Resource Adequacy For a Decarbonized Future

2024 TECHNICAL REPORT

Resource Adequacy Assessment Tool Guide

EPRI Resource Adequacy Assessment Framework

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EPRI Project Manager
M. Bello

EPRI
3420 Hillview Avenue, Palo Alto, California 94304-1338 USA
800.313.3774 ▪ 650.855.2121 ▪ askepri@epri.com ▪ www.epri.com

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EPRI prepared this report.

Principal Investigator
G. de Mijolla

Additional EPRI Contributors
A. Kelly
A. Tuohy
M. Ihlemann
E. Lannoye
R. Entriken
D. Kirk-Davidoff

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ABSTRACT

Recent supply deficiency events have shown that traditional resource adequacy (RA) processes, metrics, and tools may not be fully able to address adequacy requirements in the context of changing climate, changing resource mix, and extreme weather scenarios. One of the key factors for ensuring a successful RA assessment is that software tools are appropriate for the study at hand—the resource mix, the region to be studied and the study horizon.

This report focuses on understanding the main options available in commercial and research RA tools and aims to develop an understanding of existing RA tool gaps. It is not meant to be a comparison or cataloging of each adequacy tool or software, but rather an opportunity to understand where the industry stands as a whole in 2024. Responses to a request for information put forward as part of the initiative, in addition to subsequent discussions with both participating tool providers and participating members, form the basis for the analysis presented here.

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EXECUTIVE SUMMARY

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KEY RESEARCH QUESTION

Recent supply deficiency events have shown that traditional resource adequacy (RA) processes, metrics, and tools may not be fully able to address adequacy requirements in the context of changing climate, changing resource mix, and extreme weather scenarios. One of the key factors for ensuring a successful RA assessment is that the software tool choice is appropriate to assess the risks apparent in the region and study at hand. This report evaluates the modeling capabilities of both research-based and commercial RA tools.

RESEARCH OVERVIEW

The industry uses a plethora of tools to assess adequacy, all with different features, approaches, and treatment of resources. However, limited documentation about most of these is available online, and capabilities are constantly changing. To this end, a request for information was put forward as part of this initiative to better understand key tool functionalities used for RA analyses. This information, alongside subsequent discussions with both tool providers and project members, is the basis for this report. A tabulated summary of tool capabilities, by level of fidelity, is provided for each selected functional category.

KEY FINDINGS

- Numerous tool providers took part in this effort, highlighting the potential for collaboration within the RA research space, and the variety of tools available. Based on the survey and follow up, it is clear that there are a variety of different capabilities available to assess adequacy, and these tools are constantly evolving.
- Differences in tool capabilities exist and are assessed across analysis approaches, risk metric reporting, generator outage modeling, and ability to model resources. Some of the topics, in particular analysis approaches and generator outage modeling, have significant differences across tools.
- A number of the tools surveyed were initially developed for production cost analysis, and later developed RA functionality. As such, many of the tools use a Monte Carlo based

approach with a number of advanced modeling capabilities, but can at times struggle with computational tractability in a probabilistic framework.

- The primary gaps in RA tools to date are computational tractability, ease-of-use, transparency, and data availability. In addition, there is an increased need for integration of RA with other parts of the planning process, with a need for tools to ensure a seamless transition from one modeling process to the next.

WHY THIS MATTERS

This report is intended to help guide practitioners in their choice and use of RA analysis software. It explains existing tool capabilities to support informed choices about which ones to prioritize. It can also be used by tool developers and researchers to understand how their offerings compare to others in the field and help prioritize future software developments.

HOW TO APPLY RESULTS

Practitioners should use this to understand their current capabilities compared to industry standard as well as advanced capabilities described here. This report is not meant to be a comparison or cataloging of each adequacy tool or software, but rather an opportunity to understand where the industry stands as a whole. As such, this report does not contain individual tool-level responses, and RA practitioners are encouraged to engage directly with tool providers. It is our hope that this report will help practitioners formulate their questions and make the best software decision based on the information here.

LEARNING AND ENGAGEMENT OPPORTUNITIES

- Tool selection is not independent of modeling choices, data availability, and other real-world constraints that cannot be reflected in a single rubric. EPRI's Resource Adequacy for a Decarbonized Future initiative has a set of related documents that may be of interest to readers of this report, including information on RA Metrics and Criteria, Guidelines for Scenario Generation, Data Collection, Technology and System Modeling, and Gap Assessments. Additionally, case studies and tools for RA practitioners also developed as part of this initiative can be used to understand some of the key issues in the area.
- EPRI programs 173 (Bulk System Renewable/DER Integration), Program 246 (Electricity Markets) and Program 178 (Resource Planning) carry out work in the RA area. Project Set P173C (Resource Adequacy) is where the core work is carried out, with coordination among other programs on planning and markets implications.

EPRI CONTACTS: Genevieve de Mijolla, Technical Leader, gdemijolla@epri.com

PROGRAM: Bulk System Integration of Renewables and Distributed Energy Resources (P173), Resource Planning for Electric Power Systems (P178), Electricity Market Design and Operation (P246)

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1 INTRODUCTION

Resource Adequacy Assessment Framework

The RA problem can be defined as assessing whether a given resource mix has a high probability of meeting customer demand at any moment, accounting for uncertainty in both supply and demand. There are many factors that must be carefully considered to ensure a successful RA analysis. Figure 1 shows a simplified schematic categorizing the main components of the RA assessment process. The focus of this report is on *Tool Selection*, which is highlighted in light grey. Other topics are covered in other parts of EPRI's RA For a Decarbonized Future Initiative in other reports.[1]

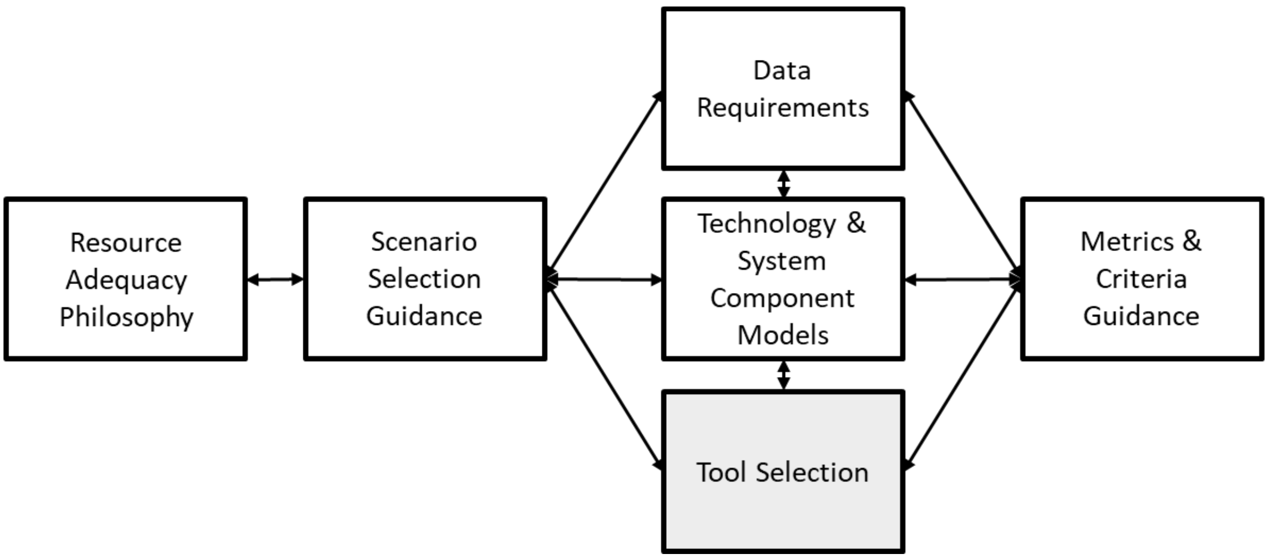

Figure 1. Simplified RA component schematic

The arrows in Figure 1, connecting the different RA components of an integrated assessment approach, are all bi-directional to illustrate component inter-dependencies. For example, Data Requirements dictate which Technology & System Component Models can be applied but also, when the need for a particular technology model arises, a model influences the Data Requirements. Collected data also constrains the selection of demand, weather, renewable energy generation, and outages represented in the Scenario Selection Guidance, and vice versa.

Leveraging the technology and system component models that have been identified and developed, along with scenarios capturing a range of possible future system conditions, RA simulation tools are employed, scheduling generation to minimize periods of lost demand, generally at the lowest production cost. The primary outputs of RA analyses come in the form of adequacy metrics such as loss of load expectation (LOLE), expected unserved energy (EUE),

[1]See www.epri.com/resource-adequacy, where reports will be available when published.

and loss of load hours (LOLH). RA assessments may also be carried out with the purpose of ascribing an accreditation to resources, often expressed as their effective load carrying capability (ELCC) or unforced capacity (UCAP), which may be then fed as an input to capacity expansion models or used to inform capacity market design.

There exists a set of traditional approaches employed for each of the RA components presented in Figure 1. However, recent supply deficiency events suggest that they may underperform in the context of a changing climate, changing resource mixes, and extreme weather scenarios. As such, work addressing challenges across all components of the RA schematic has been conducted under EPRI's *Resource Adequacy for a Decarbonized Future* initiative.

Document Organization

This report focuses on understanding the main options available in current commercial and research RA tools. The work also aims to develop an understanding of existing RA tool gaps. To this end, a request for information was put forward as part of this initiative to better understand key tool functionalities across a number of tools used for RA analyses. This information, alongside subsequent discussions with both tool providers and project members, is the basis for this report. A link to the RFI can be found at www.epri.com/resource-adequacy.

The rest of the report is organized as follows: Section 2 delves into the report development process and its intended uses. Section 3 describes the main analysis approaches used in the RA tools surveyed as part of this initiative, both probabilistic solution methods employed as well as methods tool providers have put in place to improve computational tractability. Section 4 discusses the risk metric outputs available in RA tools, both default and custom metrics output, as well as the level of granularity available for them. Sections 5 and 6 outline the generator outage methodologies used in the tools surveyed, for both forced outages and maintenance outages, respectively. Section 7 characterizes the weather uncertainty representation available in RA tools, both in terms of the representation of weather variability as well as the representation of short-term forecast error. Additionally, section 7 describes synthetic weather shape methodologies included in a subset of RA tools. Section 8 considers the transmission models available in RA tools, both in terms of transmission transfer limit modeling methodologies and transmission outage modeling capabilities. Sections 9, 10 and 11 detail available modeling methodologies available for energy storage, hydropower, and demand response technologies, respectively. Section 12 lists the key RA tool gaps identified through discussions with tool providers and project members. Finally, section 13 provides concluding remarks, including limitations of this analysis and suggestions for future work.

Tool Functionality Scale

A tabulated summary of tool capabilities by level of fidelity is provided for each section in this report. The goal of this approach is to help tool developers and users better understand how their tool's functionality compares to others in the industry. It should be recognized that tradeoffs are required in most assessment studies because of real-world constraints on resources, data, models, and toolsets. Three levels of modeling fidelity are proposed, as demonstrated in Table 1. The fidelity level of different modeling approaches is classified as follows:

- Level I: these tool modeling approaches are generally the least computationally and data intensive. Level I approaches represent the basic characteristics of a given resource or methodology but omit others. Level I approaches are generally acceptable for systems with low reliance on a particular technology, or for cases when capturing a given technology characteristic may not be needed or is unlikely to make a measurable difference to the adequacy assessment. These functionalities would be expected to be the minimum level represented in all tools, and users should ensure that tools they select have at least this level of representation.
- Level II: these tool modeling approaches may be selected when the penetration of a particular technology is growing, making it increasingly important to capture its operations with a greater level of fidelity. However, there may still be computational or data limitations, preventing the user from employing higher-fidelity approaches. Level II approaches also allow for the representation of those technology or system characteristics that are essential, while employing simpler modeling approaches for those that are less relevant. Users should be examining their current tool capabilities, leveraging where possible and looking to improve if not available.
- Level III: these tool functionalities systematically ensure the highest fidelity representation of system behavior. The level III approaches highlighted in this report are generally the most complex, and the most data and computationally intensive. While level III approaches may not be necessary in all studies, this label indicates desired tool functionalities that developers should be working towards in their tools, and users should be looking to apply where appropriate, or work with developers to implement where not currently available.

Table 1. Considerations for tool functionality by level of fidelity: Sample table

	Level I	Level II	Level III
Tool functionality	Most basic representation: may be sufficient when reliance on technology addressed is low	Mid-fidelity representation: may allow for a realistic representation of certain system characteristics but less so for others	Highest fidelity representation: this tool functionality will allow for the most realistic simulation compared to Levels I and II

2 REPORT DEVELOPMENT PROCESS AND INTENDED USES

Document Development Process

The industry uses a plethora of tools to assess adequacy, all with different features, approaches, and treatment of resources. However, limited documentation about most of these is publicly available, particularly in a manner that allows for comparison across capabilities. To this end, a request for information was issued as part of this initiative to better understand key tool functionalities across several tools used for RA analyses at the time of the project (2022-2023). This tool survey was made public as part of EPRI's *Resource Adequacy for a Decarbonized Future* initiative[2] and sent out to a number of RA tool providers. It consisted of 54 questions, mostly multiple-choice to allow tool developers to respond easily, and to allow for responses from one tool to another to be more easily compared.

The EPRI team was encouraged by the large number of tool providers who took the time to respond to the request for information and answer the team's subsequent questions. In all, 18 tools, listed in Table 2, were evaluated as part of this effort. It should be noted that several of the survey respondents develop tools that are used for both RA and production cost analysis. This should be kept in mind when reviewing responses, as certain features may be available to users, but are in practice rarely implemented in RA studies due to computational runtime challenges or for procedural reasons.

[2] https://www.epri.com/resource-adequacy has a link for the RFI.

Table 2. RA tools evaluated as part of this initiative

Tool Category	Tool Name	Tool Provider
Commercial	2-4-C	Ernst & Young (EY)
	Aurora	Energy Exemplar
	BID3	AFRY
	Crystal Super Grid	Artelys
	Enelytix	Polaris Systems Optimization and Newton Energy Group
	GridView	Hitachi Energy
	MARS	General Electric
	Plexos	Energy Exemplar
	PowerSIMM	Ascend Analytics
	PROMOD	Hitachi Energy
	SDDP	PSR
	SERVM	Astrape
Open source	Antares	RTE International
	GridPath	Blue Marble Analytics
	PRAS	National Renewable Energy Laboratory (NREL)
Custom	GRARE	Centro Elettrotecnico Sperimentale Italiano (CESI)
	MAVRIC	Western Electricity Coordinating Council (WECC)
	RECAP	Energy + Environmental Economics (E3)

After initial tool responses were reviewed, it became apparent that a number of questions had been interpreted differently from one respondent to another. Moreover, the multiple-choice nature of the questions, while allowing for a simple review of whether or not a certain functionality was implementable in a tool, did not allow for an understanding of how this functionality was implemented, or how much effort it would be for the user to apply – in some cases, a functionality may be technically available but challenging to implement in practice in certain tools. As such, a series of follow-up discussions were held with individual tool respondents, and a tool provider workshop was organized to facilitate discussion amongst various developers. This report represents not only the direct results of the tool survey responses, but also the findings from these subsequent discussions.

Intended Report Uses

This report is intended to guide practitioners in their choice of RA analysis software. It should help them understand what tool capabilities exist, so they can make informed choices about which ones to prioritize in their tool selection decisions and give them more information for discussing desired capabilities with tool providers. This report is also intended to inform regulatory stakeholders and decision makers on the state of the RA software landscape, while outlining the primary tool shortcomings is expected to help guide future research and algorithmic developments. Finally, this report can be used by tool developers to understand how they compare to others in the field and to help prioritize future software developments.

This report is not meant to be a comparison or cataloging of each adequacy tool or software, but rather an opportunity to understand the industry landscape. Throughout this project, every effort has been made to accurately represent the landscape of RA tool development to date. However, RA tools are highly complex and constantly evolving, and even a lengthy survey and an opportunity to engage with tool developers thereafter is not enough to fully describe all the specifics of every tool surveyed. As such, it must be acknowledged that this report represents but a snapshot in time, approximately representing the end of 2023, and does not provide information on individual tool capabilities. The decision to withhold individual tool responses from this report was made intentionally, both to encourage participation and collaboration from tool developers, as well as to ensure RA practitioners don't base their tool selections solely on results from this report, but rather engage with tool providers directly through pointed questions. It is also recognized that there are several ways of achieving the same objective and in many cases engineering judgement needs to be applied to adapt to the specifics of the system and the toolset available. It is our hope that this report will help practitioners formulate the questions needed to make the best software decision for themselves.

Factors to Consider in Resource Adequacy Tool Selection

With a range of different tools available, many of which can be applied to various system configurations and use cases, understanding their underlying capabilities should allow for identifying the tools best adapted for a given resource mix or use case. Some of the functionalities discussed in this report, such as the solution methods or the reporting options, can be considered core functionalities, as they are important regardless of the use case and resource mix. Other functionalities may only be needed for certain resource mixes or use cases. For example, if running an operational RA analysis, then the consideration of both unit commitment and economic dispatch, as well as generator ramping and min up/down time constraints would be necessary to appropriately assess system flexibility when responding to an event. However, this level of detail may be too computationally expensive for a longer horizon planning analysis for a large system. Similarly, while complex hydropower modeling may be necessary for a hydro-heavy system, it would not be prioritized for other use cases. Table 3 below highlights a handful of use cases and some of the corresponding tool functionalities that would need to be prioritized in a RA analysis.

Table 3. Example use cases and the corresponding tool functionalities to prioritize

If modeling a system…	Then prioritize…
… with a large amount of energy limited resources	→ dispatch-based chronological Monte Carlo sampling method (Section 3) → robust storage, hydropower and/or demand response modeling (Sections 9, 10, and 11)
… at risk of extreme weather events	→ report percentile-based metrics (Section 4) → correlated timeseries data (weather-based resources, load, temperature, etc.) (Section 7) → conditions-based forced outage modeling (Section 5) → start-up failure modeling (Section 5) → coincident outages to represent widespread outages due to fuel shortages (Section 5)
… in the operational planning timeframe	→ chronological Monte Carlo sampling method (Section 3) → multi-stage economic optimization (Section 3) → no forced outage foresight (Sections 3 and 5) → short-term weather forecast error (Section 7)
… at risk of shoulder season shortfall events	→ a robust maintenance outage modeling methodology (Section 6)

Although this report focuses on the differences in tool functionalities between tools, a lot of other factors are important when selecting a tool for a RA analysis. Different factors could be prioritized depending on the specific use case of the RA study in question, as illustrated in Table 4. The primary factors to consider include:

- The **availability of detailed models**: Note that this factor is the only one addressed in detail in this report – other factors should be directly investigated by practitioners when making their RA software selection.
- **Cost** – both the cost to license a tool but also potential added costs such as data acquisition and maintenance, cloud-based computing costs, software support costs and staff training costs.
- The **computational speed** of the tool; for small research-based studies this may be less of a concern but could be a key factor for larger regional studies.
- User experience: An intuitive **user interface** and straightforward model implementation process are important factors, the significance of which varies based on the user's skillset. These weren't directly evaluated as part of this initiative due to their subjective nature. Other important factors for a streamlined user experience include the ability to easily update data inputs, and easily review a wide range of study results. Automation capabilities, such as the ability to set a result precision criterion (often referred to as a convergence criterion) and the ability to automatically iterate runs for ELCC calculations, are potentially important features. Another key part of a positive user experience is the level of **software**

support users can expect — both from direct interactions with a tool provider's software support team but also from a clear and detailed **user manual**.

- A number of tool providers also offer **updated nonproprietary databases** for sale, which can be a key time-saving measure for users running a one-time or infrequent study who don't want to take the time to build a database from scratch.

Table 4. Tool selection factor prioritization examples for several use cases

Tool selection factors	Example use cases		
	Research project	Yearly update project	Quick turnaround screening study
Availability of detailed models	++	+++	+
Cost	+++	++	+
Computational speed	+	++	+++
User interface	+	++	+++
Software support	+	+++	++
User manual	+++	++	+
Access to nonproprietary databases	++	+	+++

\+ Low importance ++ Medium importance +++ High importance

3 ANALYSIS APPROACHES

This section presents an overview of the different solving procedures applied in the surveyed tools. An initial review of the well-known, and broadly defined for this report, convolution and Monte Carlo techniques precedes a summary of hybrid approaches employed by some of the tools surveyed. For a more in-depth explanation of the convolution and Monte Carlo approaches, the reader should refer to [1]. Additionally, unit commitment considerations and runtime improvement techniques will be discussed.

Solution Methods

Most respondents to the RFI use dispatch-based chronological Monte Carlo methods in their software tools, as shown in Figure 2. As energy and flexibility adequacy become more important, the industry is moving towards the use of dispatch-based chronological Monte Carlo methods. It can also be noted that this is partly due to the fact that a number of the tools surveyed were initially developed for production cost analysis, and later developed RA functionality, such that the Monte Carlo based method was a natural step. One of the tools surveyed as part of this initiative used a heuristics-based Monte Carlo method upon first discussions but has since transitioned to a dispatch-based Monte Carlo method. Note that multiple options in Figure 2 were selected for tools with multiple solving modules available to the user.

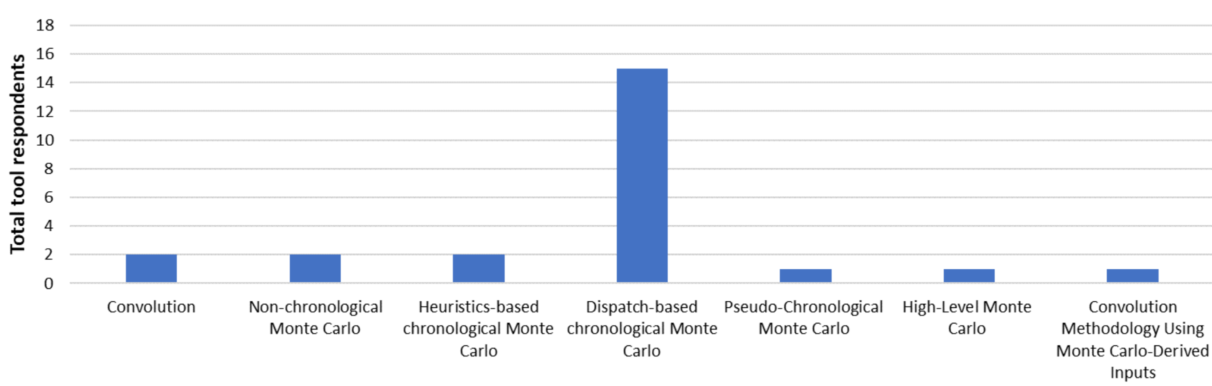

Figure 2. Solution methods used for each of the tools evaluated as part of this analysis

Convolution Method

Convolution is an analytical method that calculates a total available capacity distribution by convolving together the distributions associated with available capacity for each unit in the system. This resulting distribution is calculated for every time interval of the RA analysis, and a loss of load is identified if the available capacity is lower than the demand in the time interval being considered.

This method considers the full distribution of all discrete system states and is a computationally efficient way to exhaustively enumerate all possible states in a given interval. However, each time interval is assessed independently of all others, and as such the intertemporal nature of power systems operations and the asset-specific performance impacts are ignored, limiting the ability to consider issues such as energy storage. In its standard form, this method is not well adapted to the consideration of interface limits between areas, as that increases the number of unique system states and thus the computational complexity of the problem. As such, convolution is not well suited to multi-area RA modeling in its standard form. However, certain solution methods allow for multi-area modeling by calculating each area separately using a classic convolution method, and then consider inter-area exchanges in post-processing, as is done in the “Convolution Method Using Monte Carlo-Derived Inputs” method detailed below.

Monte Carlo Method

Monte Carlo methods rely on repeated random sampling to calculate adequacy risk indices. Here they refer to a general class of models where in each replication (or sample), uncertainty variables such as forced outage occurrences are assigned a random value from user-specified probability distributions. This process is applied repeatedly while assigning different values each time to the variables in question, until an acceptable level of statistical precision is achieved. Adequacy risk metrics are then calculated as the average of the accumulated replication data.

Although the final solution is an approximate one (in contrast to the convolution method which considers all possible system states), this method allows for simulating of more complex problems than would be possible analytically, including those with inter-regional and intertemporal constraints. Note that the more replications across the distribution are performed, the more the approximate nature of the Monte Carlo method is reduced. Monte Carlo methods can be divided into several approaches that are used in simulation tools, as is described next.

Non-Chronological Monte-Carlo Sampling Method

The non-chronological Monte Carlo sampling method is the least computationally intensive of the Monte Carlo sampling methods. This approach randomly samples system states for every time interval of the simulation to assess system adequacy, however, it doesn’t do so in a chronological manner. A key advantage of the non-chronological Monte Carlo method over the convolution method is that it easily represents inter-regional power transfer limits and line outages. A key limitation of this method is that it doesn’t account for the chronological nature of system components, such as power plant outages states and storage operation. This is not a widely used method in the tools surveyed.

Chronological Monte Carlo Sampling (Heuristics-Based) Method

The heuristics-based chronological Monte Carlo method simulates a chronological system evolution, allowing for tracking of outage states and the state of charge (SOC) of energy-limited resources. While more computationally intensive than the convolution or non-chronological Monte Carlo methods, this method remains much simpler (and therefore runs much faster) than a dispatch-based Monte Carlo method. Often-used heuristics include an assumption that all thermal units are available when not on outage (as such unit ramp rates and minimum up and down times are not considered), and an assumption that energy storage is fully charged and available for discharge at the start of a loss of load event. These approaches are well adapted to the study of capacity adequacy; however, they may be less well suited to the consideration of energy adequacy and flexibility adequacy, as they don't model a full economic dispatch process, which may require economics to understand how the system is likely to be positioned during periods of high risk.

Chronological Monte Carlo Sampling (Dispatch-Based) Method

Chronological dispatch-based Monte Carlo methods, the most common method available in all of the tools surveyed, are less computationally efficient than heuristics-based methods but provide a more accurate depiction of power systems operations. Several of the tools evaluated in this report were initially created as production cost tools that evolved to include RA functionality by adding a Monte Carlo component to existing optimization engines. As such, all of the tools in this category dispatch the system based on system costs and have the ability to model a number of temporal unit constraints such as unit ramp rates and start times. Most, but not all tools in this category minimize total system costs through the use of an optimization algorithm. In this solution method, a high penalty cost is associated with unserved energy, effectively ensuring that load loss events are minimized. If a user wants to dispatch the system to minimize unserved energy only, they can do so by setting all other system costs to zero. Note that the user is often the one responsible for assigning this penalty cost, and as such must be thoughtful of how it interacts with other penalty costs (for example, penalty costs for transmission line rating violations, or for ancillary service shortfalls, if those are modeled).

As the dispatch-based Monte Carlo method is very computationally intensive compared to other methods described here, some users often choose to forgo some of the detailed options it provides to speed up run time and ensure computational tractability. This can be done by manually omitting certain system or unit characteristics (start time, ramp rate, up and down times, etc.) from consideration in the dispatch. Alternatively, several tools in this category have the ability to switch between several modeling options to simplify the dispatch when needed (for example, some have an option to switch between a "must run" and "economic constraints" mode).

It is important to keep in mind that tools using the Monte Carlo dispatch-based method are not automatically more accurate than tools employing other solution methods. Ultimately, accuracy will depend on model assumptions made, e.g., simplifications to decrease computational burden, but also on the representation of other key RA features, such as outage modeling and weather uncertainty. However, for certain types of studies, particularly those where energy adequacy is important, they provide inherent advantages.

Alternative Approaches

The following subsection summarizes several solution methods that were reported in the survey that don't unambiguously identify as either pure Monte Carlo or Convolution techniques.

Pseudo-Chronological Monte Carlo Sampling Method

Avoiding the complexity of a full chronological Monte Carlo simulation, one of the surveyed tools approximates it in a multi-step approach.

First, the RA assessment is performed in a non-chronological Monte Carlo manner. In this assessment, each replication is evaluated for each time block with available capacity being subject to failure probabilities.

A pseudo-chronological analysis can subsequently be executed to investigate the duration and frequency of outages. For this purpose, outages identified in the preceding non-chronological step are analyzed in more detail by back-tracking hour by hour the start and end times of loss-of-load events considering failure and repair rates of each component.

In systems where small storage devices can contribute to resolving shortages, operation of these devices can be optimized for the duration of the failure state identified in the preceding pseudo-chronological step, allowing for some of the advantages of Monte Carlo simulations, but reducing runtime. Note that unit commitment chronology is not represented in this approach.

High-Level Monte Carlo Sampling Method

One of the tools uses a simplified solution method to reduce computational complexity. In this method, storage and demand response are considered chronologically, but not unit ramp rates or minimum up/down time.

For this solution method, the tightest system hours are identified based on estimated average plant availability (excluding unplanned outages) for each weather pattern. The user can either choose to select a certain number of system hours for consideration or can select to consider all hours below a certain reserve margin percentage. The solution method then selects both the tight system hours identified as well as their adjacent hours for further analysis, with the number of adjacent hours a user-set parameter which should be set based on the maximum short-duration unit length in the system being modeled. This approach allows for the number of considered timesteps, and therefore the computational complexity, to be reduced.

In the following step, plant outages are randomly sampled and aggregated into blocks of available capacities and associated probabilities for each study region. Outage rates are used for specific plants, whereas average availabilities are assumed for aggregate plants. This method resembles to an extent Monte-Carlo simulations, however, the user-defined number of capacity blocks is typically smaller than the number of generators in a system.

To account for regional effects, available capacity blocks for each region are randomly sampled and the joint relative probability of the system is calculated by multiplying the probabilities of each of these blocks. Short-term storage operation and transmission flows are then optimized over the identified critical periods and their adjacent hours to minimize unserved energy.[3]

Convolution Method Using Monte Carlo-Derived Inputs

Another solution method uses a convolution model to evaluate the adequacy of a system but uses a Monte Carlo sampling analysis to calculate unit-level availability distribution profiles for each hour of the analysis. Thermal resource availabilities are sampled on an hourly basis using two-state Markov modeling methodology (which incorporates both a time to failure and time to repair), and the results of this sampling are used to create a different unit availability distribution profile for every hour of the analysis. Historical hourly data is used to create hourly historical probability distributions for all area-level demand profiles and variable renewable energy profiles. Once area-level adequacy is calculated, the solution method considers inter-area balancing by allowing for transfers from neighboring areas and their immediate neighbors if excess generation is available and transfer capability is sufficient.

Consideration of Unit Commitment

Of the tools surveyed, only those using a dispatch-based Monte Carlo method (which make up the largest share of tools) are capable of considering economic dispatch. In addition, a portion of these tools can also consider unit commitment. Unit commitment is the process of deciding when and which generating units to start up and shut down to meet demand over a future time period, such as a day or a week. Many thermal units have multi-hour start up and shut down times, and as such their commitment is fixed, in day ahead or hours ahead, for the real-time operations. This means that the system’s ability to respond to real-time system changes such as forced outages or changes to the anticipated load or wind and solar forecast may be limited.

There are several possible methods for unit commitment consideration to capture this effect. A simplified heuristics approach could be considered, in which units are committed using a heuristic method and economic dispatch is then carried out using a linear optimization. Another

[3] Note that long-duration storage resources are considered as firm capacity.

approach uses a mixed-integer optimization approach, which allows for a co-optimization of commitment and dispatch decisions. Finally, one of the tools surveyed uses a dynamic programming approach. In this approach, the unit commitment problem is broken into a number of sub-problems. The first sub-problem includes meeting load for every hour up to a portion of the minimum load of the week. For this problem, minimum up-time and down-time and start-up time constraints can be ignored or relaxed. The next sub-problems are then set up to meet the remaining unserved load. For each subsequent sub-problem up to the final sub-problem which fully meets load plus operating reserve requirement, the unit constraints become more critical, and all relaxations are progressively dismissed.

While in general, including unit commitment can provide more insight into real world operations (at the cost of computation), it was observed that a number of the tools that have the capability to model unit commitment assume perfect foresight for outage modeling, which limits the usefulness of the unit commitment exercise. Indeed, if a solution method has perfect foresight of all future outages, it may ramp up a unit in the unit commitment pass in anticipation of a future forced outage, which isn’t aligned with real-world operations, where this would not be known. This may result in an overoptimistic result as compared to an algorithm without perfect foresight, whereas accounting for outages only as they happen would be more realistic and is something several tools are capable of.

Ensuring Computational Tractability

Probabilistic runs are computationally very expensive, especially as resource models are getting more complex and there is an increasing push to consider energy and even flexibility adequacy within the probabilistic RA framework. To this end, many of the surveyed tools have implemented methods to facilitate computational tractability. These include options for parallelization or multi-threading, various methodologies to screen for at-risk adequacy hours, methods to easily simplify or tune the model for probabilistic analysis, and the use of high-performance or cloud-computing.

Many of the surveyed tools allow for parallel processing of RA runs. This can allow for multiple weather years or even individual replications to be run in parallel. Some of the tools surveyed allowed for split runs, i.e., the ability to portion replication-level runs into smaller, independent subproblems. For example, a problem of 8760 hourly timesteps could be sectioned into 52 weekly subproblems of 168h (or e.g., 192h to account for a period of look ahead horizon). Note that while this practice is commonly used, this methodology alone is not suitable to represent chronology over longer timeframes relevant to represent the operation of generators with longer time constants, e.g., hydroelectric units or seasonal energy storages. Care should be taken to consider how tools using this practice approach this challenge, with information on the topic found in the Hydropower section of this document. Modeling choices for energy storage are also discussed in the modeling guidelines document [2], to describe accuracy of different models.

A number of the tools evaluated have developed methodologies to screen for at-risk adequacy hours. This can range from fairly simplistic methodologies, such as foregoing runs of lower load uncertainty levels if higher load uncertainty levels did not yield shortages in an hour, to more sophisticated methodologies, such as applying variance reduction techniques using purpose designed stratified sampling. One common approach consists of screening for periods at risk using a simplified representation of the system, and then performing more detailed analyses of these periods. This can be accomplished by incorporating a simplified representation of thermal resource unavailability in the initial system runs, or by ignoring certain operational constraints initially. As with the split run capability discussed above, care should be taken to ensure long-duration energy-constraints such as seasonal hydro and energy storage are appropriately captured.

Probabilistic analysis tools are increasingly being called upon to incorporate more complex resource models. As such, the ability to easily simplify and tune the model for probabilistic analysis, especially in tools initially created for production cost simulation applications, is key. This requires some level of technical know-how on the user's part to sufficiently tune optimization parameters and to understand which level of modeling detail is important to include for a specific study. The modeling reference document developed as part of this initiative [2] can help guide these decisions. Additionally, certain optimization setups, such as the use of solver warm starts (e.g., providing an initial point for the subsequent rolling horizon window) and the use of linear or dynamic programming solution methods instead of MIP programming can improve computational runtime. Finally, a useful capability for these tools is the ability to easily switch from a full optimization model to a "must-run" or "commit all" model, in which a full economic dispatch is not considered, for initial setup or testing purposes.

Several tools evaluated as part of this initiative have processes in place to allow the user to leverage high power computational resources such as high-performance clusters or cloud-computing. This capability to execute model runs remotely offers more flexibility to outsource computational time and leverage high performance computing. However, firewalls, data security and IT restrictions can be a hurdle.

Summary

The major tool functionality capability levels for RA core analysis approaches are outlined in Table 5. At level I, solution methods allow for the evaluation of probabilistic adequacy but have key limitations that can have a significant impact on results, especially in systems with inter-regional constraints or a significant penetration of energy-limited resources such as hydropower or energy storage devices. These limitations can include the inability to model inter-regional constraints, as is the case in traditional convolution methods, or a non-chronological or only partially chronological modeling approach, as is the case for the non-chronological Monte Carlo methods and the alternative solution methods outlined above. At level II, solution methods allow for a chronological evaluation of probabilistic adequacy risk for all hours of the study period and have the ability to evaluate multi-area adequacy. Tools in this category include tools with heuristics-based fully chronological Monte Carlo methods, and some tools with dispatch-based fully chronological Monte Carlo methods. At level III, solution methods allow for a chronological evaluation of probabilistic adequacy risk for all hours of the study period, while also allowing for operational constraints such as minimum up/down time and ramping constraints to be considered. Tools in this category include tools with dispatch-based fully chronological Monte Carlo methods. Note that not all dispatch-based Monte Carlo methods are automatically categorized as level III tools. A user has to be able to run a sufficiently large number of probabilistic replications to achieve sufficient statistical precision in a time-effective manner for an analysis approach to qualify as level III.

Table 5. Tool functionality levels for core analysis approaches

Tool Functionality	Level I	Level II	Level III
Analysis approaches	The solution method allows for the evaluation of probabilistic adequacy risk but has key limitations when it comes to the representation of inter-regional flows and/or the representation of the intertemporal nature of energy limited resources.	The solution method allows for a fully chronological evaluation of probabilistic adequacy risk and has the ability to evaluate multi-area adequacy.	The solution method allows for a fully chronological evaluation of probabilistic adequacy risk, while also allowing for temporal unit operational limitations such as minimum up/down time and ramping constraints to be considered. Numerous runtime improvements have been implemented to ensure computational tractability.

4 RISK METRIC REPORTING

This section outlines RA software tool capabilities as it relates to adequacy risk metric reporting. Historically, loss-of-load expectation (LOLE) in days/year was the only metric reported across many systems in North America, with single metrics often being reported elsewhere in the world also. However, increasingly studies are reporting a multitude of risk metrics with increased granularity. While the ability to report them has always been there, more attention is now being paid to this issue, and so this part of the survey focuses on tool capabilities for reporting results.

Metrics Reported

There is an increasing body of research that demonstrates that using a suite of RA metrics is essential to ensuring a full understanding of system risk. As illustrated in Figure 3, most of the survey respondents surveyed stated that standard risk metrics such as loss-of-load expectation (LOLE), loss-of-load-hours (LOLH) and expected unserved energy (EUE) were output by their tool. Several tools also have the capability to automatically output several less commonly used risk metrics, such as CVaR (conditional value at risk) and hours at VOLL. Note that these metrics may be output with varying levels of ease from one tool to another: The intent of the survey question was to evaluate which metrics are automatically output by tools as part of their standard output, but certain survey respondents included metrics that are available through their tool but may require some level of customization or calculation on the user's end to output. Users are encouraged to discuss with tool providers about the metrics available and how they can be calculated.

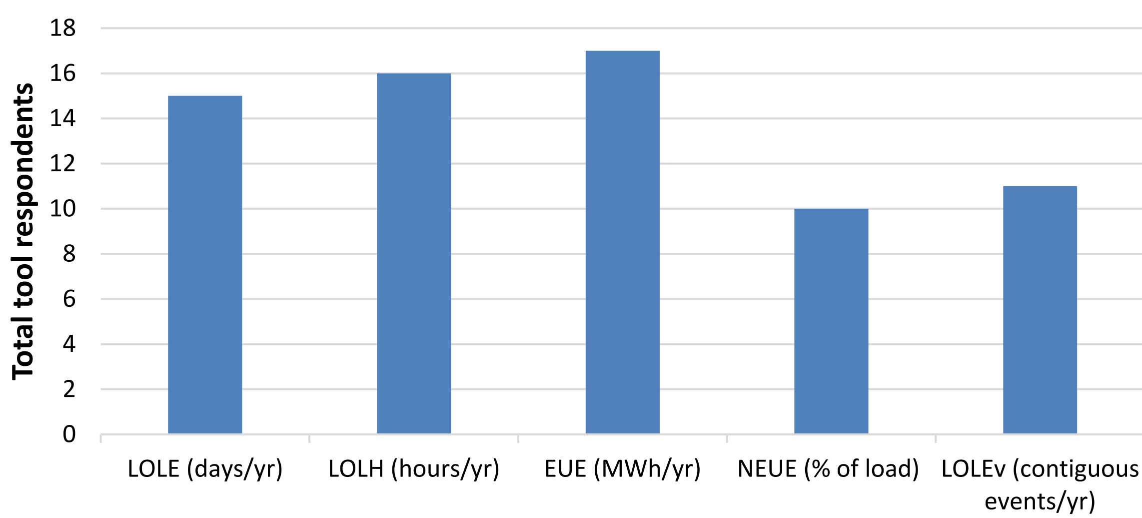

Figure 3. Tool capabilities to output key RA risk metrics

Table 6 provides a short definition of the common risk metrics covered in Figure 3, while Table 7 provides a definition of several less commonly output risk metrics that certain tools surveyed include as part of their standard output options. For further information on the various metrics, please refer to the RA summary report [3] developed as part of this initiative.

Table 6. Key RA risk metrics reported by most tools

Metric	Abbreviation	Units	Definition
Loss-of-Load Expectation	LOLE	days/yr	Average event-days per year across all of the random replications simulated
Loss-of-Load Hours	LOLH	hours/yr	Average event-hours per year across all of the random replications simulated
Expected Unserved Energy	EUE	MWh/yr	Average load not served per year due to shortfall events across all of the random replications simulated
Normalized Expected Unserved Energy	NEUE	% or ppm	Average load not served per year due to shortfall events across all of the random replications simulated, calculated as a percentage of system load
Loss-of-Load Events	LOLEv	contiguous events/yr	Average count of events per year across all of the random replications simulated

Table 7. Additional RA risk metrics not commonly reported

Metric	Definition
Annual Loss of Load Probability	Probability of having a single loss of load event in any given year
Total Value of Lost Load	Economic value of unserved energy
Intra-Hour EUE	Expected unserved energy due to short-term (intra-hour) ramping constraints.
Multi-Hour EUE	Expected unserved energy due to longer-term (multi-hour) ramping constraints.
Load shed frequency and duration	Frequency and average MW load shed for different load shed event durations.
MW Short	Highest peak loss of load event – useful when sizing units to resolve shortfall events.

Table 7 (continued). Additional RA risk metrics not commonly reported

Metric	Definition
Percentile metrics[4] (ex: UE95)	Percentile metrics can be applied to any of the metrics defined in Table 6. For example, a percentile unserved energy (UE) metric is calculated as the amount of unserved energy at or below which a given percentage of replications falls. As such, the UE95 metric (or 95th percentile unserved energy metric) indicates the amount of unserved energy in the most severe 5% of cases. Percentile metrics can be used to evaluate the impact of high-impact low-probability events to system risk.
Conditional Value at Risk (ex: UE $CVaR_{95}$)	Conditional value at risk metrics can be applied to any of the metrics defined in Table 6. The conditional value at risk metric is calculated as the average of the values that fall beyond a certain percentile threshold. For example, the UE $CVaR_{95}$ calculates the expected value of all outcomes beyond the 95th percentile. Conditional value at risk metrics can be used to evaluate the impact of high-impact low-probability events to system risk.
Metrics tracking "close call" events	Several metrics are included in this category, including hours at VOLL/scarcity priced hours, reserve shortage hours, or reporting of key adequacy metrics at various reserve margin levels (usually corresponding to the various emergency operating procedures of a region).
Metrics tracking significant events only	Metric tracking the number of loss-of-load hours within a certain gap (for example, a user can select to track events only if the loss of load is above 1 MW).

Temporal Granularity

Another variation from one tool to another is the granularity at which each of these metrics can be output. A number of tools allow for key metrics to be output at both an **annual** and **monthly granularity**, while a few tools additionally allow for **daily** and **weekly granularity**. Several of the tools surveyed allow for metrics to be output as averages by **hour of day**. Many tools allow for results to be output by **hourly granularity**, thus allowing for the user to calculate a number of custom metrics and visualizations in post-processing. Clearly, allowing for more granular outputs can enable more insightful analysis into the types of shortfalls (and is covered in the metrics report related to this initiative), but there may be data limits or other computational challenges in outputting such detail.

[4] Sometimes referred to as Value at Risk (VaR) metrics (ex: UE VaR_{95})

Replication-Level Results

In addition to varying granularity across timescales, several tools allow for results to be output **by replication**. Although many tools don't automatically output this level of detailed results due to the large amount of data this represents, many allow replication-level results to be pulled by the user if desired. These replication-level results are more or less straightforward to extract depending on the individual tool interface. Additionally, several tools also allow the option for replication-level results to be output as an **annual average by replication**, or an **hourly average across all replications**. This reduces the amount of data output to the user, while also providing relatively detailed results for review.

The ability to output replication-level results is useful not only for debugging purposes, but also if calculating custom risk metrics beyond the ones automatically output by the tool. Post-processing scripts can either be appended as part of a custom add-on to the tool, or calculated separately, after all replication-level results have been retrieved. EPRI has developed an online tool [4] which can be used in post-processing to visualize several RA metrics based off hourly replication-level results. Alternatively, a handful of the tools surveyed allowed the user to easily define custom advanced risk metrics within the tool interface itself.

Other Risk Measure Reporting

All of these metrics can usually be output for the full system, or **by geographical area**. Additionally, one of the tools evaluated as part of this initiative allows for RA metrics to be output on a **nodal level**, allowing for the marginal effect of nodal load variations on unserved energy to be captured. Although less common, the ability to automatically output key risk metrics **by weather year** is useful when evaluating the impact of potential extreme weather events on system risk. Figure 4 illustrates the possible temporal and replication-level granularity reporting options available in RA tools. Not every tool will have all outputs available, but users are encouraged to understand and use what is available to them to gain more insight into the nature of the outages they observe.

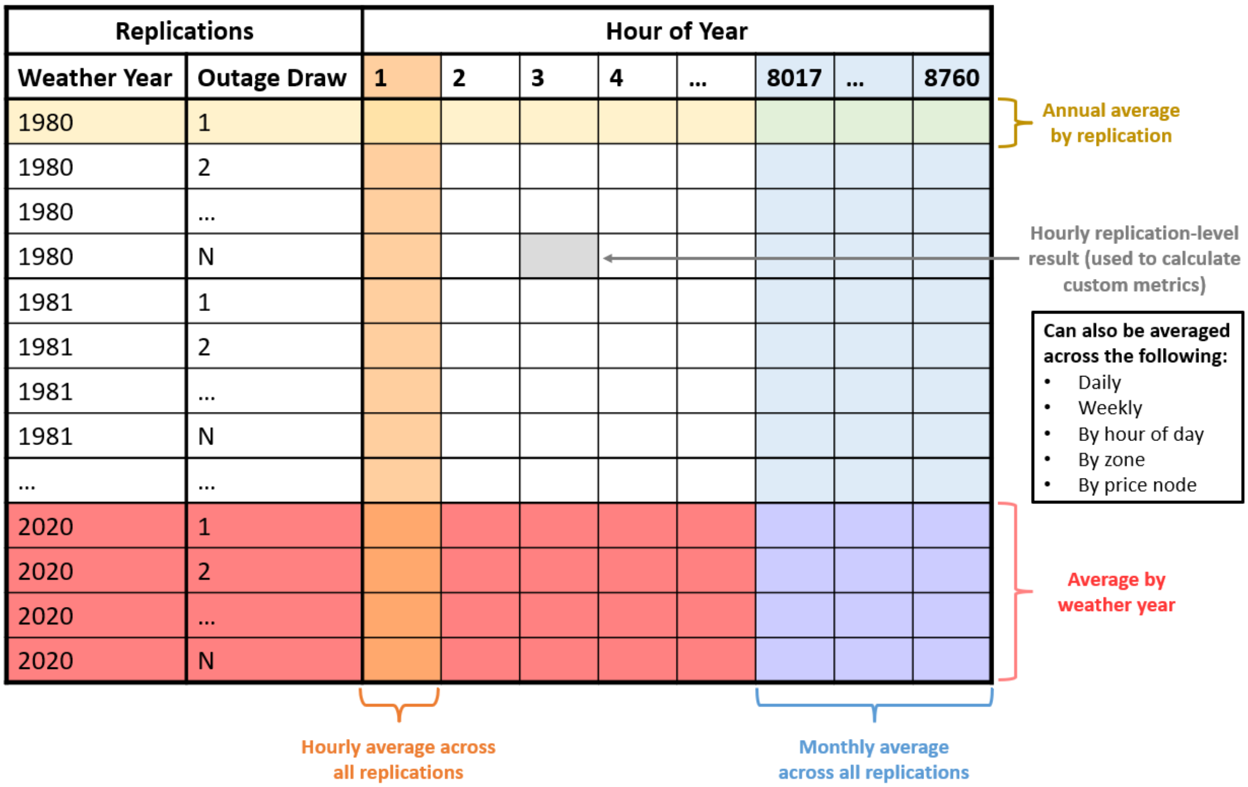

Figure 4. Possible available granularity for loss of load reporting

Summary

The major tool functionality capability levels for RA risk metric outputs are outlined in Table 8. At level I, tools output most standard risk metrics like LOLE, LOLH, and EUE for both the full system and for each of the regions modeled. At level II, tools output most standard risk metrics, but also have the capability to output replication-level results: This allows the user to calculate custom metrics in post-processing if desired. At level III, tools output both standard and advanced risk metrics automatically, that is to say, without a need for much customization on the user's end – in this category, tools should allow the user to easily define metrics to output within the tool interface itself, without any need for post-processing. In addition to outputting replication-level results, tools in this category should be able to output results at various levels of granularity (temporal, by weather year, etc.).

Many of the tools surveyed as part of this initiative are at level II: If desired, a user can calculate custom-risk metrics or obtain replication-level results, but this requires considerable effort on their part, and may require either the manipulation of large amount of replication-level data in post-processing, or requests for study-specific customizations from the tool provider (a sometimes lengthy and expensive process).

Table 8. Tool functionality levels for risk metric outputs

Tool Functionality	Level I	Level II	Level III
Metrics output	The tool outputs standard risk metrics like LOLE, LOLH, and EUE for both the full system and for each region modeled.	The tool outputs standard risk metrics like LOLE, LOLH, and EUE for both the full system and for each region modeled. Additionally, it can output replication-level results to allow the user to calculate custom metrics.	The tool automatically outputs both standard risk metrics and custom advanced risk metrics defined by the user (for example: LOLE95) for both the full system and for each region modeled. In addition to outputting replication-level results, tools in this category can output results at various levels of granularity (temporal, by weather year, etc.).

5 GENERATOR FORCED OUTAGE MODELING

Alongside the demand forecast, the treatment of forced, unplanned outages of generation resources has historically been a focal point of methodological development for RA assessment. All tools evaluated here are able to model and evaluate the impact of forced generator outages on system adequacy risk. The methods for modeling these forced outages do vary from one tool to another, however, and in some cases, a tool may offer several forced outage modeling methodologies depending on the ultimate study goal.

There are three main dimensions to evaluate when considering forced unit unavailability. The first is how unit unavailability is modeled, whether for modeling full unit forced outages, partial outages, or start-up failures. The second dimension to consider is whether outage statistic parameters can be varied throughout the study period. This can either be varied by time period or can be condition-based. The third dimension to consider is how (if at all) coincident outages are represented in a tool.

Unit Unavailability

Unscheduled unit unavailability can be due to several factors, including forced outages (defined as a state a unit enters when it is no longer capable of delivering energy to the grid), partial outages (defined as an unscheduled forced reduction in unit capacity), and startup failures (defined as a forced outage due to a failure that occurred during a unit's startup procedure).

Depending on the tool, unscheduled generator unavailability occurrences (whether from forced outages, partial outages, or startup failures) are either calculated in pre-processing, or dynamically for every time step of simulation. A unit unavailability schedule calculated in pre-processing means the tool has perfect foresight of all future outages and can adjust system unit commitment and dispatch accordingly. For example, it may start-up or ramp up a unit in anticipation of a future forced outage event, which isn't aligned with real-world operations, where this would not be known. This may result in an overoptimistic result, whereas accounting for unscheduled unit unavailability only as it happens would be more realistic. Alternatively, in some tools, unscheduled generator unavailability is identified at the start of the user-defined optimization window, giving the solver perfect foresight within the optimization window but not outside of it, somewhere between the two main methods.

The following three subsections detail the methodologies used by RA tools to model these three unscheduled unit unavailability types.

Forced Outages

Forced outage representation is approached differently depending on whether the solution method considers study hours chronologically or not. The forced outage modeling methodologies of the tools evaluated are summarized in Figure 5 and further discussed in the sections below.

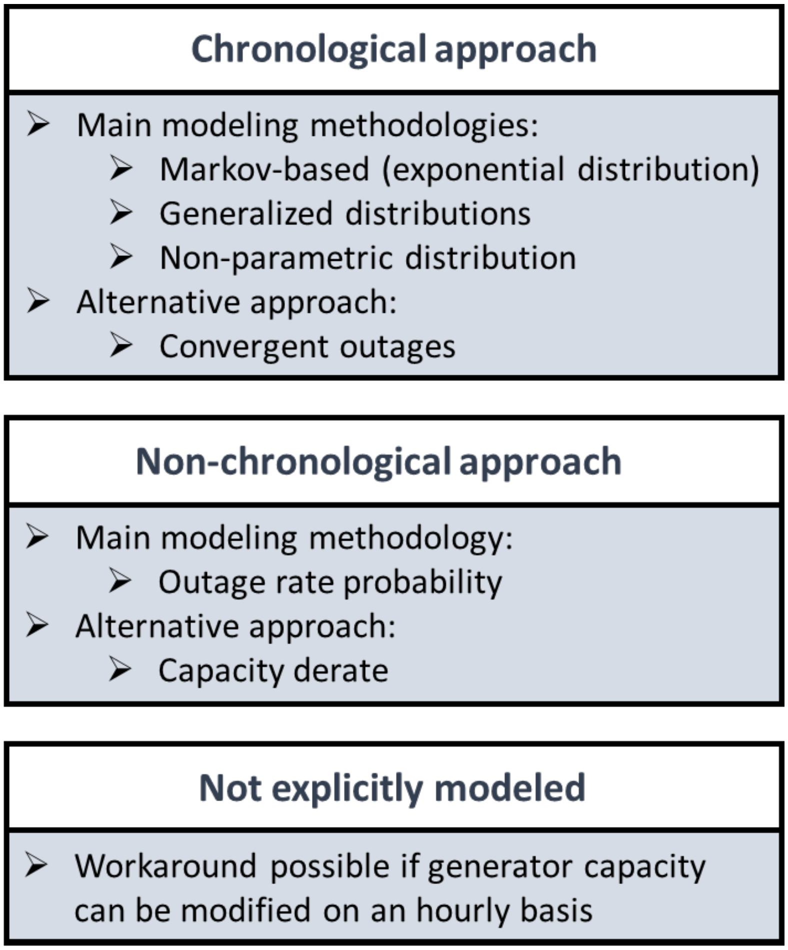

Figure 5. Forced outage modeling methodologies represented across tools

Chronological Consideration

These outage modeling methodologies are often used when the RA solution method considers hours chronologically. These methodologies recognize the fact that a unit's state in a given hour is dependent on its state in the previous hour and influences its state in the future hour.

There is some variation across tools as to how these outage modeling methodologies are implemented, but at its core, they consider both how likely a unit is to go on outage as well as how long it takes it to recover from an outage. The measure of how likely a unit is to go on outage can be input as either a mean time to failure (MTTF) or an equivalent forced outage rate - either EFOR which is the probability that a unit will be unavailable due to forced outages, or EFORd which is the probability of unavailability for times when there is demand on the unit to generate. The measure of how long it takes a unit to recover from an outage can be input either as a mean time to repair (MTTR) or an average number of outages over the study period. Alternatively, a state transition matrix can be used which indicates the probability of moving from one availability state to the next.

Markov-based*:*

Many of the tools surveyed use a Markov process to stochastically determine generator forced outages. A special property of the Markov process is that, while each new state depends on the one before it, new states do not depend on any states before the previous one. This special property is referred to as "memorylessness" and is limited to geometric distributions of non-negative integers and the exponential distributions of non-negative real numbers.

Generalized distributions:

Several tools surveyed allow for other distributions in addition to a traditional exponential distribution. Less commonly used probability distributions include the Weibull distribution (a more general distribution than the exponential distribution, where the failure and repair rate is proportional to a power of time, rather than constant as it would be for an exponential distribution) and the uniform distribution which allows outages to vary uniformly around a certain duration.

Non-parametric distribution:

Two of the tools surveyed instead ask the user to provide a discreate set of possible times to failure and times to repair, often based on historical NERC GADS outage data. This discrete set of possible times to failure and times to repair form a histogram, which the tool randomly selects from for each draw. A third tool asks the user to provide a probability of occurrence for a discrete set of outage failure durations.

Convergent outages*:*

While the user inputs a forced outage rate and an MTTR , similarly to other methods, this methodology adjusts outages in such a way that each replication run has a forced outage rate exactly equal to the EFOR entered by the user. As such, although the outage occurrence is assigned randomly, the amount of time a unit will spend on outage for each replication is fixed. This allows for more repeatable results and is sometimes used if a user doesn't have the bandwidth to run enough Monte Carlo replications to achieve sufficient statistical precision. However, it doesn't capture all possible outage scenarios, as any scenarios with a higher or lower amount of time on outage than the EFOR will not be modeled. As such, this methodology fails to capture aspects such as tail events, which are of high interest to many system planners, and the fact that an EFOR number represents the average of a wide range of outages in any given year.

No Chronological Consideration

Outage Rate Probability:

This outage modeling methodology doesn't incorporate any chronological consideration of outage probability. The probability of outage (whether full or partial outages) is input without providing information on the duration of the outage.

This methodology is traditionally used with convolution methods, in which every hour is considered independently. However, one of the tools evaluated used this outage methodology in combination with a Monte Carlo method: They run each week of the study period independently, and if a unit is on a forced outage, it is on outage for the full week.

Capacity Derate:

This outage modeling methodology applies the forced outage rate input by the user as a constant capacity derate across all time intervals of the simulation. Although this methodology results in the appropriate amount of capacity derated due to forced outages on average, it doesn't realistically represent the impact that forced outages have on the system: A unit which is on forced outage for part of the year is harder for the system to prepare for than a unit which is derated by a small amount over the full study period. This is typically more useful for resource planning studies or similar, where an approximation of unit outages may be sufficient.

Not Explicitly Modeled

One tool respondent didn't have any forced outage modeling methodology available. Instead, they had the capability for generator capacity to be specified on an hourly basis. As such, a user would need to set up a pre-processing script to create outage patterns for all generators and input them as hourly capacity profiles in order to be able to analyze the impact of forced outages on RA. In theory, this could allow for complex forced outage modeling methodologies to be represented, such as allowing for correlated outage modeling and full representation of transition rates from one outage state to another, while in practice this may be very time consuming without a well-developed pre-processing script and suitable data.

Partial Outages

While all tools surveyed allow for the option to model generator forced outages, many don't allow for the option to directly model partial forced outages, which are outages associated with a reduction in capacity, rather than full unit unavailability (these are sometimes referred to as 'forced capacity derates' and differentiated from 'capacity derates' above in that they only happen for a specific time rather than the full simulation period). The most accurate way to define partial forced outages in a chronological consideration is through the use of a multi-state Markov transition matrix. This allows for relationships between outage states to be fully defined, something that isn't possible in any of the other outage modeling methodologies. This allows for discrete combinations to be enforced, for example that a unit when returning to service always goes to full output and never a partial outage state. Note that a 2-state Markov process, which can be characterized either through a state transition matrix or by a MTTF and a mean-time-to-repair value, is a subset of a multi-state Markov process, as illustrated in Figure 6. A MTTF/MTTR process allows for the use of a generalized outage distribution, but if it uses an exponential distribution, it is considered a 2-state Markov process.

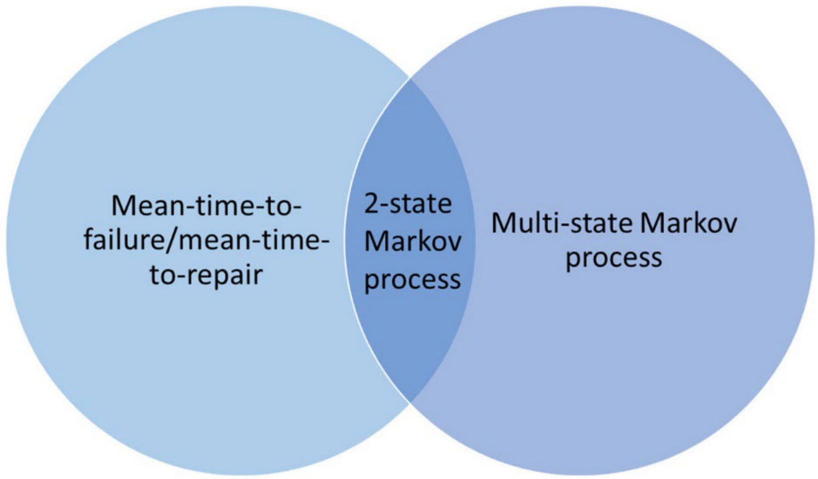

Figure 6. Intersection of Markov processes and MTTF/MTTR processes

Several tools considering outages chronologically instead allow the user to define a separate time to failure and time to repair (or similar characteristics) for partial outage states than for a full forced outage state. However, this doesn't allow for the transitions between outage states to be fully characterized.

When forced partial outage modeling is not available, a workaround sometimes used is to model multiple units within a plant or model a unit as being comprised of multiple sub-units, thus allowing the user to associate a forced outage rate to only a portion of the plant. However, this can result in complicated implementation, depending on the level of detail needed: For example, a coincident outage would need to be specified to model a plant-wide outage under this configuration.

Startup Failures

Startup failures are an unscheduled outage type where the affected unit is fully unavailable due to a failure that occurred during its startup procedure. The ability to model start-up failure isn't a widespread capability amongst RA tools: Only two of the tools reported having this capability at the time they were surveyed. Note that only one of these allowed for a time to repair value to be defined: The other assumed the generator would be available again in the next commitment cycle.

Start-up failure modeling may become increasingly important in systems with significant ramping requirements, when multiple units start in close succession to meet a net load ramp, potentially during adverse conditions. Additionally, certain units are seldom called upon for energy needs, and as such are more likely to suffer from a start-up failure when started, often during times of system stress, when reliable generation is most important to prevent a shortfall event.

Varying Outage Statistic Parameters

Static vs. varying outage statistic parameters is another key dimension to generator forced outage modeling methodology. That is to say, an outage modeling methodology can have a single transition probability at any given point in time, but with that probability changing as a function of time or as a function of some other user-defined variable. Generator outages in many RA assessments to date are often represented as static outage risks. However, incorporating varying outage statistic parameters in RA models is especially critical when considering the large impact correlated failure of generation owing to extreme weather or climate conditions can have on power systems, as illustrated by recent adequacy events.

Almost all commercial and research adequacy assessment tools surveyed have the ability to enforce seasonally or monthly adjusted forced outage rates. Additionally, a number of these tools have the ability to provide a time series for failure rates, rather than a static number. This capability to vary failure rates for each operating period of the study allows for condition-based failure rates to be considered, which is becoming a key RA tool functionality. The condition-based failure rates are determined in pre-processing for each timestep based on a trigger condition associated with the time period—e.g., hourly temperature or wildfire risk. However, this often requires some work on the user's side in pre- and post-processing, as different failure rate time series must be input for every weather year evaluated, and each weather year then run separately, and results combined in post-processing. A less intensive method is the ability to directly link forced outages rates to key model variables, such as temperature. However, only a couple of the tools surveyed had this capability.

Coincident Outages

The ability to model coincident outages is another key dimension to generator forced outage modeling methodology. That is to say, an outage modeling methodology can have unit-level statistically independent vs. dependent outage rates. This ability allows for a single failure rate to be set for an event that causes multiple generators to go on outage at once. This could be useful, for example, when modeling coincident outages due to natural gas shortage effects during a cold weather event for all units that share a natural gas pipeline. Only a couple of tools reported having this capability at the time they were surveyed.

Summary

Figure 7 illustrates the primary outage modeling tool capabilities practitioners should be considering when modeling extreme weather events- both a robust core outage modeling functionality as well as sufficient additional modeling options as to accurately represent system behavior during extreme events. Note that not all analyses will require every single functionality detailed in this figure—for example, coincident outage modeling may not be necessary in systems not prone to natural gas pipeline shortages.

The accuracy of the available core outage modeling functionalities is represented graphically, with methodologies ranked from least accurate to most accurate. The **Markov-based modeling methodology** is the most commonly used and appears to accurately represent both the probability of outages and the impact of varying outage repair times. The **generalized distributions methodology** and the **non-parametric distribution methodology** are both more comprehensive, as they extend beyond exponential distributions to also allow the user the choice of other probability distributions.

Several simplified methodologies were also offered, including the **outage probability rate methodology** which, while allowing for the probability of outages to be represented, doesn't accurately represent the repair behavior of the generator on outage. As such this method is best reserved for non-chronological modeling uses only. Several other simplified methodologies, such as the **capacity derate methodology** and the **convergent outage methodology** should be reserved for deterministic analyses, or analyses in which a full RA analysis isn't required. Indeed, although these methodologies have their utility, they fail to accurately represent all outage possibilities, particularly tail events, which are of high interest to any RA analysis.

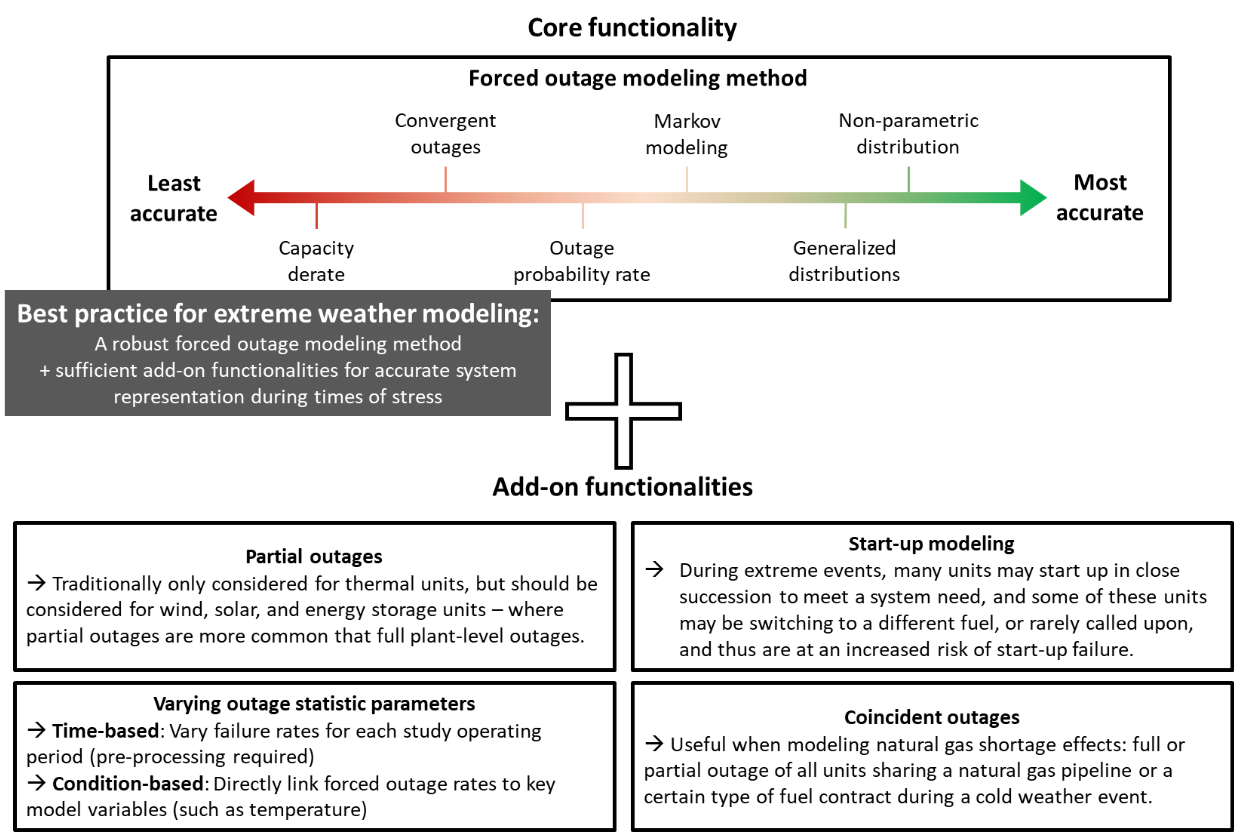

Figure 7. Outage modeling tool capability considerations for extreme weather modeling

The major tool functionality capability levels for generator forced outage modeling are outlined in Table 9. At level I, generator forced outage modeling is fairly simplistic: It is lacking some core functionalities such as a robust outage modeling methodology or partial outage rate representation and is lacking advanced functionalities such as start-up failure modeling, coincident outage modeling, or time-varying generator outage rates (beyond more simplistic seasonal variations). At level II, generator forced outage modeling encompasses many of the features RA practitioners require in more advanced analyses: a more traditional two-state Markov chronological outage modeling methodology or similar, and the ability to model partial outages states, as well as start-up failure and coincident outages. Additionally, generator forced outage modeling at this level allows outage rates to be varied for every timestep of the analysis, which allows for correlated weather impacts to be represented in thermal generators. At level III, generator forced outage modeling additionally allows for outage rates, including start-up failure and coincident outage rates, to be directly linked to key variables such as temperature. This allows for correlated weather impacts on thermal generator availability to be represented in a way which is more straightforward for the user to implement, reducing the need for pre-processing. Additionally, at level III, generator forced outage modeling uses a multi-state Markov transition matrix, which allows for the transitions between all full and partial outage states to be fully defined.

Many of the generator forced outage modeling capabilities surveyed as part of this initiative are either level I or level II. Part of the reason for this is that many of the survey respondents develop tools which are used for both RA and production cost analysis. Accurate outage modeling representation, while long considered a core functionality of RA analysis, is less important for many production cost analyses. Also, accurate outage modeling was identified as a key RA tool gap by many of the members of this initiative. Even though thermal generators make up less of the overall system capacity as systems transition to increased penetration of renewables and energy storage, many thermal units are still called upon for system support during periods of system stress. Increasingly, these periods of system stress occur during widespread extreme weather events, and the thermal resources are gas resources with potential for common outage modes, meaning the ability to easily model common mode failures and outage rate temperature dependence is of high importance.

Table 9. Tool functionality levels for forced generator outage modeling

Tool Functionality	Level I	Level II	Level III
Forced generator outages	Only allows for fixed or seasonal generator outages to be defined. Allows for either no or only limited modeling of partial generator outages. Uses either an outage rate probability methodology, or a Markov-based chronological outage modeling methodology or similar (exponential, Weibull, or non-parametric distribution). Doesn't allow for start-up failure or coincident outages to be modeled.	Allows for the modeling of either full or partial generator outages that can be varied for every timestep of the analysis. Uses a Markov-based chronological outage modeling methodology or similar (exponential, Weibull, or non-parametric distribution). Allows for start-up failure and coincident outages to be modeled.	Allows for the modeling of either full or partial generator outages which can either be varied for every timestep of the analysis or can be directly linked to key variables such as temperature. Uses a multi-state Markov transition matrix forced outage modeling methodology. Allows for condition-based start-up failure and coincident outages to be modeled.

6 GENERATOR MAINTENANCE OUTAGE MODELING

Maintenance Scheduling Methodologies

Maintenance factors are typically considered separately from forced outages, given the ability to schedule maintenance at specific times or potentially recall resources on maintenance faster than anticipated. Maintenance is traditionally scheduled during the periods of lowest system stress; however, the timing of such periods is becoming less certain as periods of system stress become increasingly decoupled from the highest load hours. While certain tool developers choose not to explicitly model resource maintenance for simplicity and computational tractability, the vast majority of tools surveyed allow for the needs for generator maintenance to be explicitly represented.

Three approaches are typically followed to reflect the need for planned resource maintenance in studies, 1) specification of fixed maintenance outage dates, 2) a heuristic maintenance scheduling approach, and 3), an optimization maintenance scheduling approach. The most widespread heuristic maintenance scheduling approach is a valley filling approach: maintenance outages are scheduled against forecasted gross or net load profiles based on the size, duration, and number of resource maintenance outages needed over the study period. The optimization maintenance scheduling approach, which is most common amongst dispatch-based Monte Carlo simulation tools, often optimizes resources maintenance outages to minimize total system cost. For further details on these approaches, please refer to [2].

An additional advanced modeling functionality available in at least one of the tools surveyed is the ability to create a planned outage schedule for each load year, for the average of selected load years, or for the highest load year. In this particular tool a daily peak load array is built using either the average or maximum of all daily peak loads for all of the weather years considered in the study. While calculating a planned outage schedule for each load year is the most widespread method used across tools, using this method assumes perfect knowledge when optimizing maintenance schedules. As such, the average daily load shape method may allow for more realistic schedules which account for the weather uncertainty inherent in long-term planning, while the maximum daily load shape method allows for a more conservative maintenance scheduling approach which may be particularly useful in regions with very volatile peak loads. The impact of these varying maintenance scheduling approaches is further evaluated in [5].

Summary

The major tool functionality capability levels for maintenance outage modeling are outlined in Table 10. Historically, maintenance modeling wasn't considered a necessary functionality of RA analysis tools, as periods of system stress were predictably occurring during peak load periods. As the timing of these periods of system stress becomes harder to predict, maintenance modeling capability becomes increasingly important. At level I, tools only allow for maintenance to be scheduled during specific dates, while at level II, maintenance can also be scheduled using a heuristics-based logic. At level III, maintenance can be optimized with imperfect foresight. RA practitioners have noted that realistic maintenance modeling functionality isn't readily available in most of the tools they use: These tools are often too prescriptive in their modeling, and don't appropriately represent the imperfect foresight or the level of operator flexibility with outage scheduling.

Table 10. Tool functionality levels for maintenance generator outage modeling

Tool Functionality	Level I	Level II	Level III
Maintenance generator outages	Allows for maintenance to be scheduled for specific dates.	Allows for heuristic maintenance schedules, or for maintenance to be scheduled for specific dates.	Allows for maintenance to either be scheduled for specific dates or to be optimized with imperfect foresight—for example, allowing for a single optimization across an average weather year.

7 WEATHER UNCERTAINTY

As systems transition to higher variable renewable penetrations, weather uncertainty plays a larger role than ever in RA. Appropriately modeling this weather uncertainty is especially important given the increased exposure to extreme weather events in many regions. Indeed, these extreme weather events will often impact multiple technologies at once. As such care must be taken to ensure correlated weather year data is used across all weather-dependent technology and load models—this includes wind and solar data, but also load data, hydro data, and any temperature dependent data—such as temperature-dependent outages or demand response. Here the focus is on load and renewable resources. The impacts of weather on thermal plants were covered in further detail in the forced outage methodology section. Likewise, the impacts of weather on hydropower reservoir resources are covered in the hydropower section.

Weather Variability

Most tools surveyed in this study, and indeed, most RA tools today, are Monte Carlo simulation tools, as described in Section 3. In these tools, the impact of weather variability on RA is evaluated by running probabilistic outage modeling for a number of weather years. All of the tools that were surveyed allow for consistent weather-based timeseries (often referred to as correlated weather shapes), where each variable is represented by a time series from the same weather year(s), ensuring an accurate representation of real-life weather patterns. One of the tools surveyed has a unique convolution-based solution method, and as such doesn't represent the weather variability in quite the same way as other tools. However, it does represent weather variability through a custom algorithm which determines probability distributions for demand and VER variability based on historical weather years.

The majority of tools surveyed allow for inter-annual weather variability to be implicitly considered by inputting multiple years of weather data, without any need for pre- or post-processing. However, a few of the tools surveyed don't allow for weather variability to be directly evaluated within the core tool framework. In this case, the user would be required either to manually set up the varying weather year scenarios, or to use an external tool to generate the weather scenarios required for the RA evaluation. One of the tools surveyed created a python script made available to users for this purpose, while other tools would require the user to create their own script to facilitate the evaluation of multiple weather years within their analysis.

Even within tools that do implicitly model inter-annual weather variability, a handful suffer from consequential limitations. One of these tools doesn't allow for load driven by weather variability to be explicitly modeled, while another tool only allows for a maximum of 7 weather years to be evaluated.

Short-Term Weather Forecast Error

Uncertainty in short-term weather forecast is something that isn't traditionally represented in RA models. Instead, many practitioners will require the system being modeled to satisfy both customer demand as well as operating reserve requirements. In many cases, this is a sufficient approximation, especially given the computational cost and data challenges associated with the modeling of short-term weather uncertainty across multiple weather years. However, in some cases, for example, when evaluating operational RA, a user may be interested in explicitly representing the uncertainty in short-term weather forecast within their model.

All tools that incorporate this functionality do so as part of their multi-stage optimization algorithm. In most tools, the user would input both a forecast and a real-time shape directly, however in a handful of tools the user would instead input a volatility distribution of the short-term forecast error. Small variations between tools exist: For example, one tool allows the user to vary the volatility distribution according to the current load on the system, or the percent output of nameplate capacity. Other tools will assume a normal distribution, and only allow the user to input a standard deviation for the short-term forecast error.

Accounting for Long-Term Climate and Economic Load Trends

RA models sometimes use a historical record for demand timeseries data, and other times use either a detrended historical record or output from a forward-looking load model. Directly incorporating the historical record time series into a RA model may be sufficient in regions that have seen little change in climate, underlying load characteristics (e.g., number of heat pumps, data centers, and so on), and economic growth over time. However, the ability to account for long-term climate trends and economic load growth trends may be necessary, depending on how far into the future the RA assessment is examining, on local rates of climate and economic and technical changes, and on the depth of available past climate and load data. A simplified approach to account for these trends consists of detrending this load data with respect to economic conditions and climate trends while maintaining short-term weather variations. However, this methodology fails to capture the changing nature of customer demand over time (for example, an increase in electric heating or electric vehicle use). As such, a forward-looking load approach that considers future climate, technological and economic trends may be recommended. Further information on this process can be found in the data collection reference document [6] developed as part of this initiative.

Given the complexity and level of expertise required to properly account for long-term climate trends and economic load growth trends, it is likely unnecessary for RA tools to have the ability to fully account for these trends within their tool framework. Indeed, many would argue that this could most effectively be handled in a separate procedure in pre-processing. Having this process directly integrated into RA tools creates increased complexity and risks users implementing load timeseries adjustments without a full appreciation of the intricacies they require. In fact, incorporating long-term climate trends into historical weather data requires a careful assessment of past climate data and future climate projections in the region of interest, as well as the expertise to access and interpret them. In addition, loads should not be scaled uniformly according to temperature, as certain load components will be more or less sensitive to temperature changes than others, so some sophistication in load modeling is also required.

Interviews with tool providers have uncovered a handful of functionalities that may be of use to a practitioner hoping to account for these trends within their analysis:

- Several of the tools surveyed as part of this initiative include an option to model economic load forecast error for each of the weather years modeled- differing load forecast error multipliers can be assigned with varying probabilities of occurrence. It should be noted that one of the tool providers surveyed intentionally omits this functionality, as they believe only inter-annual weather variability should be evaluated within the context of a RA study: They argue the economic load uncertainty should instead be evaluated within the context of a capacity expansion analysis.
- Several tools evaluated have the capability to create separate load objects that can be assigned different growth levels. This functionality allows the user the flexibility to scale the various load components differently depending on their temperature sensitivity or their expected growth. For example, this allows the user to scale electric vehicle load profiles at a different rate from other demand profiles directly within the tool framework.
- One of the tools surveyed allows the user to access the projections of precipitation and temperature available at the NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) dataset. This dataset is comprised of downscaled climate scenarios for the globe that are derived from the General Circulation Model (GCM) runs conducted under the Coupled Model Intercomparison Project Phase 5 (CMIP5) and across two of the four greenhouse gas emissions scenarios known as Representative Concentration Pathways (RCPs).

Synthetic Weather Shape Creation

In addition to allowing the user to provide their own wind, solar, and load data, several of the tools surveyed as part of this initiative offer synthetic weather creation functionality. This synthetic weather shape creation methodology can be leveraged when a user doesn't have enough historical weather data to provide a statistically relevant sample of all adequacy events. However, care should be taken to vet this synthetic weather data, and to acknowledge its potential limitations. Indeed, ESIG's Weather Datasets Project Team alerts us to a disconnect between the power system modeling and meteorology communities and cautions that the use of synthetic data in RA assessments may "lead to study results that have greater uncertainty than is typically advertised and may result in poor downstream decisions when model synthesized data that "seem reasonable" are assumed to accurately reflect actual present or future conditions" [7].

One of the tools surveyed developed a method to synthesize many years of random, but plausible, conditions using historical data. To represent each year, the method first randomly selects the hydro conditions for the year and then loops through the days of the year, randomly selecting weather-driven hourly load, wind, solar, and thermal shapes. To account for correlations between these variables due to weather, the method relies on daily weather binning. Days with similar weather conditions across the study's entire geographic footprint are grouped together into bins and the method uses a Markov Chain approach to randomly walk between weather bins based on historically observed weather day transitions. After the weather bin is selected for each day, hourly load, wind, solar, and thermal shapes are randomly selected from within the bin. Mixing and matching these shapes from within the same weather bin allows the method to synthesize many more potential system conditions than were actually recorded over the historical period from which the conditions are drawn. To preserve geographical correlations within each variable, daily shapes of each type are selected on the same day over the entire geographical footprint.

Another tool uses an artificial neural network load model to extend limited records of historical weather and load data. This process first uses a neural network regression algorithm which builds a correlation between historical load years and weather data from NOAA. This algorithm is then used to extend short load data samples across a longer time period based on key weather indicators across that longer time period. The process then uses a stochastic rolling day-matching algorithm to match a small historical sample of renewable profiles with the larger extended record of load data created in the previous step of the process, based on the time of year, the load level for that day, and the renewable generation level in previous days. This day-matching algorithm assigns a probability of occurrence to plausible combinations of load and renewable shapes based on an inverse distance algorithm that measures the similarity between each possible day of renewable profiles in the historical record and the desired day in the longer record and assigns a probability to each one.

Another tool surveyed has developed an in-house module that enables the user to generate synthetic wind, solar, and load timeseries based on a customized probability distribution and daily load profile. The parameters for the probability distribution and the daily load profile can either be input directly by the user or generated using an in-house module which fits a probability distribution to limited records of historical weather and load data and extracts a daily profile. This probability distribution (which can be chosen as either Uniform, Beta, Normal, Weibull or Gamma) can be defined on a monthly timescale and incorporates autocorrelation parameters and correlations with other timeseries. Moreover, a transfer function can be applied to the data if desired (for example, if the initial timeseries if of wind speed, but wind power is desired as the final timeseries), and data can be analyzed in either “raw” or “detrended” mode—with detrended mode used when the data to analyze are the timeseries of the deviations to average (for example, for load timeseries).

Finally, one of the tools surveyed has developed a module that enables the user to create synthetic future scenarios of variable renewable generation by defining a historical record that is either (a) the direct historical data (real measurements); or (b) created based on MERRA2 or ERA5 global reanalysis databases; or (c) a combination of (a) and (b) thus allowing for the application of a bias correction feature. The methodology maintains the spatial and temporal correlations between all weather-based timeseries variables and consists of three primary steps:

1. **Characterizing the shape of the timeseries distributions**: A kernel density estimation (KDE) method is used to estimate the probability density function of each timeseries variable (for example, wind generation for a particular renewable site) from its historical data. A Nataf transformation is then applied to convert the distributions into standard normal marginal distributions.
2. **Representing the conditional dependencies between variables**: A Bayesian network representation of the transformed variables is created using a heuristics-based methodology, thus creating a directed acyclic graph that maps the statistical dependent structure for all key variables.
3. **Generating synthetic timeseries scenarios**: Once the Bayesian network representation is created, samples of the set of variables are obtained by recursively following the graph nodes of the Bayesian network from the parent nodes to the child nodes. These samples are then transformed to convert them from normal marginal distributions back into their original distributions.

An additional functionality of this methodology is its ability to generate synthetic timeseries scenarios even when historical timeseries variables are of different resolutions. This is especially useful when seeking to capture the correlations between hydropower inflows, customer demand, and wind and solar generation. Indeed, hydropower inflows are usually available at a monthly or weekly resolution while historical demand and renewable timeseries require an hourly resolution to accurately represent their intermittency. To accomplish this, the capacity factors of the historical renewable time series are first aggregated by monthly or weekly average (depending on the hydro data resolution) to fit the Bayesian model. Once the Bayesian network representation has been constructed and the new samples created, the resulting monthly or weekly scenario data are disaggregated to hourly resolution by applying a multivariate profile identified using a Mahalanobis distance calculation: The Mahalanobis distances between synthetic scenario data and historical data are calculated, and the week in history with the smallest Mahalanobis distance is identified. The average capacity factor of the renewable generation and demand profiles associated with this specific week are then adjusted to match the generated scenario being disaggregated.

Summary

The major tool functionality capability levels for RA weather uncertainty modeling are outlined in Table 11. The ability to represent correlated inter-annual weather variability (most often through the correlation of weather and load timeseries) is a capability that is available across all tool functionality levels, as it is essential to any probabilistic RA analysis. At level I, this capability may have certain limitations, either in the number or types of timeseries that can be correlated, or the ease-of-use for implementation. At level II, this functionality is available without major limitations. Finally, tools at level III can incorporate correlated weather variability without any major limitations, while also having the ability to model short-term forecast errors, often through the use of a multi-pass optimization algorithm. Note that the ability to directly model long-term climate or economic trends and create synthetic weather shapes, while advantageous for certain use cases, isn't listed at any tool functionality level, because this can be incorporated on the front-end of any RA analysis, and as such doesn't necessarily require in-tool functionality.

Many of the tools surveyed as part of this initiative are either at level II or level III for the weather uncertainty functionality. However, as the historical records of load and weather data that are being considered in RA analyses are longer than ever before, there is a need for tools to handle this large amount of meteorological data in a way that is both efficient and intuitive. The computational tractability component of weather data consideration wasn't evaluated as part of this initiative but should nonetheless be considered by practitioners when selecting their analysis tool.

Table 11. Tool functionality levels for weather uncertainty modeling

Tool Functionality	Level I	Level II	Level III
Weather uncertainty	Correlated inter-annual weather variability, but may contain limitations on the types or number of profiles, and may require an external script to run	Fully correlated inter-annual weather variability with no limitations directly incorporated within the core tool framework	Fully correlated inter-annual weather variability with no limitations directly incorporated within the core tool framework and ability to model short-term forecast error

8 TRANSMISSION

Transmission Topology

Transmission system representations are generally split into three categories, illustrated in Figure 8: nodal (or power transfer distribution factor-constrained), zonal (also known as "pipe-and-bubble" representation), and copper sheet (no transmission constraints considered). All tools evaluated have the capability for copper sheet and zonal transmission modeling, and a significant amount also allow for nodal transmission modeling. It is worth noting that a nodal transmission model, which contains data for every bus on the system, is much more computationally intensive than a zonal transmission model. As such, it is not often used in probabilistic RA analyses. It is, however, standard practice for production cost models, and as such, many of the tools evaluated, which were initially designed for production cost modeling, allow for this functionality. At least one tool evaluated has the capability to automatically convert a nodal model to a zonal model: This functionality calculates the interface ratings between zones based on the nodal system information provided. This allows the user to easily choose the transmission system representation which is most applicable to the study they are running. Allowing joint import/export limits to be modeled is useful for models in which a zone is connected to several other zones, and for which total imports or exports out of it are constrained. About three quarters of the tools surveyed allow for this functionality.

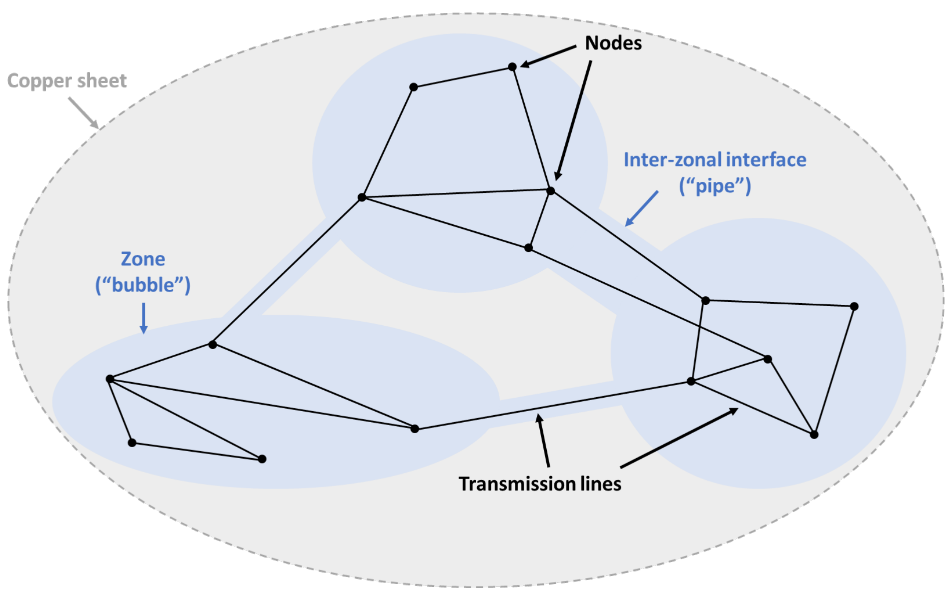

Figure 8. Illustration of transmission system topology modeling options

Transmission Outages

Generally, if transmission outages are represented in a tool, the functionality available and outage modeling methodology used is similar to that available for generator outages. Note that in some zonal transmission models, transmission interfaces between zones defined as an aggregation of transmission lines are represented through a single limit. As such, in these models, the ability to model several partial outage derate levels with associated probabilities of likelihood on the transmission interface is particularly important.

Transmission Limits

At the most basic analysis level, transmission limits (whether at a line level or an interface level) are fixed and non-varying in time. Many tools evaluated have additional functionality which allows for time-varying transmission limits to be enforced. These limits can be enforced by season, by month, by week, by time of day, or varied for every time interval modeled in the study. Note that not all tools allow for full flexibility of time-varying functionality (for example, some only allow for transmission limits to be varied monthly). Several tools evaluated have the functionality to directly link transmission interface limits to several key system variables. This functionality is useful if wanting to link transmission interface limits to temperature, area load, or online generators, or to reflect the impact of dynamic line ratings or voltage stability constraints on the system, for example. If this functionality isn't available, users may use time-varying limits as a workaround, but this can be challenging when the variables being linked are scenario dependent (for example, it is possible to use hourly time-varying limits to model the impact of temperature on transmission limits, but this would require running each weather year scenario independently and combining them in post-processing).

Summary

The major tool functionality capability levels for transmission modeling are outlined in Table 12. At level I, zonal transmission interfaces are represented, but transmission limits can only be varied seasonally, and transmission outages can't be directly modeled. At level II, full or partial transmission outages can be represented, and transmission limits can be varied for every timestep of the study period, allowing for the impact of extreme weather events on transmission interface limits to be accounted for in RA analyses. At level III, both transmission outages and transmission limits can be varied for every timestep of the study period, and transmission limits can additionally be linked to key variables, allowing for the impact of extreme weather conditions to be more easily represented, and allowing for voltage stability impacts to be accounted for.

Note that transmission outage methodologies aren't reviewed here in the same level of detail as they were for generator outages. This is partly because outage methodologies are similar across resource types within a tool, and partly because robust outage modeling methodologies are somewhat less important for transmission modeling than they are for thermal generator modeling. Users with concerns about RA being insufficient in certain pockets of their system may need to consider these issues in detail, but at present many regions consider these at a more basic level, and the tool capabilities reflect this. As locational issues become more important with increased transmission needs for decarbonization, it may become more important to represent transmission in a more detailed manner.

Many of the tools surveyed as part of this initiative have some characteristics of the level I and level II functionality levels detailed above: Although many can model some form of transmission outages and time-varying representation of transmission limits, the ability to vary transmission limits for every timestep of the study period is less common.

Table 12. Tool functionality levels for transmission modeling

Tool Functionality	Level I	Level II	Level III
Transmission	Zonal transmission interfaces are represented, but transmission limits can only be varied seasonally, and no transmission outage modeling functionality is available.	Zonal transmission interfaces are represented, with the availability to model full or partial transmission outages. Transmission limits can be varied for every timestep of the study period.	Zonal transmission interfaces are represented, with the availability to model full or partial transmission outages which can be varied for every timestep of the study period. Transmission limits can be varied for every timestep of the study period or linked to key variables.

9 ENERGY STORAGE

Energy storage resource penetration is rapidly increasing in many regions, and one of the key reasons it is added is to support RA—as such, accurate assessment of storage in adequacy assessment is likely to be important to many studies. Global installed storage capacity is projected to increase 15-fold, from 27 GW (56 GWh) in 2021 to 411 GW (1194 GWh) in 2030 [8]. Battery energy storage systems will make up the bulk of these new installations, and as such are the primary focus of this section.

Basic Storage Model Description

Most tools surveyed use some form of the energy reservoir model (ERM) to model energy storage. This means that each unit can be modeled with a specified energy capacity, power capacity, and roundtrip efficiency. Each unit can charge by consuming energy from the grid, at a rate less than or equal to its power capacity. This consumption is recorded as the stored energy within the unit and can continue until the energy capacity is reached. The unit is also able to provide energy to the grid at a rate constrained by its power capacity, until the stored energy is depleted. The ERM is discussed further in the technologies and system components modeling guidelines [2] developed as part of this initiative.

Another method used by tools to represent energy storage involves combining other unit types via the use of custom constraints. One method involves linking a generator and load source together and operating their behavior simultaneously. For example, one tool uses a pair of virtual nodes connected to the grid via one-way lines. One node act as a virtual load with zero VOLL, while the other acts as a virtual generation unit with zero cost. Flow on the two lines is bound by daily or weekly constraints, as well as with weightings to account for losses.

Alternatively, one of the tools surveyed represents storage similarly to thermal plant models. By not accounting for energy capacity, this modeling method essentially assumes that storage duration and initial state-of-charge is adequate to respond for the full duration of an adequacy event. Although this assumption may be suitable under certain conditions, it is likely to fall short in future systems where potential events are longer duration or are close enough together that storage units won't have time to fully recharge in between events. Case studies carried out during the overall initiative pointed to energy storage limits as a driving factor of risk in future years [9] [10].

These storage models are used by the tools to represent all forms of short duration energy storage. Many tools don't develop separate models for long duration energy storage, with the exception of pumped hydroelectric storage, which is discussed further in Chapter 10.

Storage Model Features

The vast majority of the tools included in the survey are capable of modeling roundtrip storage efficiency. Storage efficiency is modeled in most tools by applying a flat percentage reduction to the quantity of power consumed and discharged.

Some tools specify a difference between charging/discharging efficiency and ‘carry-over’ or ‘self-discharge’ efficiency. This explicitly accounts for the loss of energy which can occur while in storage. This functionality is particularly useful for systems in which storage which is dispatched infrequently and thus remains charged for extended periods of time, as well as for modeling storage assets that experience substantial amounts of self-discharge, such as thermal storage.

As most tools are using the ERM model, they continuously monitor the energy being utilized in the storage asset, referred to as state of charge (SOC). Once the remaining stored energy is depleted (or in some cases reaches a certain threshold), the unit will be considered empty, and be unavailable to provide power to the system until recharged. However, some tools do not continuously monitor SOC. For example, one tool only investigates storage behavior during time periods that experience loss of load. This tool uses the assumption that all storage will be full prior to the event, with storage only dispatched for reliability purposes. SOC is only monitored for the duration of the event. This approach reduces simulation times; however, it could fail to capture so called “energy charge constrained” adequacy events, defined as events where storage can't appropriately respond to an event because it didn't have time in between events to fully recharge [9].

Although almost all real-world storage installations will experience outages, not all RA tools possess the capability to represent this attribute for storage resources. As discussed in [2], length, extent, and duration of storage outages often differs from that of other resources. It was noted in conversations with tool providers that this lack of functionality is partly due to a lack of energy storage outage data for practitioners to use: As such, this implementation has not ranked very high on some tool providers’ priority list, even though it may be relatively straightforward to implement if data were available.

Energy Storage Dispatch Objectives

Storage discharging, or dispatch, is governed by dispatch objectives, in line with the tool’s overall dispatch algorithm. The three main categories of dispatch objectives are economics, reliability, and peak shaving. Peak shaving refers to restricting dispatch of storage to times of peak demand. Depending on the tool this will either be pure consumer demand (gross demand) or will be the remaining demand to be fulfilled by the grid after variable renewable generation is subtracted (net demand). Economic optimization objectives include dispatching to minimize total system cost or dispatching to maximize unit profit (arbitrage). Reliability dispatching is a heuristics-based approach that typically refers to restricting all storage discharge to hours that would otherwise experience loss of load, and charging the storage unit as soon as the reliability event is over. In some tools, reliability objectives can be constrained further to minimize specific RA metrics, such as LOLH, LOLEv, or EUE. A number of tools use economic optimization objectives to determine their generation dispatch yet want to ensure storage is also dispatched during reliability events. These tools incorporate a high value of lost load (VoLL) into their models, which ensures that units are dispatched economically, while still minimizing reliability events.

As discussed in [2], many storage installations are dispatched for multiple purposes in actual operations. In order to represent this, some tools use heuristics such as allocating a certain proportion of capacity to each dispatch purpose. For example, one tool will allow some portion to be modeled as peak shaving, with the rest reserved in case of loss of load. If this functionality isn't available for a certain tool, a resource could be modeled as two separate sub-units to mimic a similar effect. Alternatively, some tools allow for multi-purpose dispatch objectives, which often allow for a better representation of actual system behaviors. For example, two tools surveyed use two passes of dispatch optimization, with the first pass minimizing total system cost, and the second pass adjusting the storage dispatch schedule to minimize reliability events. This is often in line with operational practice, in which energy storage dispatch schedule would be adjusted in the case of a system emergency. Although two tools implement this feature, there are slight nuances in the implementation from one to the other. One tool only allows for storage to be re-dispatched in the second pass if it contains enough available energy at the time of the reliability event, while another tool adjusts the pre-event charging schedule to ensure reliability events were mitigated. Although operators often have some level of foresight into times of system stress, the second approach could at times over-optimize storage response.

For tools dispatched using optimization objectives rather than heuristics, the length of the period over which storage operation is optimized, known as optimization window, can dramatically affect the behavior of storage resources, and the resulting RA metrics. Further discussion of different optimization window lengths can be found in [2]. RA studies that consider multiple different types of storage resources may wish to compare the effects of different optimization window lengths. Therefore, the flexibility provided by a tool in choosing optimization window is of particular importance to practitioners.

Finally, some tools have the capability to apply additional constraints to storage charging. Possible constraints include restricting charging to periods with surplus renewable generation, or periods with sufficiently low system marginal cost, as well as ensuring that charging is only scheduled for periods with sufficient surplus generation (after reserves requirements are met). One tool surveyed even allows for the priority order of charging individual units to be modeled.

Hybrid Resource Modeling

Hybrid resources are resources which provide both generation and storage capacity to the grid. Largely consisting of renewable generation sources paired with collocated storage, these resources allow for variable generation to be stored and used at a later point in time where it will be more valuable to the grid and allow excess generation to be captured for later use rather than spilled.

Hybrid systems can be either AC-coupled or DC-coupled, with DC-coupled configurations allowing for clipped energy to be used to charge the storage unit [2], as illustrated in Figure 9. In order to model DC-coupled systems, tools must be able to account for multiple different inverter efficiencies, as well as differentiate power flow paths.

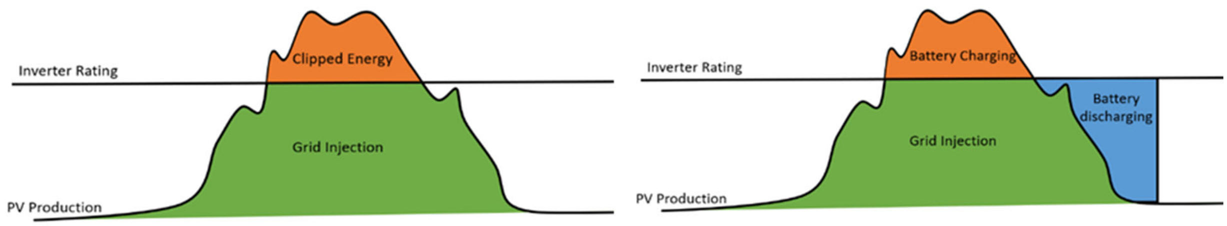

Figure 9. DC-coupled systems have the capability of reducing clipped energy

Various different combinations of generation sources and storage types occur in power systems, and the tools surveyed use a variety of different methods to model hybrid resources. Only a few tools use explicit hybrid models, whereas the majority of tools employ constraints between storage and generation models to link their behavior. Characteristics specific to hybrid resources include coupling type, interconnection limits, and grid charging capabilities.

Of the tools evaluated that use explicit hybrid models, one tool's model consists of a storage capacity that can be 'charged' via two inflows: a time-varying exogenous inflow and a grid withdrawal capacity. This time-varying inflow can either be directly input into the grid or can be stored for later use. One efficiency is applied to the entire resource, as it is modeled as a single unit. Another tool with an explicit model possesses less expansive capabilities: While the storage generator that comprises the hybrid plant can be charged from the associated non-dispatchable energy source, it can't charge from the grid. In this model, the user can specify the capacity of each of the components of the hybrid plant as well as its interconnection limit, allowing for the representation of clipped energy.

Summary

Figure 10 illustrates the options available for the ERM across the tools surveyed as part of this initiative, with text in blue containing advice on when a certain functionality is important to incorporate. Boxes with numbers indicate where there are several options to choose from—other boxes show constraints to consider. Note that not every modeling option will be necessary for every RA analysis—a review of the modeling reference document developed as part of this initiative [2] can help guide this choice.

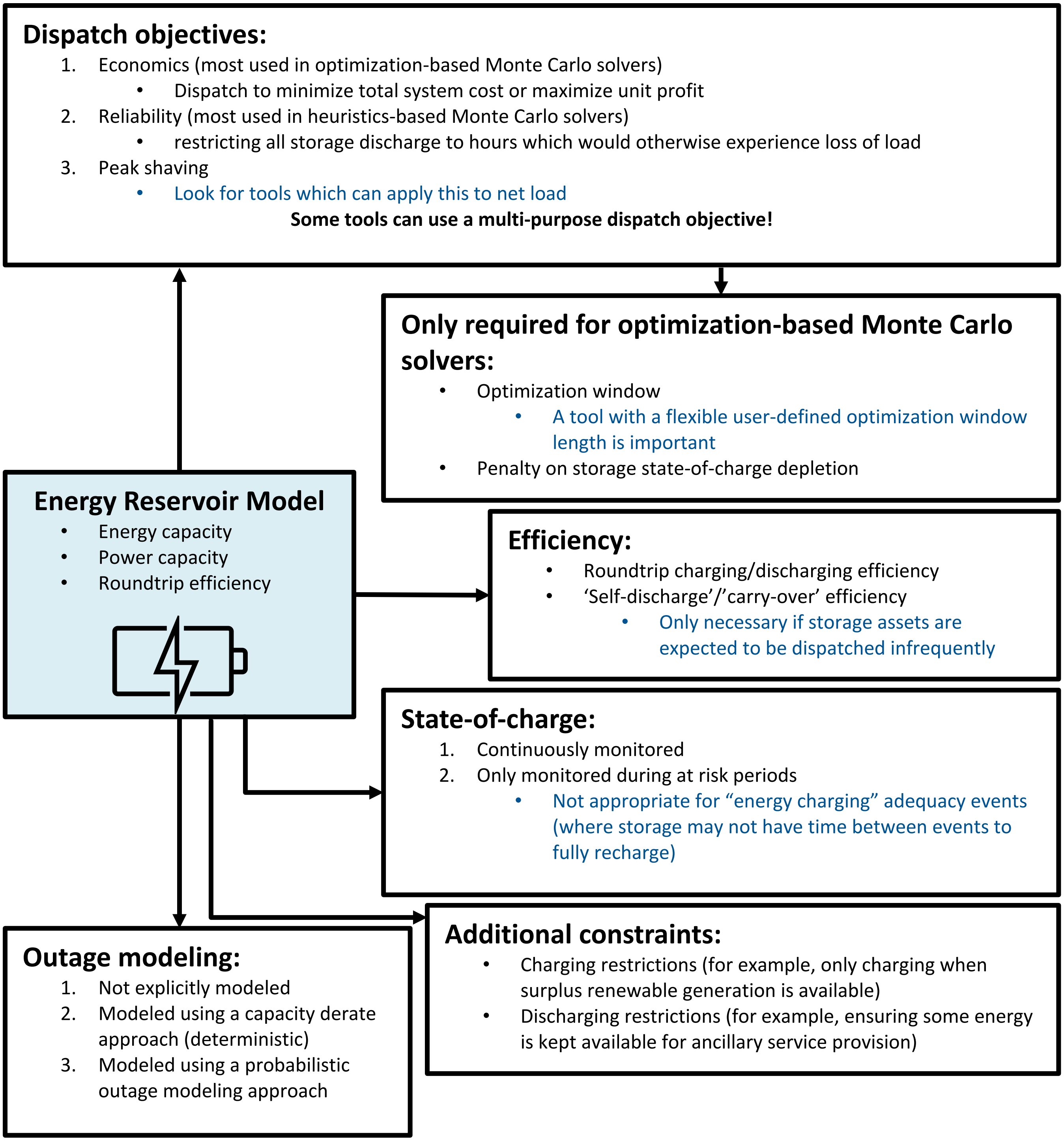

Figure 10. Illustration of options available for the ERM across the tools surveyed

Table 13 summarizes the current tool capability levels for storage and hybrid resource representation. At level I, storage is represented using simplified models such as through a thermal module or with an energy reservoir module which doesn't continuously monitor state-of-charge. At level II, storage is represented with an energy reservoir module which monitors state-of-charge for all hours of the analysis. However, a limited number of dispatch objectives are available at this level. At level III, storage representation is very sophisticated, allowing for characteristics such as carryover efficiency and storage outages to be monitored. At this level, storage representation can be customized, allowing the user to choose from a variety of dispatch objectives and to set the optimization window length.

Hybrid units are a newer resource type, and as such are not represented at all in level I of the tool functionality—instead, they will be modeled as their individual components. Level II of the tool functionality allows for constraints to be created which link the operation of the generation and storage modules, while level III additionally allows for hybrid-specific characteristics such as coupling type, interconnection limits, and grid charging capabilities to be modeled.

As relatively new technologies, short duration storage and hybrid modeling capabilities can vary significantly between tools. However, while a tool may not currently have built-in storage or hybrid modeling, it may have known 'workarounds' allowing storage or hybrids to be represented, or specific modeling capabilities may be available in future updates. An important consideration for realistic energy storage and hybrid resource modeling is to ensure modeling assumptions are consistent across all planning tools and studies conducted, and that they are benchmarked against historical resource behavior, or against a more detailed production cost model, if historical data isn't available.

Table 13. Tool functionality levels for energy storage and hybrid resource modeling

Tool Functionality	Level I	Level II	Level III
Energy storage	Storage is not directly represented, but it is approximated using capacity constrained thermal modules. If represented using an ERM, its SOC is not continuously monitored.	Storage is represented with the ERM, and SOC is monitored for all hours of the analysis. A limited number of dispatching objectives are possible.	Storage is represented using the ERM, and additional storage specific characteristics such as carryover efficiency, or realistic outage rates and repair times are available. The length of the storage optimization window is user-defined, and a variety of dispatching objectives are available, as well as the possibility for multi-purpose dispatch.
Hybrid resources	Hybrid resources are not represented.	Constraints are used to link the operation of generation and storage modules, allowing storage to charge from excess generation.	Constraints link the operation of generation and storage. Storage modules can also charge from the grid. Specific interconnection limits can be specified.

10 HYDROPOWER

All tools included in the survey were capable of representing the three major types of hydroelectric generation: Run-of-River (RoR), Reservoir Hydropower, and Pumped Storage Hydropower (PSH), however implementation methods can vary widely.

A key modeling complexity of systems relying on hydropower is the fact that water flows can connect almost any combination of the three main plant types. When hydroelectric plants are connected, waterflows through one plant affects operations for all connected downstream plants. These connected hydroelectric plant configurations are known as cascading hydropower. Almost half of the tools surveyed as part of this initiative have the ability to evaluate a hydroelectric unit as part of a cascading hydropower system. However, modeling cascading hydro operations is highly data and computationally intensive, and as such should be done only where cascading hydropower plays a key role in RA.

There is also large variation in possible unit modeling resolution across the tools surveyed. Hydroelectric units may be aggregated by the tool by zone, type, or both. While aggregation can increase computational tractability, representation of some hydropower specific characteristics such as cascading waterways may require individual unit modeling. The influence of unit aggregation is discussed further in [10].

Run-of-River Hydropower

RoR generation is often represented as scheduled generation. Typically, these schedules are modeled either as constant outputs, or as time varying outputs based on historical generation data, similar to wind and solar PV. One tool instead uses the unique approach of representing generation as a probability distribution, derived from historical data. This tool does not use a chronological modeling approach, instead using convolution to assess adequacy. Across most tools, RoR hydropower generation is either represented as a must-run zero-cost resource, or added to minimum generation constraints for aggregated reservoir hydropower units within the same zone.

Reservoir Hydropower

Most tools represent reservoir hydropower as a form of energy limited dispatchable generation. These units can be dispatched as needed to meet system demand, however, face additional constraints when compared with other dispatchable resources. Energy constraints are imposed due to the unique characteristics of reservoir resources, such as physical reservoir volume limitations, the uncontrollable nature of inflows, and restrictions due to irrigation, environmental, and recreational needs. Indeed, failure to assign additional constraints beyond capacity constraints to reservoir hydropower units would result in the resources being dispatched until they are empty in each optimization period, due to their zero marginal cost, which is not representative of real-life operations, where the energy would have value. Alternatively, one tool represents reservoir hydropower as a probability distribution, derived from historical data, while another tool models it similarly to a thermal generator (considering only its power constraints, and not its energy constraints), assuming that hydro will be dispatched at its maximum level during reliability events.

Energy constraints governing hydropower dispatch are represented differently from one tool to another, with the main methodologies outlined in Table 14. Tools that utilize heuristics for hydropower dispatching such as to minimize LOLE, or to shave peak load, require constraints such as energy allotments or trajectories, which restrict the amount of generation a resource can provide over a given time period. The usage of allotments or trajectories depends on how each tool represents the reservoir of each unit and is discussed further in [2]. Some tools that utilize economic dispatch, such as those dispatching to minimize system costs, will use constraints such as energy allotments or trajectories, while others will assign a value to the water stored within the reservoir. Known as water value, or the shadow value of hydropower, this represents the opportunity cost of dispatching hydropower at a given time rather than waiting until later. Some tools utilize this so that the 'cost' of hydropower generation can be compared with other forms of generation.

Table 14. Hydropower dispatch constraints

Dispatch constraint	Description	Computational intensity
Energy Allotments	A volume of water is assigned to be dispatched by the unit during a given time period	Low
Energy Trajectories	A target reservoir level is provided for the start and end of each time period	Low
Water-values	Water stored in the reservoir is assigned a value/ cost of dispatch depending on the time of year	Medium
Water value curve	Water stored in the reservoir is assigned a value based on the quantity of water currently in the reservoir	High

In order to determine reservoir hydropower dispatch energy limits, such as allotments, annual flow volumes for a given unit are divided among shorter periods such as months or weeks. The expected water inflow for each period is determined using historical data, the weather conditions of a given simulation, or through user input. This inflow volume provides a 'budget' for the total reservoir volume available for power generation during this period, subject to environmental, operational or policy constraints that affect maximum and minimum reservoir level. Hydropower energy trajectories are similar to energy allotment constraints and are often implemented for systems which record reservoir levels rather than flow volumes.

Tools obtain water curves in three main ways: through user input, via the results of initial deterministic runs, or by dynamically assessing the current reservoir status and hydro forecast. While user input and preprocessed curves will require dramatically less computing power, dynamically generated curves can respond much better to system events, and more closely represent real world hydropower operations.

Possible horizons for dispatched hydropower optimization vary across tools, with the most common options being weekly and monthly. Although shorter time frames can reduce computational intensity, hydro data is typically available at monthly resolution. Interpolating this data to weekly resolution can mask inter-week variability in water supply. Shorter optimization horizons could also be less likely to anticipate future needs, such as upcoming droughts, or periods of high demand. Further discussion of various horizons is available in [2]. As with energy storage modeling, tools that allow for user-defined optimization horizon lengths are preferable to those without this flexibility.

Energy limits can be employed as either hard or soft constraints, with a number of tools allowing for some carryover of unused capacity to the next month, rather than complete utilization. The amount of maximum carryover permitted is constrained by the amount of storage space remaining in the reservoir, and environmental or regulatory constraints. A few tools also have the capability to provide updated budgets closer to dispatch, and accordingly alter resource allocations. These features allow for better reflection of real-life reservoir operation, however, will also increase computational intensity.

A handful of tools evaluated run an in-depth deterministic analysis to set preliminary hydropower profiles, and then allow the hydropower units to deviate from that profile by a certain amount in each of the probabilistic replications to account for short-term uncertainty. In the initial deterministic analysis, forced generator outages are either unaccounted for, or modeled using a simplified fixed derate across all hours of the year, and hydropower dispatch is optimized alongside other system resources: This in-depth optimization is possible for a deterministic run, but would be computationally intensive if done probabilistically.

One of the tools evaluated allows the user to specify an “emergency hydropower” unit class. This type of unit is linked to a reservoir hydropower unit and is assigned both a capacity and energy value upon which the dispatch can draw upon in emergency situations, as well as a payback period during which the dispatched energy must be restored following the emergency event.

Pumped Storage Hydropower

Many of the surveyed tools use a single storage model to represent all types of storage, however some tools either have specific PSH models, or allow for extra constraints to be enacted in order to represent the characteristics of PSH. This can include the ability to specify distinct operating constraints and costs for every pumping and generating unit within a PSH plant. A couple of the tools surveyed also have the ability to incorporate reservoir constraints such as minimum storage level that are variable through time.

Tools using a specific PSH model have the ability to model inflows into the upper or lower reservoir, thus realistically representing open-loop PSH units that use rivers as their source of water. This ability is important for the representation of electrical systems with large cascading hydropower systems, in which the outflows of one hydropower unit feed into another unit.

Summary

The major tool functionality capability levels for hydropower modeling are outlined in Table 15. At level I, hydropower resources can be represented either through a pre-established generation schedule or as energy-limited resources scheduled using heuristics. At level II, reservoir hydropower can additionally be optimized using energy allotments or energy trajectories, with user-defined optimization horizons, and the ability to set either hard or soft constraints. At level III, reservoir hydropower can be optimized using a water values approach (either dynamically assigned or assigned depending on the time of year). Additionally, open-loop PSH systems and cascading hydropower systems can be represented.

Note that not every modeling option will be necessary for every RA analysis—a review of the modeling reference document developed as part of this initiative [2] can help guide this choice. Many of the functionalities listed as level III of the hydropower tool functionality table are computationally intensive, and as such should only be leveraged when doing so would have a measurable impact on study results.

Table 15. Tool functionality levels for hydropower modeling

Tool Functionality	Level I	Level II	Level III
Hydropower	Hydropower resources can be represented either through a pre-established generation schedule, or as energy-limited resources scheduled using heuristics. Open-loop PSH systems and cascading hydropower impacts are not represented.	Hydropower resources can be represented either through a pre-established generation schedule, or as energy-limited resources scheduled using heuristics or optimized using energy allotments or energy trajectories. Dispatch optimization horizons are user-defined, and energy limitations can be represented as either hard or soft constraints, depending on user choice. Open-loop PSH systems and cascading hydropower impacts are not represented.	Hydropower resources can be represented either through a pre-established generation schedule, or as energy-limited resources scheduled using heuristics or optimized using energy allotments, energy trajectories, or water values. Dispatch optimization horizons are user-defined, and energy limitations can be represented as either hard or soft constraints, depending on user choice. Open-loop PSH systems can be represented, and important cascading hydropower impacts can be modeled.

11 DEMAND RESPONSE

Demand response can be incorporated in various ways into a RA study, as detailed in [2]. While some implementations may require specific tool functionality, others do not: For example, many studies incorporate demand response impacts as part of the regional load curve, which is created in pre-processing.

Models Available

Demand response can be either flexible—meaning load can decrease its consumption in response to price or dispatch signals without a need for deviations from baseline consumption at a later time, or shiftable—meaning load can be reduced during a scarcity or high-priced event but will need to be made up at an earlier or later time.

Flexible demand response is most often represented in RA models and can be modeled as a price-responsive load, or as generation resource. If modeled as price-responsive load, this would require the model to have a dispatch-based solution method rather than a heuristics-based solution method. If modeled as a generation resource, it can either be dispatched at a certain activation price (marginal cost) or dispatched if the system is at risk of a scarcity event. In the latter method, demand response is usually the last resource dispatched by the tool before a loss of load event occurs. Assuming the activation price has been set at a sufficiently high level, it is expected that demand response dispatched based on reliability would yield similar, or even identical, results to dispatch based on economics during high LOLP hours.

If modeled as a shiftable resource (meaning changes in consumption would need to be made up within a certain timeframe), the demand response resource would be modeled very similarly to an energy storage resource but would require the use of additional constraints specifying how quicky the energy payback needed to occur.

Case Study: Demand Response Representation

Six case studies were conducted as part of EPRI's *Resource Adequacy for a Decarbonized Future* initiative using a number of different software tools. Each of these case studies represented demand response slightly differently, as summarized in Table 16. This illustrates the many ways in which demand response is regularly represented from one study to another, and from one tool to another.

Table 16. Demand response representation in each of the *Resource Adequacy for a Decarbonized Future* initiative case studies

Case Study	Demand Response Modeling	Constraints
Texas	3 types of flexible loads were modeled—two as high-priced generators, and one as a price-responsive load	Max capacity (defined monthly or by season depending on the flexible load type)
SPP	Modeled as price responsive loads	Max capacity for varying bid prices
Southeast	Modeled as energy-limited resources	Max capacity (defined monthly) Max daily energy (defined monthly) Day-of-week availability
Northeast	Modeled as emergency resources	Max capacity
MISO	Modeled as emergency resources	Max capacity Hour per day limitations Hour per year limitations Dispatches per year limitations Seasonal availability (summer only or annual)
WECC	None modeled	N/A

Operating Constraints

All of these approaches can rely on a number of operating constraints to represent the limitations of demand response programs, the main categories of which are detailed in the subsections below. Note that some tools have quite a range of operating constraints available while others have none. The constraints can either be directly represented as options available or must be written up by the modeler as custom constraints. As such, there is a great amount of flexibility and nuance as to how they are incorporated from one tool to another. Table 17 illustrates the main demand response constraints available across the RA tools surveyed.

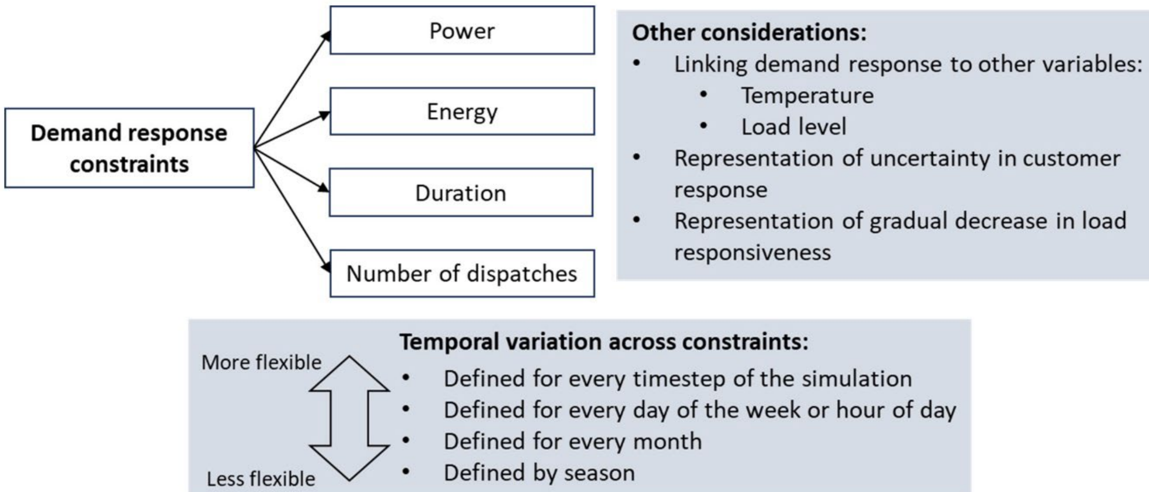

Figure 11. Visual representation of demand response constraints available across tools

Power Constraints

In its simplest form, a power constraint consists of a maximum demand response capacity available. In more advanced implementations, this constraint can be customized to account for the time-varying nature of demand response dispatch availability. For example, critical peak pricing programs may only be active for certain pre-determined hours of the day. This customization can either be implemented through an hourly timeseries input by the user, or can be specified by month, by day (for example, only available on weekdays) and/or by hour of day.

Energy Constraints

This type of constraint is less often employed for demand response programs, but one tool does provide the user with the ability to specify the maximum amount of energy provided by a demand response program, by month or by day. Additionally, the user can specify whether the program allows for excess unused energy to be carried over from one month to another.

Representation of Customer Fatigue

Customer fatigue, or the idea that demand response programs may become less effective if they are called on too frequently or for too long, can be represented in quite a number of different ways from one tool to another. Most tools which have this functionality represent it either as a limit on the duration of demand response calls, or a limit on the number of times for which demand response can be called upon. The limit of the duration of demand response calls is sometimes represented as a maximum duration of an individual demand response call or is represented as a limit on the total number of dispatch hours (per day, week, month, or year) or dispatch days (per week, month, or year). Additionally, one tool surveyed allows for the user to set a limit on the number of consecutive days for which a demand response resource can be called upon.

It is worth noting that in many cases, demand response will not drop off sharply after a certain usage threshold is hit, but rather will taper off gradually. One tool surveyed captures this behavior by allowing the user to specify a derate for demand response efficacy after a certain threshold is hit. Even when a tool lacks this explicit operating limitation option, it may be possible to implement it using a workaround: For example, the user could implement different demand response programs switching off a various usage levels, to simulate a partial derate.

Representation of Uncertainty

At least one tool has the capability of representing uncertainty in price-sensitive load response. In addition to specifying the price at which demand starts to react to market prices, the user can specify an envelope of possible technology response, with the likelihood of responsiveness varying within this envelope.

Linking Customer Response to Other Variables

Demand response is not a uniformly available resource, but rather is dependent on a number of factors. One such factor it may depend on is weather conditions. For example, extreme temperature conditions may reduce the desire of customers to respond to demand response incentives or time-of-use pricing, as maintaining a livable indoor environment will become a principal concern. Additionally, if HVAC systems aren't sized appropriately for extreme temperature conditions, they may be run in continuous operation mode at maximum capacity, with no room for duty-cycling, diminishing the ability of programmable and smart thermostats to provide load reduction services.

None of the tools surveyed allow for the capability to tie demand response to temperature profiles, although one tool did allow for it to be tied to load levels.

The tools evaluated have varying levels of flexibility in terms of the temporal specifications for each of these constraints. Some tools allow for all constraints on their system to be specified at any user-defined timestep, while others are more limited. It should be noted that forecasting customer response to demand response programs is nuanced and system- and situation-dependent. As an active area of research, it is anticipated that additional modeling constraints may be needed in future RA analyses.

Electric Vehicle Representation

Similar to demand response, electric vehicles can be represented in a variety of different ways, which are detailed in [2]. They are often modeled as a load, energy storage, or demand response asset (or some combination of these). From a tool's perspective, available electric vehicle modeling representations echo the demand response and energy storage representations available in each tool.

One tool does have a unique electric vehicle modeling functionality, which includes the availability to specify a curve of arrival (when the vehicles are plugging into the system) and a curve of departure (when the vehicles are plugging out of the system). From there, the user can select from 3 possible behaviors:

- Basic charge (in this behavior, the EVs are treated similar to a traditional load resource and charged as soon as they are plugged in)
- Smart charging (in this behavior, EV charging behavior is optimized, but the model doesn't allow for discharging to support the grid)
- Vehicle-to-grid (in this behavior, EV charging behavior is optimized, and the model allows for discharging to support the grid)

Summary

The major tool functionality capability levels for demand response modeling are outlined in Table 17. At level I, demand response is not directly represented as a separate unit type, but can be represented using other modules, such as pre-processing the load shape, or representing it as an energy storage unit or a negative load unit. At level II, demand response is directly represented in the tool as a flexible resource and allows for the use of a limited number of operating constraints. At level III, demand response can be represented as either a flexible or shiftable resource and allows for the use of a wide range of operating constraints, including the representation of customer fatigue, demand response uncertainty, and the time-varying nature of demand response availability.

Most of the tools evaluated as part of this initiative can be categorized as level II, with some within this category allowing for a wider range of operating constraints than others. While a sophisticated modeling capability of demand response is likely not needed in most short-term and medium-term RA studies, it is becoming increasingly important in long-term adequacy studies, as demand response programs become more widespread and substantial.

Table 17. Tool functionality levels for demand response modeling

Tool Functionality	Level I	Level II	Level III
Demand response	Demand response is not directly represented as a separate unit type, but can be represented using other modules, such as pre-processing the load shape, or representing it as an energy storage unit or a negative load unit.	Demand response can be directly represented in the tool as a flexible resource. A limited number of operating constraints are available.	Demand response can be directly represented in the tool as either a flexible or shiftable resource. A wide range of operating constraints are available, allowing the user to accurately represent customer fatigue, demand response uncertainty, and the time-varying nature of demand response availability.

12 KEY TOOL GAPS

As seen in the rest of this report, there are a variety of capabilities across RA tools surveyed, and many recent issues can be represented (sometimes requiring significant computational runtime or data). However, there are still some significant gaps in the ability to best use the tools for RA assessment. The gaps listed below were primarily identified through discussions with project members as well as through individual user experiences with a number of tools. These were also considered when developing overall gaps for RA assessment, as outlined in the gap assessment summary document developed as part of this initiative [11].

Computational Tractability

Computational tractability is perhaps the largest RA tool gap identified as part of this effort. Indeed, many of the respondents to the EPRI RA tool survey are primarily production cost tools that have been adapted for use in RA analysis. These by their nature require more computational capability. Furthermore, as RA moves beyond capacity adequacy into the consideration of energy and flexibility adequacy, there is a demand for tools with the capability for realistic unit commitment and economic dispatch capabilities, and a level of detailed modeling usually found in deterministic analyses. This comes at a high computational cost, and even if these features are in theory available in many tools, it may not be computationally feasible to include them for large system studies over multiple years.

Additionally, longer historical records of load and weather data are being considered in RA analyses than ever before, due to the increased penetration of variable renewable energy resources in many systems, and due to the outsized impact of extreme weather events on system adequacy. Some of these are being adjusted for present and future climate conditions, adding even more uncertainty and potential scenarios. As such, there is a need for RA tools to be able to handle larger amounts of meteorological data than ever before, and to manage the correlations between weather driven resources efficiently and intuitively.

Ease-of-Use

Another key gap identified as part of this effort is the usability of the various tool functionalities. There are a number of functionalities described here which are in theory implementable in a given tool, but which would require either the utilization of workarounds or pre- or post-processing on the part of the user. A good example of this is the ability to represent temperature-dependent outage rates: a number of tools allow for this functionality, but separate hourly outage rate profiles for each weather year need to be input, with each weather year run separately, and results then combined in post-processing. Another example is the calculation of specialized risk metrics: This often requires the user to download large amounts of data and calculate custom metrics using a post-processing script.

Moreover, RA tools require a high level of training and expertise to set up, run, and debug. This is especially true if utilizing some of the more advanced modeling functionalities highlighted in this report. An intuitive user interface, and an up-to-date, clear user manual allow for a better user experience, and ultimately a more robust RA analysis.

Integration with Other Parts of the Planning Process

RA analysis is only one facet of comprehensive power system planning. A key tool gap identified in discussions with project members is the need to bridge the gap between RA tools and production cost, network analysis and capacity expansion tools. Additionally, the ability to integrate gas-electric system modeling in RA considerations was also identified as a key missing functionality.

A number of the tools evaluated as part of this initiative do allow for use across a number of these planning processes, in particular across RA analysis, capacity expansion planning, and production cost modeling. This is particularly important as it allows companies to use the same software and the same database across various parts of their long-term planning process, allowing for increased consistency and efficiency.

However, directly combining these analyses, while mathematically possible, would result in major computational tractability issues. As such, tools must ensure a seamless transition from one process to the next and should have automation capabilities in place to allow users to easily use the full suite of capabilities. For example, a useful tool functionality would be the automation of the round-trip analysis required for a capacity expansion buildout which optimizes economic efficiency while also guaranteeing a consistent reliability output.

Transparency

Transparency is another key gap identified as part of this analysis. RA analysis, and thus by extension RA tools, are by nature complex. It can be challenging as a user to navigate the RA tool landscape to truly understand the individual tool capabilities available. There is often limited information available online, and a lot of nuances in terms of how the same functionality is implemented from one tool to another.

Moreover, as the value of interregional coordination for the assessment of RA is increasingly recognized, there is an increased need for interoperability and common structures and models amongst RA tools. This need is well illustrated in the European Resource Adequacy Assessment developed by ENTSO-E. Increased transparency and increased consensus amongst RA tool providers would allow for better consistency from one study to the next and would allow for a more straightforward comparison of RA analysis results from one region to another.

Data Availability

Although not a tool gap per se, the lack of data availability is in many instances driving a lack of tool development in certain areas. Indeed, if a user doesn’t have the data necessary to implement a certain feature, they won’t request this functionality from their tool provider. This chicken-and-egg problem is driving some of the lack of tool development: Often, a tool capability isn’t prioritized because there is either a lack of data or no process in place for it, but at times the data or processes aren’t being developed due to lacking tool capability. Ensuring that tool providers continue to be an integral part of RA research will enable them to play a key role in new methodological developments, rather than being reactive to change.

13 CONCLUSIONS

A tabulated summary of tool capabilities by level of fidelity is provided in Table 18. This table summarizes the tool functionality level tables provided for each section of the report.

Table 18. Summary of fidelity levels for all tool functionalities reviewed

Tool Functionality	Level I	Level II	Level III
Analysis approaches	The solution method allows for the evaluation of probabilistic adequacy risk but has key limitations when it comes to the representation of inter-regional flows and/or the representation of the intertemporal nature of energy limited resources.	The solution method allows for a fully chronological evaluation of probabilistic adequacy risk and has the ability to evaluate multi-area adequacy.	The solution method allows for a fully chronological evaluation of probabilistic adequacy risk, while also allowing for temporal unit operational limitations such as minimum up/down time and ramping constraints to be considered. Numerous runtime improvements have been implemented to ensure computational tractability.
Metrics output	The tool outputs standard risk metrics like LOLE, LOLH, and EUE for both the full system and for each region modeled.	The tool outputs standard risk metrics like LOLE, LOLH, and EUE for both the full system and for each region modeled. Additionally, it can output replication-level results to allow the user to calculate custom metrics.	The tool automatically outputs both standard risk metrics and custom advanced risk metrics defined by the user (for example: LOLE95) for both the full system and for each region modeled. In addition to outputting replication-level results, tools in this category can output results at various levels of granularity (temporal, by weather year, etc.).

Table 18 (continued). Summary of fidelity levels for all tool functionalities reviewed

Tool Functionality	Level I	Level II	Level III
Forced generator outages	Only allows for fixed or seasonal generator outages to be defined. Allows for either no or only limited modeling of partial generator outages. Uses either an outage rate probability methodology, or a Markov-based chronological outage modeling methodology or similar (exponential, Weibull, or non-parametric distribution). Doesn't allow for start-up failure or coincident outages to be modeled.	Allows for the modeling of either full or partial generator outages that can be varied for every timestep of the analysis. Uses a Markov-based chronological outage modeling methodology or similar (exponential, Weibull, or non-parametric distribution). Allows for start-up failure and coincident outages to be modeled.	Allows for the modeling of either full or partial generator outages which can either be varied for every timestep of the analysis or can be directly linked to key variables such as temperature. Uses a multi-state Markov transition matrix forced outage modeling methodology. Allows for condition-based start-up failure and coincident outages to be modeled.
Maintenance generator outages	Allows for maintenance to be scheduled for specific dates.	Allows for heuristic maintenance schedules, or for maintenance to be scheduled for specific dates.	Allows for maintenance to either be scheduled for specific dates or to be optimized with imperfect foresight— for example, allowing for a single optimization across an average weather year.
Weather uncertainty	Correlated inter-annual weather variability, but may contain limitations on the types or number of profiles, and may require an external script to run	Fully correlated inter-annual weather variability with no limitations directly incorporated within the core tool framework	Fully correlated inter-annual weather variability with no limitations directly incorporated within the core tool framework and ability to model short-term forecast error

Table 18 (continued). Summary of fidelity levels for all tool functionalities reviewed

Tool Functionality	Level I	Level II	Level III
Transmission	Zonal transmission interfaces are represented, but transmission limits can only be varied seasonally, and no transmission outage modeling functionality is available.	Zonal transmission interfaces are represented, with the availability to model full or partial transmission outages. Transmission limits can be varied for every timestep of the study period.	Zonal transmission interfaces are represented, with the availability to model full or partial transmission outages which can be varied for every timestep of the study period. Transmission limits can be varied for every timestep of the study period or linked to key variables.
Energy storage	Storage is not directly represented, but it is approximated using capacity constrained thermal modules. If represented using an ERM, its SOC is not continuously monitored.	Storage is represented with the ERM, and SOC is monitored for all hours of the analysis. A limited number of dispatching objectives are possible.	Storage is represented using the ERM, and additional storage specific characteristics such as carryover efficiency, or realistic outage rates and repair times are available. The length of the storage optimization window is user-defined, and a variety of dispatching objectives are available, as well as the possibility for multi-purpose dispatch.
Hybrid resources	Hybrid resources are not represented.	Constraints are used to link the operation of generation and storage modules, allowing storage to charge from excess generation.	Constraints link the operation of generation and storage. Storage modules can also charge from the grid. Specific interconnection limits can be specified.

Table 18 (continued). Summary of fidelity levels for all tool functionalities reviewed

Tool Functionality	Level I	Level II	Level III
Hydropower	Hydropower resources can be represented either through a pre-established generation schedule, or as energy-limited resources scheduled using heuristics. Open-loop PSH systems and cascading hydropower impacts are not represented.	Hydropower resources can be represented either through a pre-established generation schedule, or as energy-limited resources scheduled using heuristics or optimized using energy allotments or energy trajectories. Dispatch optimization horizons are user-defined, and energy limitations can be represented as either hard or soft constraints, depending on user choice. Open-loop PSH systems and cascading hydropower impacts are not represented.	Hydropower resources can be represented either through a pre-established generation schedule, or as energy-limited resources scheduled using heuristics or optimized using energy allotments, energy trajectories, or water values. Dispatch optimization horizons are user-defined, and energy limitations can be represented as either hard or soft constraints, depending on user choice. Open-loop PSH systems can be represented, and important cascading hydropower impacts can be modeled.
Demand response	Demand response is not directly represented as a separate unit type, but can be represented using other modules, such as pre-processing the load shape, or representing it as an energy storage unit or a negative load unit.	Demand response can be directly represented in the tool as a flexible resource. A limited number of operating constraints are available.	Demand response can be directly represented in the tool as either a flexible or shiftable resource. A wide range of operating constraints are available, allowing the user to accurately represent customer fatigue, demand response uncertainty, and the time-varying nature of demand response availability.

The large number of tool providers who took the time to respond to the request for information put out by the EPRI team and answer the team's subsequent questions is a testament to the potential for collaboration within the RA research space. Additionally, the EPRI team was encouraged by the number of respondents with advanced modeling capabilities across a number of the tool functionalities evaluated. Note that a case could be made for the use of a framework/toolset that focuses more on core capabilities for adequacy assessment, and less on the aspects related to data input and post processing. While this approach would require users or vendors to develop pre- and post-processing methods outside of the main tool framework, it would allow some of the data input and post processing functions to be independent of core capabilities, and advances made in one area not be tied to the others—for example, allowing for improved weather modeling that could be leveraged by any well-functioning adequacy assessment tool, rather than needing to change tools to a lower performing adequacy assessment tool for the sake of better weather data.

It should be noted that many of the tool respondents provide tools which are used for both RA and production cost analysis. As such, although certain features are in theory available to users, they aren't being implemented due to challenges with data availability, ease of implementation and computational runtime. Additionally, although every effort was made to accurately represent the state of the RA tool space to date, fully understanding the inner workings of each tool would have taken significantly longer than the length of this work, while also being challenged by the fact that the tools themselves are evolving, in some cases due to the very questions being asked in this initiative.

EPRI plans to continue surveying and understanding tool capabilities and readers are encouraged to contact the project team to further discuss this. Subsequent tool evaluation work should consider not only the functionalities available for each tool, but also their ease of use and computational cost, and should enforce a clearer boundary between RA and production cost analysis capabilities. A key recommendation for tool providers, especially those well-established in the production cost modeling space but newer to the RA space, is to allow the user the capability to easily toggle between less computationally expensive screening analyses and more accurate but computationally expensive analyses.

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For more information, contact:

EPRI Customer Assistance Center
800.313.3774 • askepri@epri.com

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EPRI

3420 Hillview Avenue, Palo Alto, California 94304-1338 USA • 650.855.2121 • **www.epri.com**