impacts of all resources can be measured. Additionally, this approach sends economically efficient signals to the market for entry (i.e., new investment), retention, and exit (i.e., exit) that minimize total consumer cost.

In theory, each resource in an electricity system has a distinct and unique marginal ELCC value that reflects its specific operating characteristics and limitations. In practice, it is impractical to calculate individual marginal ELCCs due to both data availability and computational tractability.[34] To address this issue, it is common practice to group similar resources together into "resource classes" and calculate marginal ELCCs for the entire group. Market operators then commonly differentiate resources within each class based on a simple heuristic such as average capacity factor during high reliability risk hours.

PJM Approach

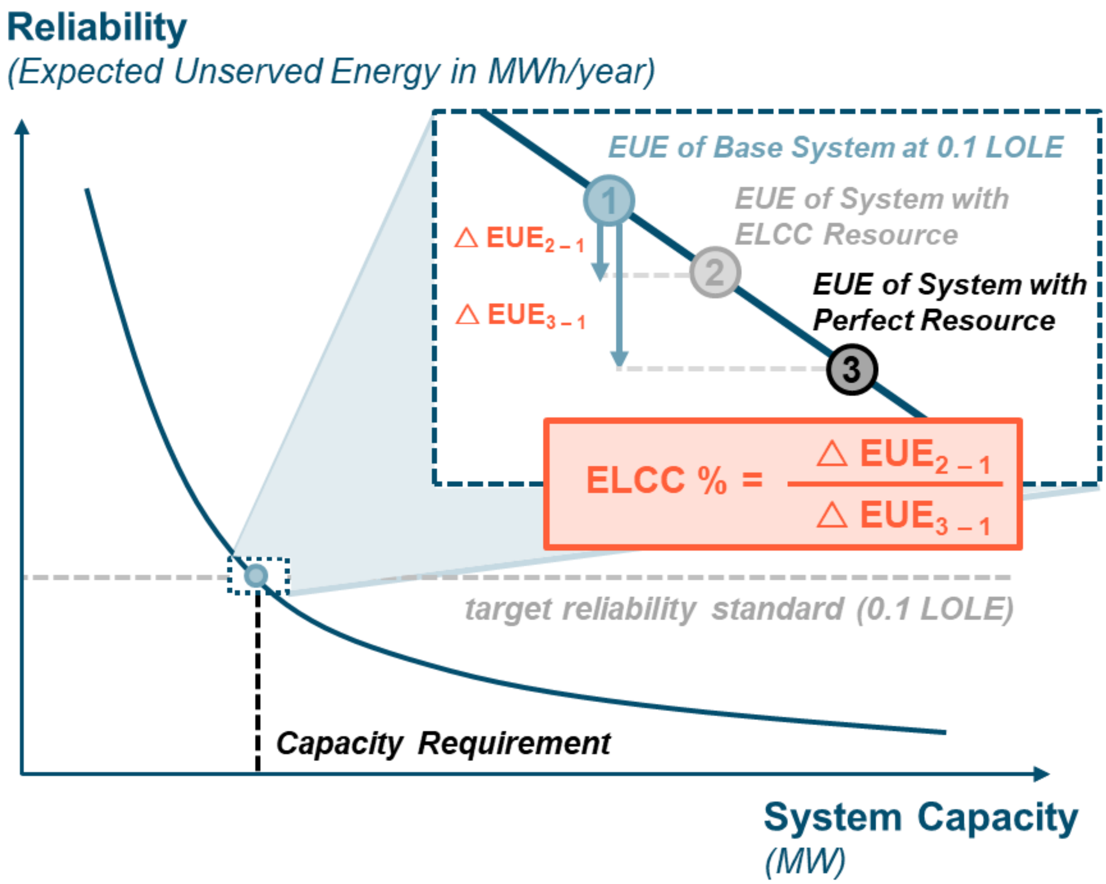
PJM calculates marginal ELCC values for a defined set of "resource classes," listed below.

- **Onshore Wind**
- **Offshore Wind**
- **Fixed-Tilt Solar**
- **Tracking Solar**
- **Landfill Intermittent**
- **Hydro Intermittent**
- **4-hr Storage**
- **6-hr Storage**
- **8-hr Storage**
- **10-hr Storage**
- **Demand Resource**
- **Nuclear**
- **Coal**
- **Gas Combined Cycle**
- **Gas Combustion Turbine**
- **Gas Combustion Turbine Dual Fuel**
- **Diesel Utility**
- **Steam**
- **Waste to Energy Steam**
- **Oil-Fired Combustion Turbine**

For each resource class, PJM calculates a marginal ELCC value that represents the incremental improvement to reliability that would be achieved by adding a small or "marginal" quantity of that resource class. All measurements for incremental improvement to reliability are performed on a system that has been calibrated (by scaling load) to the 0.1 LOLE days/year reliability target. The metric for measuring incremental improvements to reliability due to adding a resource to this system is measured in terms of MWh of reduction in Expected Unserved Energy. All resource class marginal ELCC values are measured in a relative % to how much the additional of an equivalent amount of a perfect resource would marginally improve system reliability. This calculation process is outlined in the figure below.

[34] Pg 42, https://www.ethree.com/wp-content/uploads/2025/08/E3_Critical-Periods-Reliability-Framework_White-Paper.pdf

Figure 21: Illustration of PJM's Resource Class Marginal ELCC Calculation

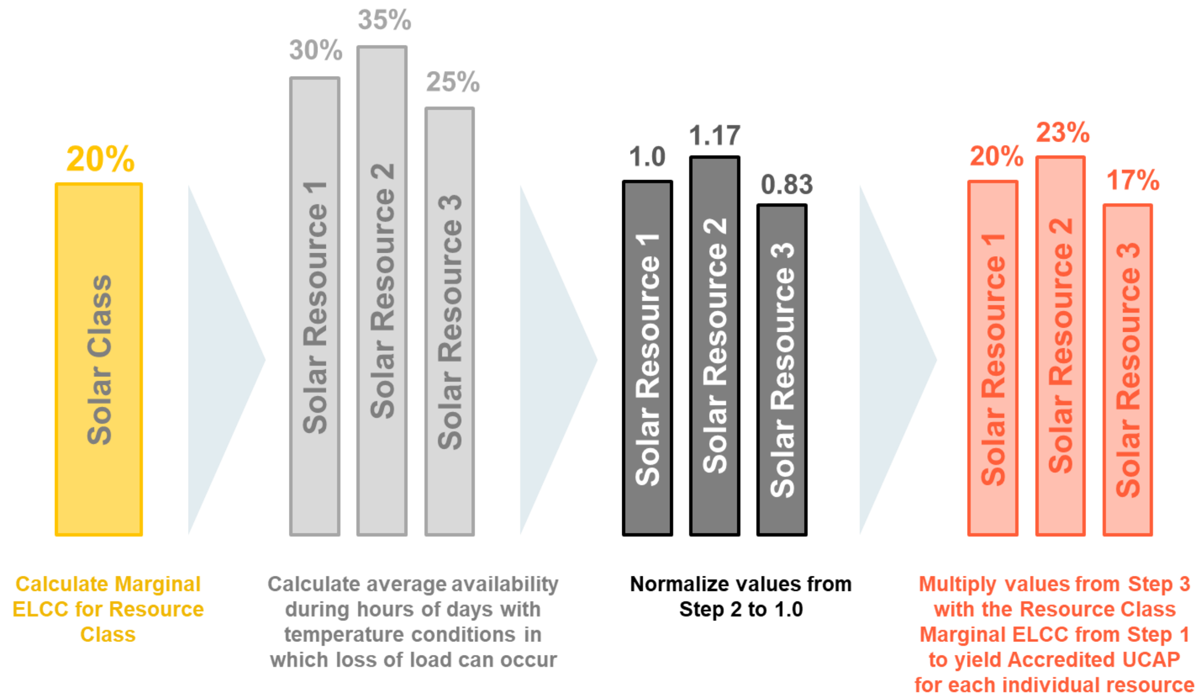


To assign a capacity accreditation value to each individual resource, PJM calculates "Performance Adjustment" factors for each individual resource to adjust the resource class ELCC assigned to each individual resource. PJM uses this approach to tractably differentiate the capacity accreditation of resources within a class while ensuring that the average accreditation for all resources within the class equals the resource class marginal ELCC.

PJM calculates the performance adjustment factor for each individual resource as the average availability of a resource during the hours of the day that have a temperature condition in which loss of load occurs. For example, if Days 3, 8, and 12 comprise Temperature Bin 1, and there is a loss of load event during the hours from 4-6pm on Day 3, then the performance adjustment factor is calculated as average resource availability from 4-6pm across all days in the Temperature Bin (Days 3, 8, 12).

PJM then normalizes the performance adjustment factor for all resources in the class to 1.0 and multiplies these values by the resource class marginal ELCC to determine the final Accredited UCAP (AUCAP) value that is assigned to each individual resource. This value forms the basis of both individual resource compensation in the capacity market and the determination of the total capacity requirement through the "pool-wide accredited average UCAP". An illustration of this calculation process is provided below.

Figure 22: Illustration of Performance Adjustment Process

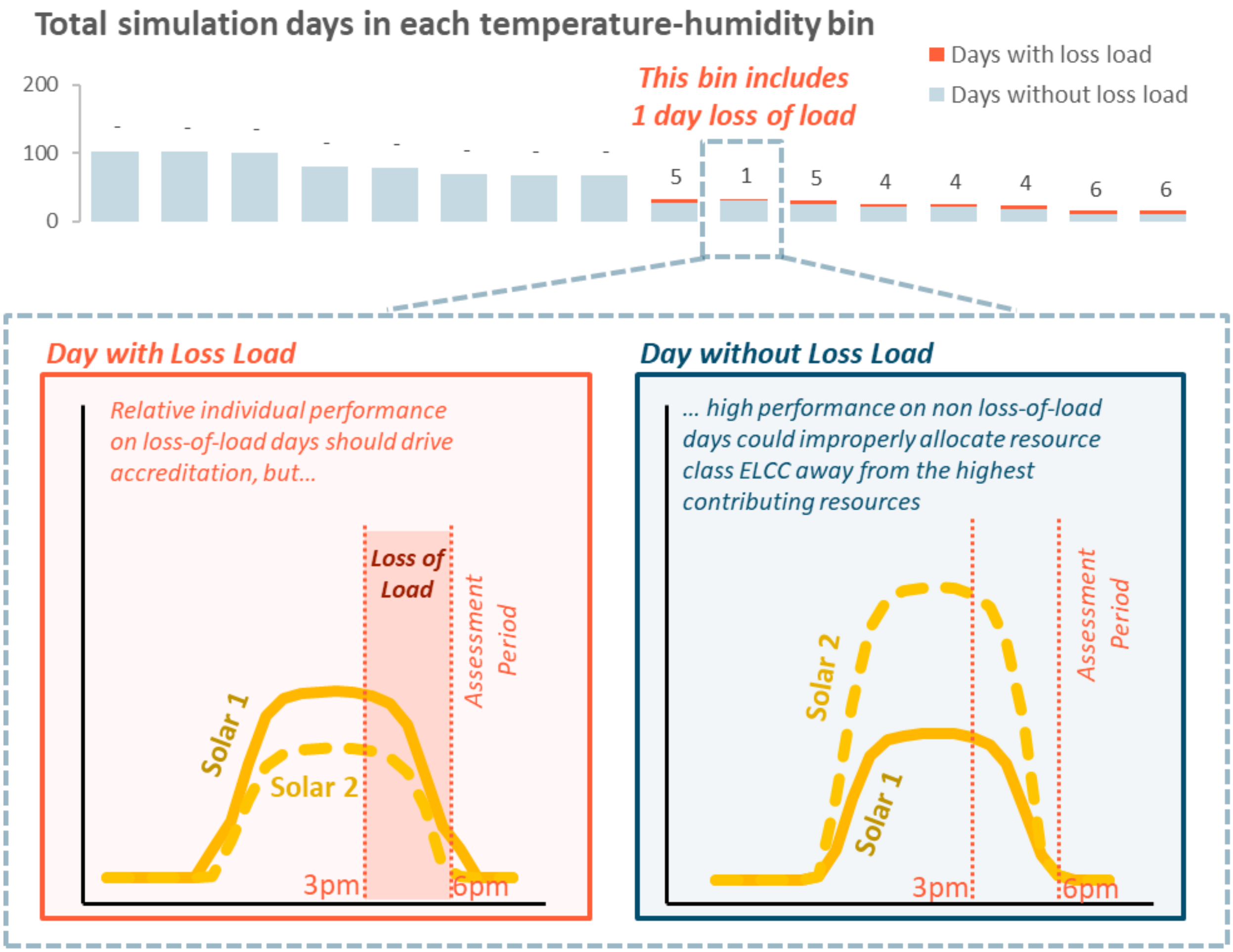


E3 Evaluation

PJM's tractable approach to calculating marginal ELCC for each resource class appropriately represents the marginal reliability contribution of each resource class and aligns with industry best practice.

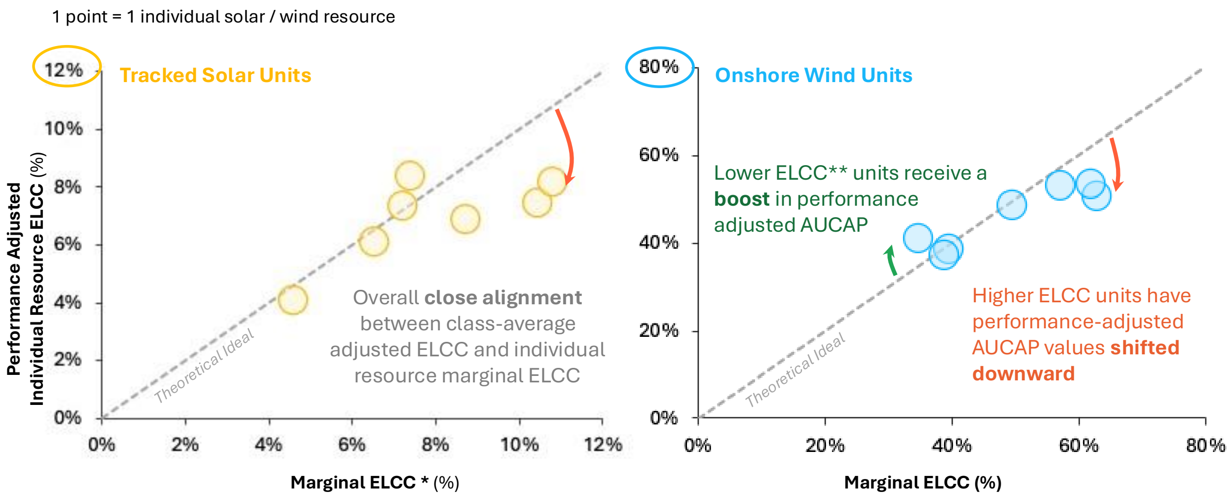
PJM's approach to calculating individual Performance Adjustment values is based on the performance of resources during any day with weather conditions that have loss of load. A shortcoming of this approach is that loss-of-load events are not exclusively driven by temperature. For example, a very cold day that is cloudy is much more likely to have loss of load than a very cold day that is sunny. The end result is that PJM's current approach considers performance in hours that are not determinative of a resource's marginal ELCC, for the purposes of individual Performance Adjustment. An illustration of this effect is provided in the figure below.

Figure 23: Illustrative Example of PJM's current performance assessment periods



Despite this theoretical misalignment, PJM's approach yields individual capacity accreditation values that are close to the theoretical ideal. An ideally performing methodology would yield an individual Performance Adjusted Resource Class marginal ELCC that is exactly equal to an individual resource marginal ELCC, assuming sufficient and appropriate data. The figure below compares PJM's approach to the theoretical ideal for a limited number of individual resources across different resource classes. Perfect performance would yield dots that fall exactly on the diagonal line. This chart shows that PJM's results are reasonably accurate.

Figure 24: Comparison of PJM Performance Adjustment ELCC with Marginal ELCC



* Marginal ELCCs are approximated with average resource generation during critical hours (more are discussed in the section b elow)
** Lower ELCC for certain units may reflect inherently low performance quality or over-penalization for unavailability during historical critical hours

Another attribute of PJM's approach is that it mitigates some of the "noise" present in historical availability data of individual resources. In other words, PJM's approach avoids over-penalizing resources that may have not been available during historical critical hours and avoids over-rewarding resources that were. The impact of this approach, as shown in the figure above, is a general "flattening" of resource accreditation values within each resource class toward the class average. In other words, resources with a higher "true" marginal ELCC generally receive a lower capacity accreditation value, and vice versa.

The table below summarizes E3's evaluation of how PJM's representation of load aligns with industry best practice.

Resource Accreditation: E3 Evaluation Summary	
Pros	**Cons**
+ Accreditation founded on a marginal ELCC metric accurately and fairly accredits resource classes + Individual performance adjustment approach yields AUCAP accreditation values that reasonably align with individual marginal ELCC values + Performance adjustment approach flattens noise in historical data that may yield anomalous results	

Validation of PJM Model Performance

This section evaluates the performance of the PJM ELCC/RRS model to validate that the inputs, processes, and outputs are consistent with the stated model design. This section is divided into two parts:

+ **Critical Hours Review**: Assessment of the "critical hours" of the model to validate key model outputs, namely the Forecast Pool Requirement ("FPR") and Effective Load Carrying Capability ("ELCC") values
+ **Model Validation Tests**: Select additional tests designed and performed by E3 to validate the PJM Model

Critical Hours Review

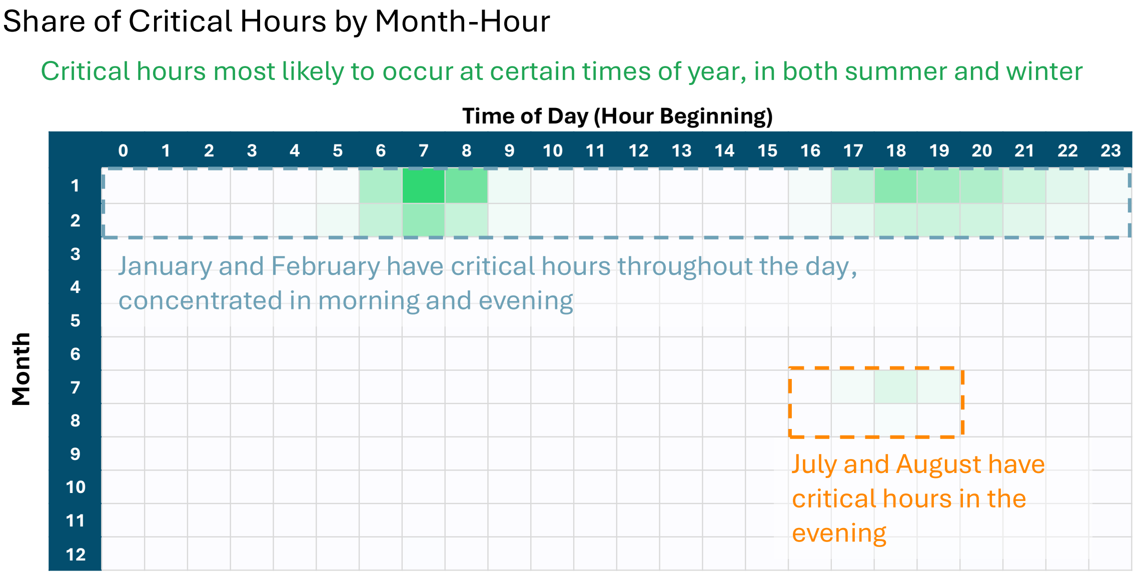
"Critical hours" are an increasingly well-understood concept as hours that impact system reliability.[35] Historically, standard industry practice only treated "loss of load hours" as relevant to system reliability. However, the growth of energy-limited resources (namely energy storage) shows that some non-loss-of-load hours are also relevant to system reliability if additional energy in these hours can help preserve energy storage state of charge for use during loss-of-load hours.

PJM currently estimates critical hours in a post-processing step to the ELCC/RRS model. Specifically, PJM uses a heuristic method to approximately identify critical hours by identifying both loss-of-load hours and what they term "energy benefit hours", which are hours where additional energy allows energy storage to save charge for later in the day.

An overview of the timing of critical hours in PJM based on post-processing outputs from the PJM ELCC/RRS model is provided below.

[35] https://www.ethree.com/new-framework-resource-adequacy/

Figure 25: Critical Hours Timing by Month-Hour



The outputs of the PJM ELCC/RRS model show critical hours in both the winter and summer season, with the majority occurring in the winter. Specifically, the model shows critical hours in the winter season during mornings and evenings on severe cold days and in the summer season on hot days during early evening hours when net load is high after solar declines.

While PJM has not had any loss-of-load events due to resource adequacy related issues in recent decades, PJM has had several close calls, including periods where operating reserves have dropped below minimum required levels. In some events, PJM has enacted a "Performance Assessment" that requires all resources to generate at their committed levels or be financially penalized to avoid imminent load shed. A list of these actual historical scarcity events is provided in the table below. These historical events have occurred in both the summer and winter but are more common in the winter. In this regard, the PJM ELCC/RRS model outputs are consistent with available historical data.

Table 5: List of Historical Scarcity Events in PJM

Historical Scarcity Event	Season
Polar Vortex of 1994	Winter
2012 Heatwave	Summer
2013 Heatwave	Summer
Polar Vortex 1 (2014)	Winter
Polar Vortex 2 (2019)	Winter
Winter Storm Elliot (2022)	Winter

Despite model consistency with historical scarcity events, validating the timing of critical hours must ensure that the model is consistent with *future* expectations of system risk. The PJM system is evolving in several ways that increase winter risk relative to the past. Solar penetration is increasing, which is most available in the summer. Winter loads are growing as customers electrify heating in some states. Therefore, E3's assessment is that a majority of risk in the winter is consistent with historical and future expectations of system risk.

Forecast Pool Requirement

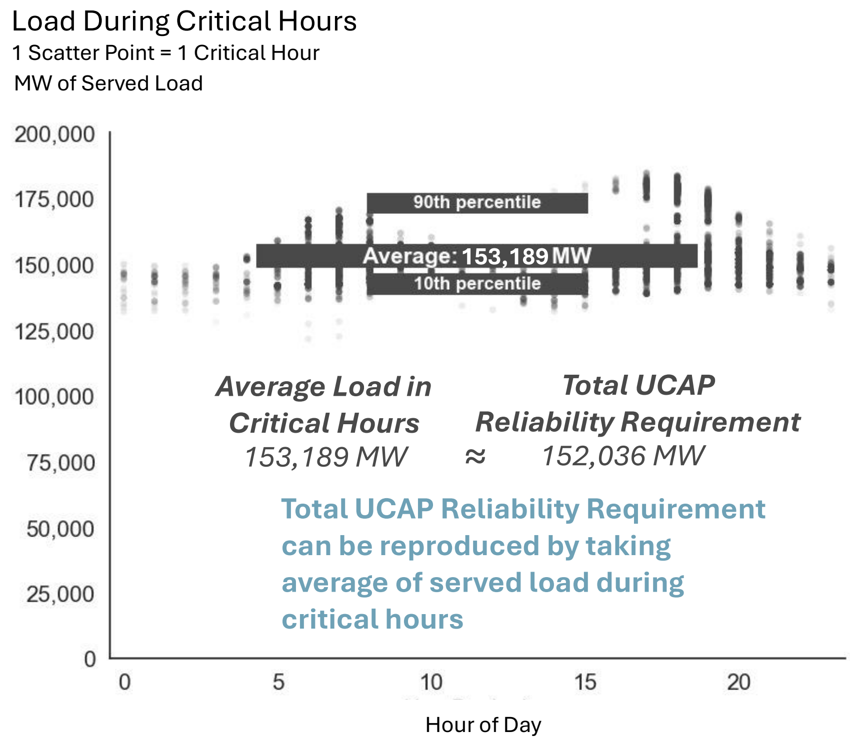
The Total UCAP Reliability Requirement is theoretically identical to average load during critical hours. The Total UCAP Reliability Requirement in the 2027/2028 BRA is 152,036 MW. Average load during PJM-identified critical hours in the model is 153,189 MW. The relative alignment between these two values (<1% difference) indicates that the model is accurately calculating the reliability requirement. The lack of exact alignment is due to the post-processing heuristic approach used by PJM to identify critical hours that is not perfectly optimal.

Table 6: 2027/2028 BRA Total UCAP Reliability Requirement vs Average Load During Critical Hours

Item	Value	Formula
Forecasted Peak	164,186 MW	[A]
Forecast Pool Requirement (FPR)	92.6%	[B]
Total UCAP Reliability Requirement	152,036 MW	[C] = [A] x [B]
Average Load During Critical Hours *Can be used to approximate Total UCAP Requirement*	153,189 MW *Within 1% of Total UCAP Requirement*	[D]

The 153,189 MW value in the table above represents average load during all critical hours. This value is a product of some load hours that are higher than this average and some that are lower. To provide transparency into this value, the figure below shows all load levels during all critical hours. The average, 90th percentile, and 10th percentile load during critical hours are specifically highlighted as horizontal bars.

Figure 26: Load During Critical Hours



ELCC Results

Marginal Effective Load Carrying Capability ("ELCC") values are theoretically identical to average resource availability during critical hours. These values represent the marginal contribution of a resource toward reliability. Resources that consistently produce during critical hours achieve higher marginal ELCC values. Conversely, resources available at low levels during those hours receive lower marginal ELCC. Comparing PJM-calculated marginal ELCC values with average availability during critical hours can help provide transparency into model outputs and validate that the model is working correctly.

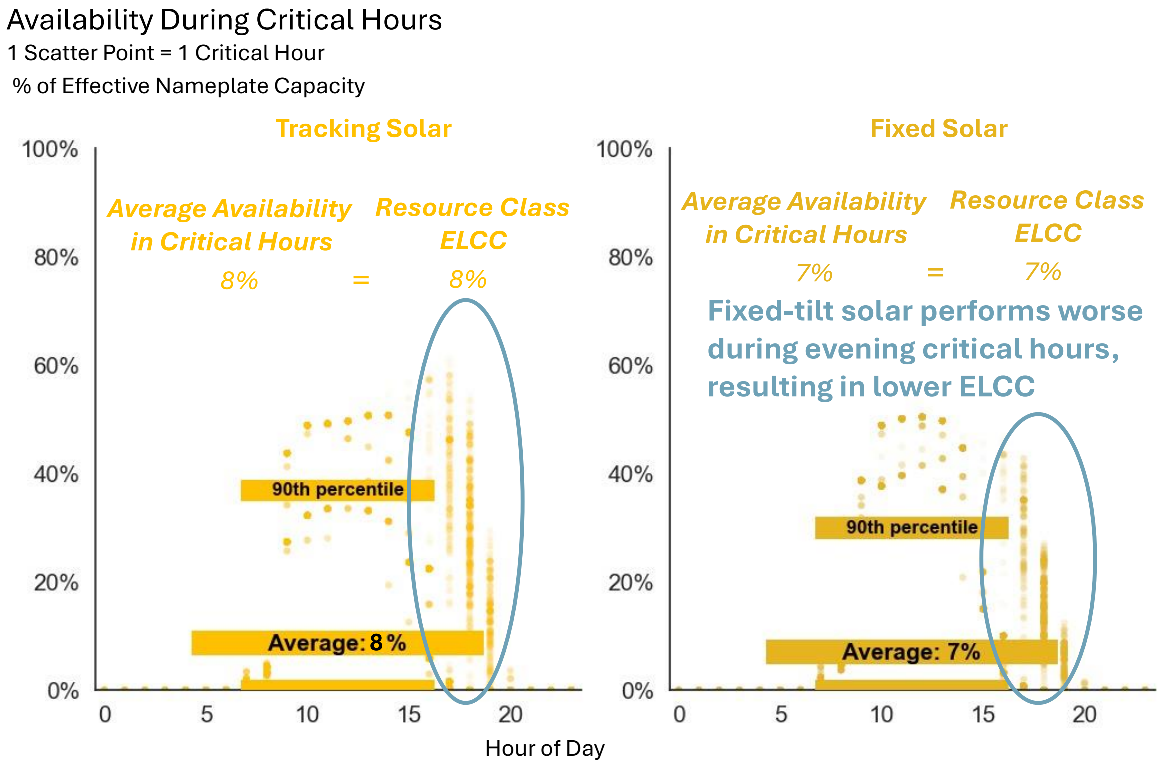
The table below shows the alignment between the marginal ELCC values calculated by the ELCC/RRS model and the average availability of each resource class during critical hours. The very close alignment between these two validates that the ELCC values calculated by the model accurately represent the availability of these resource classes during the hours most critical to system risk.

Table 7: PJM 2027/28 BRA ELCC Results vs Average Availability in Critical Hours

Resource Class	Average Availability in Critical Hours (%)	Marginal ELCC (%)	Difference (%)
Onshore Wind	40%	41%	-1%
Offshore Wind	67%	67%	0%
Solar Fixed	7%	7%	0%
Solar Tracking	8%	8%	0%
4hr Storage	58%	58%	0%
6hr Storage	67%	67%	0%
8hr Storage	70%	70%	0%
10hr Storage	78%	78%	0%
Demand Response	92%	92%	0%

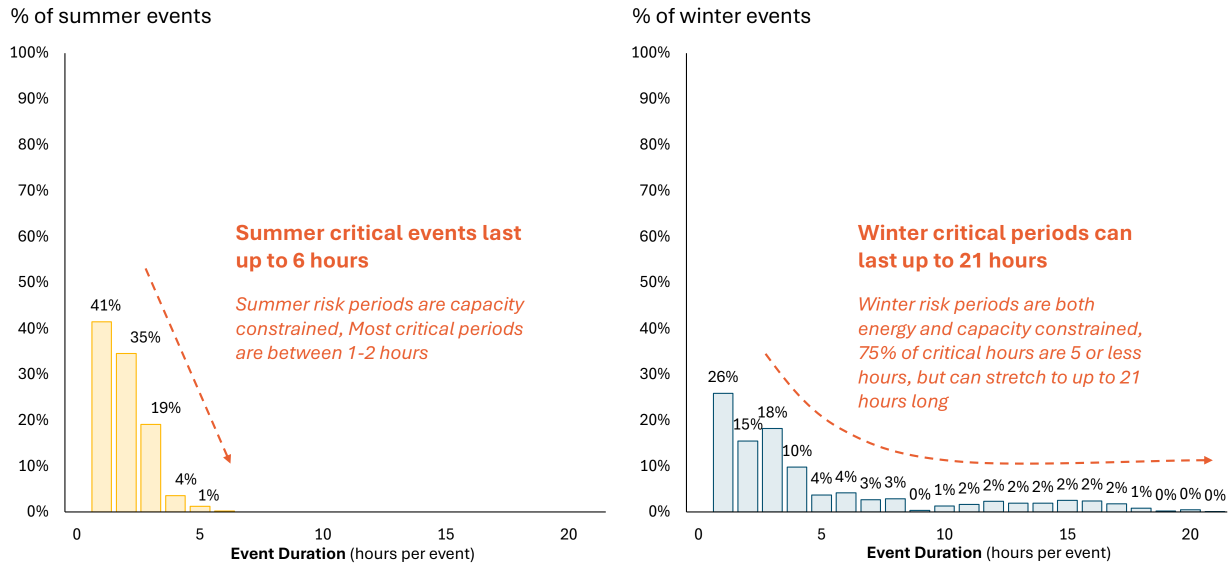
The marginal ELCC values in the table above represent average resource availability during all critical hours. This value is a product of some resource availability hours that are higher than this average and some that are lower. To provide transparency into this value, the figures below show all resource availability levels during all critical hours for solar. The average, 90th percentile, and 10th percentile resource availability during critical hours are specifically highlighted as horizontal bars. This chart shows the wide variability of solar generation during critical hours, including many hours at 0% availability and some hours that exceed 60%. Nonetheless, the average contribution of solar is less than 10% relative to a perfect resource.

Figure 27: Solar Availability During Critical Hours



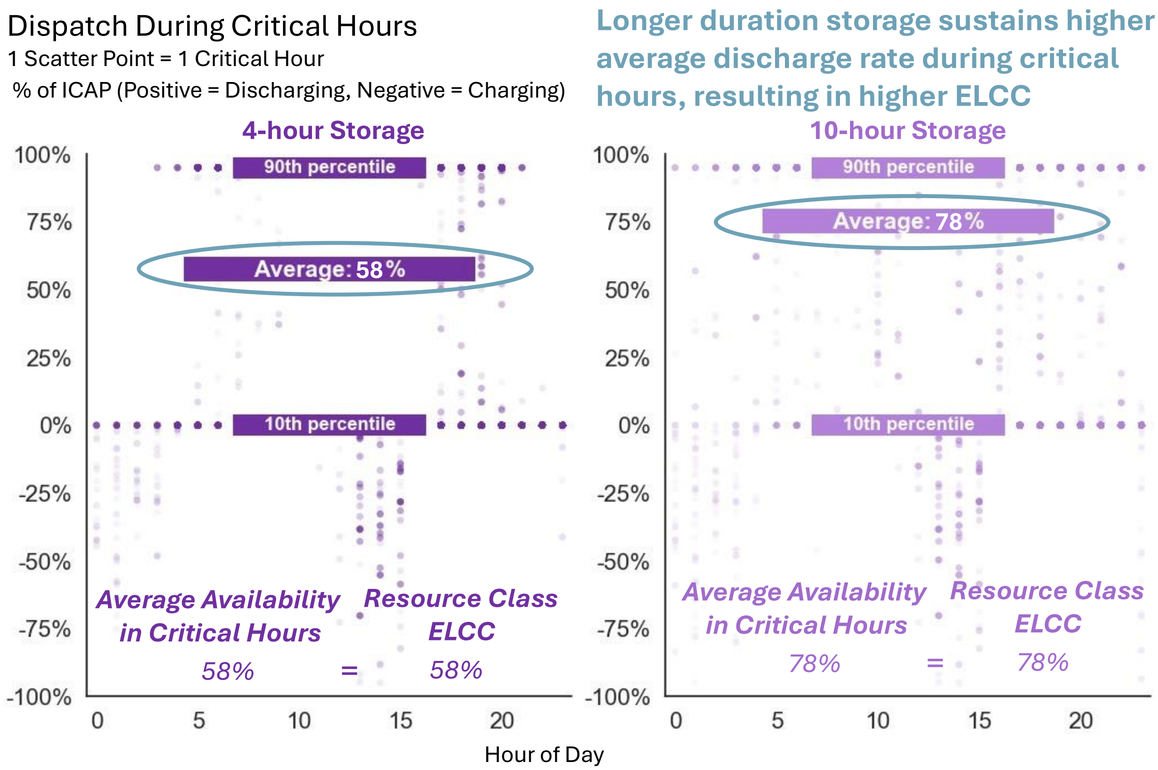
As with all resources, the average dispatch of energy-limited resources during critical hours is equivalent to these resources' marginal ELCC. Because the dispatch of energy-limited resources is controllable, the most relevant factor that limits the ELCC of these resources is the *duration* of critical events. For example, a 4-hour duration battery would run out of charge during a 5-hour critical event and not be available for dispatch in the last hour. The figure below shows the duration of critical events in the ELCC/RRS model. The prevalence of many long-duration critical events (particularly in winter) explains the ELCC values calculated by the ELCC/RRS model for energy-limited resources.

Figure 28: Duration of Critical Hour Periods



To provide more transparency into battery storage marginal ELCC values, the figures below show all resource availability levels during all critical hours for energy storage with 4 and 10-hour durations. The average, 90th percentile, and 10th percentile resource availability during critical hours are specifically highlighted as horizontal bars. This chart shows the wide variability of energy storage dispatch during critical hours, including many hours at 100% discharge, many hours at 0% discharge, and a small number of hours below 0% discharge (which represent charging hours). Storage resources may charge during critical hours if it enables discharging at a later hour during a critical period. The average availability of energy storage during critical hours ranges from 58% to 78%.

Figure 29: Storage Dispatch in Critical Hours



Model Validation Tests

E3 designed and performed a series of tests to further validate that the PJM Model is internally consistent and works as intended to produce transparent, explainable reliability results. This section summarizes the validation tests conducted by E3, using both public information and additional data provided by PJM.

E3 performed three validation "Test Types":

1. **Verification**: confirm that model inputs, intermediate data, and outputs align with PJM's documentation[36]
2. **Replication**: reproducing selected model results using model inputs or upstream model components
3. **Assessment**: evaluating whether model inputs, intermediate data, and outputs fall within expected value ranges

[36] Specifically, the 2025 PJM ELCC and RRS Study Report: https://www.pjm.com/-/media/DotCom/planning/res-adeq/elcc/2025-pjm-elcc-rrs.pdf and public data on PJM ELCC webpage: https://www.pjm.com/planning/resource-adequacy-planning/effective-load-carrying-capability

E3 designed and prioritized tests based on E3's assessment of the importance to model results. While it was not possible to validate every aspect of the model, these tests comprehensively show that the model is working as intended for all areas that E3 evaluated.

Each table in the following sections describes the validation tests performed on a key feature of the PJM Model. Each validation test is categorized by "Test Type", corresponding to classification described above. The "Data Access" column also indicates if the data is public or non-public.

Variable Resources

E3 performed the following tests to validate the representation of variable resource classes, with the focus on tracking solar and onshore wind. Key elements evaluated include effective nameplate capacity, availability profiles, and deliverability constraints. The first two tests focused on raw generation profiles prior to the application of deliverability caps. These tests required non-public information, because PJM publishes availability profiles with deliverability caps applied.

Data Access	Test Type	Description of Test
Non-Public	Assessment	E3 validated that the 12 years (June 2012- May 2024) of historical uncapped generation profile shows annual capacity factors ranging between 20% - 23% for tracking solar and 30% - 34% for onshore wind, consistent with expected solar & wind output in the region.
Non-Public	Assessment	E3 validated that hourly solar generation profiles align with Eastern Time Zone sunrise and sunset times, accurately accounting for Daylight Saving Time.
Non-Public	Verification	E3 verified that the difference between deliverability-capped and uncapped variable resource profiles aligns with published deliverability constraints.

Unlimited Resources

E3 performed the following tests to validate the representation of unlimited resources classes, with the focus on Gas Combined Cycle and Gas Combustion Turbine class. Key aspects evaluated include resource class ICAP, forced and ambient derate profiles, and the methodology for planned and maintenance outage scheduling. These tests involved the planned and maintenance outage scheduling module in model codebase, which is not publicly available. The methodology for planned and maintenance outage scheduling is described in PJM's 2025 ELCC/RRS Report.

Data Access	Test Type	Description of Test

Public	Verification, Assessment	E3 validated that the 12 years (June 2012- May 2024) of unlimited resource ambient derate profile show expected positive correlation with hourly THI (up to 2.4% derate in hottest hours for Gas Combined Cycle)
Non-Public	Verification, Replication	E3 reviewed and verified that the planned and maintenance outages code module provided by PJM schedules outages into weeks with lowest weekly-gross-peak-load, before forced-in outages are applied (See Figure 8: Weekly Average Maintenance and Planned Outages)
Non-Public	Verification	E3 verified that forced-in maintenance overrides planned and maintenance outage rate in peak-load weeks of simulation year where weather pattern is similar to summer of 2012 or 2013, or winters of 2014, 2019, or 2022. This is consistent with PJM documentation

Load Profiles

E3 performed the following tests to validate load profiles. Key aspects evaluated include the shape of the load profiles and the implementation of load rotation in the model. These validation tests only involved publicly available information.

Data Access	Test Type	Description of Test
Public	Assessment	E3 validated that 31 years (June 1993 – May 2024) of simulated load profiles show reasonable variability in annual peak (1-in-10 peak load is ~7% higher than 1-in-2 peak load)
Public	Assessment	E3 validated that simulated load profiles month-hour shapes and temperature correlations align with historical PJM load profiles from the last 10 years. (See Figure 3: Daily Peaks of Simulated & Historical Load in Summer and Figure 4: Daily Peaks of Simulated & Historical Load in Winter)
Public	Assessment	E3 validated that peak load timing aligns with historical records (summer loads peak between 3-6 PM, driven by air conditioning loads; winter loads peak between 6-8 AM and 6-7 PM, driven by heating loads)
Public	Assessment	E3 validated that the 12 rotated load profiles maintain similar load variability as the original unrotated load scenario

Load and Resource Scrambling

E3 performed the following tests to validate the load and resource scrambling process. The focus was to confirm implementation of scrambling for the variable and unlimited resource classes with load profiles. These validation tests rely on the Temperature-Humidity Index as a key input.

Data Access	Test Type	Description of Test
Public	Verification, Replication	E3 tested and verified that applying Freedman–Diaconis rule to THI data replicates the same 31 winter bins and 20 summer bins published by PJM (pre-merge)
Public	Verification, Replication	E3 verified that assigning June 1, 2012 – May 31, 2024 resource performance days to summer and winter THI bins using hourly THI profile replicates resource performance days in each THI bin published by PJM
Public	Assessment	E3 validated that scrambling of renewable generation and thermal availability profile based on PJM published “Montecarlo by date” mapping file reproduces the scrambled profiles which are in the PJM model and published in “info for loss of load hours” file (for days with publish data)
Public	Verification	E3 verified that in the “Montecarlo by date” mapping file all of the 100 resource performance days come from the same THI bin as the load day they are matched to
Public	Verification, Assessment	E3 replicated and validated that scrambled net load profiles (gross load net of variable and unlimited resource availability) has a distribution of daily peak net load aligned with unscrambled net load profiles (see Figure 17: Daily Peak Load Net of Availability Resources Before and After Scrambling)

Dispatch of Energy Limited Resource and Demand Response

E3 performed the following tests to validate the dispatch of energy-limited resources and demand response. The focus was on verifying the implementation of designed model dispatch rules. These validation tests involved 8760 hourly dispatch data for 100 simulated years. This relied on non-public information, because PJM only publishes hourly dispatch results for loss-of-load hours.

Data Access	Test Type	Description of Test
Non-Public	Verification	E3 reviewed and validated that demand response is only dispatched in hours where load exceeds the total availability of variable,

		Intermittent hydropower, and unlimited resource classes. This aligns with PJM documentation
Non-Public	Verification	E3 reviewed and validated that energy-limited resources (hybrid or standalone battery storage, hydro with non-pumped storage) are only dispatched after demand response is dispatched. This aligns with PJM documentation
Non-Public	Verification	E3 reviewed and validated that shorter-duration battery storage is only discharged when longer-duration battery storage is already discharging at its maximum power output, or that longer-duration energy is depleted. This aligns with PJM documentation
Non-Public	Verification	E3 reviewed and validated that battery storage of all duration charges simultaneously. This aligns with PJM documentation

Reliability Results

E3 performed the following tests to validate reliability results produced by PJM's model. The validation focused on two key aspects of system reliability outcomes: magnitude and timing of loss-of-load risks. In addition, the stability of the model results was evaluated to confirm the convergence of system reliability metrics. These validation tests only involved publicly available information.

Data Access	Test Type	Description of Test
Public	Verification, Replication	E3 calculated and verified that published loss of load hours achieves PJM's 1-day-in-10-years Loss-of-Load-Expectation (0.1 LOLE) reliability standard
Public	Assessment	E3 validated that most of loss of load risks (87%) occur in winter months consistent with scarcity events observed in the last decade (Winter Storm Elliott, Polar Vortex 1, Polar Vortex 2). Winter loss of load is concentrated within 5:00am – 11:00am and 4:00pm – 12:00am in January, aligned with hours featuring cold temperatures, high load, and low resource performance. Summer loss of load is concentrated within 4:00pm – 8:00pm in July, aligned with hours featuring high temperatures, high load, and reduced solar performance
Public	Assessment	E3 calculated and validated that across 100 resource performance repetitions, system reliability converges to 0.1 LOLE, with variation no more than ±0.002 LOLE. This demonstrates strong stability in reliability results

Public	Verification, Assessment	E3 validated that load rotations B-M each exhibit higher reliability compared to load rotation A due to weather rotation misalignment in scrambling process as described in ELCCSTF Package C. (see Figure 18: PJM 2027/28 BRA Simulated LOLE results by Load Rotation Scenario)

Reliability Requirement and Resource Class Accreditation

E3 performed the following tests to validate the reliability requirement and resource accreditation results. The most important aspects of these results validate the model's internal consistency and alignment with the theory of marginal accreditation in LOLP modeling. These validation tests required several unpublished pieces of data: (1) hourly dispatch data in all critical hours based on PJM's critical-hour identification methodology, (2) hourly dispatch results for perfect capacity run, tracking solar class ELCC run, and 4-hour storage class ELCC run.

Data Access	Test Type	Description of Test
Non-Public	Verification, Assessment	E3 calculated and validated that total AUCAP Reliability Requirement is close to average load served during critical hours (within 1% difference)
Non-Public	Verification, Assessment	E3 calculated and validated that Class ELCCs of variable resources are close to average availability during critical hours (within 1% difference)
Non-Public	Verification, Assessment	E3 calculated and validated that Class ELCCs of energy-limited resources and demand response are close to average availability during critical hours
Non-Public	Verification, Replication	E3 replicated the class ELCC for tracking solar and 4-hour storage by taking the ratio of Expected Unserved Energy (MWh) reduction in storage class and solar class ELCC run divided by the Expected Unserved Energy (MWh) reduction in perfect capacity run
Non-Public	Verification	E3 validated that energy-limited resources are re-dispatched in the storage class and solar class ELCC run
Non-Public	Verification, Replication	E3 replicated the weight of each timestamp for the calculation of resource Performance Adjustment for ELCC Classes; E3 verified that they are consistent with weights published in "hours and weight for performance adjustment calculation" spreadsheet on PJM website

Considerations for Improvement

E3's review finds that PJM's ELCC/RRS model is reasonable and fit-for-purpose for calculating the "Effective Load Carrying Capability" and "Reserve Requirement" values for use in PJM's capacity market. E3's review also identifies several aspects of the model where PJM may consider making future improvements. Rather than recommend specific changes to the ELCC/RRS model, this report evaluates potential considerations for improvement according to the following criteria: **accuracy, objectivity, stability, transparency, tractability, impact, and ease of implementation**, as described below.

Key Evaluation Criteria

1. **Accuracy**
   How well a model change improves the model's representation of system reliability risks or resource capacity accreditation?
2. **Objectivity**
   Does a model change increase or decrease subjective modeling inputs or methods?
3. **Stability**
   How well a potential model change improves the ability of the model to produce robust results that do not significantly change due to small input changes?
4. **Transparency**
   How clearly model methods, inputs, and results are documented and communicated?
5. **Tractability**
   Does a model change increase or decrease the computational and human effort to run the model ?
6. **Impact**
   The magnitude of impact on system reliability risks or resource capacity accreditation of a model change
7. **Ease of Implementation**
   The level of effort for PJM to implement a model change

In some cases, model changes that improve performance along one dimension may reduce performance along another dimension. Balancing these tradeoffs will ultimately require the judgment of PJM, PJM stakeholders, and policymakers. E3 does not view implementation of any of these considerations as strictly necessary for the continued use of the current model in the administration of the capacity market. Instead, they are intended to support continued improvement of PJM's reliability modeling framework over time.

Summary of Evaluation of Considerations for Improvement

The table below provides a summary of E3's considerations for improvement and how each consideration scores along the aforementioned evaluation criteria. Green boxes represent the benefits of implementing a potential improvement, whereas yellow and red boxes represent tradeoffs that may caution against implementing a particular improvement. Gray boxes represent criteria that are not relevant for evaluating a particular consideration. More detail on each consideration is provided throughout this section.

Table 8: Summary of Evaluation of Considerations for Improvement

Consideration *In order of approximate prioritization*	Accuracy	Objectivity	Stability	Transparency	Tractability	Impact	Ease of Implementation
1) Improve identification of critical hours							
2) Publish critical hours, including load and resource availability data during these hours							
3) Update the scrambling process to draw resource performance from the same weather condition used to synthesize load							
4) Use more temporal granularity to model availability and deliverability of unlimited resources							
5) Schedule planned maintenance based on net load							
6) De-weight historical resource performance events as new resource performance events under similar weather conditions occur							
7) Increase the number of load rotations to balance days-of-week							
8) Calculate solved load by adding or subtracting "flat" load instead of scaling load							
9) Stochastically model hydro resources and extend hydro record							
10) Stochastically model forced outages for storage resources							
11) Evaluate improved mapping of deliverability constraints to system conditions							

12) Represent "Capacity Benefit of Ties" on a more time-granular basis							
13) Study updates to resource performance sampling methodology to capture multi-day events							
14) More optimally dispatch energy storage, demand response, and hydro							

Considerations for Model Improvements

Consideration 1: Improve identification of critical hours

"Critical hours" are an increasingly well-understood concept within the context of resource adequacy.[37] As described earlier in the report, critical hours are periods when additional energy (or load reduction) would improve system reliability by reducing unserved energy. Critical hours include both loss-of-load hours and adjacent periods where additional energy improves system reliability.

The concept of critical hours is relevant to PJM because it is the load and resource availability during these hours that drive the outputs of the PJM ELCC/RRS model. Specifically:

- Weighted average load during critical hours[38] = the Forecast Pool Requirement
- Weighted average resource class availability during critical hours[39] = resource class marginal Effective Load Carrying Capability (ELCC) values

At the same time, accurately identifying critical hours is *not* strictly necessary to accurately calculate either the Forecast Pool Requirement or resource class marginal Effective Load Carrying Capability values. PJM's approach that measures the reliability improvement of the marginal quantity of a resource class is implicitly driven by resource class availability during critical hours and accurately captures all relevant critical hour dynamics. Nonetheless, explicitly identifying critical hours and the availability of each resource class during these hours *would* provide significant transparency benefits to stakeholders. This is important because some stakeholders critique LOLP models as a "black box" that doesn't provide visibility into model outputs.[40]

In an effort to improve transparency, PJM does currently attempt to identify critical hours in the model. It should be noted that while the identification of loss-of-load hours is standard practice in LOLP modeling, it is not industry standard practice to identify *all* critical hours.

PJM currently uses a heuristic method to approximately identify critical hours by identifying both loss-of-load hours and what they term "energy benefit hours." The average availability

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[37] https://www.ethree.com/new-framework-resource-adequacy/

[38] Weighted by the "criticality" of each critical hour. The "criticality" of a given hour is defined as how much 1 MWh of additional energy reduces system unserved energy. 1 MWh of additional energy in an hour that reduces unserved energy by 0.8 MWh has a criticality factor of 0.8. In general, loss-of-load hours have a criticality of 1.0, because additional energy in those hours directly reduces unserved energy. However, some hours where additional energy is used to charge storage may have a criticality of less than 1.0 due to storage roundtrip losses. Non-critical hours by definition have a criticality factor of 0. Ideally, the criticality of each hour would be measured and published by the loss-of-load-probability model without any necessary post-processing.

[39] Ibid.

[40] For example, see IMM Dec. 21, 2023 Answer to PJM Deficiency Letter Response, Docket No. ER24-99

of resource classes during these critical hours should approximately equal resource class ELCCs as calculated by the model.[41]

PJM currently uses the following methodology to identify critical hours:

1. PJM identifies all loss-of-load hours in a base case and classifies these hours as critical
2. PJM runs another simulation with an incremental 100 MW of perfect capacity in all hours to identify the reduction in unserved energy in each hour. When the reduction of unserved energy in a loss of load hour exceeds 100 MWh, this indicates that there are additional critical hours that precede this hour
3. PJM then identifies preceding hours where the dispatch of energy storage changes between the base case and the case with 100 MW of incremental perfect capacity. These are hours where the addition of perfect capacity either allows energy storage to save charge for later in the day or charges energy storage when it was otherwise unable to. PJM terms these "energy benefit" hours and classifies them as critical

PJM's process is a reasonable method to identify critical hours, but there is opportunity to improve accuracy. For example, PJM's process identifies each hour as critical or non-critical, but does not measure the "criticality" of each hour. This is particularly important for "energy benefit hours" where the addition of 1 MWh of energy may reduce system unserved energy by less than 1 MWh due to energy storage roundtrip losses. Options for more rigorously identifying critical hours and their criticality include:

- Using an optimization model that identifies the "shadow price" of energy in each hour toward the objective function of minimizing system unserved energy.
- Using a brute force method that adds energy in each hour and observes the impact on system unserved energy. This would, however, require many model runs. Smart strategies to parallelize or only test during plausible critical hours would be required.

PJM could consider enhancements to refine its approach to identifying critical hours. Ideally, the model would produce the criticality of each hour as a direct output without any post-processing or heuristic approximation.

A summary of the evaluation criteria for this consideration is provided in the table below.

Consideration 1: Improve identification of critical hours	
Accuracy	N/A
Objectivity	More robustly identifying critical hours removes the need for a heuristic method to approximately identify critical hours
Stability	N/A
Transparency	Improved identification of critical hours supports a more transparent model by facilitating stakeholder vetting and understanding

[41] The link between these is only "approximate" because PJM identifies critical hours using a heuristic that does not measure the criticality of each hour

Tractability	An automatic model process to identify critical hours (as opposed to a post-processing heuristic) reduces burden on the modeler and improves tractability	
	Implementing optimization or a "brute force" method into the model increases computational requirements and decrease tractability	
Impact Level	While identifying critical hours would not have any direct impact on results, identifying critical hours would improve transparency and have a significant impact on stakeholder understanding of the model and the ability to vet and check results	
Ease of Implementation	More rigorously identifying critical hours through optimization requires a moderate to large implementation effort	

Consideration 2: Publish critical hours, including load and resource availability data during these hours

The key results of the model (e.g., FPR and ELCCs) are fundamentally driven by conditions simulated during critical hours. Specifically, load during critical hours determines the FPR, and resource availability during critical hours determines ELCC values.

LOLP modeling has traditionally been used to produce planning reserve margin and ELCC results without explicitly associating these results with critical hours. The publishing of results without publishing the underlying drivers of these results has contributed to some PJM market participants, stakeholders, and policymakers arguing that the model is "black box."[42]

Accurately identifying and publishing critical hours (both loss-of-load and "energy benefit" hours), including all load and resource availability during these hours, is the single biggest step that PJM can take to increase model transparency. Currently, PJM only publishes load and resource class dispatch for loss-of-load hours. Including all critical would allow market participants, stakeholders, and policymakers to review the underlying data that drives FPR and ELCC values. This consideration will be increasingly important as storage penetrations increase and expand the set of non-loss-of-load periods that are also critical to system reliability.

E3's "Critical Hours Review" earlier in this report demonstrated some of the results and insights that would be available to stakeholders if PJM were to make this data publicly available, including better understanding of:

+ The timing and duration of critical hours
+ The distribution of load levels during critical hours
+ The distribution of resource class availability during critical hours

[42] For example, see IMM Dec. 21, 2023 Answer to PJM Deficiency Letter Response, Docket No. ER24-99

In particular, publishing critical hours would provide stakeholders with useful information to inform an understanding of why different resource classes receive a specific marginal ELCC, since marginal ELCCs are equal to weighted average[43] resource class availability during critical hours. Additionally, weighted average load during critical hours will equal the total Forecast Pool Requirement.

PJM could consider publishing all critical hours, including load and resource availability data during these hours. PJM could also consider publishing calculations demonstrating how model results (FPR and ELCC) align with load and resource availability during critical hours. It should be noted that this supplemental informational posting to improve transparency would not change the implementation or outcomes of PJM's approach and would therefore not require changes to PJM's tariff.

A summary of the evaluation criteria for this consideration is provided in the table below.

Consideration 2: Publish critical hours, including load and resource availability data during these hours	
Accuracy	N/A
Objectivity	N/A
Stability	N/A
Transparency	Publishing critical hours allows stakeholders to scrutinize and understand how FPR and ELCC results are derived, reducing the "black box" element of LOLP modeling. This is the single most important step PJM can take to increase model transparency
Tractability	N/A
Impact Level	N/A
Ease of Implementation	Small to moderate effort to publish critical hours and load and resource availability during these hours

Consideration 3: Update the scrambling process to draw resource performance from the same weather conditions used to synthesize load

The current PJM modeling approach samples resource performance values for each day from the weather bin associated with that particular date. A concern with this approach is that PJM rotates different weather through that same day for the purpose of introducing different loads. This leads to misalignment between the weather conditions reflected in the load profile and the weather conditions reflected in the resource performance assumptions for certain load scenarios. For example, resource performance conditions from non-extreme weather conditions might be paired with load profiles from extreme weather conditions when rotation introduces a more severe weather pattern.

[43] Weighted by the "criticality" of each hour

As demonstrated earlier in this report, this over-scrambling overstates the reliability of the system and should be corrected. PJM could instead consider drawing resource performance values from the same weather bin that was used to synthesize the load on each day. This approach would more accurately capture the correlation between temperature, load, and resource performance.

This consideration for improvement is aligned with PJM Package C. PJM studied the impact of this change for 2026/2027 BRA inputs and determined that when implemented on a standalone basis, there is a measurable increase in overall system risk (IRM increases 3.3%) and a decrease in accreditation for most resource classes. The improved alignment between resource performance and loads also results in over 96% of loss-of-load hours occurring in the winter season.[44]

A summary of the evaluation criteria for this consideration is provided in the table below.

Consideration 3: Update the scrambling process to draw resource performance from the same weather condition used to synthesize load	
Accuracy	Improved model accuracy by ensuring load and resource performance is drawn from consistent weather conditions to capture correlations.
Objectivity	N/A
Stability	N/A
Transparency	N/A
Tractability	N/A
Impact Level	Modest to high impact on IRM and ELCC values as indicated by PJM sensitivity analysis
Ease of Implementation	Low implementation effort given that PJM has already built this functionality to test impacts as part of Package C

Consideration 4: Use more temporal granularity to model capability and deliverability of unlimited resources

PJM currently limits the deliverability and resulting modeled availability of "unlimited" resources to their ICAP rating in all hours, with additional de-rates applied based on ambient conditions. As described earlier in this report, the ICAP rating of unlimited resources is the lesser of each resource's Summer Net Capability and its Capacity Interconnection Rights (CIRs),[45] both of which are tied to summer peak conditions. However, the PJM ELCC/RRS

[44] *See PJM Executive Summary and ELCCSTF Presentation on PJM Package C:* https://www.pjm.com/-/media/DotCom/committees-groups/task-forces/elccstf/2025/20250711/20250711-item-03---pjm-proposal---executive-summary.pdf *and* https://www.pjm.com/-/media/DotCom/committees-groups/task-forces/elccstf/2025/20250522/20250522-item-02---elcc-accreditation-methodology-update-on-sensitivity-analyses---pjm-presentation.pdf

[45] For more information on Capacity Interconnection Rights (CIR), see page 22 of PJM Manual 21b

Model simulates unlimited resources across all hours of the year, not just summer peaks. Unlimited resources generally have higher availability outside of summer peak conditions due to colder ambient temperatures. Capping resource availability at ICAP, therefore, under-represents the potential deliverability and resulting modeled availability of unlimited resources in periods outside of summer peak conditions. To more fully and accurately represent the availability of unlimited resources, PJM could consider representing potential deliverability and resulting modeled availability with more temporal granularity, specifically on a "seasonal" or "daily" basis. These options are both described and illustrated below.

Seasonal Granularity

One option to improve the current methodology is to introduce different resource capability ratings for summer and winter (where summer is defined as May - Oct and winter is defined as Nov - Apr). Winter capability ratings would be higher due to colder ambient conditions. PJM studied this modification as part of the ELCCSTF Package C, where in non-summer months, PJM increased maximum thermal availability to a newly termed "winter ICAP" rating, defined as Winter Net Capability with all deliverability constraints removed.[46] The removal of all deliverability constraints in this study was a simplifying assumption that presented a bookend of how much available capacity could possibly increase. The result of this change, when implemented on a standalone basis, yielded 8,561 MW of additional unlimited resource ICAP in the winter months, 33% less unserved energy in winter months, and a 1.1% lower IRM relative to the 2025/26 BRA model results. PJM's study demonstrates the potential upper-bound impact of replacing the current use of ICAP ratings with seasonal ICAP ratings.

In this option, PJM would still implement downward ambient de-rates from seasonal ICAP values during higher temperature periods.

Daily Granularity

Another option to improve the current methodology is to introduce a daily maximum capability approach. Even the "seasonal" approach described above still caps summer availability at the capability of a resource during summer peak periods, with additional ambient de-rates applied when the temperature increases. However, many periods of the summer are cooler than peak conditions and a seasonal approach does not reflect increased capability due to cooler ambient conditions. A "daily" approach could more accurately represent resource capabilities changing with ambient conditions throughout the year by applying ambient de-rates to a resource's Maximum Facility Output, with appropriate more granular treatment of deliverability.[47]

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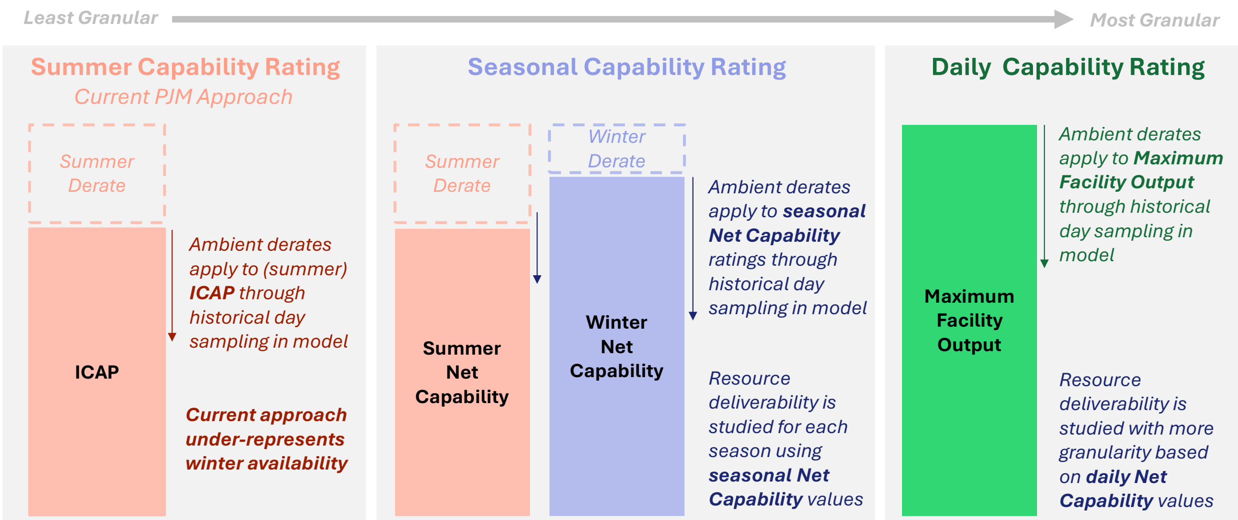
[46] For more information on the seasonal capability assessment in ELCCSTF Package C, see: https://www.pjm.com/-/media/DotCom/committees-groups/task-forces/elccstf/2025/20250522/20250522-item-02---elcc-accreditation-methodology-update-on-sensitivity-analyses---pjm-presentation.pdf

[47] Currently, ambient derate profiles are developed from the historical record of generator ambient derates reported in eDART from 2012-2024 and applied to ICAP. Additional data may be required to develop ambient derate profiles which apply to Maximum Facility Output.

The figure below illustrates these three potential approaches: Summer Capability Rating (Current PJM Approach), Seasonal Capability Rating, and Daily Capability Rating.

Figure 30: Consideration to Increase Temporal Granularity of Deliverability and resulting Availability Inputs of Unlimited Resources



A summary of the evaluation criteria for this consideration is provided in the table below.

Consideration 4: Use more temporal granularity to model capability and deliverability of unlimited resources	
Accuracy	Reflects resource capability changing with temperature conditions, increasing model accuracy
Objectivity	N/A
Stability	N/A
Transparency	N/A
Tractability	More granular data increases complexity of model
Impact Level	High impact. Approximately ~8 GW of additional unlimited resource capability in the winter months, ~1% IRM reduction.
Ease of Implementation	Low difficulty to implement a seasonal approach (which PJM has already done)
	High difficulty to implement daily approach

Consideration 5: Schedule planned maintenance based on net load

Many resources have a pre-defined number of weeks per year where they must be offline to perform regular maintenance. As described earlier in this report, the PJM model currently "schedules" maintenance outages in a manner intended to both mimic actual operations and minimize system risk by concentrating maintenance during periods of lower risk, typically the spring and fall shoulder seasons. The PJM model currently performs scheduling based on periods of lowest *gross* load. However, as renewable penetration increases and system risk patterns evolve, gross load may no longer serve as the biggest predictor of system risk. Instead, PJM could consider scheduling maintenance into periods of lowest *net* load. In making any potential changes, PJM will need to ensure that its LOLP modeling is consistent with expected system operations.

A summary of the evaluation criteria for this consideration is provided in the table below.

Consideration 5: Schedule planned maintenance based on net load	
Accuracy	Scheduling planned maintenance based on net load rather than gross load improves accuracy by better aligning maintenance with periods of lower reliability risk. However, modeling maintenance inconsistently with operational practices could reduce accuracy.
Objectivity	N/A
Stability	N/A
Transparency	N/A
Tractability	N/A
Impact Level	Likely small to moderate impact level in the near-term Larger impact in the long-term as risk periods become increasingly dissociated with gross load peaks and more associated with periods of low resource availability
Ease of Implementation	Small to moderate implementation effort; dependency exists for operational practices

Consideration 6: De-weight historical resource performance events as new resource performance events under similar weather conditions occur

The current PJM model methodology draws resource performance profiles from historical performance during the years 2012-2024. Any resource performance day within that time period is selectable by the model with equal probability (provided it falls within the appropriate weather bin). A potential concern with this approach is that it does not consider that more recent performance observations may be a better indicator of upgrades and enhancements that units can make to improve their performance over time. For example, a dispatchable (or "unlimited" in PJM terminology) resource that performs poorly but implements weatherization, better fuel security, or other enhancements would still be modeled with its pre-enhancement performance.

This methodological decision has multiple impacts. First, it may understate the reliability of the system. Second, if units do not perceive an economic benefit (such as increased accreditation) to undertaking performance enhancement measures, then they may not, to the detriment of system reliability.

On the other hand, using only the most recent data after purported resource enhancements have been undertaken is also problematic. Verifying the impact of resource enhancements is difficult, and the most objective way to do this is to observe actual performance during challenging system conditions. Resource enhancements do not always perform as expected given the high level of outages that occurred during cold snaps in 2019 and 2022 after many resources undertook enhancements after wide-spread outages during the cold snap of 2014. Disregarding historical data after purported resource enhancements can actually disincentivize resources to implement quality enhancements if they know that they poor historical performance will be disregarded. It is therefore important that risks that have materialized multiple times in recent history are included in the model.

One option to provide a balanced pathway to reflect performance enhancement measures is to allow recent unit performance to gradually replace old performance data. Under this framework, unit performance would be probabilistically de-weighted based on how many events have occurred in the interim. Such an approach would only de-weight historical performance events if a sufficient number of more recent events have occurred for the resource to "prove" its enhanced performance. A formulaic representation of the current PJM process and E3's proposed consideration is provided in the figure below

This consideration for improvement is aligned with PJM Package C. PJM studied the impact of implementing different weights and determined that when implemented on a standalone basis, there is a minor impact on overall system risk (IRM increases by less than 0.4%, with the exact magnitude varying by alpha value assumption). However, the lower weights placed on high forced outage observations in the hottest bins that occurred in the past resulted in a higher loss of load risk contribution from the winter season.

Table 9: Example Formulaic De-Weighting of Historical Events

Event	Year	Weight	
		Current PJM Approach	E3 Consideration
1 (most recent)	2024	1	α
2	2024	1	α
3	2022	1	$\alpha(1-\alpha)$
4	2022	1	$\alpha(1-\alpha)$
5	2018	1	$\alpha(1-\alpha)^2$
6	2018	1	$\alpha(1-\alpha)^2$
7	2014	1	$\alpha(1-\alpha)^3$
8 (oldest)	2014	1	$\alpha(1-\alpha)^3$

Ultimately, implementing any framework that reflects performance enhancement measures will introduce some level of subjectivity into the modeling. Nonetheless, sending an economic signal that performance enhancement is rewarded incentivizes units to undertake these measures. Therefore, PJM could consider a resource performance weighting approach that de-weights historical resource performance events as new resource performance events under similar weather conditions occur, without fully disregarding historical performance data.

A summary of the evaluation criteria for this consideration is provided in the table below.

Consideration 6: De-weight historical resource performance events as new resource performance events under similar weather conditions occur	
Accuracy	Weighting more recent resource performance events likely improves accuracy by reflecting performance enhancement measures
Objectivity	De-weighting historical performance necessarily requires some level of subjectivity to decide how to de-weight these events
Stability	De-weighting historical performance as new events occur gradually phases out historical performance relative to removing specific historical events in a manner that is not clear or systematic. This has the potential to increase model stability
Transparency	N/A
Tractability	De-weighting historical performance is more complex than all performance days being equally probable, which decreases tractability
Impact Level	Modest impact on IRM as showed in Package C sensitivity analysis; higher impact on seasonal risk allocation depending on how much forced-outage observations in the most extreme historical bins are de-weighted.
Ease of Implementation	Moderate effort to develop appropriate weighting factors and implement in model

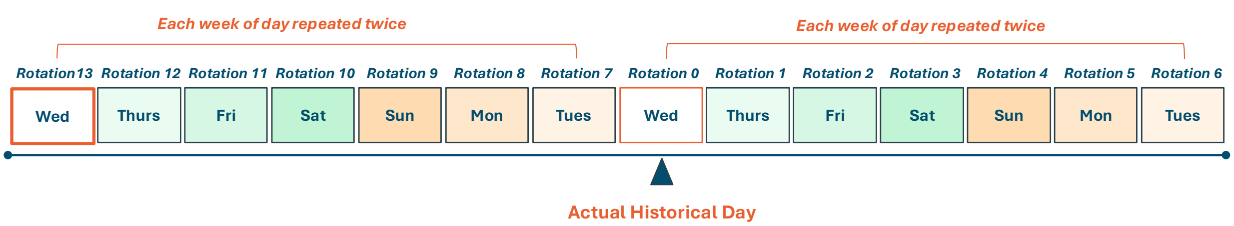
Consideration 7: Increase the number of load rotations to balance days-of-week

PJM currently develops load profiles using 30 years of historical weather data. PJM additionally "rotates" the weather forward and backward by 6 calendar days for a total of 13 load rotations. This weather rotation method ensures that historical weather days will be simulated across all days of the week as opposed to just the date from the original load profile. This is important because an extreme weather day that occurred on a Sunday may not yield high load whereas that same weather on Monday would yield high load. PJM's weather rotation appropriately reflects that extreme weather can occur on any day of the week.

An issue with PJM's approach is that rotating weather 6 days forward and 6 days backward means that each day of the week is represented twice *except* for the actual day of week for the historical date. An overview of PJM's load rotation methodology is provided in the figure below.

PJM could consider increasing the number of weather rotations to **7** calendar days forward and **6** calendar days backward for a total of 14 weather rotations, so that each day of the week is represented twice. Since PJM's model currently handles 13 rotations, adding one more rotation would not substantially increase computational complexity, but it would provide a more balanced representation of all days of a week. However, because the hourly load scenarios are developed by the PJM Load Forecast team outside of the ELCC/RRS modeling process, any adjustments to the number of load rotations would need to remain consistent with the Load Forecast team. An illustration of this consideration is provided below.

Figure 31: E3 Load Rotation Consideration



A summary of the evaluation criteria for this consideration is provided in the table below.

Consideration 7: Increase the number of load rotations to balance days-of-week	
Accuracy	Improved accuracy due to uniformly sampling the days of the week
Objectivity	N/A
Stability	N/A
Transparency	N/A
Tractability	N/A
Impact Level	Modest impact on reliability statistics and ELCC values
Ease of Implementation	Would require coordination with PJM Load Forecast team to ensure consistency

Consideration 8: Calculate solved load by adding or subtracting "flat" load instead of scaling load

PJM's current approach to calibrating the system to the target reliability of 0.1 days/year loss-of-load-expectation is to scale load up or down. The 50/50 peak of the scaled load profile that yields target reliability is called the "solved load." This approach yields slightly different results from an approach where an equal amount of "flat" load is added or subtracted in all hours. The benefit of adding flat load in all hours is that it more similarly represents the addition or subtraction of firm generation and preserves the original load shape and relative magnitude of load across hours. Because flat generation is the least interactive resource, adding flat load will shift critical hours in the lowest possible manner. For this reason, it is the most neutral and non-interactive means of calibrating system reliability. An approach where flat load is added or subtracted is consistent with a commonly used approach in other studies. PJM could consider updating its methodology to calibrate system reliability by adding or subtracting flat load across all hours.

A summary of the evaluation criteria for this consideration is provided in the table below.

Consideration 8: Calculate solved load by adding or subtracting "flat" load instead of scaling load	
Accuracy	Improved accuracy by calibrating target reliability without shifting critical hours
Objectivity	N/A
Stability	N/A
Transparency	Flat load addition or subtraction is more transparent than a scaling factor
Tractability	N/A
Impact Level	Likely minimal impact on results
Ease of Implementation	Low implementation effort

Consideration 9: Stochastically model hydro resources and extend hydro record

Unlike variable and unlimited resources, PJM models hydro resources (i.e. the "hydro intermittent" resource class) by matching each load year (1993 – 2024) to one specific hydro year (2012 – 2024). For load years between 2012 and 2024, dedicated historical hydropower generation data are used; for load years without a corresponding hydro year, PJM selects a hydro year based on the similarity of the peaks in the load years. These pairings are then used across all simulations. In other words, PJM does not scramble load and hydro years to incorporate situations where historical hydro generation data were matched with different load years.

The primary issue with PJM's approach is that hydroelectric conditions and peak demand are driven by different fundamentals that would not suggest a strong natural correlation: hydro conditions are driven by multi-month precipitation or drought patterns, while peak loads are driven by weather events that are relatively short duration (e.g. less than one week) that may occur during entirely different times of year than the precipitation patterns that drive hydro production. Therefore, matching each load year to a single hydro year may overlook plausible reliability risks, such as a drought year coinciding with an exceptionally high-load year, which could occur and meaningfully affect system reliability but are excluded in the simulation due to the fixed pairing.

Additionally, PJM's hydro dataset which includes the years 2012 – 2024 may not capture the full range of potential interannual hydrological variability. Hydro availability can fluctuate significantly on a year-to-year basis. If data is available, extending the hydro dataset back to 1993, consistent with the period covered by load and weather data, would allow a broader sample of wet, dry, and average conditions to be represented in PJM modeling.

PJM could consider stochastically pairing hydro years with load years and extending the hydro record to capture a wider range of potential hydro conditions, if data is available.

A summary of the evaluation criteria for this consideration is provided in the table below.

Consideration 9: Stochastically model hydro resources and extend hydro record	
Accuracy	Stochastically representing hydro years and extending the hydro record would improve the accuracy of the model
Objectivity	N/A
Stability	Stochastically representing hydro years and extending the hydro record would increase stability of the model by reducing the influence of any single wet or dry year on reliability outcomes across simulations. For reference, the Northwest Power and Conservation Council utilizes an 80-year water record for use in reliability modeling
Transparency	N/A
Tractability	N/A
Impact Level	Likely a small to moderate impact given hydro's relatively small share of the resource portfolio
Ease of Implementation	Moderate implementation effort to develop extended hydro record

Consideration 10: Stochastically model forced outages for storage resources

PJM currently uses three approaches to represent forced outages that vary by resource type:

1. **Unlimited resources:** forced outages are explicitly modeled by stochastically sampling historical forced outage data via the scrambling process

2. **Variable resources:** forced outages are captured implicitly through stochastically sampling historical availability days, where forced outages are represented in the availability profiles
3. **Storage resources:**[48] forced outage resources are modeled by statically de-rating the maximum discharge and charge rate by the historical Equivalent Forced Outage Rate on Demand ("EFORd") in all hours

The approaches above demonstrate that while unlimited and variable resource outages are modeled stochastically, storage resource outages use a static de-rate that is always equal to the average outage level. While this approach approximates average levels of forced outages for storage resources, it does not capture expected periods where battery storage forced outages are higher than average that can occur in real operations. As a result, the model may overstate available battery capacity during challenging system conditions and underrepresent periods of elevated reliability risks due to stochastic storage outages, which will become increasingly important as storage penetrations grow over time.

PJM could consider enhancements to represent storage resource forced outages stochastically, consistent with the treatment of other resource classes. Several options could be considered:

1. One potential enhancement is to draw battery forced outages from a historical sample of days, similar to the approach used for thermal resources. However, implementing this approach would require a significant amount of data that PJM may need to gather and develop.
2. In the absence of extensive operational data, another potential enhancement is to develop generic assumptions to model storage forced outages stochastically. This approach would increase subjectivity to the extent that these assumptions are not tied to actual historical data.

A summary of the evaluation criteria for this consideration is provided in the table below.

Consideration 10: Stochastically model forced outages for storage resources	
Accuracy	Stochastically modeling battery forced outages improves accuracy of the model
Objectivity	N/A
Stability	N/A
Transparency	N/A
Tractability	Stochastic modeling battery forced outages modestly increases model complexity
Impact Level	Low impact in the near term while batteries comprise a small share of the system portfolio

[48] This includes 4-hour, 6-hour, 8-hour, and 10-hour duration storage resource classes.

	Grows to moderate impact in the longer term once battery penetrations increase to a larger share of the portfolio
Ease of Implementation	Moderate effort, primarily due to gathering and developing battery forced outage data or making generic outage assumptions

Consideration 11: Evaluate improved mapping of deliverability constraints to system conditions

Generator deliverability represents the ability of the transmission system to deliver generation from a particular resource to load. When PJM performs capacity accreditation calculations, it limits resource availability profiles by deliverability constraints developed in PJM's Regional Transmission Expansion Plan (RTEP). These deliverability constraints are a function of network congestion which vary throughout the year based on underlying system conditions. For example, conditions with higher load mean more resources are generating and congesting the transmission system, reducing deliverability (all else equal).

PJM's RTEP study calculates deliverability constraints across three different conditions: "Summer", "Winter", and "Light-Load".[49] As described earlier in this report, "Summer Deliverability" applies to all hours from May through October, "Winter Deliverability" applies from 6pm-9am from November through April, and "Light-Load Deliverability" applies from 9am-6pm from November through April. As an example of these constraints, the "Light-Load" deliverability constraint for solar is 53% of Effective Nameplate Capacity, while the "Winter" deliverability constraint for solar is 5% of Effective Nameplate Capacity.

For variable resource classes, PJM maps these RTEP deliverability constraints to hours in the model using a "time-of-year" methodology. For non-variable resources, PJM currently maps "Summer" deliverability constraints to all hours of the year. However, PJM is in the process of introducing "Winter" deliverability constraints to non-variable resource classes in future versions of the PJM Model.[50]

To improve its representation of deliverability constraints, PJM could consider improved mapping of RTEP deliverability constraints to hours in the model based on system conditions rather than "time-of-year." Specifically, deliverability constraints could be assigned to hours in the PJM model with the most similar system conditions (i.e. load levels or resource performance). As an example, this could lead to conditions where "Light Load" deliverability constraints are applied to all hours of a winter day if the day is mild. Alternatively, "Winter" deliverability constraints could be applied to all hours of a winter day

[49] For more information on tests on Deliverability of Generation, see page 92 of PJM Manual 14b: https://www.pjm.com/-/media/DotCom/documents/manuals/m14b.pdf

[50] For more information on the introduction Winter Deliverability for non-variable resources, see: https://www.pjm.com/-/media/DotCom/committees-groups/task-forces/elccstf/2025/20250403/20250403-item-05---reflecting-winter-capability-in-accreditation-education--design-considerations---pjm-presentation.pdf

if it is a cold peak winter day. Determining appropriate mapping of deliverability constraints to hours in the model would require evaluation and study by PJM.

This consideration is based on the premise that PJM has a set of deliverability constraints that are developed through a process outside of LOLP modeling, namely the RTEP process. It thus assumes that the LOLP model is limited by available inputs. To the extent that more granular deliverability constraints were available, that would improve the accuracy of the model, but this would come with the tradeoff of more complexity and less tractability.

E3 does not recommend that increasing the temporal granularity of deliverability constraints be a near-term priority but does expect this issue to become more important in the long-term for two reasons. First, the magnitude and variability in grid congestion is higher on systems with higher quantities of variable resources. Second, as the system evolves to higher penetrations of variable and energy-limited resources, the timing of critical hours will expand beyond just peak hours to an increasingly diverse set of hours driven by low generation availability. Deliverability constraints that are primarily tied to peak conditions will impact the model's ability to accurately calculate resource class ELCCs.

A summary of the evaluation criteria for this consideration is provided in the table below.

Consideration 11: Evaluate improved mapping of deliverability constraints to system conditions	
Accuracy	Improved mapping of deliverability constraints would more accurately represent congestion in the LOLP model.
Objectivity	N/A
Stability	N/A
Transparency	N/A
Tractability	Determining appropriate mapping of deliverability constraints to model hours would likely be a difficult and ongoing process, reducing model tractability
Impact Level	Medium impact from updating assignment of deliverability constraints to hours in PJM Model
Ease of Implementation	Medium to high implementation difficulty given large volume of data and cross-functional organizational coordination

Consideration 12: Represent "Capacity Benefit of Ties" on a more time-granular basis

The Capacity Benefit of Ties (CBOT) is an assumption that is utilized in the PJM ELCC/RRS model that represents the ability of PJM to import uncommitted resources from external neighboring electricity systems during times of system stress. The current CBOT value is administratively set to 1.5% of 50/50 peak load that is available in all hours of the year.[51] This value has remained constant for several years. The Installed Reserve Margin (IRM) would be 1.5% higher if the CBOT were set to zero.

To improve the accuracy of this model parameter, PJM could consider representing CBOT on a more time-granular basis. In the past, a static CBOT assumption may have been reasonable if it represented the ability to lean on neighbors during PJM's peak load periods. However, critical hours for system reliability are increasingly occurring across a broader set of hours, including hours outside of peak load conditions. Levels of neighbor support during these different conditions may vary, just as the availability of different resource classes varies on a time-granular basis. Utilizing time-granular values for CBOT would more accurately capture these dynamics.

A summary of the evaluation criteria for this consideration is provided in the table below.

Consideration 12: Represent "Capacity Benefit of Ties" on a more time-granular basis	
Accuracy	Representing CBOT on a more time-granular basis would improve the accuracy of the model
Objectivity	N/A
Stability	N/A
Transparency	N/A
Tractability	Increasing time granularity of CBOT would increase complexity of model
Impact Level	Likely a modest impact in the near-term, but representing CBOT on a more time-granular basis could yield larger impacts over time as critical hours shift
Ease of Implementation	High effort to conduct study of external zones to understand ability to support PJM in different time periods

Consideration 13: Study updates to resource performance sampling methodology to capture multi-day events

PJM's current methodology draws resource performance for each day based on that day's temperature without taking into account the prior day's resource performance. This approach accurately replicates the historical distribution of low/med/high resource performance across all days on average, but the days are not necessarily clustered together in ways that mimic history, as demonstrated earlier in this report. In actuality, high

[51] *See page 11 of PJM 2025 PJM Effective Load Carrying Capability and Reserve Requirement Study (ELCC/RRS):* https://www.pjm.com/-/media/DotCom/planning/res-adeq/elcc/2025-pjm-elcc-rrs.pdf

performance days (e.g., sunny or windy days) are more likely to be followed by high performance days (and vice versa).

Whether or not this potential shortcoming impacts results depends on the resource portfolio. To the extent that the resource portfolio contains large quantities of energy storage, particularly long-duration energy storage, PJM's current approach may overestimate system reliability (and by extension resource ELCCs). This is because the under-representation of multi-day low resource performance events can deplete energy storage and expose important reliability risks.

Several potential modeling changes could help better reflect multi-day resource performance patterns in PJM's simulations. One option is to introduce the prior day's resource performance as a factor in drawing the resource performance profile for a particular day. In other words, instead of drawing from a set of resource performance days with equal probability with a particular THI-bin, resource performance days that are most similar to the prior day could be weighted higher. Determining specifically how to structure this weighting would require study to observe which approaches most accurately mimic historical multi-day patterns. While such an approach would reflect multi-day resource performance patterns, it would also increase model complexity.

PJM could consider studying an approach to capture multi-day resource performance events. Publishing the results such as how well simulated multi-day resource performance events mimic historical events will help inform appropriate model design decisions.

A summary of the evaluation criteria for this consideration is provided in the table below.

Consideration 13: Study updates to resource performance sampling methodology to capture multi-day events	
Accuracy	Reflecting multi-day resource performance events increases model accuracy and exposes potential reliability risks and resource limitations in some resource portfolios
Objectivity	N/A
Stability	N/A
Transparency	N/A
Tractability	Implementing a persistence factor introduces some additional complexity
Impact Level	The potential impact is likely to be small at present due to limited quantities of long-duration storage. As storage penetrations grow, the impact is likely to become larger
Ease of Implementation	Moderate to high implementation effort. Capturing multi-day events will require study to identify different approaches and the performance and tradeoffs of those approaches

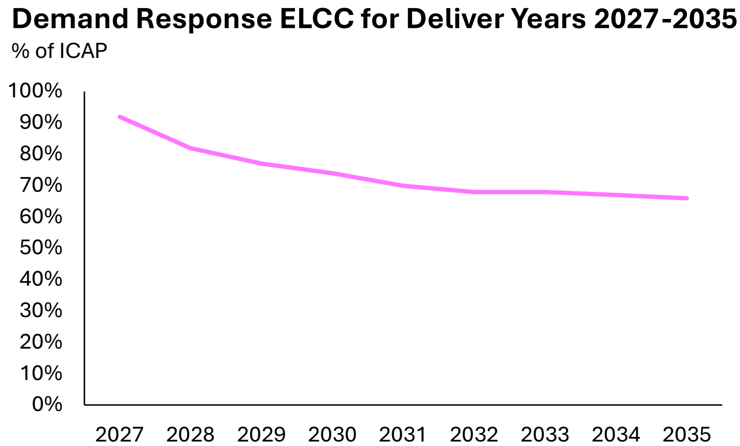
Consideration 14: More optimally dispatch energy storage, demand response, and hydro

Dispatching energy-limited resources is a key function of loss-of-load-probability models. Unlike other resources, using energy-limited resources in one hour means they are less available to serve load in other hours. Therefore, the model must decide how to use these resources in a manner that maximizes system reliability. The theoretically optimal approach to dispatching energy-limited resources is to use an optimization framework with the objective of minimizing unserved energy. However, the number of years to optimize in a loss-of-load-probability model often makes this approach intractable. Instead, many loss-of-load-probability models use a heuristic dispatch approach that approximates optimization but is much faster computationally.

The PJM ELCC/RRS model uses a heuristic that they describe as "more available resources are dispatched first", with more available resources defined as those with longer durations. Discharging longer duration resources first is often a smart decision because it maximizes the amount of remaining *capacity* from energy-limited resources by retaining both longer and shorter-duration resources. However, a fully optimized dispatch approach can account for other factors beyond just duration. Longer-duration resources often have lower roundtrip efficiency which means they take more energy to re-charge when they are dispatched. If, during multi-day winter risk periods with low renewable output, longer-duration resources are discharged first, the system may have insufficient surplus energy to recharge these more inefficient resources, and as a result encounter a loss-of-load event. This risk of limited energy is not typically seen on systems without high penetrations of long-duration storage but is relevant to consider when planning for future systems with significant storage and renewables.

Additionally, deciding how to stagger the dispatch of energy storage and demand response is often a non-trivial decision that requires optimization. The PJM model dispatches demand response before energy storage based on the fact that demand response in PJM is a 24/7 resource with no dispatch limitations. Even so, PJM's approach does not fully utilize demand response to maximize system reliability because it does not allow the system to dispatch demand response to free up other generating resources to *charge* storage if storage is not fully charged. It is this phenomenon that explains why PJM forecasts that demand response sees declining forecasted capacity accreditation even though it is a 24/7 resource, as shown in the figure below.

Figure 32: ELCC Forecast for Demand Response Class[52]



Dispatching energy-limited resources is complex and one that heuristic approaches will be increasingly ill-suited for as the resource portfolio becomes more saturated with these resources. PJM could investigate implementing a more optimal dispatch of energy-limited resources, while considering tradeoffs among accuracy, tractability, and ease of implementation. This is an important area of research that the industry is currently exploring, that PJM could lead in.

A summary of the evaluation criteria for this consideration is provided in the table below.

[52] See Discussion of Preliminary ELCC Class Ratings for Period 2027-2028 through 2035-2036: https://www.pjm.com/-/media/DotCom/planning/res-adeq/elcc/discussion-of-preliminary-elcc-class-ratings-for-period-2027-2035.pdf

Consideration 14. More optimally dispatch energy storage, demand response, and hydro	
Accuracy	Improved accuracy of model due to more optimal dispatch, although PJM will need to ensure modeling is consistent with operational practices
Objectivity	Optimized dispatch is more objective than a heuristic approximation that requires estimations and subjective ordering of resource dispatch
Stability	N/A
Transparency	N/A
Tractability	Implementing optimization would likely increase computational requirements of the model and increase run-time. Maintaining tractability would require smart modeling strategies such as parallelization of different dispatch windows
Impact Level	In the near term, the impact of this change is likely to be small to moderate, as energy storage penetrations are still relatively low
	In the medium and longer term, the impact of this change is likely to be large as energy storage penetrations grow and coordination between demand response and storage dispatch becomes more important
Ease of Implementation	Implementing optimization would likely require significant effort to build the functionality and develop strategies to ensure it is tractable

Conclusion

E3's independent evaluation concludes that PJM's Effective Load Carrying Capability / Reserve Requirement Study (ELCC/RRS) Model is a technically sound, well-structured, and transparent reliability modeling framework that accurately determines PJM's capacity requirements and resource capacity accreditation values. The model aligns closely with established industry best practices for Loss-of-Load-Probability (LOLP) modeling and provides a robust foundation for ensuring that PJM is positioned to achieve its "one day in ten years" reliability standard.

The ELCC/RRS model effectively captures a wide range of weather, load, and resource performance conditions through its use of 31 years of weather data, 12 years of resource performance data, stochastic outage simulation, and probabilistic resource performance sampling. E3's validation testing confirms that the model's core reliability metrics, including timing of critical risk periods, the Forecast Pool Requirement, and Effective Load Carrying Capability values are consistent with theoretical expectations and observed system performance. E3 also identifies opportunities to strengthen its accuracy and transparency as PJM's resource mix evolves.

Overall, E3 finds that the PJM ELCC/RRS model is fit for its intended purpose and well-positioned to facilitate efficient capacity market outcomes. Considerations for model improvements will ensure the model continues to reflect the realities of an evolving grid. These continuous improvements will help PJM sustain its leadership in reliability planning and uphold its commitment to a reliable, cost-effective, and equitable capacity market framework.