EPRI

Resource Adequacy For a Decarbonized Future

2023 TECHNICAL REPORT

Modeling New and Existing Technologies and System Components in Resource Adequacy

EPRI Resource Adequacy Assessment Framework

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ABSTRACT

The focus of this report is to provide practitioners with information regarding the breadth of options available to model conventional and emerging technologies in resource adequacy. This report is intended to be used as a reference document by practitioners for how to incorporate existing or new resource types into the resource adequacy assessment process. The document is intended to guide the practitioner towards the relevant set of options available, along with information that may be relevant to the selection of one modeling approach or another. The modeling of utility-scale resources, demand-side and customer-scale resources, networks, and other energy carriers is addressed in this report.

Keywords

Resource adequacy
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EXECUTIVE SUMMARY

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KEY RESEARCH QUESTION

This report is intended to be used as a reference document by practitioners for how to incorporate existing or new resource types into the resource adequacy assessment process. The document is intended to guide the practitioner towards the relevant set of options available, along with information that may be relevant to the selection of one modeling approach or another.

RESEARCH OVERVIEW

This report investigates available modeling options for a range of relevant system components and technologies and categorizes them by level of modeling fidelity. Recommendations are put forward for system planners regarding which modeling option may be most appropriate under different circumstances. Three levels of modeling fidelity, ranging from low to high fidelity, are proposed. Level I fidelity modeling, presenting the lowest fidelity options, is generally suitable for low technology shares coupled with low system reliance on the system component to meet adequacy standards. Level III fidelity modeling ensures the highest accuracy when capturing component characteristics and operations. These are generally more computational and data intensive than lower fidelity models, however, they may need to be considered for systems with high reliance on a particular system component to meet adequacy standards.

WHY THIS MATTERS

The choice of model representing the operations of a given system component or technology can have significant implications on resource adequacy. Modeling simplifications when it comes to key technologies for system adequacy may result in underestimating system risk or, on the other hand, overestimating it and sending signals for investment that are too conservative. Similarly, complex modeling options may result in increased efforts and cost of data collection and computation. It is essential for planners to understand the range of modeling options available for different system components and to be able to match them to their specific system needs.

LEARNING AND ENGAGEMENT OPPORTUNITIES

- It is intended that this document will be updated as practices evolve and processes or technologies are added.
- Model choice is not independent of tool selection, data availability, and other real-world constraints which cannot be reflected in a single rubric. EPRI's Resource Adequacy for a Decarbonized Future Initiative has a set of related documents that could be of interest to readers of this report, including information on RA Metrics and Criteria, Guidelines for Scenario Generation, Data Collection, RA Tool Guides, and Gap Assessments. Additionally, case studies and tools for RA practitioners have also been conducted and developed as part of this initiative, that the reader may also be interested in.

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PROGRAM: Bulk System Integration of Renewables and Distributed Energy Resources, P173

ACRONYMS AND ABBREVIATIONS

BESS	Battery Energy Storage System
BTM	Behind the Meter
CAES	Compressed Air Energy Storage
CAISO	California Independent System Operator
CCGT	Combined Cycle Gas Turbine
CHP	Combined Heat and Power
CPUC	California Public Utilities Commission
DC	Direct Current
DER	Distributed Energy Resources
DSF	Demand-Side Flexibility
EFOR	Equivalent Forced Outage Rate
EFORd	Equivalent Forced Outage Rate on Demand
EIA	Energy Information Administration
ELCC	Effective Load Carrying Capability
ENTSOE	European Network of Transmission System Operators for Electricity
ERAA	European Resource Adequacy Assessment
ES	Energy Storage
EUE	Expected Unserved Energy
EV	Electric Vehicle
GADS	Generator Availability Data System
GATS	Generation Attribute Tracking System
HRSG	Heat Recovery Steam Generator
HVDC	High Voltage Direct Current
ICAP	Installed Capacity
ILR	Inverter Loading Ratio
IRA	Inflation Reduction Act
IRP	Integrated Resource Plan
ISO	Independent System Operator
ISO-NE	ISO New England
MCMC	Monte Carlo Markov Chain
MISO	Midcontinent Independent System Operator
NEM	Net-Energy Metering

NERC	North American Electric Reliability Corporation
NYISO	New York Independent System Operator
LNG	Liquified Natural Gas
LOLE	Loss of Load Expectation
LOLH	Loss of Load Hours
O&M	Operation and Maintenance
PEM	Polymer Electrolyte Membrane
PRM	Planning Reserve Margin
PSH	Pumped Storage Hydro
RA	Resource Adequacy
RoR	Run-of-River
SEI	Solid Electrolyte Interphase
SOC	State of Charge
SOEC	Solid Oxide Electrolyzer Cell
TOU	Time-of-Use
TSO	Transmission System Operator
UCAP	Unforced Capacity
UCED	Unit Commitment & Economic Dispatch
V2G	Vehicle to Grid
VRE	Variable Renewable Energy
WECC	Western Electricity Coordinating Council

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1 INTRODUCTION

1.1 A Recipe for Resource Adequacy

The resource adequacy (RA) problem can be defined as assessing whether a resource mix has a high probability of meeting customer demand at any moment, accounting for uncertainty in both supply and demand. The main factors influencing adequacy at any given moment in time are resource availability and demand, however, developing (efficient) models capturing their real-life behavior, under a wide range of possible economic and weather scenarios, is not a straightforward task.

Figure 1 shows a simplified schematic categorizing the main components of the resource adequacy problem. The focus of this report is on Technology and System Component Models.

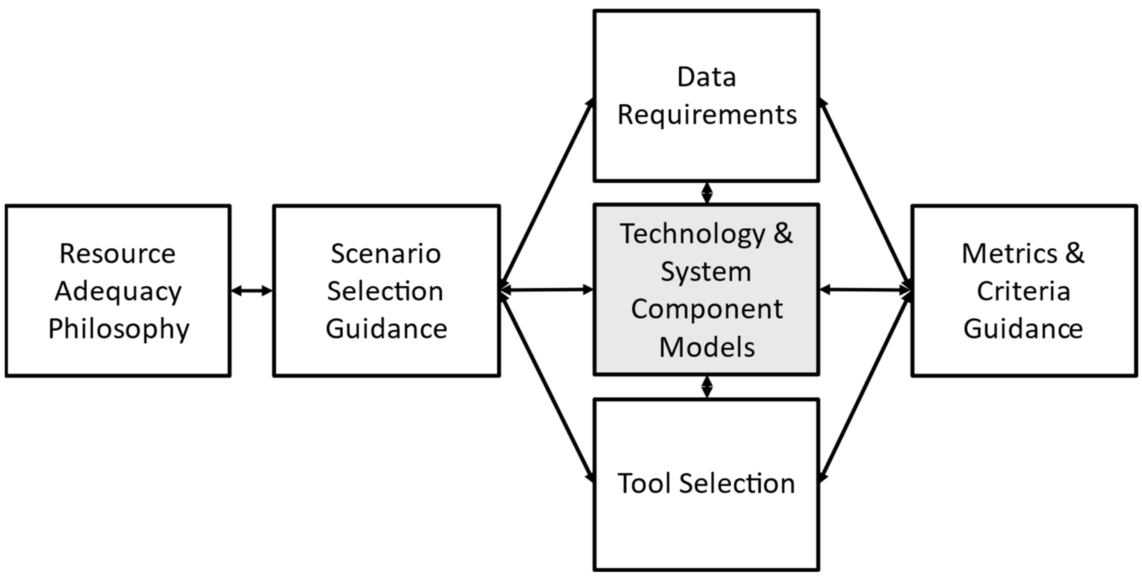


Figure 1. Simplified resource adequacy component schematic. This report will focus on *Technology and System Component Models*.

The arrows connecting the different RA components of an integrated assessment approach in Figure 1 are all bi-directional, illustrating their inter-dependency. For example, collected data dictates which technology models can be applied but also, if the need for a particular technology model appears, this will influence data collection guidelines. Collected data also constrains the selection of demand, weather, renewable energy generation, and outage scenarios tested, and vice versa.

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

(LOLH). Resource adequacy assessments are also 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 exist a set of traditional approaches employed for each of the RA components presented in Figure 1. However, recent supply deficiency events suggest that these traditional approaches to resource adequacy may underperform in the context of a changing climate, changing resource mixes, and extreme weather scenarios. After the August 2020 rolling blackouts in California, CAISO's retiring president and CEO stated the need to rethink the way adequacy assessments are run and systems planned [1].

An analysis detailing how the different components that make up resource adequacy (see Figure 1) need to develop to adapt to evolving power systems is presented in [2]. The authors argue that evolving power systems require new data, models, tools, methods, and metrics to address the adequacy problem, particularly as the shares of weather-sensitive generation increase in a world with a changing climate. The authors outline the need to collect as much hourly chronological weather, demand, and outage data as possible but also to assess whether historical data is sufficient for generating scenarios capturing climate change. The report also points out that modeling generator outages as independent events may have been appropriate in the past, however, forward-looking resource adequacy assessments will require scenarios capturing correlated, or common-cause outages. The need for chronological, 8760-hour modeling tools is also suggested in the report. Looking only at peak periods not only fails to adequately capture the operation of energy-limited resources, such as energy storage and demand flexibility, but also, peak periods may no longer be the higher periods of risk in future power systems, but rather those periods with sustained and coincident low wind and solar outputs.

Finally, a growing body of work is advocating relying on more than a single adequacy risk metric. Literature shows that reliance on a single metric may conceal important aspects of system risk. Using a combination of metrics evaluating different aspects of system risk such as loss of load frequency, duration, and magnitude is recommended. Furthermore, existing literature recommends that existing metrics be better leveraged by evaluating their distribution rather than focusing on averaged results [2] [3]. The 2020 California events and 2021 Texas events suggest that it may be particularly helpful to pay closer attention to outlier and tail events, which can have a disproportionately large impact on the power system.

Work addressing challenges across all components of the resource adequacy problem has been conducted under EPRI's *Resource Adequacy for a Decarbonized Future* initiative.[1] A summary of the initiative's deliverables can be found in Table 23.

[1] https://www.epri.com/resource-adequacy

1.2 Focus on Technology and System Component Models

This report focuses on understanding the breadth of options available to model conventional and emerging technologies in resource adequacy. This can be read in the context of the other reports from the initiative, to provide a holistic view of adequacy assessment.

In this context, the term *technology and component model* refers to the way in which the characteristics of different generation technologies and other system components (i.e., storage, flexible demand, and networks) are represented within adequacy assessments. The operational decisions involving these component models are typically made by operations planners and system operators, from several days in advance to real time, and include maintenance scheduling, unit commitments, and energy dispatch. Note that this focus on the model for different technologies is separate from how resource capacity is accredited. Accreditation analyses look at *how much a given amount of a given resource contributes to meeting adequacy requirements*, whereas the focus of this document is on *how to model those resources in the adequacy assessments*. Capacity accreditation can be carried out based on the system modeling and is best when reflecting an accurate underlying model of the resource type as described here.

Section 2 constitutes the core of the report, where existing modeling approaches, classified by level of fidelity, are discussed for a comprehensive set of technologies and system components. Analyses are presented outlining the implications that different modeling approaches may have on adequacy results. Section 3 summarizes and discusses the findings of this report.

1.3 How to Use This Report

This report is intended to be used as a reference document by practitioners for how to incorporate existing or new resource types within the resource adequacy assessment process. The document is intended to guide the practitioner towards the relevant set of options available along with information that may be relevant to the selection of one modelling approach or another. Model choice is not independent of tool selection, data availability and other real-world constraints which cannot be reflected in a single rubric. It is intended that as practices evolve and processes or technologies are added, this document will be updated in line with current thinking. It thus reflects the current state of knowledge based on an extensive literature review and range of studies in 2022-2023.

2 REFERENCE MODELS FOR NEW AND EXISTING TECHNOLOGIES

2.1 Reader's Guide

An overview of the resources and system components addressed in this work is presented in Figure 2. These are divided into utility-scale resources, demand-side and customer-scale resources, networks, and alternative energy carriers.[2]

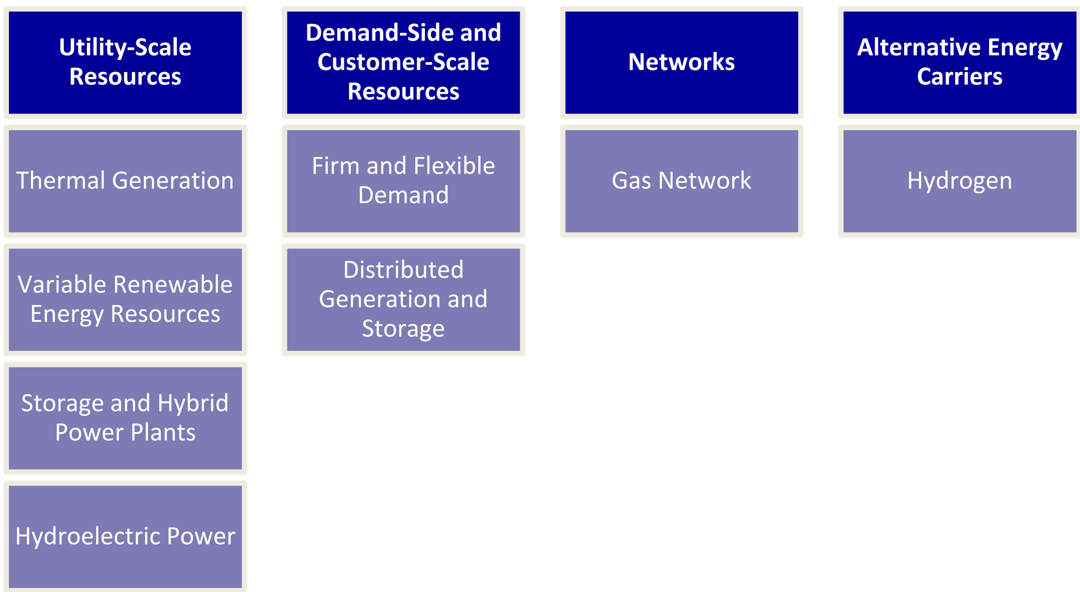


Figure 2. Technologies and system component models addressed in this deliverable.

Each technology and system component in Figure 2 is individually addressed. Each section contains an outline of the key characteristics of each individual technology or system component as well as a review of available modeling approaches, classified by level of fidelity. Recommendations are put forward for system planners regarding which modeling option may be most appropriate under different circumstances.

[2] The alternative energy carriers section focuses specifically on hydrogen, additional technologies could be added to future versions of this document, and existing sections updated with new information.

The different sections may contain ***Case Study Boxes*** as well as ***Info Boxes***.

- **Case Study Boxes** present relevant findings from case studies conducted as part of the EPRI's *Resource Adequacy for a Decarbonized Future* Initiative, as well as other related EPRI work.
- **Info Boxes** provide detailed information to facilitate a deeper understanding of certain key features of a given technology, modeling approach, or other related information that may be relevant to the reader.

2.1.1 Model Fidelity

A tabulated summary of modeling approaches by level of fidelity is provided for each technology and system component addressed in this report. The goal of this approach is to provide a simplified set of modeling options for practitioners. Three levels of modeling fidelity are proposed. A sample table is presented in Table 1. The fidelity level of different modeling approaches is classified as follows:

- **Level I:** these modeling methodologies are generally the least computationally and data intensive. Level I approaches may capture some of the basic characteristics of a given resource but omit others. Level I approaches are generally acceptable for systems that have low levels of reliance on a particular technology, or for cases when capturing a given technology characteristic may not be material to the adequacy assessment results for that system.
- **Level II:** these resource models may be selected when the penetration of a particular technology is relatively high or growing, making it important to capture its expected operations with a greater level of fidelity. However, there may still be computational, tool, or data limitations, limiting the use of higher fidelity approaches. Level II approaches also allow practitioners to capture those technology characteristics that are essential, while employing simpler modeling approaches for those that are less relevant for the system considered.
- **Level III:** these modeling approaches systematically ensure the highest fidelity representation of resource performance. Level III models may be required for systems that heavily rely on a given resource, or when a given resource's characteristics are significantly material to adequacy outcomes. However, they are also the most data and computationally intensive. Level III approaches may not always be needed, or justified, depending on a specific system's characteristics.

Table 1. Considerations for technology models by level of fidelity: sample table.

	Level I	Level II	Level III
Technology or technology characteristic	Most basic model: may be sufficient when system reliance on technology addressed is low.	Mid-fidelity models: may employ advanced modeling techniques for certain aspects of a technology and basic ones for others.	Highest fidelity models: these models will systematically capture technology behavior with the highest level of accuracy compared to Levels I and II and generally employ state-of-the-art modeling approaches.

2.2 Utility-Scale Resources

Bulk generation technologies, built mainly to inject power into the bulk power system are addressed in this section. These generation assets are generally connected to transmission and sub-transmission networks. However, exceptions may be found, particularly with VRE and energy storage.

Despite the growth in demand-side resources, utility-scale technologies continue to play a central role in maintaining adequacy. It is therefore necessary to consider in detail how these are modeled, and how these models should be adapted as power systems evolve.

2.2.1 Thermal Generation

Table 2. Thermal generation modeling by level of fidelity.

	Level I	Level II	Level III
Capacity limits	Maximum generating or contractually declared capacity.	Seasonally adjusted capacity rating or declared capacity for dispatch.	Condition-based capacity rating.
Maintenance modeling	Heuristic maintenance schedules.	Optimized maintenance schedules for long-term assessments. Forecasted maintenance schedules for short or near-term assessments.	Optimized (long-term) or forecasted (short or near-term) maintenance schedules with provisions for delays and recall.
Forced outage modeling	Monte Carlo Markov Chain hourly simulation with seasonally adjusted forced outage rates.	Monte Carlo Markov Chain hourly simulation model with daily condition-based failure rates.	Monte Carlo Markov Chain hourly simulation model incorporating weather dependent/condition-based failure rates by interval.
Failure to start	Not included.	Start failure.	Condition-based start failure.
Energy limits	No model.	Fuel Pool.	Hourly fuel offtake limit and fuel pool.
Flexibility constraints	None.	Minimum generation, minimum up/ down time.	Advanced constraints plus start up, ramp rate.

Background

Thermal resources represent the largest group of generation capacity for most systems and remain likely to provide dispatchable capacity in deeply decarbonized systems into the future. Resource adequacy assessment practices, processes and assessment criteria have been developed around the paradigm of conventional thermal generation resources meeting firm demand. Thermal generation resources are grouped in three main thermodynamic cycle classes: Rankine cycle, Brayton cycle and reciprocating internal combustion engine (RICE). While other classifications schemes (e.g., fuel source) could be considered, plant availability is most impacted by the design of the resource.

Table 3. Summary of main thermodynamic cycle classes.

Cycle	Description	Flexibility	Fuels
Rankine	Steam turbine and boiler or heat recovery steam generator (HRSG)	Lower	Uranium, Coal, Fuel oil, Gas, Waste, Biomass, Peat, Geothermal, Hydrogen
Brayton	Combustion turbine	Higher	Gas, Distillate, Synthetic gas, Hydrogen, Ammonia
RICE	Engines	Higher	Diesel, Distillate

There are two notable resource types that combine elements of two cycles: combined cycle gas turbines (CCGT) and combined heat and power (CHP). The case of CCGT incorporates some combination of combustion turbines and steam turbines with intermediate heat recovery in a variety of potential configurations. In the case of CHP, combustion leads to the raising of steam within boilers. Steam is then used to both generate electricity in a steam turbine and then either provide process steam or feed heating water circuits. Modeling considerations specific to CHP are addressed in further detail in Section 2.3.2 of this report.

All thermal plants can respond to dispatch instructions, though response rates vary based on both plant design, the availability of fuel, and operational conditions. RICE and aeroderivative gas turbines respond the fastest and may sustain flexible operation over extended periods, at the expense of part load efficiency penalties. Rankine cycle steam units can also respond, but over a longer time frame, that is limited by thermal properties of the plant components, boiler dynamics, the operation of coal mills, and management of reactor cores. New forms of thermal resources, such as small modular reactors or H2 turbines, are under active development but fit within the framework presented. The availability, efficiency, and flexibility of each of these plant and fuel types is dependent on a number of factors as summarized in Table 4.

Table 4. Factors affecting availability and efficiency by thermodynamic cycle class.

<table>
<tr><th rowspan="2">Cycle</th><th colspan="2">Factors influencing availability</th><th colspan="2">Factors influencing efficiency</th></tr>
<tr><th>Common factors</th><th>Specific factors</th><th>Common factors</th><th>Specific factors</th></tr>
<tr><td>Rankine</td><td rowspan="3">Fuel,
Age,
Maintenance practices,
Operational history,
Extreme weather,
Design basis</td><td>Secondary fuel capability & storage</td><td rowspan="3"></td><td>Coolant source / sink temperature</td></tr>
<tr><td>Brayton</td><td rowspan="2">Fuel supply logistics</td><td>External air temperature</td></tr>
<tr><td>RICE</td><td>External air temperature</td></tr>
</table>

Aside from the risks associated with the underlying energy conversion process, each fuel source has its own risks, as summarized in Table 5.

Table 5. Risk influencing factors and trigger conditions by fuel source.[3]

Fuel source	Risk Influencing Factor	Trigger Condition
Natural Gas	Pipeline supply restrictions due to local gas demand priority	Cold weather
	Pipeline supply restrictions due to gas infrastructure outages	Multiple, including cold weather
	Insufficient LNG inventory	LNG prices, LNG infrastructure availability
Uranium	Prolonged refueling outages	Plant or fuel condition
	Reduced operational range based for crud management	Fuel cycle
Coal	Coal pile freeze	Cold weather
	Coal supply constraint, waterway	Drought
	Coal supply constraint, rail	Floods, rail infrastructure damage
Oil	Insufficient inventory resupply	Cold weather, flooding
Distillate	Insufficient inventory resupply	Cold weather, flooding
Biomass	Unavailability of fuel source	Drought, flood, travel constraint
	Varying calorific value of feedstock	
Hydrogen	H2 inventory	Renewable production, or other

[3] Geopolitical risks are not explicitly mentioned in the table but can also impact the availability of most fuels.

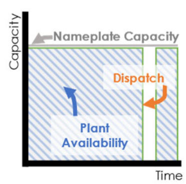
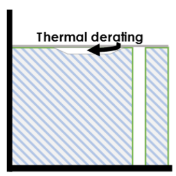
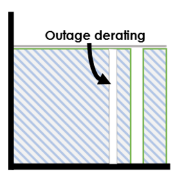
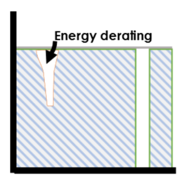
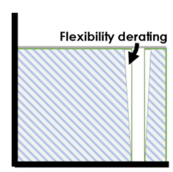
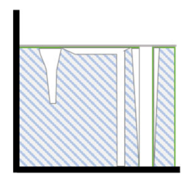
Conventional Modeling Approaches

A summary of key considerations for thermal generation modeling by level of fidelity is presented in Table 2. There are a number of key factors influencing thermal generator operations, these include:

- Capacity limits.
- Asset availability: maintenance and forced outages.
- Failure to start.
- Energy limits.
- Flexibility limits.

Table 6 provides a visual illustration of how the above factors may affect thermal operations.

Table 6. Example impact of including various thermal modeling constraints.

100% Availabiltiy	Capacity Limits	Asset Availabiltiy	Energy Limitations	Flexibility Limitations	All Limits
					
Assumes plant is 100% available	Include deratings to capacity available	Include asset availability outages	Include energy constraints	Include flexibility constraints	Include all constraints

Capacity Limits

For the purpose of this work, capacity available for dispatch is understood as the maximum output that a resource can sustain for an extended period, excluding the impact of maintenance, fuel supply interruption, or forced outage related causes. The standard measure for capacity available is the maximum generating capacity of a unit. Capacity available for dispatch may be reduced when one of the factors influencing efficiency outlined in Table 4 becomes active, such as high temperature derating.

While capacity availability varies continuously for renewable resources, the use of **seasonally adjusted ratings** is the most common approach taken for thermal resources. Winter and summer ratings are derived based on climatological assessments of the temperature at the plant location and assessed on a plant-by-plant basis, reflecting the design, location, and other plant specific factors.

Declared capacity for dispatch commonly represents the plant's self-assessment of the capacity available for dispatch at a given time. It is generally known with high certainty hours to days ahead when weather and fuel availability is well established. Further out, it may be estimated based on contractual obligations to provide capacity in capacity markets.

Condition-based assessment of plant capacity ratings is possible. This method differs from the above by incorporating a range of forecasted conditions such as temperature, emissions limits, or availability of cooling water to estimate the maximum production capacity of a plant under a given condition at a specific time. When these conditions are triggered in a model, an update to the expected capacity available for dispatch can be made. This approach is typically not implemented in long-term resource adequacy studies but may be in short-term studies given the extensive data input required.

Water-Related Deratings

Experience from 2021 and 2022 has highlighted the vulnerability of resources whose capacity available for dispatch is limited based on either the availability, or temperature, of cooling water (either inlet or ultimate heat sink). A common mode impact associated with river system drought was experienced in several jurisdictions during 2022, most notably the case of the Rhone River in France that resulted in the simultaneous derating of several nuclear power plants owing to low river flow levels and high temperatures. Such conditions may have been beyond the original plant design considerations but may occur more frequently for a variety of reasons, including anthropogenic climate change.

Asset Availability: Maintenance and Forced Outages

Resource availability represents a given resource's capability to deliver its declared capacity available for dispatch at any time, considering the possibility of maintenance or forced outages occurring. Maintenance and forced outage factors are typically considered separately, given the ability to schedule maintenance at a specific time or potentially recall the resource faster than anticipated. Both topics are separately addressed below.

Maintenance Outages

Approaches to incorporate maintenance outages in RA depend on the scope of the study. In the season to days ahead time frame, maintenance schedule information, indicating maintenance timing and duration, is likely to be available for most resources. The availability of this information greatly reduces the uncertainty associated with estimating the set of available units during a study period. Considerable uncertainty arises in the timing and nature of planned resource maintenance periods that are years or decades ahead. While maintenance is highly likely to continue to be scheduled during the periods of lowest system stress, as illustrated in Figure 4, the timing of such periods may be less certain and have varying durations.

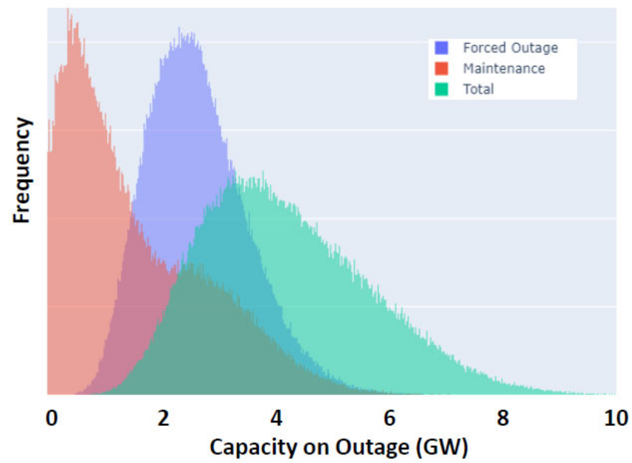


Figure 3. Simulated occurrence of forced and maintenance outages for the ERCOT power system: 15 Monte Carlo outage draws were run across 40 weather years [4].

Research into, and experience with, the operation and reliability of thermal plants also points to the changing nature of operation and maintenance (O&M) activities as plants change operational mode to provide more flexibility across fewer running hours. The impact of flexible operations varies depending on plant type, location, the extent of cycling, hot and cold starts carried out, as well as individual plant strategies. While, at present, major work is typically focused on one or two extended maintenance periods per year requiring a plant outage, as illustrated in Figure 4, future O&M strategies are likely to adapt to the extent they can, to shorter and less certain maintenance windows. Three approaches are typically followed to reflect the need for planned resource maintenance in studies, depending on the horizon for the study:

- Heuristic maintenance schedules.
- Forecasted maintenance schedules.
- Optimized maintenance schedules.

Forecasted and optimized maintenance schedules may include provisions for delay and recall.

Heuristic maintenance schedules are employed to schedule resources for maintenance based on past operational data. A valley filling approach may be employed, scheduling maintenance events based on the size and duration of the resource outage in descending order and aligned with minimizing the forecasted net load profile. Most dedicated RA tools implement a version of this to generate a reasonable approximation to maintenance schedules.

Forecasted maintenance schedules are known in advance and updated based on progress. This information is provided as an input into the RA assessment directly. For assets with no declared maintenance but where maintenance is likely, the heuristic approach can be taken to fill in expected maintenance based on forecasted conditions. Forecasted maintenance schedules are common practice for short term assessments.

Provisions for delays and recalls may be considered, foreseeing the ability to recall a limited amount of ongoing maintenance under emergency conditions. This approach is achievable by additional sampling of planned outage completion times by generating alternate outage schedules with a certain portion either prolonged or delayed beyond the forecasted schedule, informed by operational experience and the nature of the assets under maintenance.

Optimized maintenance schedules apply a pre-processing optimization to schedule the set of maintenance events across a study period using forecasted demand and renewables profiles as well as maintenance profiles by asset type. Optimization functions are typically formulated to reduce the potential for system stress, similar to the heuristic method. Delay and recall may be modeled by including the option to curtail maintenance and by generating additional maintenance samples testing the impact of unexpectedly prolonged maintenance periods.

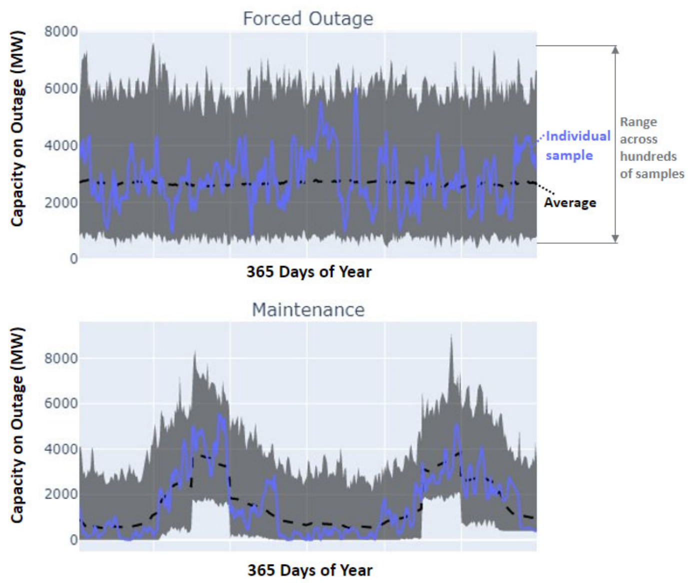


Figure 4. Scheduling of maintenance outages vs. forced outage occurrence for an ERCOT test system [4]. Maintenance outages are mainly scheduled during periods of lowest system stress: mainly during the spring and fall months.

Forced Outages

Along with demand forecasting, the treatment of forced, unplanned outages of generation resources has historically been a focal point of methodological development for resource adequacy assessment.

There are two categories of approaches to model forced outages: deterministic and probabilistic. The general characteristics of each approach differ substantially, meaning that either may be more or less suited to different types of use cases:

- **Deterministic methods** entail the estimation of the likely availability of a resource type over an assessment period and aggregate resource availability to develop a supply-side availability profile.
- **Probabilistic approaches** aim to represent the stochastic nature of the failure and repair of generating resources, reflecting the variance in resource availability that is possible at any moment.

Deterministic approaches take a predefined view on how much capacity will be available at any one time. These approaches may be informed by previous resource performance in stressful operating conditions and result in assessments of the contribution of a resource towards meeting demand. Examples of this may include:

- Performance during the top 10 (or other number) demand (or net demand) periods across a three-year sliding window.
- Historical performance during conditions defined by capacity market rules.

Overall, these methods measure the gap between anticipated available resource capacity and projected demand, utilizing a form of derated or dependable capacity rather than nameplate capacity. Such assessments are commonly used in short- and near-term capacity assessments.

Deterministic methods have historically been relied upon as the mainstay of resource adequacy assessment, particularly when a simplified check is required as part of a capacity adequacy, capacity procurement, or operational assessment.

If systems had homogenous, large generating fleets and relatively small generating unit sizes, the use of derating factors could represent average fleet availability with sufficient accuracy. However, with smaller shares of individual resource types, common cause outages result in significant reliability outcomes. Similarly, under constant asset sizes but smaller fleets, the distribution of asset availability for any asset class widens away from the mean. Furthermore, the availability of specific units interacts with the operational profile of energy limited resources and storage, resulting in a greater requirement for availability profiles for each asset, rather than the aggregate representation.

As a result of the above, deterministic models are not recommended as a principal resource adequacy assessment methodology. Notwithstanding this fact, deterministic methods may still have value in certain operational conditions (e.g., real time operations) or as part of an approach to influence planning models or other procurement mechanisms, such as capacity markets, to produce or incentivize asset portfolios that are likely to be reliable when assessed with a probabilistic RA method.

> **Installed and Unforced Capacity (ICAP & UCAP)**
>
> Installed and unforced capacity are commonly used capacity accreditation metrics used in deterministic approaches to assess resource adequacy through the planning reserve margin approach.
>
> *Installed capacity (ICAP)* refers to the nameplate or offered capacity associated with a generating resource.
>
> *Unforced capacity (UCAP)* refers to a deration factor applied to the installed capacity, typically derived from the forced outage rate.

Probabilistic methods fall into two general approaches: *analytical and simulation based*. Both approaches rely on the same standard variables – a failure rate, a repair rate, and their derivatives. These rates govern the transition of a resource between availability states in a Markov process. The most common configuration of states is a two-state model (available and unavailable) that is stationary over time. While the goal of this document is not to provide detailed derivations of each of the approaches, a summary is provided below. Further information is available on the *EPRI Resource Adequacy Resource Center.*[4]

In *analytical approaches*, the probability that a unit is in the available and unavailable state at any point in time is derived from its failure and repair rates. The most commonly used derivative variable is the Equivalent Forced Outage Rate (EFOR) or the Equivalent Forced Outage Rate on Demand (EFORd), representing the probability that a unit is unavailable, in the latter case conditional on periods when the resource would be required to meet demand.

This simple resource-level availability distribution is combined across all resources to form a cumulative distribution of available capacity through iterative convolution. The system-level distribution of available capacity can then be used to determine the probability that less than a given amount of capacity will be available at any time. The most common approach is to establish a capacity requirement consisting of demand and necessary operational reserves and then to determine the probability of not having sufficient available generation in that interval to meet the requirement – the so-called loss of load probability (LOLP).

The analytical approach has some implicit assumptions, inherent to many adequacy studies and that modelers need to be aware of:

[4] http://gridops.epri.com/adequacy - note that this website has information about modeling for different technologies also and can be used as a resource to support reading of this paper. It reflects previous EPRI efforts in the area but will be updated in 2024 with the findings in this report.

- Each resource's behavior is assumed independent of others.
- Failure and repair rates are typically assumed to be stationary.
- Resource availability in one interval is independent from the previous interval.
- It is assumed that operational, or energy-related, constraints do not limit the availability of a resource.

Simulation based approaches typically rely on Markov Chain Monte Carlo simulations. Here, the evolution of generator availability from one interval to the next is modeled by drawing a random variable, and then evaluating whether its value corresponds to a change in state at a given time – either moving to an *unavailable* state from *available* or from *unavailable* to *available*. Since this approach draws a random variable in each interval, multiple samples need to be studied to achieve convergence of the ultimate risk metric (LOLE, EUE, or other). The addition of further states, such as *available and offline* and *available and online*, allows for start-up failure to be modelled. This feature 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.

For each sample, there is a definitive MW capacity available or unavailable in each interval, as compared to the analytic approach where a probability of exceedance is used for given capacity levels. This approach therefore allows for other considerations in system performance to be incorporated, such as commitment and dispatch constraints, fuel availability or potentially forecast error. The approach also allows for conditions present during each specific interval to inform the rate of change between states – e.g., weather conditions. This is achieved by adapting the failure rates in a dynamic manner, which is different from classical time-invariant Markov sampling. Finally, the approach provides insight into how events unfold, allowing for interrogation of each event's duration, unserved energy per event, timing and the factors driving the events.

Key Issues for Methodological Selection

Operational experience has pointed towards the need to address critical issues in how plant availability is modelled in resource adequacy assessments. Examples have been alluded to previously but include:

- The need to incorporate common-mode failure of generation owing to weather or climate conditions. e.g., cold weather-related forced outages.
- The need to provide additional dimensional information related to load shedding events to inform mitigation measures, such as event duration, severity, and root causes.
- The impact of destructive vs. nondestructive events on plant repair times. For example, plant repair following hurricane damage differs to that of simple component replacement.
- The need to project future expected failure and repair performance of new generation technologies.

In this guideline, it is proposed that the standard approach to representing the failure of conventional generators be based around a *Monte Carlo, Markov Chain (MCMC) simulation approach, using seasonally adjusted forced outage* rates. The key features of such approach are:

- A Monte Carlo sampling approach is applied to generate hourly profiles of generator availability using at least a two-state Markov Chain model (available, unavailable).
- The failure and repair rate used should change on a seasonal basis to be commensurate with the projected seasonal average Effective Forced Outage Rate.

This methodology is available across many commercial and research adequacy assessment tools. The benefits of the MCMC simulation approach when compared to the convolution approach is that individual asset availability can be queried at any hour, allowing for system level optimization or simulation to consider the loss of a specific asset, rather than the expected cumulative unavailability of the resource fleet taken in aggregate. Simulation-based approaches also preserve inter-temporal state transitions, an important feature that enables the consideration of energy and flexibility constraints as part of overall system modeling.

An advance upon seasonal rates is to consider *condition-based failure rates* that are *updated on a daily basis***.** In such a case, the failure and repair rates are determined for each unit for each day based on a trigger condition associated with that day, such as mean temperature or wildfire risk. No other changes are required to the MCMC simulation approach. Daily failure rates are recommended in any system where thermal resources are exposed to temperatures below 32°F (0°C) or above 95°F (35°C).

Level III models (see Table 2) improve further by updating *failure rates based on the conditions present in each simulation interval,* allowing for improved granularity about the timing of return to service and failure within a day as conditions deteriorate. Implementation of this approach does not influence the core MCMC process but does require updates to the failure and repair simulation parameters that may require changes to certain adequacy assessment tool capabilities.

Case Study: Weather Dependent Outages

One of the key findings from Winter Storm Uri in 2021, Winter Storm Elliott in 2022, and other cold weather events, is the need to better incorporate the impact of cold weather on the performance of generation. Figure 5 shows the outage rates of natural gas-fired capacity during Winter Stoms Uri and Elliott. Going beyond an inflection point, close to -10°C (14°F) gas fired plant outage rates rapidly increase.

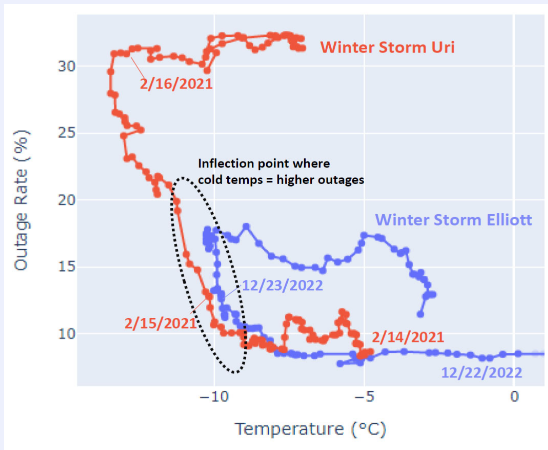


Figure 5. Outage rates of natural gas-fired capacity during Winter Stoms Uri and Elliott [4].

Figure 7 shows results from analyses conducted to study how modeling weather-dependent combined cycle unit outages can impact loss of load expectation calculations. The results are presented for a 2030 ERCOT test system. Due to limited public data availability, average generator forced outage rates as a function of temperature were leveraged from PJM data presented in [5]. However, based on historical data, it was found that ERCOT generators perform better at high temperatures and worse at low temperatures than the data in [5]. To correct for this, outage rate curves were shifted 10°C to the right, as illustrated in Figure 6. This can also be seen as a sensitivity on how much the plants are weatherized compared to performance during historical conditions.

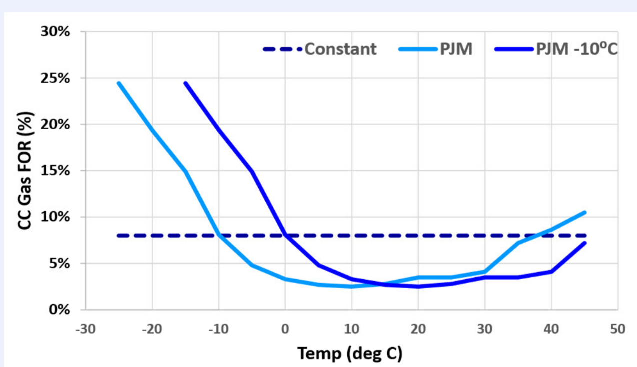


Figure 6. PJM CC Gas FOR – temperature curve from [5] and PJM curve shifted by 10°C to the right to better approximate ERCOT generator performance.

Case Study: Weather Dependent Outages (continued)

Looking at Figure 7 shows that LOLE values are almost 3 times greater when CC weather dependent outages are accounted for vs. when they are not (comparing the 1st and 2nd bars). When accounting for the fact that generators may perform worse under cold conditions than estimated in the original curve, LOLE values may be over 4 times bigger (comparing 1st and 3rd bars) than originally estimated through simulations not considering weather impacts on outages.

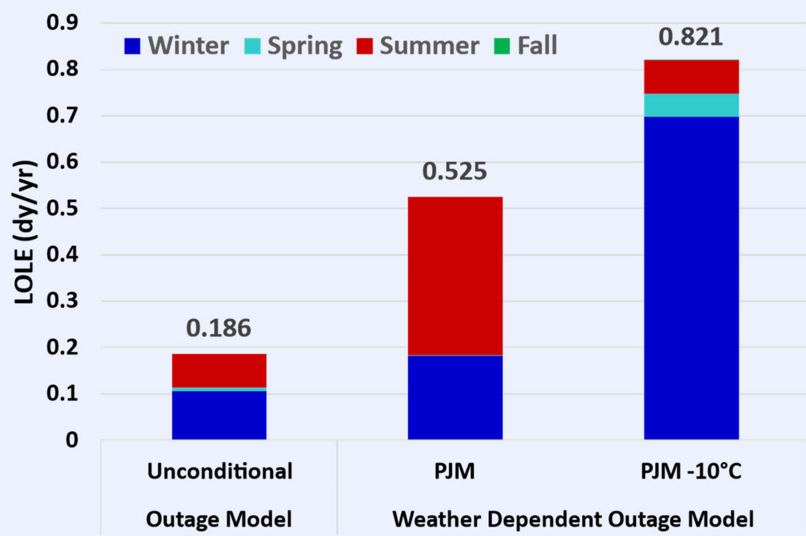


Figure 7. Simulated LOLE for a 2030 ERCOT test system with, and without, accounting for weather dependent outages [4]. *Unconditional Outage Modeling* shows results where weather-dependent outages are not modeled. *PJM* results are calculated directly based on the data published in [5]. *PJM -10°C* results show LOLE impacts shifting data in [5] by 10°C to the right, which may better represent actual ERCOT generator weather-dependent outage rates.

Failure to Start

Aside from failure while running online and constraints in changing dispatch setpoint, generators can fail to transition between offline and online. Start-up failure is an issue of importance due to the potential for generators to fail at the same time as net demand is increasing. Failure to start is often different from forced outage failure in that, in many cases, the failure is related to start procedure issues and may be quickly recovered. With greater projected net load variability, cycling of generating assets is likely to increase. With increased cycling, a greater potential opportunity arises for startup failure.

Start failure can only be modelled in simulation approaches where generator dispatches are included. Such methods are typically combined with MCMC forced outage modeling. The **standard practice** in RA is to **not include start up failure** on the grounds that thermal generation do not experience frequent cycling.

However, under cases where thermal generation is exposed to increased cycling, beyond its original intended operating profile, or has passed the midpoint in the asset's design age, including a model for **start-up failure** becomes recommended practice. Start-up failure models can be implemented using a Markov chain process that is contingent on the generator being started by a chronological dispatch model. When a generator is committed after being offline a post-processing step overlays the failure state. This may, or may not, result in load shedding depending on the system state.

In systems where thermal resources are exposed and vulnerable to common cause start failure, such as cold weather in regions with lesser hardening to such conditions, startup failure rates estimates may be varied based on the prevailing condition (e.g., temperature). The application of this method is restricted based on the data available similar to conditional forced outage assessment.

Energy Constraints

Limitations associated with fuel supply may also need to be considered for thermal resources. While energy constraints have traditionally been associated with hydro and energy storage resources, increasing emphasis has been placed on the energy constraints associated with gas, liquid fuel, and dual fuel resources.

Constrained gas supply and reliance on LNG or gas storage for units with limited on-site fuel storage have become more commonplace. Coal units may have sufficient fuel on site but during cold conditions, frozen coal piles or non-performant fuel handling equipment may result in reduced fuel availability to a plant.

Similarly, emissions constraints may limit the running hours of resources, potentially reducing plant availability during unforeseen periods of system stress. In many cases these emissions limits may be lifted under emergency situations, but in an ideal case these would be planned against at the outset.

The standard modeling approach for thermal resources is not to include any energy related constraints on plant availability, operating under the assumption that any thermal resource operator will have sufficient foresight or back-up options to procure and manage fuel in order to meet any potential system stress condition. It is also envisaged that emissions limits would be removed when a system faces a high likelihood of load shedding, making those limitations immaterial to reliability outcomes.

When energy limits are introduced into RA, the **recommended approach is to model a 'fuel pool'**, which is suitable within chronological MCMC RA simulations. A constraint is introduced to limit fuel consumption for a set of generators reflecting the assumed availability of that fuel. Simplified heat rate and start up heat estimates are made for each resource associated with a fuel group to produce an estimate of the fuel demand required by the resource set. This is then limited by a daily or weekly fuel availability, representing the gas pipeline and LNG daily contracted or delivery capacity, net of non-power demand for gas (e.g., residential gas consumption).

Fuel pool constraints are recommended if gas supply is known to be a limiting factor in operations, additional gas supply is required to facilitate the addition of new generating capacity, significant additional gas demand is forecasted downstream of the study region, or in cases where rapid population growth is forecasted to increase the demand for natural gas in a region. For dual fuel units it is recommended that resources be associated with the central fuel pool for the primary fuel source and to include secondary constraint on the availability of the secondary fuel in line with site storage capability and realizable fuel deliveries by day. A similar approach can be taken to associate resources with two fuel pools, representing firm and non-firm fuel supply pools in cases where generators are known to depend significantly on spot gas contracts.

In cases where daily pipeline capacity does not offer an accurate representation of the gas available to generators, time of day related constraints affect the availability gas supply to power plants, or downstream fuel supply is prone to weather related outages, **it is recommended to model energy limits at an hourly granularity** and, where data permits, to incorporate condition-based fuel supply estimates. Derating of fuel supply based on temperature, environmental or other condition should be based on a data supported approach. These constraints have the same form as the fuel pool but with a smaller time constant.

Flexibility Constraints

Flexibility constraints are the most recent modeling consideration to be added to resource adequacy assessments. The nature of demand variability and uncertainty has historically lent itself to highly predictable load ramping periods that could readily be managed by the flexibility inherent in most economic generation mixes. Flexibility issues, where they did arise, were mostly related to the change in setpoint around an hour-long interval, resulting in frequency excursions. Resource adequacy assessment was developed around the principal that flexibility issues, such as they existed, were operational time frame constraints that could be resolved by means available to dispatchers. The need for flexibility was not so great that it would present the basis on which resource investment would be required to mitigate.

As grids incorporate greater shares of wind and solar power, the operational uncertainty and variability that systems face can be considerably greater than in the past and may exceed the magnitude of what can be managed exclusively through operational means. Previous assessments have shown the potential for flexibility constraints to have a material impact upon the estimation of LOLE [6]. Forward monitoring and assessment of the potential for load shedding to be driven by flexibility related limitations may be critical, particularly while grids are transitioning from legacy to future-state generation mixes. These assessments require chronological simulation and the addition of some operational policies, such as operating reserve and advanced storage modeling. The need to model RA at a sub-hourly resolution may also need to be considered in flexibility-constrained systems, however computational limitations may need to be addressed. EPRI has previously investigated methods for assessing system flexibility needs including a discussion of when sub-hourly modeling may be beneficial for ensuring sufficient operational flexibility [7].

In practice, most analyses do not include flexibility constraints associated with thermal generation. This is likely to remain valid for systems that do not experience net load ramping substantially exceeding historical demand ramps and sustains a hydro-thermal fleet where a significant portion of the resources are able to start and stop within the same day on a consistent basis.

For most systems, the first instance in which the addition of flexibility is recommended occurs when the forecasted net load profile displays a midday valley (e.g., a duck curve), with a delta in peak to valley net load approximately equivalent to the addition of fast start thermal, battery storage, and demand response resources available to the system. Under this scenario, the potential exists for traditionally inflexibly operated plants to be required to cycle, particularly during maintenance periods for peaking plant. **It is recommended that the addition of minimum online generation and minimum up and down time constraints be added to the simulation model** in order to capture issues related to minimum turn down, and double-two-shift cycling of thermal plant. The addition of those constraints represents a minimum required to diagnose the potential for flexibility shortfalls owing to commitment-related limitations. Commitment-related constraints are known to considerably increase the time associated with the execution of simulations, limiting RA analyses to a reduced number of samples. Adaptive approaches to screening net load profiles for potential flexibility related constraints are under exploration but may aid support in sample scenario selection in future.

In cases where the magnitude of the midday valley to peak range exceeds the capacity of fast responding resources and demand response, **the addition of startup time and ramp rate constraints to the operational simulation may be warranted.** The addition of such constraints significantly increases run time and may only be required as a supplementary check after an initial screening process.

Open Modeling Gaps

Thermal modeling approaches have evolved over the past 70 years in response to changing technologies, exposure to risk, and common cause events. Thermal resources will likely continue to play an important role in many low carbon systems, so understanding how to accurately represent them in RA in the context of evolving power systems is essential. A set of open modeling gaps relating to thermal power generation is presented in Table 7.

Table 7. Open Modelling Gaps by Modeling Approach.[5]

Modeling Approach	Gap	Severity	Comment
Capacity Limits	Cooling water	Low	Derating owing to reduced cooling water availability or elevated temperatures in ultimate heat sinks is a challenge to implement (models) and estimate (data) from a long-term planning point of view. Targeted scenario analysis or stress testing may be a prudent approach under such circumstances.
Asset Availabiltiy	Time and condition-based outage rates	High	The integration of condition and time-dependent failures and repair rates requires improved estimates (data), modeling approaches (models) and integration into tools (tools). Studies that implement condition-based outage rates can be achieved at present, but largely through extensive scripting and with limited consistency between approaches.
	Maintenance Forecasting	Medium	As net loads evolve, traditional shoulder maintenance seasons may be at elevated risk of load shedding should maintenance practices remain unchanged. Anticipating how maintenance strategies will evolve (data) and how to approximate that behavior in adequacy assessments (models) will play a significant role in determining risk during the shoulder months.
	Maintenance Recall	Low	The ability to recall resources from ongoing maintenance is an operational time frame action that can be taken to reduce the impact or likelihood of load shedding. Building an estimate (data) and approach to recall a portion of plant on maintenance during load shedding events is likely to be material to the outcome of adequacy studies (models).

[5] “Models”, “data”, and “tools” gaps are identified.

Table 7 (continued). Open Modelling Gaps by Modeling Approach.

Modeling Approach	Gap	Severity	Comment
Energy Limitations	Fuel Networks	Medium	In cases where the performance of fuel delivery networks requires more granular representation than that achieved through a fuel pool or hourly offtake constraint implementation, fuel network elements (e.g., compressors, pipelines, extraction facilities) may need improved representation within adequacy studies. This is currently an open gap to determine the level of detail and functionality that would be required in such as case.
	Emissions limits	Low	Medium term scheduling may be required in cases where emissions limits require reduction in available capacity and when stressful conditions may be anticipated with high certainty.
Flexibiltiy Limitations	Impact of carbon capture	Low	The potential addition or retrofit of carbon capture technology at thermal power plants may alter the flexibility profile of the resources resulting in a need to assess flexibility in a wider range of conditions than carried out at present.

2.2.2 Variable Renewable Energy

Table 8. VRE modeling by level of fidelity.

	Level I	Level II	Level III
VRE	Fixed capacity derate calculated based on estimated power output during stress periods.	Several years to decades of hourly data. Correlation amongst weather-dependent generation, outages, and load shapes is enforced.	Several decades of hourly data, with correlation amongst weather shapes enforced and operational forecast uncertainty considered.

Wind and solar generation, collectively referred to as Variable Renewable Energy (VRE) will contribute about 16% of total electrical generation in the United States in 2023, up from 8% in 2018 [8]. This increase in VRE shares is expected to accelerate and its impacts must be considered in RA models.

Although onshore wind, offshore wind, solar PV and concentrating solar power are all very different technologies, they are modeled similarly within resource adequacy studies. Because of the dependence of VRE on stochastic weather phenomena, representing VRE generation is an important source of uncertainty to capture in RA modeling. Unlike technologies like coal, natural gas, and nuclear generation, the output of VRE generators is strictly dependent on environmental factors: mainly wind speed and solar irradiance. Historically, VRE generators have been treated as non-dispatchable resources: they could be curtailed but did not generally participate in real-time electricity markets [9]. However, with the development of advanced control strategies, VRE generators can provide a range of grid services, including frequency regulation and synthetic inertia, much like conventional generators, within the envelope allowed by varying environmental conditions.

Distributed solar shares many of the same characteristics as bulk system solar power, however, it brings the challenge of limited visibility for system operators. This technology is addressed in greater detail in Section 2.3.2. Hybrid VRE and energy storage installations are becoming more common, and similarly bring with them a specific set of modeling challenges. Hybrid technologies are addressed in Section 2.2.3.

Modeling Approaches

A summary of VRE modeling approaches by level of fidelity is presented in Table 8.

Certain RA studies still model VRE using a fixed capacity derate, which may be calculated based on median net real power output during pre-determined *reliability hours,* as in [10]. While significantly simplifying modeling, this approach doesn't account for the impact that hour-to-hour wind variability can have on the system. The use of pre-determined *reliability hours* also presupposes a perfect foresight of at-risk adequacy periods which may not hold true in all scenarios, especially as increased renewable and storage buildouts are shifting periods of peak risk. As such, **it is a widely accepted best practice, and recommended here, for VRE generation to be modeled using timeseries.**

Timeseries data can be either collected from historical plant operating data, or by using remotely sensed or reanalysis data generated from weather records.[6] For offshore wind power plants, or all types of VRE in regions with less current installed capacities, synthetic data is often utilized due to the limited availability of historical data. For all technology types, a large number of weather years are required to fully capture weather-driven uncertainty and extreme weather

[6] Reanalysis data relies both on historical observations and model-based forecasts to estimate future weather conditions. Reanalysis data is heavily employed for weather and climate modeling [121].

events. The specific number of years depends on the region and the relative share of VRE. It is recommended that this should be examined for the system by looking at longer datasets to determine whether shorter sets could be used. Additionally**, care should 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 and any temperature dependent data – such as temperature-dependent outages or demand response. Further information on best practices for timeseries creation can be found in the *Data Collection Guide: EPRI Resource Adequacy Assessment Framework* report.[7]

Aggregation

Aggregation of wind and solar plants within resource adequacy models is often used to reduce model complexity and overcome data availability issues. Aggregation involves summing hourly generation over a geographical region, often across a climatic zone, to produce an equivalent aggregated generation profile. These aggregated units are then included in the overall resource adequacy model as if they are a single unit.

Operational Forecast Uncertainty

Historically, VRE operational forecast uncertainty was not considered in resource adequacy modeling. Today, certain tools are starting to include operational constraints, to evaluate whether the system has sufficiently flexible capacity to respond to potential shortfall events. Accounting for operational forecast uncertainty may be material to RA outcomes for systems with sufficiently high levels of VRE shares and is recommended to be examined in regions where shares are above 25%-30% annual energy penetration, if not lower.

Resource Availability

There are a number of factors that can impact the ability of wind and solar plants to generate electricity. These include planned and forced outages due to equipment maintenance or malfunction, but also unavailability or reduction in generation due to environmental factors, such as pollen accumulation or snow cover for solar PV plants, or blade icing for wind turbines. Additionally, age-related degradation can impact power delivery over the unit's lifetime.

It is general practice in most resource adequacy models to date to implicitly incorporate these factors affecting resource availability within the power generation timeseries, rather than explicitly modeling them. This is because historical generation data is usually reported inclusive of outages and derates. Furthermore, outage data for solar and wind installations is often unavailable or of poor quality. Finally, including these derates and outages implicitly as part of the generation timeseries decreases the resource adequacy model complexity. Future efforts may be required to more explicitly model outages, for example during cold weather or dust storms, where outages might be higher than the weather timeseries alone would suggest.

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[7] https://www.epri.com/research/products/000000003002027831

Open Gaps

Resource adequacy models for variable renewable energy are relatively well established and in widespread use. Two primary gaps remain that will need to be addressed as VRE shares continue to grow. First, the collection of appropriate and good quality data informing weather-dependent, correlated, VRE power outputs and outages. Secondly, further understanding the need, and establishing industry standards, for modeling VRE output uncertainty within RA.

2.2.3 Storage and Hybrid Power Plants

Table 9. Short-term storage and hybrid plant modeling by level of fidelity.

	Level I	Level II	Level III
Modeling storage dispatch	*Option 1:* Storage operations are not explicitly modeled; they are implicitly accounted for in net-load profiles. *Option 2:* Storage is modeled as a marginal thermal unit, assuming capacity is available during shortfall events. *Option 3:* Storage is dispatched based on generation shortfall prevention heuristics.	Storage economic dispatch is modeled through in 8760 optimizations, explicitly modeling linked storage dispatch and state of charge.	Storage economic dispatch is modeled in 8760 optimizations, explicitly modeling linked storage dispatch and state of charge. The impact of value stacking on the capacity availability to support RA is accounted for.
Outage modeling	Battery outages are not explicitly modeled.	Periodic planned outages are accounted for. Unplanned outages are accounted for through fixed EFORd rates.	Periodic planned outages are accounted for and may be calculated endogenously as a function of battery cycling. Unplanned outages are modeled using both mean-time-to fail and mean-time-to-repair rates.
Degradation	Energy storage degradation is not explicitly modeled.	Energy storage capacity degradation is calculated as a function of the calendar life of the unit. Cycling limits on storage units to limit degradation may be recognized when relevant.	Energy storage capacity degradation is calculated endogenously as a function of storage operation.

Table 9 (continued). Short-term storage and hybrid plant modeling by level of fidelity.

	Level I	Level II	Level III
Optimization window	Daily optimization window with static (exogenous) boundary constraints.[8]	Choice of optimization sub-problem and lookahead window lengths are informed through prior analysis.	Choice of optimization sub-problem and lookahead window lengths are informed through prior analysis. Boundary constraints are calculated endogenously as part of the optimization process and are linked between subsequent optimizations.
Hybrid energy systems representation	Hybrid systems are modeled as separate renewable and storage systems.	Hybrid systems are modeled as AC-coupled systems, with operational constraints linking the renewable and energy storage units.	Hybrid systems are mostly modeled as AC-coupled, however, a simplified set of assumptions may be employed to model DC-coupled resources.

Energy storage (ES) resources are rapidly being deployed. Global installed storage capacity is projected to increase 15-fold, from 27 GW (56 GWh) in 2021 to 411 GW (1194 GWh) in 2030 [11]. There are a large variety of energy storage resources in use. The most prevalent for grid-scale applications are pumped storage hydro (PSH) and batteries. Other, less prevalent, types of storage include flywheels, compressed air energy storage (CAES), and molten salt (thermal) storage [12].

The focus of this section is on *bulk (mainly short-term) storage* and *bulk hybrid power plants*. For the purpose of this document, short-term storage is loosely defined as storage that is mostly cycled daily, sometimes across several days, in operations. Even though there are overlaps in the modeling framework proposed for all types of ES, many of the considerations specific to long-term storage management are addressed in Section 2.2.4. Similarly, considerations that are specific to distributed energy storage are addressed in Section 2.3.2.

When it comes to short-term storage, battery energy storage has seen the largest growth of all technologies, accounting for 94% of non-pumped hydro energy storage installations in the USA in 2022 [13].

[8] Level I optimization window modeling considerations may require for other storage aspects to be modeled at higher levels of fidelity. For example, optimization window considerations are only relevant when employing optimization models, requiring a Level II approach to model storage dispatch.

Energy Storage Modeling

Various aspects of ES modeling are discussed below, these include:

- Modeling dispatch
- Outage modeling
- Degradation
- Optimization windows
- Hybrid energy system representation

A summary of the key energy storage modeling considerations, covering the above, is presented in Table 9. Energy storage units are often aggregated in RA representations. Aggregation is mainly conducted by storage duration; however, it may also be dependent on transmission network modeling assumptions and transmission constraints. Average efficiency rates are employed to aggregate storage clusters. The modeling considerations examined below are applicable to both disaggregate and aggregate storage representations.

Modeling Dispatch

The most common approaches to model ES dispatch in RA assessments are:

- Modeling storage as a thermal unit.
- Modeling storage operations through timeseries based on historical data.
- Using heuristic dispatch models (often within heuristic tools).
- Explicit modeling of storage dispatch and state of charge within 8760 optimizations.

ES Use Cases and Potential to Participate in Grid Services

Arbitrage is often the key driving factor for energy storage operations. That is, charging storage during low marginal price periods and discharging during high price periods, maximizing storage revenues. However, energy storage may also be operated to provide a range of grid services including:

- Renewable smoothing or capacity firming: utilization of storage to reduce the rate of change of power output from variable generation resources. Firming is conducted to provide a flat or predictable aggregate power output from storage coupled to another generation resource [14].
- Adequacy support: ES capacity is used to alleviate or prevent shortfall events.
- Ancillary services: ES can provide a range of ancillary services such as ramping support, various reserve categories, and other grid services, including volt/VAR regulation.
- Transmission network support or upgrade deferral: ES deployed to support transmission operations by temporally shifting electricity transport needs.

Storage use cases directly influence how units are represented in RA. Although the precise set of services provided by ES depends on the market environment storage is operated in, EIA data shows that ES often engages in value stacking, providing two or more services simultaneously. Additionally, value stacking is becoming increasingly common for ES installations: units providing 2+ services increased from 51% in 2016 to 69% by 2021 in the US [13].

The most basic ES dispatch modeling involves **modeling ES as a thermal unit**, assuming full availability during times of system stress, or exogenously including expected ES operations through **timeseries based on historical operational data** that may be netted from system demand [15]. The thermal unit approximation method can assume that storage is only dispatched during high system stress time periods at a high marginal cost, mostly limiting its usage to providing RA support. The thermal unit approximation also assumes that storage is fully charge prior to risk hours. Neither the thermal unit approximation nor the timeseries methods explicitly models storage intertemporal constraints, reducing the complexity of RA model formulations. However, modeling ES as a thermal unit, which is fully available to respond to system stress events, does not realistically capture real-life storage operations, and may result in an over-estimation of storage availability during stress events. Furthermore, it does not capture the potential impact of energy storage charging on the system. The time-series modeling approach does not optimize storage dispatch as part of the RA model. As such, dispatch may not be coordinated with actual system needs, particularly for those systems with greater uncertainty in generation and demand [16].

Heuristic models are mainly employed using heuristic, rather than optimization, tools and base storage charge and discharge on a set of thresholds, or rules, which vary depending on storage use cases.[9] Heuristic models may be employed to represent ES operations for [17] [18] [19]:

- Curtailment prevention: charging to absorb excess VRE generation whenever it exceeds system needs or activates transmission constraints.
- Peak shaving: ES units are charged and discharge once load increases up to a certain threshold.
- Renewable firming: ES units charge once renewable generation hits a certain threshold and discharge when generation drops below another.
- Generation shortfall prevention: ES discharges only when the system is at risk of a loss of load event.

The *generation shortfall prevention heuristic* is particularly common in resource adequacy analyses. The underlying assumption being that storage will be fully charged until the system is at risk of a shortfall event. ES units then re-charge as soon as they are no longer needed for resource adequacy purposes. Heuristic models do not capture arbitrage operations and do not accurately represent real-world dispatch decisions. Much like the thermal unit approximation model, the *generation shortfall prevention heuristic* provides an upper limit on the capacity contributions of storage to resource adequacy [16].

The highest fidelity approach for representing ES dispatch in RA is by explicitly modeling linked storage dispatch and state of charge within 8760 optimizations. This is the recommended approach for any regions where storage is non-negligible (e.g., more than 1%-2% of peak demand).

[9] For further information regarding the difference between optimization and heuristic models see *Resource Adequacy Assessment Tool Guide: EPRI Resource Adequacy Assessment Framework (3002027832)* https://www.epri.com/research/products/000000003002027832

Modeling Linked ES Dispatch and State of Charge in RA

Three parameters are used to represent storage operations: rated power capacity, energy capacity, and roundtrip efficiency.

1. *Rated power capacity* is the total possible instantaneous charge/discharge capability or the maximum charge/discharge rate. Its unit of measurement is kilowatts (kW) or megawatts (MW).
2. *Energy capacity* is the maximum amount of stored energy of a battery energy storage. It is measured in kilowatt-hours (kWh) or megawatt-hours (MWh). Dividing the total energy capacity by the rated power capacity provides information on the duration of the storage unit at full power output in hours (h).
3. *Roundtrip efficiency* refers to the ratio of the energy charged to the energy discharged from the storage unit. It represents the unit's total efficiency, including losses from self-discharge and other electrical losses.[10]

Model fidelity increases when accounting for additional factors influencing ES dispatch that are relevant in the RA time frame, such as value stacking across various storage use cases. For example, if a unit is used for both frequency regulation and energy arbitrage, its capacity to perform arbitrage may be derated. Assuming that a portion of capacity is reserved for frequency regulation services and is therefore unavailable for day-to-day arbitrage operations may be reasonable in this scenario.

Outage Modeling

The reader is encouraged to refer to Section 2.2.1 for a detailed description of planned and forced outage modeling, as many of the modeling suggestions outlined are applicable to storage outage modeling.

Planned storage maintenance should, in theory, have minimal impact on adequacy, as long as it is appropriately scheduled during expected periods of minimal disruption to the system. Planned maintenance may be carried out to replace degraded storage components, including battery cells, as well as to upgrade and maintain equipment. Scheduling is often conducted based on calendar year intervals (i.e., quarterly, or yearly), which can be directly represented as regular battery capacity derates within RA. However, maintenance may also be conducted as a function of battery cycling, requiring a more detailed model linking cycling and maintenance to be accurately tracked in RA.

Unplanned outages cannot be anticipated and often result in long, severe outages, including temporary plant shutdowns. Triggered by environmental conditions, equipment degradation, or other issues related to malfunctioning equipment, these shutdowns typically remove entire storage plant capacities, rather than derating a portion [20]. Such events may need to be

[10] It should be noted that DC-DC efficiency is often used by battery manufacturers. On the other hand, AC-AC efficiency is often more useful to utilities as they only see battery charging and discharging from the point of interconnection to the power system [11].

explicitly modeled, particularly as storage technology matures. Data may not be widely available, so it may be treated as a scenario analysis, while as data is gathered from across the world, models should be updated to reflect learnings.

The Case of Batteries Catching Fire

The term *thermal runaway* is used to describe the scenario where internal battery temperature increases faster than heat can be dissipated to ambient surroundings. This rise in heat degrades the battery rapidly, releases explosive gases, and starts to warm nearby batteries. Short circuits arising due to degradation can cause ignition of both the explosive gases and flammable battery components, such as graphite electrodes. Due to these risks, battery energy storage systems typically have battery management systems able to shut down entire plants under thermal runaway situations. However, when battery managements systems do not control rising temperatures, battery storage plants can be at high risk of fire and explosion [21]. Such events can put units out of service for extended periods of time without any notice to system operators. For RA assessment, this may be quantified in scenarios where higher risk of such events is assessed.

Commonly employed methodologies to capture forced storage outages in RA involve:

- Considering a fixed equivalent forced outage rates on demand (EFORd), such as [22], where a fixed 5% EFORd is modeled.
- More advanced methods consider probabilistic modeling of forced outages, through *mean time to fail*, and *mean time to repair* parameters. Mean time to fail and repair values may be adjusted depending on the type of unit, for example, longer mean times to repair may be considered for hybrid plants.

A key gap in outage modeling for certain storage power plants is the lack of data availability: certain studies need to use estimated forced outage rates due to low data availability [23].

Degradation

All storage units experience degradation, which results in a progressive reduction in storage capacity accompanied by an increase in the probability of unexpected outages.

Mechanisms causing degradation are technology dependent. Lithium-ion battery degradation is most affected by charging rates and depth of discharge.[11] Other battery technologies, such as redox flow batteries, degrade at a constant rate throughout their lifespan that can be

[11] During a Li-Ion battery's lifetime, solid electrolyte interphase builds up at electrode-electrolyte interface, leading to short circuits. High charging rates (and high temperatures) accelerate solid electrolyte interphase growth. Graphite electrodes expand up to 8% during charging, causing mechanical stress and material fatigue. Rate of change of volume is influenced by depth of discharge [20].

accelerated by environmental factors.[12] Mechanical storage units, including PSH tend to experience mechanical degradation of their equipment, in a similar way to thermal generators.

While many RA assessments do not explicitly account for storage degradation, and may not need to do so, degradation considerations do impact how storage operators run their assets.[13] At sufficiently high levels of reliance on storage this may in turn impact system adequacy. A set of established modeling considerations and constraints exist to account for different aspects of storage degradation within RA and operational models. Certain models calculate *degradation as a function of calendar life, not accounting for the impact of operations on ES units*. Calendar life models assume a constant percentage capacity loss per year, regardless of operations and other factors.

Other models endogenously optimize, or constrain, degradation as part of studies, by either adding constraints on battery operations to limit degradation or directly taking into account the impact of operations on degradation. Some of these models, listed by order of increasing modeling complexity, include:

- *Cycling constraints*: limit on the number of unit cycles for a given time period (day, week, year) is enforced. This methodology does not consider the tradeoff between the economic/system benefit of cycling vs. the marginal cost of degradation.
- *Energy throughput modeling:* battery capacity degradation is calculated proportionally to ES energy throughput.
- *Power degradation modeling:* battery degradation rates are calculated as a function of the magnitude of storage charge and discharge power. Higher discharge rates incur higher capacity degradation penalties.
- *Cycle depth modeling:* degradation rates are calculated as a function of cycling range. Increased cycling induces greater capacity degradation.

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[12] Temperature fluctuations can encourage electrolyte precipitation in redox flow batteries, causing mechanical failures due to blockages. Through usage, vanadium ions can diffuse through membrane separators, reducing the capacity which the battery can store [21].

[13] Resource adequacy analyses are generally run for one year; the effects of degradation over that period are generally negligible. Degradation impacts on storage units can therefore be reflected in the unit's charge, discharge, and storage capacities.

Optimization Windows

An optimization window is the continuous snippet of time across which an optimization is carried out. ES operations are time dependent. That is to say that charging or discharging at time *t-1* has a direct impact on storage state of charge, which in turn defines how much ES can charge or discharge at time *t*. Other unit categories, such as VRE, do not have time-dependent operations and are therefore not impacted by modeling decisions involving optimization windows. There are two separate considerations relating to optimizations windows that are of relevance for energy storage representations in RA and operational models:

- Boundary constraints, and
- Look-ahead periods.

Boundary constraints, also known as start and end conditions, are applied to link resource operations across a set of optimization sub-problems. They are required when a long optimization horizon, i.e., a year, is broken up into smaller optimization windows, often daily or weekly, to maintain computational tractability. It is key to ensure that sub-problems are broken down in a way that boundary constraints have minimal impact on dispatch. For this purpose, typically, daily optimizations begin and end at midnight.

Even when year-long optimizations are tractable, they are not necessarily desirable as they can result in *over-optimization* of energy storage, whereby storage operations are overoptimistic with respect to reality.[14] For storage, start and end conditions are imposed through its state of charge.

[14] ES over-optimization results from assuming that storage operators have perfect visibility regarding system conditions for the full optimization window, i.e., 1 year. This is unrealistic, particularly in systems with growing VRE shares.

The main methods for applying boundary conditions to ES are:

1. Setting, **static, pre-defined**, boundary conditions, that could be based on past storage behavior. An example would be imposing that storage units must always start and end each day fully charged.
2. Calculating **dynamic** boundary constraints as part of the optimization process. This can be done either by:
   - Running a preprocessing (lower resolution) optimization to determine "realistic" weekly or daily start and end values for storage. This methodology is particularly useful to capture medium and long-term storage operations, where cycling may not occur on a daily or weekly basis.[15] This methodology can be found implemented along with a state of charge depletion penalty constraint, or water usage cost (specific to hydro storage), ensuring that the usage of medium to long-term storage is not rapidly depleted under normal operational circumstances.
   - Linking sub-sequent optimization state of charge values. That is, the state of charge at the final hour of the optimization of day *D*, will be set as the initial state of charge for the *D+1* optimization.[16]

Boundary conditions can change the outcome of RA studies, particularly for those systems that have a significant level of reliance on storage units.

Optimization **lookahead** periods are an additional period of time that is added at the end of each optimization sub-problem. Optimizations with lookahead optimize across the sub-period plus the lookahead window. The duration of lookahead can be calculated as a function of system storage duration to ensure that end constraints do not impact storage operations. Most optimization-based storage dispatch models consider lookahead.[17] While lookahead periods increase the computational requirements of optimizations they also provide the ability to dynamically link storage behavior across sub-sequent optimizations, providing the most accurate representation of ES operations.

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[15] See Section 2.2.3 for further information on managing long-term storage.

[16] It should be noted that if lookahead periods are not included into optimization sub-problems, the most economic behavior for storage is to fully discharge by the end of every day. That is, to end all optimization periods with zero state of charge.

[17] Lookahead periods are only relevant for optimization models as heuristic models do not optimize storage behavior, rather dispatch it based on a set of threshold triggers (EUE, price, etc.).

Case Study: Impact of Lookahead on EUE

As part of the *Resource Adequacy for a Decarbonized Future* Initiative a SPP US case study was conducted looking at the impact of lookahead on EUE for a high VRE system with 4-hour, 6-hour and 8-hour duration storage [24]. The system studied had over 80% VRE shares, and significantly relied on storage for reliability. Figure 8 shows the results from these analyses. The heatmap on the left shows EUE for simulations with a 1-day lookahead, the heatmap on the right shows results for simulations with no lookahead. Simulations with lookahead were able to anticipate day-ahead system needs and optimize charging and discharging strategies to minimize loss of load. Simulations without lookahead fully discharged storage at the end of each day, failing to anticipate system needs on the following day and leading to significantly greater yearly EUE values.

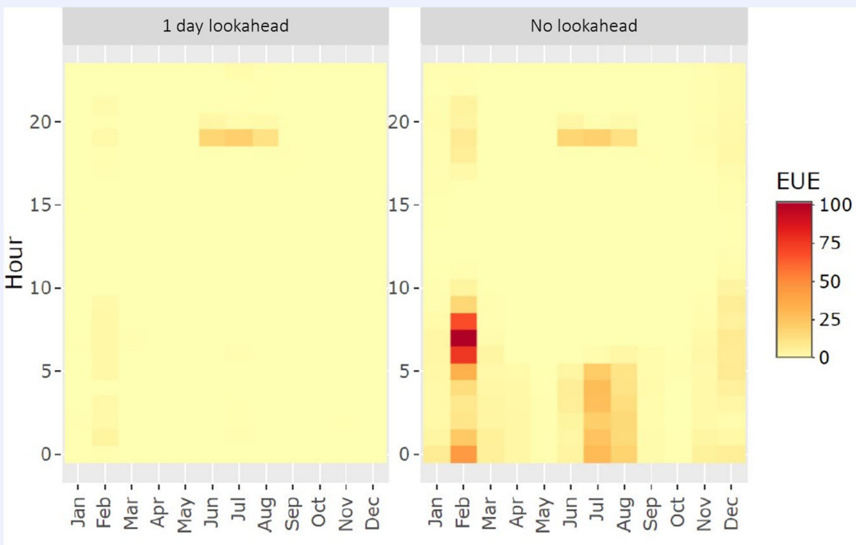

Figure 8. Month by hour of day EUE heatmaps for simulations with, and without, lookahead for a high VRE + storage portfolio [24].

The Western US case study, also conducted as part of the *Resource Adequacy for a Decarbonized Future Initiative,* shows similar findings [25]. Results are presented in Figure 9. Five different total optimization windows (results + lookahead) were tested; the 1-day window has no lookahead, the 4-day window has a 3-day lookahead, and so on. These analyses were conducted on a high VRE system with a combination of 8-hour and long-term (multi-day) storage. Longer optimization windows reduce LOLE by better optimizing storage usage and preparing for highest system risk situations. However, care must be taken with over-optimizing storage operations, leading to overly optimistic results given that real-life foresight is limited. As such, shorter lookaheads, typically one week, were chosen for most of the analysis in that study, reflecting a case where week ahead forecasting is relatively accurate in terms of knowing overall energy needs on a day, but beyond that assumed less accurate.

Case Study: Impact of Lookahead on EUE (continued)

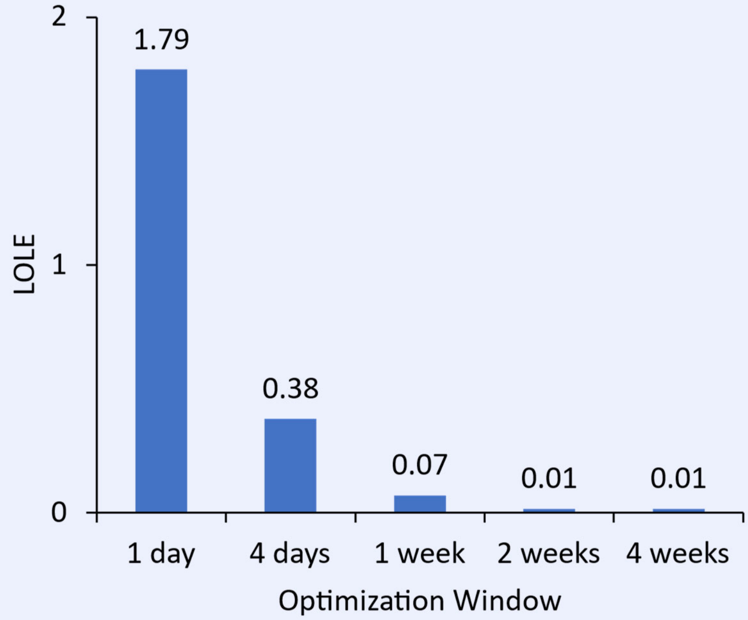

Figure 9. LOLE as a function of lookahead for high VRE + storage portfolio [25].

Hybrid Energy System Modeling

Hybrid systems link generation and storage resources, often behind a single interconnection point. Although a range of different hybrid configurations are possible, this section mainly focuses on hybrid energy systems connecting storage and VRE units. Hybrid installations are increasingly popular and are expected to outpace standalone storage installations in the coming years [26].

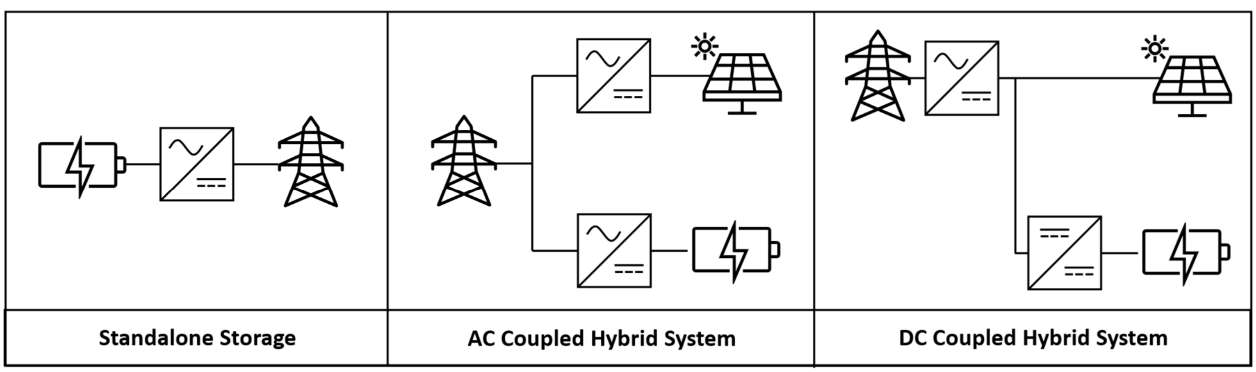

Figure 10. Common storage and hybrid configurations.

Many of the considerations related to storage and VRE models discussed in this Section and in Section 2.2.2 directly apply to hybrid energy system modeling. However, there are certain modeling considerations that are specific to hybrid systems.

Figure 10 shows three common storage and VRE configurations. Hybrid resources are often composed of the connection of solar and storage resources. Both solar and storage units output DC current, requiring DC-AC inverters to connect them to the (AC) bulk power system.

A common practice, driven by economic considerations, is to slightly undersize inverters with respect to the PV installations that they are connected to. That is, the rating of the inverter is generally lower than the maximum DC power output of the PV plant, resulting in PV clipped energy, as illustrated in Figure 11. Connecting PV to storage in certain hybrid configurations allows for this clipped energy to be used to charge storage.

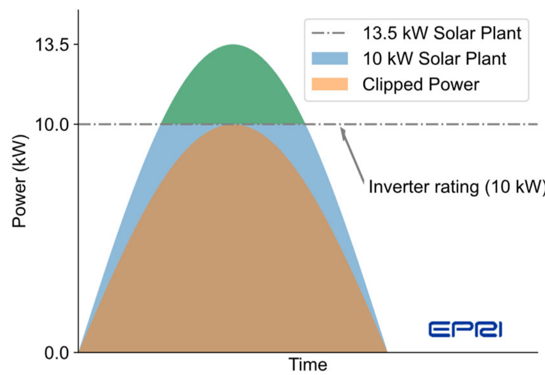

Figure 11. Clipped energy for two solar power plant installed capacities (10 kW and 13.5 kW) generating at peak power output with an inverter rated at 10 kW.

Two hybrid resource configurations are illustrated in Figure 10: AC and DC coupled. **AC coupled resources** consist of generation and storage units with individual DC-AC inverters. In this configuration, battery storage units can charge from either the grid or the attached VRE resource. However, since ES is not connected behind the PV inverter, it is unable to store clipped energy. This configuration is typical of retrofitted hybrids [27]. Currently, most utility-scale hybrid plants are AC-coupled, largely due to tax credits incentivizing the addition of storage to pre-existing solar plants such as the USA IRA [28].

In order to be able to charge using clipped energy, battery storage must be connected to PV generation on the DC side of the inverter. These **DC coupled configurations** economically allow for higher inverter loading ratios, increasing the utilization of peak PV generation.[18] DC-coupled systems can use either mono- or bi-directional inverters. Mono-directional DC coupled systems

[18] An inverter loading ratio is calculated as the ratio of the DC capacity of a solar panel to the AC capacity of an inverter.

only allow for energy to flow into the grid, not allowing for storage to charge from the grid. Bi-directional inverters allow for storage to be charged from either attached generation or from the grid.

AC coupled resources can be represented in RA by connecting a generation and storage resource through a set of operational constraints, such as common interconnection constraints, or an obligation for storage to absorb any VRE that would otherwise be curtailed.

Detailed modeling of DC-coupled hybrids requires consideration of a set of additional characteristics [29].[19] These include:

- *DC generation profiles rather than AC:* The power output of most generation resources is modelled with an AC output. While the inverter output that is injected to the grid from the hybrid would remain AC, to model ES charging from of otherwise clipped energy, DC PV output profiles are required.
- *Separate efficiencies for battery charging via grid vs. renewable resource:* Since DC coupled storage charges directly from the renewable resource, the power stored will not be reduced due to inverter inefficiency. Conversely, power stored from the grid will pass through the inverter, requiring inverter charging efficiency modeling. Therefore, different charging pathways, and associated efficiencies, must be modelled.
- *Separate efficiencies for battery DC-DC converter and grid inverter*: Similarly, power can be injected to the grid from the hybrid resource either directly from the renewable resource, or from the storage resource. Thus, the model must be capable of differentiating the pathway, and applying the relevant efficiencies.

Due to the very large increase in model complexity associated with representing DC-coupled hybrids and the (common) lack of necessary data, AC-coupled models may suffice for RA studies [29].

[19] See for more information relating to the capacity value of hybrids https://gridops.epri.com/Adequacy

2.2.4 Hydroelectric Power

Table 10. Hydroelectric power modeling by level of fidelity.

	Level I	Level II	Level III
Aggregation and constraint modeling	Hydro power units are aggregated by unit type or watershed connection. Constraints for individual units are aggregated and simplified.	Hydro power units are aggregated by unit type or watershed connection. PSH is represented individually. Simulation outputs are post-processed and new constraints are iterated back into the optimization if necessary to ensure that individual unit constraints are not violated.	Each hydro plant is modeled individually. A full set of applicable operational, environmental, and regulatory constraints are modeled for all hydro power units.
Cascading operations	Cascading impacts on hydro operations are not recognized.	Key cascading dependencies are recognized in the model.[20]	Cascading impacts on hydro dispatch are recognized, including the distinction between cascading and non-cascading water inputs.[21]
Run of River (RoR)-specific considerations	RoR outputs are modeled through timeseries based on historical data, without explicit consideration for pondage.	RoR outputs are modeled through timeseries based on historical data with expected pondage outputs integrated into timeseries.	Pondage is explicitly modeled as a reservoir connected to RoR operations. Pondage outputs may be dynamically modeled as part of an optimization or input through a lower resolution pre-processing run.
PSH-specific considerations	Virtual node model without consideration of state of charge, or dispatched employing heuristics.	PSH dispatch and state of charge are explicitly represented within 8760 optimizations.	PSH dispatch and state of charge are explicitly represented within 8760 optimizations, recognizing distinctions between closed and open-loop PSH.

[20] Key cascading dependencies need to be identified on a system-by-system basis.

[21] It should be noted that detailed modeling of cascading hydro operations can be highly data and computationally intensive. This is only recommended for those systems that are heavily reliant on hydro, or where cascading hydro power plays a key role in RA.

Table 10 (continued). Hydroelectric power modeling by level of fidelity.

	Level I	Level II	Level III
Reservoir hydro-specific considerations	Hydro reservoir outputs may be modeled through input timeseries, implicitly accounting for output constraints and long-term energy management. Long-term reservoir management constraints are determined from historical data.	Hydro reservoir is dispatched as part of the optimization. Long-term energy management is achieved through the implementation of energy, reservoir or time based (e.g., seasonal, or monthly) targets. Long-term reservoir management constraints are determined from optimization or heuristic dispatch preprocessing.	Hydro reservoir is dispatched as part of the optimization. Long-term energy management is achieved through the implementation of: energy allotments, reservoir trajectories, or water value curves. Long-term reservoir management constraints are determined from optimization or heuristic dispatch preprocessing. Water value curves are dynamically calculated as part of the optimization.
Outage modeling	Outages are not explicitly modeled but are implicitly accounted for through input data.	Periodic planned outages are accounted for. Unplanned outages are accounted for through fixed EFORd rates. The impact of sedimentation on generator availability may be considered through capacity derates.	Periodic planned outages are accounted for. Unplanned outages are modeled using both mean-time-to fail and mean-time-to-repair rates. The impact of sedimentation on generator availability may be considered through capacity derates. Outages due to water shortages may be accounted for probabilistically, as well as correlated outages.

Background

Hydroelectric power is one of the oldest sources of electricity generation, with its introduction quickly following the invention of the electric generator. Worldwide installed hydro power capacity reached 1,360 GW in 2021, including 165 GW of pumped storage [30]. Hydro power has a number of highly valuable characteristics for operations and RA:

- It can be dispatchable.
- It can provide long- and short-term energy storage.
- Installations generally have high capacity and long lifetimes.
- It is renewable and largely carbon free.

Hydro power plays a key role in RA in many parts of the world, with some systems being particularly dependent on it [31].

Modeling Hydroelectric Power Generation

Hydroelectric power representations in RA can have significant implications on adequacy [32]. A study from Politecnico di Milano found that system LOLE values could vary by up to 35% depending on hydro power modeling assumptions made in the European Resource Adequacy Assessment (ERAA) [33]. A summary of the key considerations for hydro power generation modeling by level of fidelity can be found in Table 10.

This section considers the following aspects of hydroelectric power modeling:

- Differentiating hydroelectric generators and global modeling considerations
- Generation constraints
- Outage modeling
- Reservoir limits and long-term energy management

Differentiating Hydroelectric Generator Types and Global Modeling Considerations

There are three main categories of hydro power plants:

- Run-of-river (RoR), with, and without, pondage.
- Reservoir hydro power.
- Pumped storage hydro (PSH).

Run-of-river units generate electricity by diverting a portion of river flow through hydroelectric turbines. RoR generation is largely dependent on natural water flows as most plants do not have reservoirs. However, certain larger installations may have a small reservoir, known as pondage [34].

RoR shares certain key characteristics with VRE; generation is most often non-dispatchable (except for RoR with pondage) and dependent on hour-to-hour water inflow availability. RoR water inflow timeseries are often obtained from historical generation data. Other than water availability, RoR outputs are also constrained by operational, environmental, and regulatory considerations, as outlined in Table 11.[22]

Pondage RoR is rarely explicitly modeled in RA: pondage generation outputs are often considered through RoR water outflow timeseries. However, in systems with large pondage capacity, it may be necessary to model it explicitly as a form of reservoir to appropriately capture its capacity to provide system flexibility and RA support [33].

Reservoir hydro power plants use a dam to store water in a reservoir for later use. Operators can choose when to generate electricity by opening the dam and running water through a turbine, subject to the operational, environmental, and regulatory constraints outlined in Table 11 [35]. Energy availability is influenced by water inflows, as is for RoR, but also by reservoir capacity. Reservoir hydro power is dispatchable, and water used to generate energy may or may not equal water inflows.

Pumped storage hydro plants connect two water reservoirs, storing, and generating electricity by moving water from a low elevation to a high elevation reservoir, and vice-versa. Closed-loop PSH installations are not connected to an outside body of water, whereas open-loop PSH is connected to a natural body of water. As for other energy storage units, explicitly modeling linked dispatch and state of charge within 8760 optimizations is the best approach to capture PSH operations. Additional constraints, outlined in Table 11 are added as needed. Although alternative modeling methodologies exist, these are often less accurate.

Alternative PSH Model

PSH can be modeled as a pair of virtual nodes, used to separately represent generating and pumping operations [33]. A generation unit with unlimited capacity discharges when generation is required and is bound by constraints to match the power consumed by the linked unlimited demand node. Either weekly or daily cumulative constraints ensure that the PSH pumping and generating power are equal once efficiency is considered. While this method offers computational advantages, one of its key disadvantages involves the lack of state of charge monitoring, which could result in behaviors outside of those physically permitted, such as excessive continuous generation that would deplete the reservoir if implemented in the real world.

[22] The structure of electricity markets may also influence or constrain hydroelectric power operations. However, implications of market design on asset operations are region-specific and are not directly addressed as part of this report.

One of the key factors making hydro power modeling a complex area for planners and operators is 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 hydro plant configurations are known as cascading hydro power.

To represent cascading hydropower in an RA model, the relationship between different units must be known. Water inputs to a given plant may be separated into inflows that are dependent on the operations of up-stream plants, and those that are not.[23] Representing cascading behavior increases the accuracy of RA and operational models, however, many systems do not consider it as it can significantly increase modeling complexity and reduce computational tractability. The tradeoff between RA model tractability and hydro power representation accuracy needs to be considered on a system-by-system basis, based on the amount of hydro in the resource mix as well as the complexity of the hydro plant operations.

An additional commonly used simplification to represent hydro power in RA is unit aggregation. Hydro power generation is often aggregated at the watershed level. However, it may also be clustered by unit type, where PSH may be clustered with other, non-hydro storage resources. Potential issues associated with aggregation include the violation of constraints for individual units, incorrect evaluation of hydro capabilities and contributions to RA, and reduced ability to account for maintenance and outages [32]. Certain models may carry out a post-processing step to check whether optimized hydro dispatches violate individual unit constraints, iterating through the problem as necessary until an acceptable solution, with no constraint violation, is found [36].

[23] Water inflows that are not dependent on the operations of up-stream plants in cascading hydro power may come from other water sources (i.e., rivers with no upstream hydro power generation) or precipitation.

Generation Constraints

Hydro power dispatch is constrained by **operational** and **environmental and regulatory constraints**. A common set of these constraints are summarized in Table 11.

Table 11. Common constraints by hydroelectric power resource type.

Category	Type	Constraint	Run of River	Reservoir	Closed loop PSH	Open loop PSH
Operational	Turbine	Max/min power (MW)	X	X	X	X
		Ramping ability (MW/min)	X	X	X	X
		Up/downtime (h)	X	X	X	X
	Reservoir	Absolute capacity (MWh)	X*	X	X	X
		Quantity stored (MWh)	X*	X	X	X
	Pump	Max/min power (MW)			X	X
		Ramping ability (MW/min)			X	X
		Up/downtime (h)			X	X
Environmental and Regulatory	Flow	Max/min flow constraint (m^3/s)	X	X	X	X
		River flow variation (m^3/s^2)	X	X		X
	Reservoir	Level restrictions (l or m^3)		X	X	X
		Restriction of prolonged storage (h)	X*	X	X	X

* Applicable to RoR units with pondage

Operational constraints capture the physical and technical limitations of hydro power plants. All forms of hydropower generation utilize turbines to generate electricity and are therefore limited by their technical specifications, including maximum and minimum power outputs, ramping capabilities, and turbine up and down times.[24] Constraints relating to reservoir capacity apply to PSH, reservoir hydro, and RoR with pondage. Pump constraints only apply to pumped storage hydro, and include power, ramping, and up and down time constraints.[25] PSH pump and turbine constraints can either be the same, or different, depending on specific unit characteristics [35].

Cavitation Damage

Cavitation damage arises through the rapid collapse of vapor bubbles within the water flowing through hydroelectric turbines. Output restrictions at high head or low tail-water levels may be applied to prevent cavitation damage for hydro generators [37]. Output restrictions due to cavitation, when represented in RA, are often set as soft constraints that can be broken at a high cost.

Environmental and regulatory constraints *arise from the opportunity cost of using waterflow, rivers and reservoirs for power generation versus using them for recreation, irrigation, human consumption, or as a habitat for wildlife* [38]. In order to balance needs across each of these uses, environmental and regulatory constraints are often imposed on hydro generation.

Flow constraints, summarized in Table 11, limit the flow of water released by hydro units. Maximum and minimum flow constraints are required to ensure adequate river flow for wildlife welfare, crop irrigation, as well as to control impacts on additional downstream hydropower installations.

The level of variations in river flow may also be restricted to reduce turbulence. Certain restrictions are specific to reservoirs, including those on reservoir level limits, and prolonged water storage. To reduce dramatic fluctuations in reservoir level, and maintain adequate habitats for wildlife, minimum and maximum reservoir levels are often imposed. Many large

[24] Most hydroelectric power plants are able to go from a cold start to full operations in less than 1-hour. Making start-up and shut down constraints non-binding in most RA modes. However certain exceptions exist [123].

[25] It is rare for hydro pump up and down times to exceed 1 hour and therefore to be constraining at the RA level, however exceptions may exist.

reservoirs are also used for flood prevention and are required to have ample space to store flood inflows at certain times of the year, further restricting maximum reservoir levels. Restrictions on prolonged storage exist to minimize thermal stratification. That is, the deterioration of water quality through the reduction of its oxygen content and increased algae growth. To prevent this, limits on how long the water can remain in one reservoir may be applied [35].

To comply with environmental, regulatory, and operational restrictions on flow and flow variations, RA models may constrain power output or power output variation hourly, daily, or weekly.

Finally, anthropogenic climate change may not be explicitly considered today when modeling hydro generation, however it continues to impact hydro generator outputs. Impacts such as reduced icy seasons, greater precipitation during flood seasons, or reduced overall precipitation are affecting operator decisions, as well as altering patterns of water availability. As hydrologic conditions continue to change, models will need to reflect new restrictions on usage.

Any constraint may be implemented either as a hard or a soft constraint in RA and operational models, depending on its nature and the real-world repercussions of breaking it. Hard constraints cannot be broken by the solver and are used to represent physical limitations to hydro power operations, i.e., those related to physical reservoir size and storage capacity or turbine capabilities limitations on power outputs. Soft constraints may be broken, often at a high penalty cost. For example, excess water spillage may be allowed during a flood, at a penalty cost representing the cost of the fines that would be imposed in real life. The value of the penalty cost associated with each constraint determines the order in which constraints will be broken if needed to support system operations, with lower penalty costs broken first [35]. Implementing a combination of hard and soft constraints, when representative of real-life hydro power operations, results in higher RA support to power systems from hydro units vs. scenarios when only hard constraints are implemented, as highlighted in [33].

Outage Modeling

As with other forms of generation, outages can either be planned or unplanned/forced. Planned outages include periodic maintenance, scheduled upgrades, or minor repairs. Forced outages can include equipment failures, or shutdowns due to extreme weather conditions. The reader is encouraged to refer to Section 2.2.1 for a detailed description of planned and unplanned outages.

Factors Influencing Hydro Generation Availability

There are a number of factors specific to hydro generation impacting the ability of plants to store and produce electricity. Some factors affect only certain plant types, whereas others affect all. Table 12 displays a selection of factors affecting each plant type.

Table 12. Factors affecting hydroelectric power availability.

Factors Affecting availability	RoR	Reservoir	Open-Loop PSH	Closed-Loop PSH
Sedimentation		X	X	X
Drought and Aridification	X	X	X	
Icing	X	X	X	X

Sedimentation occurs when sediments carried by rivers deposit when flows slow as they reach a reservoir. Sediment built up in reservoirs reduces the reservoir volume available for water storage. This happens in every reservoir worldwide [39]. Unless removed during maintenance, sediments will continue to accumulate, progressively reducing the volume for water storage available. The impact of sedimentation is usually reflected in hydropower models by increasing minimum reservoir level constraints as capacity is depleted.

Drought is defined as short term reductions in water availability, whereas **aridification** involves long-term climate change [40]. These climatic phenomena reduce the ability of hydroelectric power plants to generate electricity due to reduced water availability. Additionally, as reservoir levels drop, greater outflows are required to maintain the same power output. As a result of droughts and aridification, RoR plants experience lower inflows, reducing their non-scheduled output, whereas open-loop PSH units may experience restrictions on capabilities to extract water from surrounding water sources. Water shortages such as these are modeled through changes to expected inflows.

Icing arises when there are prolonged low temperatures conditions, facilitating the formation of ice in water reservoirs and around hydroelectric generation equipment. Hazards associated with ice include intake blockages, river flow reductions, and icing of structures, which can damage them. Specific operational constraints may be required for units at risk of icing to ensure their appropriate maintenance and operations, as well as reducing risk to surrounding ecosystems. These can include maintaining reservoir levels during freezing temperatures to ensure stable ice covers or reducing variability in discharges to prevent ice releases from the frozen cover [41].

Outages can be represented in a number of ways. Maintenance and forced outages are generally considered separately. Maintenance outages may be deterministically input into the model when the timing of these is known, or pre-processing runs may be conducted to probabilistically schedule maintenance outages, based on a pre-established maintenance rate, as in [42]. As outlined in Section 2.2.3, commonly employed methodologies to capture forced storage outages in RA involve:

- Considering a fixed Equivalent Forced Outage Rates on Demand (EFORd).
- Advanced methods consider probabilistic modeling of forced outages, through *mean time to fail*, and *mean time to repair* parameters. Mean time to fail and repair values may be adjusted depending on the type of unit, for example, longer mean times to repair may be considered for hybrid plants.

Finally, a number of RA models do not explicitly account for hydroelectric outages, and instead rely on these being implicitly represented in input data through capacity derates [43].

Correlated outages are not often captured in RA; however, hydro generators may be particularly susceptible to these, particularly under cascading configurations, where outages affecting one unit may have an impact on downstream units which utilize the same water flows.

Reservoir Limits and Long-Term Energy Management

Models treating hydropower as a dispatchable resource and assuming a low variable cost value in their economic optimization run into problems appropriately dispatching reservoir hydro power.[26] Hydroelectric generators have very low variable costs, especially when compared to thermal units. While entering RoR units into economic optimization models with zero cost ensures that their must-run generation is always taken, modeling close-to-zero cost reservoir hydro units would result in the immediate dispatch of hydro generation as soon as water is available. This would result in suboptimal hydroelectric resource usage, leading to periods requiring more expensive generators to be utilized and overall resulting in a suboptimal use of system-wide resources.

To allow for the optimization of hydro power over optimization windows as short as days or weeks, while taking into account the seasonal patterns of water inflow and electricity demand, historical data may be used directly to set water usage constraints. These constraints may also be calculated using heuristics or through preprocessing simulations. Pre-processing runs often involve running optimizations with timesteps greater than 1 hour, e.g., 4 hours, and use historical inflow, outflow, and reservoir level data to set appropriate usage constraints. These constraints are often implemented through:

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[26] Long-term energy management is most relevant for reservoir hydro. While certain PSH units may be concerned by long-term energy management, they are mostly dispatched in a similar fashion to short-term storage units, as outlined in Section 2.2.2.

- Energy allotments
- Reservoir trajectories
- Water values

Energy allotments limit hydro power generation by providing a discrete amount of energy that can be dispatched each week. Often, the hydro resources are constrained to dispatch exactly the allotted amount, with no, or minimal, carryover allowed between optimization horizons (see Figure 12), however some models do include iterations, in which the energy allotments can be adjusted and fed back into the dispatch model if shortfalls are found to occur.

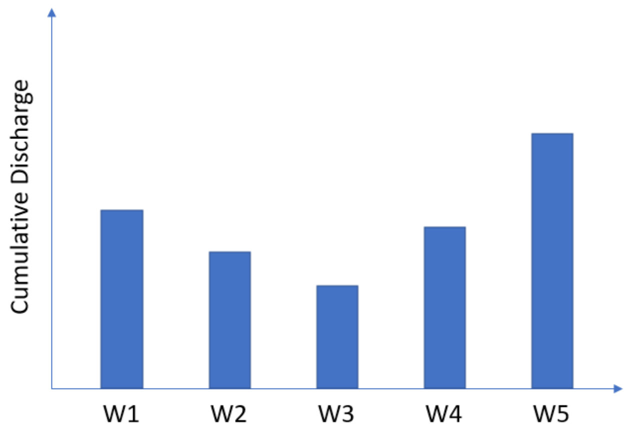

Figure 12. Example of weekly allotted energy for a sample reservoir unit.

Reservoir trajectories are an alternative to the energy allotment method. Here, a target reservoir energy value, sometimes within an envelope of possible values, is provided. Targets, or values within the reservoir trajectory envelope, must be met at the end of each time period, for example each week (see Figure 13). Contributions to RA may be greater when allowing trajectory flexibility within an envelope, rather than constraining reservoir levels to meet discrete values.

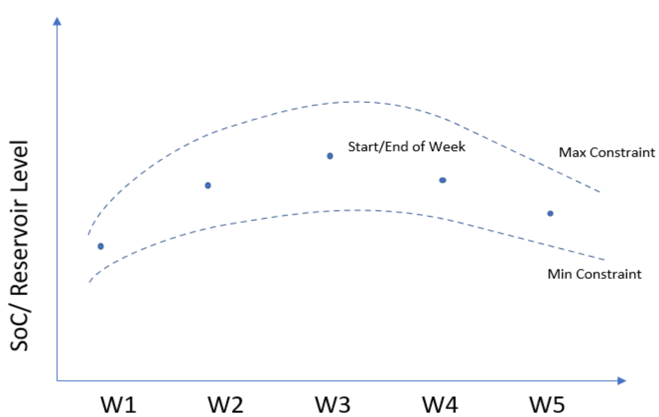

Figure 13. Example of reservoir trajectory constraint.

Example: ERAA reservoir trajectory compilation

The ERAA employs a pre-processing hydro optimization that provides weekly reservoir trajectory data to be used as input for the dispatch optimization, setting minimum and maximum reservoir levels for each week, which are then input into the RA model as soft constraints. If appropriate data is not available, TSOs may provide fixed weekly targets which are then used as hard constraints to ensure reservoir levels reflect real world behavior. Deterministic targets are the less preferred option as they restrict the ability of hydro power to provide real-time flexibility in the simulation [43].

Water values are another tool employed by modelers to ensure that the opportunity cost of reservoir water usage is captured within RA. One option is to set fixed, seasonal, or monthly water values, and employ hard constraints on maximum and minimum generation. This method sets a value for reservoir hydro usage within the merit order. However, if system prices are sufficiently high, the reservoir hydro can still be inefficiently dispatched.

Another option is to use water value curves. Here, hydro reservoir water is discretized into a number of blocks, each of which have a different water value, as illustrated in Figure 14. Water closer to the top of the reservoir will have low value to prioritize evacuation to make room for inflows. Water closer to the minimum reservoir level will be extremely highly priced, either high enough that it will never be dispatched, or alternatively, with a water value that will only be reached during severe contingency events, allowing it to provide emergency dispatch.

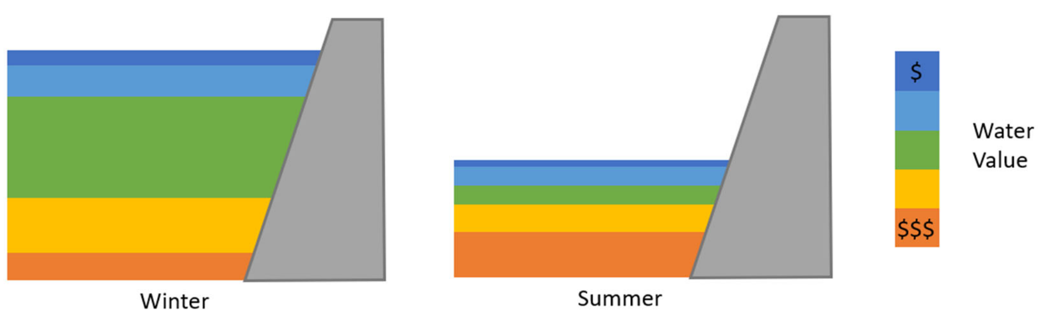

Figure 14. Example of water value curve.

Water value curves can be obtained in three main ways: through user input based on historical data, via a preprocessing simulation, or by dynamically assessing the current reservoir status and hydro forecast during each optimization horizon. While user input and preprocessed curves require less computing power, dynamically generated curves can respond much better to system events, and more closely represent real world hydro operations.

It should be noted that there is a lack of consensus regarding best practices in the area of reservoir management modeling. Nonetheless, drastic differences in the adequacy contribution of reservoirs can exist when employing different modeling approaches.

Case Study: Impact of Boundary Conditions on LOLE for Long-Term Storage Managed

As part of the *Resource Adequacy for a Decarbonized Future Initiative* a Western US case study was conducted looking at how simulation start, and end dates can impact adequacy risk metrics. The test system considered was a decarbonized, high VRE system, highly relying on short and long-term storage for balancing. To incentivize appropriately using long-term storage over the year, a penalty on energy depletion was implemented through a cost per MWh generated.

As outlined in Section 2.2.3, boundary condition selection can play an important role in simulation outcomes, particularly for those systems with energy storage, and other time-dependent resources. Analyses were carried out for a system showing most stress conditions arising during the winter. Two boundary conditions were tested: simulations starting and ending in January and in June. Long-term storage was required to be fully charged both at the start and end of the simulations for both scenarios.

Results are presented in Figure 15. The choice of boundary conditions in June resulted in generation schedules that were better able to manage long-term storage by shifting winter shortage conditions to the late winter/early spring period, where load was lower. Applying boundary conditions in January resulted in severe shortages arising in December, when loads were higher, resulting in 0.09 LOLE/year vs. 0.07 LOLE/year when June boundary conditions were applied.

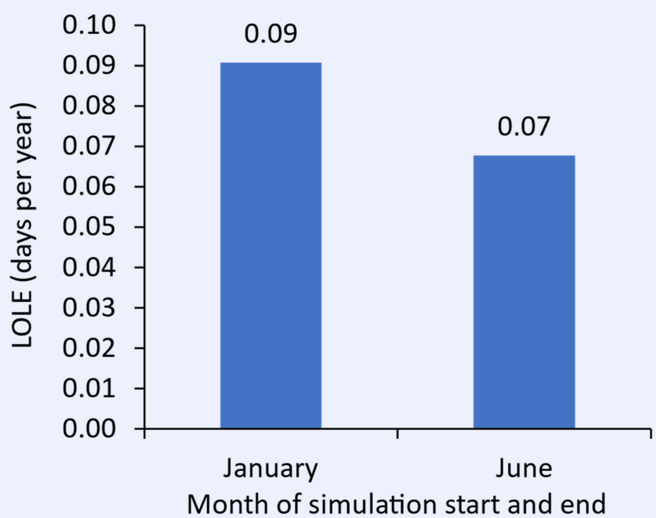

Figure 15. Impact of start and end dates on LOLE for high VRE + storage system [25].

2.3 Demand-Side and Customer-Scale Technologies and Load Shape Forecasting

The work presented in this section classifies demand-side component and technology modeling into two separate sections: firm and responsive loads are addressed in Section 2.3.1, distributed generation and storage are addressed in Section 2.3.2.

2.3.1 Firm and Responsive Loads[27]

From an operational and modeling perspective, demand, or total system load, can be divided into two distinct categories, illustrated in Figure 16:

1. **Firm** or **essential** loads that have no, or very little price elasticity and are not responsive to market or dispatch signals. These loads may include:
   - Loads from all customers that are not exposed to incentives to modify their consumption in any way.
   - Commercial or industrial loads where any modification in consumption, or process interruption, can incur high costs.
   - Critical or uninterruptible loads.

   Certain firm loads may have the technical capability to provide a certain level of demand-side flexibility but may remain firm due to a lack of exposure to demand response signals, as is the case for customers on flat rate tariffs.
2. **Loads that are responsive to market and dispatch signals** are classified into two sub-categories:
   - **Flexible loads,** comprising all load types that can increase or decrease consumption in response to price, or dispatch, signals. These loads **do not need to make up for deviations from baseline consumption at a later time.** An example may be dimming the lights at a commercial establishment in response to a price signal (i.e., time-of-use prices). Flexible loads can be permanently lowered after activation (i.e., the lights stay dimmed until the next day) or reset to their previous consumption levels. This category includes curtailable, as well as turn-up (load-building) loads, although the latter has been less commonly deployed to this date.
   - **Shiftable loads**, unlike flexible loads, **need to make up for deviations from baseline consumption when providing demand flexibility**. For example, electric vehicle charging may be deferred; however, vehicles need to make up for missed charging after a scarcity event is over. Shiftable loads may be compounding or non-compounding:

[27] Note to reader: the terms *load* and *demand* are used with a certain level of interchangeability since no clear consensus regarding their distinction when relating to energy assessments had been established at the time of writing this report.

- Non-compounding shiftable loads are typified by (smart) washing machine loads. The load is shifted from one period to the next, with no change in overall energy used.
- Energy consumption of compounding shiftable loads changes based on the duration of the advance or deferral of consumption, relative to immediate use. Electric vehicles, energy storage, and electric heating and cooling can behave in this way, owing to efficiency losses or changing background variables such as weather. It should be noted that some non-compounding loads may become compounding if consumption has been deferred for a sufficiently long time.

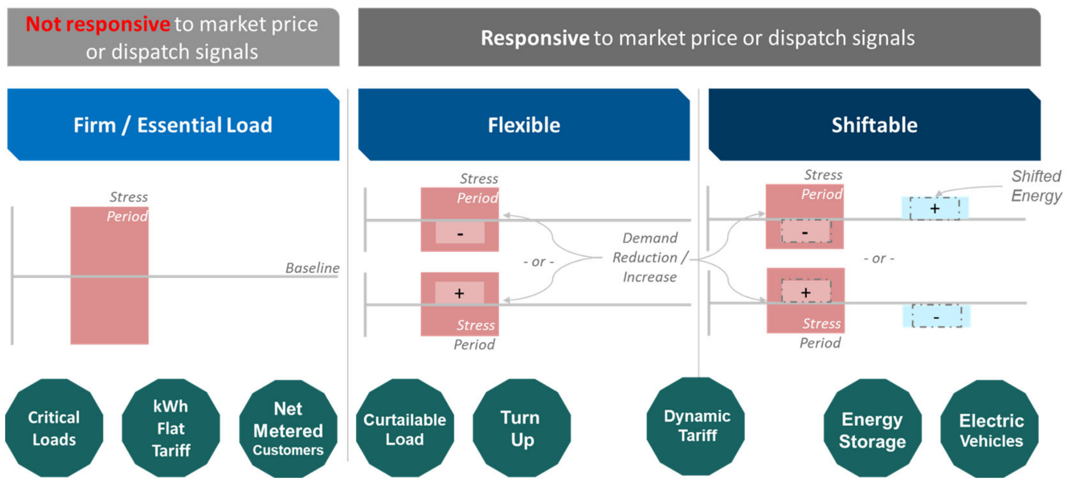

Figure 16. Load categorization [44].

Adequacy assessments have traditionally focused on utility-scale, supply-side generation meeting a (mostly) firm demand. While firm demand forecasting is still a key component for resource adequacy, with growing automation, connected devices and the internet of things, accurately capturing flexible load operations is becoming increasingly important. Demand-side response has the potential to not only be used as an emergency procedure in case of severe system contingency, but to become a part of daily planning and operations, much like supply-side units.

A 2019 Brattle study finds that 200 GW of demand-side flexibility (DSF) is expected in 2030 in the US, up from 60 GW in 2019 [45]. This growth in DSF will be significant for planning and operations as it is equivalent to 20% of the expected US peak demand in 2030.[28] Similarly, a study conducted by the European Commission estimates that 160 GW (equivalent to 28% of the expected peak load) of DSF will be available in the European Union in 2030, up from 23 GW in

[28] Peak load is used here as a measure of the potential for demand flexibility. However, this is not to say that demand-side resource availability will be coincident with the peak load.

2016 [46].[29] Given the high potential for flexible loads to contribute to planning and operations, accurately capturing their behavior is increasingly important.

Different modeling considerations are required depending on whether loads are firm or responsive.

Firm Loads

Table 13. Firm load modeling by model fidelity.

	Level I	Level II	Level III
Firm load models	Fully deterministic model with limited firm demand uncertainty considered.	Hybrid model considering multiple deterministic firm load uncertainty scenarios.	Fully probabilistic model considering a range of possible future load scenarios and weather-correlation across all weather-dependent timeseries.

The industry standard is modeling *firm* loads through *forecast timeseries data*. From a resource adequacy modeling perspective, the differences between Level I and Level III implementations are based on how uncertainty is considered (see Table 13). That is, whether, and how, multiple future load forecasts are accounted for.

Assuring the quality of firm load forecast timeseries heavily depends on the capabilities of *load forecasting* and *scenario generation approaches.*

Load forecasting involves the generation of (often probabilistic) future firm load timeseries based on predicted weather patterns (including impacts from anthropogenic climate change), economic factors, end-use technology and DER adoption, demographic change, the rollout of energy efficiency schemes, and other socio-economic factors potentially impacting electricity demand – not all these factors are used in current forecasts, but this is the general industry trend. Advanced load forecasting approaches may consider a wider range of weather years as well as track large industrial load, hydrogen generation, transport electrification and DER growth closely. Additionally, higher fidelity load forecasting accounts for weather-correlation across all weather-dependent timeseries, including wind and solar outputs, as well as generator outages.

Scenario *generation* tools then assure that the appropriate set of future load forecasts are selected and included in RA assessments such that a suitable range of risk is captured in models.

[29] Same as above.

Responsive Loads

Table 14. Responsive load modeling by level of fidelity.

	Level I	Level II	Level III
Static vs. dynamic modeling	Static timeseries approach applied to model aggregated response from all responsive loads.	Most responsive loads are modeled using a static approach, however dynamic approach may be used to represent emergency load curtailment programs.	Both static and dynamic approaches are used and are matched to the appropriate demand-side response programs. Load building programs are considered as well as load reduction. Probabilistic nature of demand-side response is modeled.
Constraining resource availability	Implicitly captured in timeseries.	Certain constraints are applied to dynamically modeled *flexible* loads.	All relevant constraints are applied to dynamically modeled *flexible* and *shiftable* loads.

Demand-side flexibility, or responsive demand, are both taken to refer to the capacity for responsive loads to respond to incentivized consumption changes, measured at the customer meter. There are two ways of activating DSF [47]:

- **Price-based programs** use price signals or tariffs to incentivize consumers to flex or shift consumption. Prices serve as an incentive; the customer decides whether and when to respond. Price-based programs include time-of-use tariffs, critical peak pricing, demand charge programs and real-time pricing programs.
- **Dispatchable load programs** where customers subscribe to programs allowing for certain loads to be flexed or shifted subject to a set of constraints limiting the timing, duration, or total energy that is dispatched. Dispatchable load programs include reliability dispatch, emergency load reduction, and interruptible load programs.

The way DSF is activated has implications on dispatch and therefore on modeling flexible loads in RA.

Table 15 shows an overview of some of the key factors influencing responsive load behavior and availability, affecting operations and adequacy.

Table 15. Factors influencing responsive load behavior and availability.

	Factors influencing response and availability	
	Common factors	**Specific factors**
Flexible demand	• Tariff or flexible dispatch incentive design • Dispatch number and duration limits • Weather • Time of day • Time of week • Season • Customer fatigue • End-use technology availability	
Shiftable demand		Ability to shift consumption economically and technically.

Modeling Responsive Loads

Models capturing supply-side technologies in RA and operational models are well established for most technologies, as described in the previous section. There is a common framework through which planners understand the basic features that must be modeled to represent supply-side assets. For example, most modelers know that modeling a thermal power plant requires some representation of minimum and maximum power limits, and potentially could include ramping constraints, minimum up and down constraints, start-up and shut down delays, as well as some representation of maintenance and forced outages. When it comes to demand-side assets, in particular responsive loads, a similar industry-wide framework has not yet been established.

A summary of the key considerations for modeling responsive loads in RA by level of modeling fidelity is presented in Table 14. The key areas of focus for responsive load modeling proposed are:

- Static vs. dynamic response
- Resource availability and constraints
- Resource degradation and weather-dependent response

Static vs. Dynamic Response

The most commonly employed method for capturing responsive load impacts on resource adequacy is through the inclusion of static timeseries, aggregating expected demand-side response across a range of demand-side programs. This approach assumes that customer behavior is consistent in response to consistent signals, which are not always influenced by real-time system conditions. Response is modeled in a **static** manner, meaning that it is pre-determined and *exogenous* to internal RA optimizations.

Static modeling is appropriate for capturing demand-side flexibility that is responsive to signals that are consistent over time and that do not necessarily reflect real-time system conditions. For example, customer response to time-of-use tariffs is best captured using static approaches. However, this approach underestimates the potential capabilities of DSF able to provide flexibility in response to real time or near real time signals – this can become important for RA given these may reflect scarcity conditions, and so may underestimate ability to support the system (or overestimate if too optimistic about the response during scarcity). The lower complexity and computational burden of aggregated static modeling may be acceptable under low DSF rollout scenarios but will likely misrepresent responsive demand operations under higher rollouts.

Dynamic models represent responsive demand *endogenously* in RA, capturing the ability for loads to respond to real-time system conditions. The *flexible generator* modeling approach is often used, representing responsive loads through a pseudo-generator with unlimited ramping capability, dispatching at a set activation price. Today, the flexible generator model is mostly used to represent emergency demand response programs, such as critical peak pricing and emergency load reduction programs. The activation price for responsive demand is often higher than that of most other generators, ensuring that demand-side flexibility resources are exclusively used as a contingency resource, as in [48], [49] and [50]. However, dynamic modeling is also appropriate to represent day-to-day responsive load operations from loads subscribing to programs such as real-time pricing.

Dynamic models have mainly focused on capturing load reduction. However, certain systems are starting to develop dynamic models representing load building programs. The Australian Energy Market Operator (AEMO) implements a *negative generator* model, with the capacity to increase demand when prices go below 0 $/MWh [50].

An additional consideration is that dynamic models today mainly model *flexible* loads but do not model *shiftable* response (see Figure 16). However, responsive *shiftable* loads are likely to rapidly grow; electric vehicles, heat pumps, and electric water heaters all require load shifting when operated flexibly. That is; any deviation from their baseline consumption needs to be made up for at a later time. Load shifting can have impacts on RA that need to be carefully studied given that moving consumption from one period to another could also shift RA stress periods.

Finally, there is an inherent uncertainty in responsive load behavior, particularly under programs when customers decide when and how to respond to signals. Advanced representations, both static and dynamic, recognize this uncertainty and deploy probabilistic models based on historical response data.

Highest fidelity models match demand-side response programs to their appropriate, static, or dynamic probabilistic representations.

Case Study: Probabilistic Real-Time Pricing Load Response Modeling

EPRI has conducted studies as part of its *Resource Adequacy and Flexibility Assessment* and *Grid Edge Customer Technologies* Programs looking into developing models representing common programs targeting demand-side response. Results for these studies can be found in [51] and [52].

As part of this work, a probabilistic price-responsive *dynamic* load model was developed based on real-life trial data and was then implemented within an RA framework. Price-responsive load consumption as a function of day-ahead system price is plotted in Figure 17.

For this particular program, approximately 30% of the total load subscribed to the real-time pricing program was price-responsive, while the other 70% was firm. Demand reduction started at prices above 30 $/MWh. A probabilistic, price-dependent response model was implemented, capturing envelopes of probabilistic load response for 10 $/MWh price tranche increments.

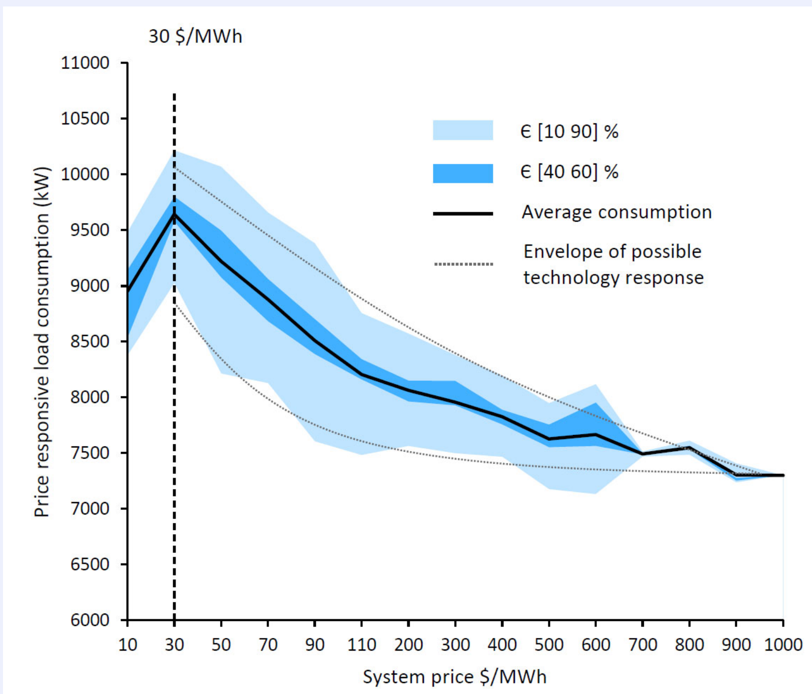

Figure 17. Load model for real-time price responsive loads [51].

Resource Availability and Constraints

When static timeseries modeling approaches are selected to represent responsive loads, load operational constraints should be implicitly captured in the input timeseries and are not explicitly modeled as part of RA optimizations. While simpler to model, this will miss some of the key characteristics of demand flexibility that can support adequacy. However, when responsive loads are modeled dynamically, the explicit formulation of operational constraints is required in order to accurately capture demand-side response contributions to adequacy. Accurately capturing DSF constraints can be especially relevant when modeling programs that target response from a particular technology, such as smart thermostat reliability dispatch programs. A summary of modeling considerations and constraints, specific to static and dynamic models can be found in Figure 18.

Constraints applied to dynamic responsive load models can be divided into those that apply to both *flexible* and *shiftable* loads, and those that apply exclusively to *shiftable* loads.

Certain studies exist applying constraints to *flexible* loads. In California Public Utilities Commission (CPUC) studies constraints are imposed setting a limit to the maximum number of dispatches from responsive loads, as well as setting a maximum number of dispatch hours per day, month, and year [49]. A monthly varying availability from responsive loads is also accounted for. Similar constraints are found in the Australian Energy Market Operator (AEMO)'s studies [50].

Highest fidelity modeling approaches consider constraints on both *flexible* and *shiftable* responsive load dispatch. However, it should be noted that certain RA tool capabilities may still require development in order to enable full representation of *shiftable* load modeling constraints, particularly for those constraints on shifted energy.

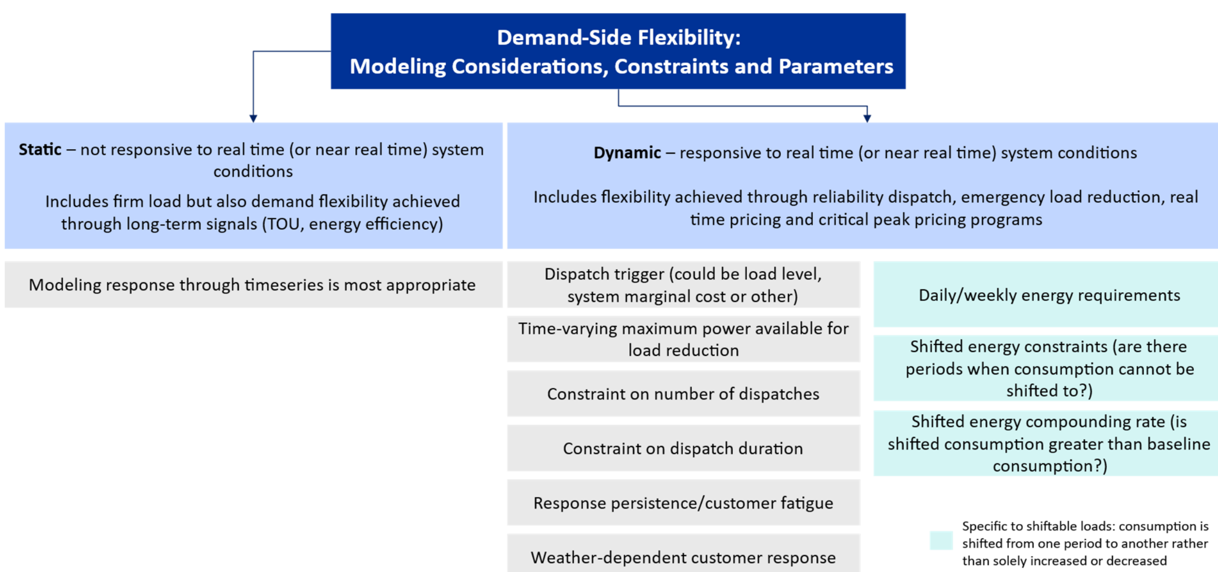

Figure 18: Modeling considerations, constraints, and parameters for static and dynamic responsive load models [53].

Case Study: Modeling Responsive Loads in RA

EPRI's work conducted jointly under the *Resource Adequacy and Flexibility Assessment* and *Grid Edge Customer Technologies Programs* in [51] and [52] developed models representing common programs targeting demand-side response and studied how these could impact adequacy.

Figure 19 shows results comparing a base case scenario without any responsive loads to scenarios where 900 MW of existing demand (3% of system peak load) was converted into responsive load. Three different types of DSF were tested:

- Time-of-use, which was modeled using a static approach based on historical consumption data,
- Price responsive loads, which were modeled dynamically based on the price – load response curve plotted in Figure 17, and
- Smart thermostat loads responding to a reliability dispatch program, which were modeled dynamically based on historical trial data and whose response was constrained based on the technical specifications of smart thermostats.

The type of response provided to the system differed depending on technology type. Overall results showed that there was a significant potential for responsive loads to contribute to RA.

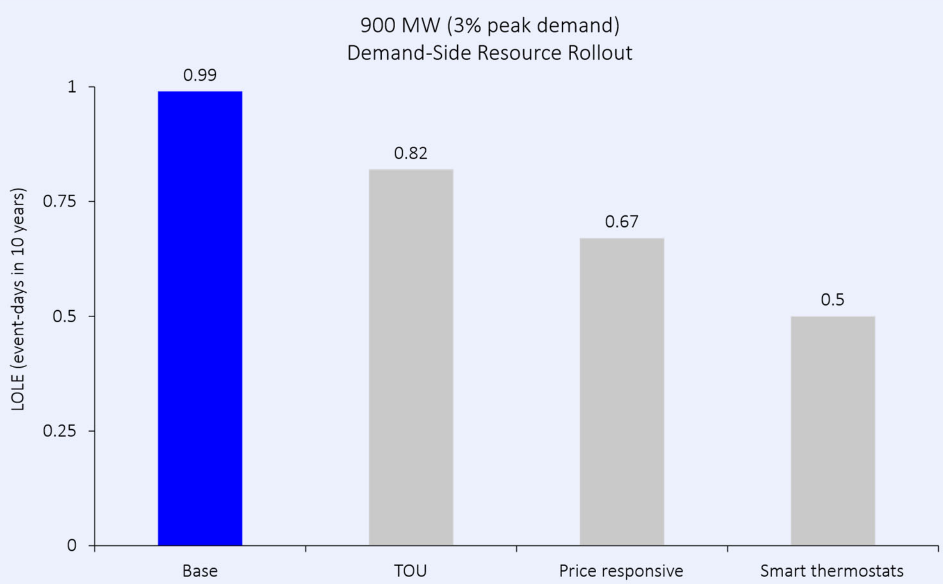

Figure 19. LOLE for scenarios with a rollout equivalent to 3% of peak demand of time-of-use, real-time pricing, and smart thermostat programs, compared to a base case scenario without responsive demand [52].

Response Degradation and Weather-Dependent Response

All responsive loads may be subject to response degradation, as a result of customer fatigue or technology-related factors. For example, customers may override reliability dispatch signals or choose not to respond to critical peak prices if these occur at a frequency that is subjectively perceived as being too high. Similarly, weather conditions, particularly extreme weather conditions, may need to be considered. For example, under extreme heat or cold conditions customers may override smart thermostat load reductions.

Modeling response degradation as well as weather-dependent demand-side response is incipient and industry standards have not been established yet. Data based on trials or real-life programs quantifying the impact of customer fatigue, technology-based factors, or extreme events on demand-side response is hard to come by, and therefore models accounting for response degradation or weather-dependent demand-side response are rare. For this reason, modeling recommendations are not put forward for this section.

However, understanding how customer response may degrade and the factors influencing degradation, as well as weather impacts on response will be imperative in the future, particularly if systems are to rely on responsive loads for operations and adequacy.

2.3.2 Distributed Generation and Storage

Distributed generation and storage encompass any small, generally less than 10 MW, generation and storage resources located behind the customer meter [54]. Only those technologies whose end-use is to generate or store energy are addressed in this section, focusing on distributed PV, distributed energy storage, and co-generation, also known as combined heat and power (CHP). A summary of considerations for distributed PV and storage modeling by level of fidelity can be found in Table 16 and in Table 17 for CHP.

The key additional challenge arising when modeling certain distributed assets is that system operators may have limited visibility of installations and their operation. Data collection challenges related to distributed energy resources are addressed in EPRI's Resource Adequacy Assessment Framework Data Collection Guidelines [55].

Distributed PV and Storage

Table 16. Distributed PV and storage modeling by level of fidelity.

	Level I	Level II	Level III
Distributed PV	Heuristic approach netting distributed PV generation from demand based on expected irradiance.	Distributed PV outputs are modeled based on several years of historical hourly PV output timeseries data.	Distributed PV output forecasts are generated based on several decades of hourly data, with correlation amongst weather shapes enforced. The impact of pitch angles on PV outputs is accounted for.
Distributed storage	Heuristic approach netting estimated storage outputs from load based on averaged demand and distributed PV profiles.	Storage static profiles are generated based on years of historical PV output data assuming that batteries are charged from excess rooftop solar and discharged when household load exceeds rooftop PV production. Battery roundtrip efficiency is accounted for.	Distributed storage static forecast timeseries are generated based on decades of historical data accounting for weather-correlated distributed PV outputs and battery roundtrip efficiency. Customer net-energy metering tariffs may be considered when forecasting distributed storage operations.

Distributed PV and Storage

Distributed PV modeling requirements are mostly the same as those for bulk-system PV, covered in Section 2.2.2.

At low distributed PV shares, heuristic approaches, netting expected distributed PV generation from demand based on averaged irradiance patterns may suffice. At higher shares, distributed PV requires similar treatment to bulk system installations, including the generation of forecasts based on several years to decades of hourly historical PV output data. Additionally, care should be taken to ensure correlated weather year data is used across all weather-dependent technology and load models.

An additional consideration when modeling distributed PV is that while optimal pitch angles are obtained with large-scale solar installations, they are not always possible with rooftop PV, leading to lower power outputs. The influence of distributed PV pitch angle on generation, and other factors such as shading from trees or overhead lines, as well as lower maintenance levels resulting in increased outages, may need to be explicitly considered when forecasting distributed PV outputs at high rollout levels, as in [48].

Customer-located **distributed storage** is most commonly found connected to PV systems. Many adequacy assessments account for distributed PV, however, those explicitly modeling distributed storage are rare.

Many of the considerations for modeling short-term storage developed in Section 2.2.2 apply to distributed storage, however, operational strategies can significantly differ between bulk and distributed storage. Customer-located storage is largely dispatched to minimize customer electricity costs, regardless of whether operations support the bulk system or not and is therefore heavily influenced by customer demand and solar power availability.

At very low levels of distributed storage shares, the impact of distributed ES on net demand may be considered through the use of heuristics, assuming that most customer-located distributed storage assets reduce net consumption in the early morning and evening, at times when there is no PV output, or it is low. At higher levels of distributed ES rollouts, static storage profiles may be generated based on years of historical PV output data assuming that batteries are largely charged from excess rooftop solar and discharged when household load exceeds rooftop PV production, accounting for storage roundtrip efficiency losses. Alternatively, when historical distributed storage operation data is available, forecasts may be built based on existing data.

The highest fidelity modeling involves understanding how storage responds not only to customer demand and PV availability, but considers how customer tariffs, including adherence to time-of-use or net-energy metering may impact response.

Distributed PV and Storage Impacts on RA

Many customers owning PV and storage subscribe to traditional net energy metering (NEM) programs, allowing them to inject excess generated power into the grid. However, as DER shares grow, traditional NEM-incentivized customer behavior can raise distribution network, as well as bulk system, operational challenges. Traditional NEM programs remunerate customers for exporting power at a flat rate, not considering system and network conditions. Customers are not encouraged to export power at times when the system needs it the most, nor to maximize self-consumption when the system does not require additional generation, or the distribution network cannot support further injection from customers. Issues regarding fair compensation and equity have also been raised regarding traditional NEM compensation schemes.

Advanced NEM tariffs, such as the NEM 3.0 tariff proposed by the California Public Utilities Commission in [56], aim to incentivize distributed generation exports to the grid at those times when it is most valuable to the system, as well as incentivizing self-consumption at those times when the system does not need, or cannot handle additional power injections. Remuneration for exported power in advanced NEM programs is based on hourly avoided system costs [57].

If advanced NEM tariffs take off in the future it is likely that the current timeseries-based modeling approaches for distributed storage will no longer suffice, requiring for distributed ES to be explicitly modeled and dispatched as part of RA optimizations.

Combined Heat and Power (CHP)

Table 17. CHP modeling by level of fidelity.

	Level I	Level II	Level III
CHP	CHP impacts on the net load are implicitly accounted for in net-load timeseries but are not explicitly modeled.	CHP units are explicitly modeled as part of RA. Some differentiation between flexible and inflexible CHP plants may be considered.	CHP units are explicitly modeled in RA, separately capturing operations from inflexible and flexible plants. Flexible operations are captured by enabling the ramp up of production and exporting power to the grid under power shortage situations or ramping down production under excess generation and low market prices. CHP asset availability, weather impacts on operations, and energy limitations may be considered.

Combined heat and power (CHP), or cogeneration, refers to the same technology. Both describe the simultaneous generation of electricity and heat serving (partially or completely) commercial, industrial, and district heating loads that would otherwise be largely served by the grid.

Table 17 provides an overview of CHP-specific modeling considerations classified by level of fidelity. CHP plants are thermal power plants and can therefore be subject to the modeling requirements highlighted in Section 2.2.4, particularly for those systems with high CHP shares. CHP units are mainly gas-fueled, although dual-fuel plants also exist to enhance fuel security.

CHP Power to Heat Ratios and Flexibility

CHP units can be more power- or heat-driven. Power to heat ratios are used to express the relationship between power and heat CHP outputs. Inflexible pure back-pressure CHP units have fixed power to heat ratios. Other CHP plant types, often larger CHP units such as extraction/condensing turbines, offer more flexible operations and are able to vary their power to heat ratio.

Many small-scale CHP units are designed as baseload and are operated to meet customer heat demand making them inflexible, must-run capacity. Baseload operations grant these CHP plants forced outage rates that are often lower than those of bulk system gas units.

For systems with low CHP rollouts, accounting for its impacts on demand implicitly through net load profiles may suffice. At higher CHP rollout levels, some level of differentiation between flexible and inflexible CHP units may be necessary, as in ENTSO-E's European Resource Adequacy Assessment (ERAA) [48]. Small, non-dispatchable units may be modeled as must-run units based on historical generation data. Larger, dispatchable CHP units should be considered separately. These units may be modeled using partial must-run constraints while allowing some flexibility to meet bulk-system needs.

Systems with high levels of CHP rollout may require similar modeling considerations to those outlined in Table 2, including more detailed modeling of planned and forced outages, weather impacts on operations, as well as energy limits due to fuel availability.

2.4 Networks

In RA assessment, the ability to supply the demand can be impacted by several networks, in particular the power transmission network (direct connection between supply and demand), and the gas network (which can impact supply). As such, how these are modeled is also very relevant to RA studies and reviewed here.

2.4.1 Transmission Network

In power system modeling tools, transmission network representations are generally split into three categories of complexity: nodal, zonal, and copper sheet. While nodal topologies provide the most accurate reflection of the actual power system, they are also the most complex to solve and require the most data. As for many of the other technologies considered in this report, there is an inverse relationship between model complexity and simulation runtime.

A summary of the considerations for transmission network modeling by level of fidelity is presented in Table 18. Factors such as system size, model runtime/performance, and study intent factor into the decisions for which model type is used.

Table 18. Transmission network modeling by level of fidelity.

	Level I	Level II	Level III
Network model	Copper sheet.	Zonal.	Flow based zonal or nodal, if relevant.
Network outages	Not applicable.	May model network outages.	Models network outages.
Transmission line limits	Not applicable.	Models fixed transmission line limits. May recognize joint import limits.	Models time-varying transmission line limits and joint import limits.

Copper Sheet Models

Many planning studies utilize a **copper sheet,** or copper plate, model that does not represent any intraregional transmission infrastructure limits in resource adequacy. In this approach, all transmission constraints are unaccounted for by connecting all loads and generators to a single, lossless bus.[30] While this type of simplification allows for the fastest runtimes, not accounting for transmission constraints may underestimate reliability risks. By definition, a true copper sheet analysis would only evaluate supply adequacy since no transmission data is considered.

A key issue that arises with copper sheet models is that, while system-level shortfall events are reported, information about where they are located is missed. If a zonal model is used instead, information about where system events occur is available, along with information on whether individual events occur due to insufficient generation or transmission limitations.

Zonal and Flow-Based Models

In **zonal** models, systems are divided into regions separated by the major transmission corridors. The interface limits between the zones are often determined up-front using production cost models simulating the network in detail, and then identifying interface limits based on this. Zonal models simplify the grid model by assuming point-to-point HVDC connections between zones, and copper plates within each region. The model implemented often follows a 'transport model' approach, limiting flows based on import and export limits, but does not have regard for the physical flow of electricity across an AC system.

In an advance on the zonal approach, **flow-based zonal models** can be implemented where the inter-regional transfer limits are based on a reduced order model of the transmission system (AC and DC). In this type of model, regard is given to the physical flow of electricity by considering some version of a power flow: this could be DC power flow, linearized AC, or full AC power flow in limited cases.

Nodal Models

A **nodal** transmission model contains data for each bus, transmission line, and transformer on the transmission network. Typically, nodal analyses are used together with DC power flow analyses and detailed production cost models in operational settings.

In 2016, MISO performed an exploratory nodal RA analysis which observed that loss of load events occurred at 11 buses of the 8,635 that were modeled, identifying local issues that would have been missed with a less granular transmission model [58]. However, MISO staff also noted that the simulation required approximately 140 hours to evaluate 1000 samples for a single week, a substantial computational burden. Despite growing adoption of cloud computing, advancements to computational hardware, and software parallelization, such an exercise may

[30] Electricity exchange with other regions is considered separately, when relevant, and may be implemented by using a zonal-like approach, by employing import price curves, or through other methodologies.

still require a substantial amount of time to be performed. As such most resource adequacy models do not contain a nodal level of granularity.

Other Considerations for Transmission Network Modeling in RA: Joint Interface Limits, Line Limits, and Line Outages

In studies utilizing a zonal model, each zone is typically connected to at least one other zone by a line that has representative transmission limit applied. These limits must be calculated in careful consideration of the existing transmission network and are a critical modeling component. However, depending on the system, some zones may be connected to multiple zones. While each individual interface has a limit, there may be a need to model a joint limit between two or more interfaces to reflect additional limits in the underlying transmission system. For example, consider two 100 MW lines entering a zone but a joint import limit of 160 MW. By excluding this joint limit, a resource adequacy event could be missed. Zonal models that do not account for joint import/export limits may underestimate reliability risk.

Further, transmission lines can have different limits in real time operations depending on ambient conditions, series compensating devices, or whether specific resources are providing voltage support. If a line limit in an RA study is set at its annual maximum value and does not consider factors that could reduce its limit, then events caused by transmission limitations can be missed. For example, NYISO periodically evaluates the sensitivity of a group of lines that are subject to a voltage limit that can change depending on which units are online [59]. A simplified version of this model is incorporated into their RA analyses to reflect the importance of unit availability on the transmission system. While the representation of the interface in the RA model is simplified, the value is based on separate, exogenous, and highly detailed AC power flow analysis. Failure to account for time-varying or other large impacts in transmission limits may result in underestimating reliability risk. Similarly, always using the most restrictive representation of a limit may overestimate reliability risk and lead to unnecessary mitigation at great cost to consumers.

Transmission outages are another important consideration for overall system adequacy. If the transmission system is modeled as lossless, but large outages are observed in real-time impact regional transfer capabilities, then the model is likely under-estimating reliability risk. Such outages could be caused by insulator failure, environmental events, or other equipment failures. For a nodal model, adding outage rates is straightforward, but this is complicated in zonal models since multiple lines may aggregate to the interface modeled between zones. Choosing if, or how, to incorporate transmission outages into the model may impact the nature of reliability risk. For example, NYISO uses a zonal model and assumes all overhead lines are always available but that underground transmission cables are subject to failure.[31] In their model the individual cables are bundled and many derate levels are modeled with associated probabilities of likelihood.

[31] Page 63 in [122]

Another aspect that can then be modeled if transmission is appropriately modeled is the benefit of increasing transmission connection, whether between regions or within a region. As such, the benefits of increasing transfer capacity between zones can be examined. This can result in allowing the transmission between zones to be recognized as a resource (see Case Study box below).

Case Study: Transmission Between and Within Regions in RA Assessment

EPRI examined the implications of transmission in two different case studies to examine different issues.

In the case study based on the Midcontinent US system, a transfer analysis was carried out to examine the benefits of transfer capability between North and South MISO [60]. This first required a zonal model between the regions to be developed, starting with an arbitrarily large constraint (10,000 MW in below figure) at which there is a 0.1 LOLE, and then gradually lowering the capability to zero. As can be seen, somewhere around 7500 MW, separation between the zones occurs, with the North zone seeing a shortfall and south seeing an excess (though across the system, LOLE was larger as a whole as transmission capability reduces).

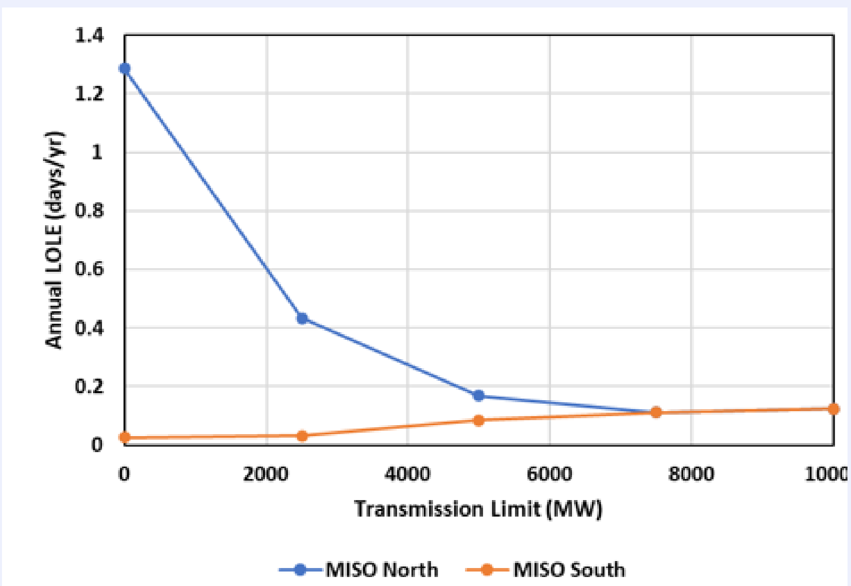

Figure 20. Impact of internal transmission in MISO region, between North and South.

Case Study: Transmission Between and Within Regions in RA Assessment (continued)

This can be extended to the concept of *an ELCC for transmission*, where the benefits of transmission to both sides of the constraint can be recognized as the additional load that can be carried based on the transmission. More details are provided in the relevant report[32], but in summary it was shown that, as risk periods were not entirely coincident across both sides of the north-south constraint, the increased in transmission capability could result in an ELCC equivalent to more than the transfer capacity, i.e. an ELCC of greater than 100%, as it can provide support on both sides of the constraint, particularly when the limits are lower.

The examination of zonal levels of outages and LOLE also brought up the question of how unserved energy is allocated in models – whether equally shared with assumption of copper plate, based on load in the region, or based on the balance prior to transfers. In the case of equal shares, when transmission is included, it can result in non-convergence. However, that is often the default method used in studies. As such, it would be recommended to allocate outages based on the resource balance prior to transfer. This better allows for identification of where the shortages might be and can be addressed by either additional transmission or increased resources within the region (which should be studied for economics and capability to build transmission).

In the **Northeast US and Canada case study**, implications of changing intra-region and inter-regional transmission between the six balancing authorities modeled were also examined **[61]**. There, each region was included in the overall model, with inter-regional and intra-regional constraints included. Each individual region was brought to criteria of 0.1 LOLE, allowing for neighbors to support through an iterative modeling process, where each region is modeled first, and then available energy transferred between regions.

[32] https://www.epri.com/research/products/000000003002027837

Case Study: Transmission Between and Within Regions in RA Assessment (continued)

Table 19. LOLE from test cases in Northeast US and Canada case study for changes to assumed intra- and inter-regional transmission between the balancing authorities studied. All base cases had 0.1 LOLE.

LOLE	REGION					
Transmission Sensitivity	A	B	C	D	E	F
ALL 1.5X	-	0.04	0.02	-	-	-
ALL 2X	-	0.01	-	-	-	-
ALL COPPER SHEET	-	-	-	-	-	-
INTER 1.5X	-	0.10	0.06	0.03	-	0.07
INTER 2X	-	0.10	0.05	0.01	-	0.05
INTER COPPER SHEET	-	0.10	0.05	-	-	-
INTRA 1.5X	0.07	0.04	0.05	-	0.05	-
INTRA 2X	0.07	0.02	0.05	-	0.05	-
INTRA COPPER SHEET	0.07	-	0.05	-	0.05	-

The main result of interest here showed that both intra-region and inter-regional constraints can be important, depending on the region. As such, it shows that just increasing inter-regional transmission may not help RA, unless intra-regional constraints are relieved. In other regions, intra-regional constraints do not impact results as much as inter-regional constraints. This is an insightful result in terms of how one represents neighbors and internal transmission, and why modelers should include some representation of both important internal constraints and transmission to neighbors. In that particular study, all six regions were modeled simultaneously, which allows for greater identification of how risk is able to be relieved by transmission to other regions.

2.4.2 Gas Networks

Table 20. Gas network models by level of fidelity.

	Level I	Level II	Level III
Gas network models	Implicit gas network model through gas plant capacity derates informed by historical data.	Fuel pool model.	Steady-state or linearized transient gas network model.

With the growth in VRE, many systems have increased their reliance on gas power plant flexibility to balance net load variations. Gas is one of the primary fossil fuel sources used for power generation today. Gas is usually delivered "just in time", with a limited amount of gas power plants having on-site storage capabilities. As such, the gas and power sectors are highly intertwined in day-to-day operations.

The challenges for planning and operations associated to the increased dependency of the power sector on the gas sector have been flagged by regulatory bodies, including NERC [62]. Despite this, most RA studies do not explicitly model gas networks today. This is often due to a combination of lack of reliable data, computational limitations, and lack of appropriate simulation capabilities.

However, appropriately representing gas networks in RA studies would allow for a deeper understanding, and pathways to mitigation for adequacy issues including those arising from:

- Gas deliverability issues arising due to weather-dependent outages of the gas infrastructure.
- Gas deliverability issues related to insufficient gas supply.
- Ramping flexibility constraints related to offtake pressure requirements and gas transport lags.

A summary of modeling considerations by level of fidelity for representing gas networks in adequacy studies is presented in Table 20. These are discussed in further detail in the sections below.

Implicit Gas Network Modeling

In most adequacy models, constraints in gas availability and deliverability are not considered, nor is the gas network represented. This is a similar approach to the copper plate transmission network assumption described in Section 2.4.1, whereby gas is assumed to always be available when needed. However, motivated by the increasing reliance on gas for power generation, some studies do implicitly account for potential gas network issues. This is mainly achieved at present by de-rating gas units, where capacity de-rates are calculated based on historical observations including past gas network outages, fuel inventory limits, and gas offtake pressure constraints limiting ramp rates.

Implicit modeling approaches partially capture gas network constraints without including a full representation of the gas network, lightening the computational burden of RA assessments, and limiting the scope of the data collection and modeling work. However, this methodology does not provide information on the root-cause of gas-related outages. That is, no distinction is provided between plant outages, network outages, fuel insufficiency, or pressure-related issues. As such, it limits the capability for planners to devise targeted siting and network hardening actions to improve system adequacy.

Resource Adequacy Fuel Insufficiency Screening Tool (RAFIS)[33]

EPRI has been developing a screening tool that takes information about how much gas is available through firm and non-firm contracts, the temperature dependence of non-firm contracts and how much gas is available based on firm and non-firm power and gas storage. It then examines gas generation, dual fuel capabilities and the rest of the system (load and other generation), to provide a first pass estimate of how much gas availability constraints may impact on loss of load, including whether dual fuel is recognized. While not a full probabilistic RA assessment, this can allow for an initial understanding of the potential for gas limits to impact on adequacy, and how different solutions (gas pipeline, gas storage, dual fuel, and firm contracts) may potentially help reduce risk. It can also be used to develop inputs for implicit modeling in the more detailed RA assessments.

Explicit Gas Network Modeling

Implicitly accounting for technology derates based on historical data is a top-down approach. A bottom-up, or engineering, approach is to explicitly model selected parts or the full gas network, its components, and interactions with the electricity system through a mathematical model.

Key Components of Gas Networks [63]

- Production fields
- Liquid Natural Gas (LNG) terminals
- Underground gas storage facilities
- Pipelines
- Compressor stations (to compensate for pressure losses across pipelines)
- Cross-border entry and exit stations
- City gate stations (where gas enters the distribution chain)
- Stations of direct served customers

[33] https://www.epri.com/research/products/000000003002028168

The two predominant approaches for explicit gas network modeling are steady-state and transient flow (or dynamic) models.

Steady-state models rely on the assumption that the gas in pipelines is incompressible, i.e., the inflow to a pipeline equals the outflow at each timestep. Depending on how sophisticated a model is, only transport capacities may be limited (i.e., transport model), or other constraints, such as pressure constraints, may be accounted for. The main advantage of this approach is that it can be formulated as a linear, convex optimization problem that could be integrated into RA models, provided sufficient data availability. However, steady-state models do not capture non-linear gas behaviors, such as gas compressibility. As such, certain pressure-related constraints (i.e., insufficient gas offtake pressure) are missed in steady state models.

The most advanced method to simulate gas networks is through **transient gas flow models**, also known as hydraulic gas network models. Here, dynamic flow of gas is represented through a set of non-linear non-convex equations. This type of model is not only able to capture constraints related to gas network topology, but also line pack flexibility, that is, how much gas can be stored and withdrawn from the gas network, depending on pipeline pressure. Furthermore, transient gas flows are explicitly captured as a function of pipeline geometry and network pressure differentials. While the level of detail provided by these models is high, their non-linear non-convex nature is highly computationally intensive and cannot be directly solved within a resource adequacy model today. In order to account for gas network constraints identified through hydraulic models in an RA model, these can be iteratively run for selected stress time periods. It is also possible to linearize and convexify full hydraulic models, while mostly preserving line pack and dynamic flows, that could then potentially be directly integrated in RA models as in [64].

Despite their greater accuracy in capturing gas network behavior when compared to implicit gas network modeling approaches, steady state and transient models are not often employed by RA planners today. A less accurate but easier to implement alternative to these involves **fuel pool modeling**. Here, fuel consumption is exogenously energy-constrained based on daily or weekly intervals (see Section 2.2.4). This method allows for explicit differentiation between energy-related (i.e., insufficient fuel) and capacity-related (i.e., gas plant maintenance outages) outages, while abstaining from developing mathematical models representing gas networks.

Modeling Gaps

One of the most challenging gaps when it comes to incorporating gas networks into RA models is the lack of gas network data availability. Data needs are further discussed in [55]. Additionally, to the best of our knowledge, no industry guidelines have been set, containing thorough quantitative analyses comparing the value of the different gas network modeling approaches for different power system configurations, making it difficult to estimate which level of detail is required for different types of RA assessments. Finally, few tools exist providing the capability to link power system models with transient gas models, and those that are available may lack resource adequacy functionality.

2.5 Alternative Energy Carriers

Energy carriers are defined as *a substance or phenomenon that can be used to produce mechanical work or heat, or to operate chemical or physical processes* [65]. While the focus of RA studies is ensuring adequate electricity supply, it is important to note the interdependence of the electric grid with alternative energy carriers. These include:

- Heat
- Gases such as hydrogen, ammonia, and methane
- Synthetic fuels such as methanol, synthetic diesel, and LNG

Gaseous and liquid energy carriers will remain necessary in an increasingly electrified energy system, for use in transportation and industry [66]. Energy carriers allow for the storage of energy in a high-density form, detachable for the electrical grid, and that can be transported through long distances, providing flexibility in operations and contributing to power system adequacy [67] [68].

This section focuses specifically on hydrogen, given significant recent interest in that energy carrier, with a focus on understanding modeling requirements to ensure that the impacts of hydrogen generation, storage, and usage as a fuel are appropriately captured in RA assessments.

2.5.1 Hydrogen

While hydrogen generation through electrolysis has existed for many decades, the use of hydrogen in the power sector, as well as interest in the large-scale deployment of electrolyzers is nascent. As such, the higher fidelity modeling approaches outlined in Table 21 are likely not justified at current electrolytic H_2 production shares in most systems but may become relevant in the coming years as electrolysis and hydrogen use for power applications becomes more widespread.

Table 21. Considerations for hydrogen generation, storage, and usage as a fuel by modelling by level of fidelity.

	Level I	Level II	Level III
Electrolyzer load modeling	Electrolyzer loads are implicitly accounted for in net-load timeseries but are not explicitly modeled. Demand is assumed to be firm.	Electrolyzer loads are explicitly modeled in RA and their potential to provide demand-side flexibility is recognized. No detailed distinction between electrolyzer technologies is considered.	Detailed constraints including ramp rates, overloading capabilities, and partial load efficiencies are modeled for relevant electrolyzer technologies. Unit-specific dispatch prices are accounted for.
Hydrogen end-use modeling: power generation	Projected hydrogen generation may be modeled statically using timeseries. Fuel availability constraints are not considered. No distinction between generator types is provided. Outages are not modeled.	Power generation using hydrogen is explicitly modeled within 8760 optimizations. Some level of fuel availability constraints may be recognized through fuel pools.	Power generation using hydrogen is explicitly modeled within 8760 optimizations. Fuel availability constraints are recognized and implemented using hourly offtake limits or fuel pools. Appropriate constraints and outage rates are modeled, making the distinction between fuel cells and gas-fired generation.
Hydrogen end-use modeling: storage	Hydrogen storage is not considered. Fuel is assumed to be available when needed.	Long-term hydrogen storage is modeled, and reservoir management constraints are applied.	Long-term hydrogen storage is modeled, and reservoir management constraints are applied. Storage technology-specific considerations are accounted for, including operational constraints, storage leakage, and fuel conversion efficiency. Impact of optimization windows and end conditions are considered.

An overview of different hydrogen pathways and utilizations is illustrated in Figure 21. The figure shows that hydrogen can be produced either directly from a primary energy carrier, for example through steam methane reformation, or through electrolysis using electric power.

Once hydrogen is generated, there are many uses for it. Predominant uses today include the production of ammonia (NH_3) for agricultural fertilizers and for fuel refining purposes, such as removing sulfur from diesel fuels [47], [69]. However, as illustrated in Figure 21, hydrogen can also serve the purpose of energy storage. Stored hydrogen can either be directly used as a fuel or converted to synthetic gas, ammonia, or other components.

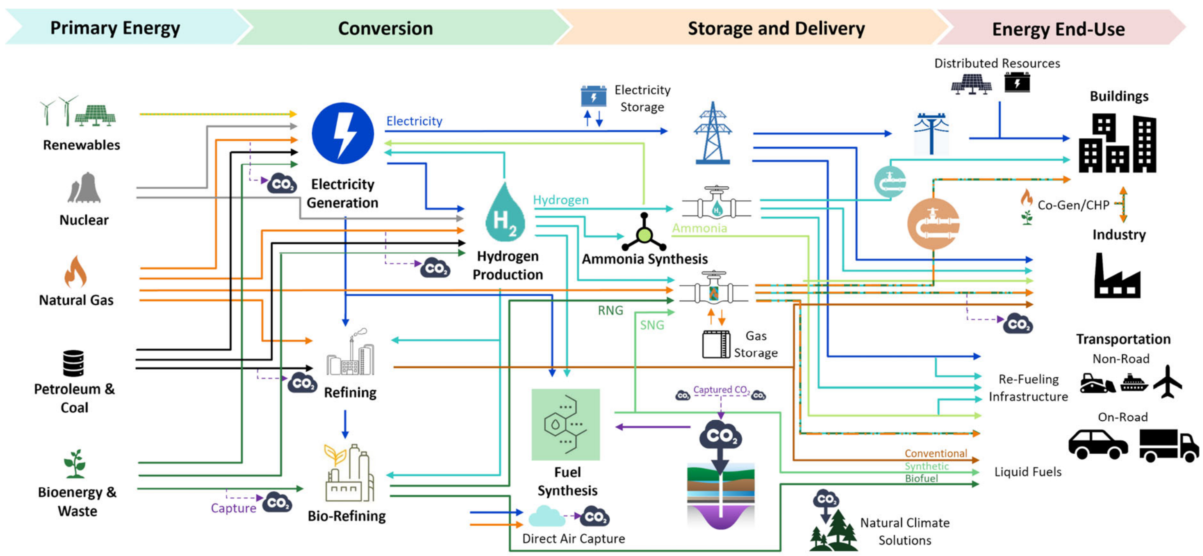

Figure 21. Hydrogen Pathways. [34]

[34] https://lcri-netzero.epri.com/en/description-model.html

Existing Processes for Hydrogen Production

The two main processes used to produce hydrogen are steam methane reformation and electrolysis.

In **steam methane reformation**, methane (CH_4) reacts with high-temperature steam, splitting into hydrogen and carbon dioxide [70]. Carbon capture and storage may be considered to reduce the carbon footprint of this process, although this is not common practice today. Steam methane reformation requires heat input, often from on-site generation or heat exchangers connected to other processes.

The process of **electrolysis** uses electricity to split water molecules into hydrogen and oxygen, collecting oxygen at the cathode of the electrolyzer and hydrogen at the anode. The main biproduct of electrolysis is oxygen. Different types of electrolyzers exist for hydrogen production, each having different operational constraints. These include:

- Alkaline
- Polymer Electrolyte Membrane (PEM)
- and Solid Oxide Electrolyzer Cell (SOEC)

Alkaline and PEM are both commercially mature technologies, whereas SOEC is not yet commercially ready [71].

Both alkaline and PEM electrolyzers offer a certain level of operational flexibility, while SOEC is not currently able to do so. Alkaline electrolyzers are the most mature and cost-effective technology today, but it is expected that the costs and efficiencies of PEM will improve over the next decade, making them competitive with Alkaline electrolyzers [71]. Even though both alkaline and PEM technologies can provide flexibility, PEM have faster ramp rates, and start-up and shutdown times, making them better candidates for operations in systems with high VRE shares and high net-load variability (see Table 22).

Table 22. Current technology performance characteristics for alkaline and PEM electrolyzers [71].

	Alkaline	PEM
Load range	10 – 110% of nominal load	0 – 160% of nominal load
Start-up (warm – cold)	1 – 10 minutes	1 second – 5 minutes
Ramp up and ramp down	0.2 – 20% per second	100% per second
Shutdown	1 – 10 minutes	1 second – 5 minutes

SOEC technologies may provide higher efficiency processes than existing technologies and offer the possibility to operate in reverse mode (i.e., as a fuel-cell) as they mature.

A key source of complexity in modeling hydrogen as an energy carrier in RA is that it needs to be considered from the demand, supply, and storage perspectives:

- On the **demand side**, there is a growing interest in flexibly generating H_2 molecules through the process of electrolysis to balance bulk system net load variability. Hydrogen production can behave as a fixed or flexible load, bringing many of the modeling needs outlined in Section 2.3.1.
- On the **supply side**, hydrogen combustion turbines (CT), or fuel cells, used to generate power using hydrogen directly as a fuel, may be considered within the modeling framework presented in Section 2.2.1 for thermal power plants. Nonetheless, despite similarities with fossil fuel CTs, the energy-limited nature of hydrogen may be more constraining than that of fossil gas and other fuels and should be considered within RA. Additionally, round trip efficiencies may be very low, so it may not be needed unless there are few other options for fully decarbonizing the power system.
- Finally, some of the modeling considerations outlined in Sections 2.2.3 and 2.2.4 could also be of relevance in the future if hydrogen is used as a vector for short and long-term **energy storage**.

Modeling Hydrogen Production, Usage, and Storage in RA

Table 21 provides a summary of considerations for modeling hydrogen production, storage, and usage as a fuel by level of modeling fidelity. Due to limited hydrogen production from electrolysis today and its current set of users (mainly ammonia production and petroleum refining, rather than power system applications), it is rare for adequacy assessments to incorporate hydrogen production and usage explicitly as a demand-side, supply-side, or storage resource. Nonetheless, the electricity demand arising from electrolyzers may be implicitly embedded in overall system load forecasts as firm demand.

Certain exceptions exist where electrolyzer operations have been explicitly modeled in RA, such as the Long-Run Resource Adequacy under Deep Decarbonization Pathways for California conducted by E3 for Calpine Corporation, where hydrogen production is modeled as a flexible load [72]. However, these as rare, making this section is mostly forward looking.

Regardless of the pathways or end-uses for hydrogen, there are common parameters that should be considered within a resource adequacy modeling context at significant shares of hydrogen production and usage. There are two broad categories that require attention when it comes to modeling hydrogen as an energy carrier for power system applications:

- Representing electrolyzer loads
- Representing hydrogen end-uses

Representing Electrolyzer Loads

Hydrogen production using Alkaline and PEM technologies can provide flexibility by modulating consumption to balance net load variability and even overloading the electrolyzer to accommodate very high periods of clean electricity production. Modeling the flexible load of electrolyzers can have impacts on RA: electrolyzer loads could be dispatched by grid operators much like existing demand-side response and other peaking resources (see Section 2.3.1).

However, accurately representing load shapes and demand-side response potential requires an understanding of electrolyzer operating characteristics. It should be noted that there is still uncertainty regarding how the flexible operation of electrolyzers will impact the lifetime of these assets, nor how this should be modelled.

Since hydrogen production using steam methane reformation is not directly coupled to the electricity system, but it is indirectly coupled through gas networks, demand-side flexibility from steam methane reformers would come from the reduction of natural gas consumption under tight gas supply events, freeing up gas fuel for residential and power system consumption. However, modeling this would require electricity-gas network co-simulation, which does not lie directly in the scope of this report.

Many considerations developed in Section 2.2.4 relating to maintenance and forced outages also impact electrolyzers. Since this is a nascent area, data quantifying outages on the electrolysis process is scarce. However, electrolyzer outages would not only impact load and the potential for demand-side response, but also the availability of hydrogen fuel and storage, and may become a relevant consideration in the future.

Representing Hydrogen End-Uses: Power Generation and Storage

Hydrogen may be used directly for **power generation** by blending H_2 into gas networks or combustion chambers in gas-fired units, or by using fuel cells. The discussion presented in Section 2.2.4 on the importance of representing energy adequacy and fuel availability may be particularly relevant when it comes to hydrogen. If hydrogen production is tied to renewable energy outputs, hydrogen availability will be variable unless it is firmed with VRE overbuild or back-up storage units.

Hydrogen **storage** has been attracting interest for electricity balancing, particularly long-term storage. There are several different technologies for **storing hydrogen** that are currently under consideration to meet the expected increase in H_2 demand over the coming decades. Common options include high pressure storage vessels, liquid hydrogen, chemical hydrides (such as ammonia and methanol), and metal hydrides. Hydrogen storage will be subject to many of the considerations for storage modeling developed in Sections 2.2.2 and 2.2.3, including modeling the usage of long-term fuel stocks, energy losses and fuel leakages in the hydrogen conversion process, potential storage unit degradation, and accounting for optimization window and end-condition impacts.

Finally, hydrogen production, storage, and usage links multiple sectors, including the electric, transportation, and industrial process sectors. This can generate conflicts between **competing end-uses**, particularly under fuel scarcity scenarios. When it comes to natural gas, usage for residential heating can be favored over usage for electricity generation when gas supplies are tight. In the case of hydrogen, the economic implications of fuel shortages across competing sectors will need to be further studied to understand which uses are likely to be prioritized under fuel scarcity conditions.

3 CONCLUSION

The choice of model representing the constraints and operations of a given system component or technology can have significant implications on resource adequacy. Modeling simplifications when it comes to key technologies for system adequacy may result in underestimating system risk or, on the other hand, overestimating risk and sending signals for investment that are too conservative. Similarly, complex modeling options may result in increased efforts and cost of data collection and computation. It is essential for planners to understand the range of modeling options available for different system components and to be able to match them to their specific system needs. This report has focused on providing an overview of existing modeling approaches and putting forward modeling recommendations for modeling a range of system components and technologies in RA. These are based on practices in the timeframe for which this study was completed (2022-2023) and are expected to continue to evolve over time.

Throughout the *Resource Adequacy for a Decarbonized Future* project, EPRI has sought to accelerate the evolution of RA processes and tools in collaboration with industry partners. The *Resource Adequacy for a Decarbonized Future* initiative has developed a series of reports and guidelines targeting a range of topics elements that are critical to setting up robust RA studies. A list of the *Resource Adequacy for a Decarbonized Future* Initiative's outputs is presented in Table 23.

Table 23. Deliverables under EPRI's Resource Adequacy for a Decarbonized Future Initiative.

	Deliverable	ID and link
Reports	Metrics and Criteria for Resource Adequacy	3002023230
	Metrics and criteria (Part II) deliverable[35]	
	Resource Adequacy Scenario Selection Guide	3002027829
	Modeling New and Existing Technologies and System Components in Resource Adequacy	3002027830
	Data Collection Guide	3002027831
	Resource Adequacy Assessment Tool Guide	3002027832
	Resource Adequacy Gap Assessment	3002027833
Case studies	EPRI Resource Adequacy for a Decarbonized Future Case Study: Western US	3002027834
	EPRI Resource Adequacy for a Decarbonized Future Case Study: Northeastern US and Canada	3002027835
	EPRI Resource Adequacy for a Decarbonized Future Case Study: Southwest Power Pool	3002027836
	EPRI Resource Adequacy for a Decarbonized Future Case Study: Midcontinent	3002027837
	EPRI Resource Adequacy for a Decarbonized Future Case Study: Texas	3002027838
	EPRI Resource Adequacy for a Decarbonized Future Case Study: Southeastern US	3002027839
Tools	Resource Adequacy Viewer Tool (RAVT)	3002026144
	Resource Adequacy Fuel Insufficiency Screening Tool (RAFIS)	3002028168
	Materiality Calculator	

[35] All outputs from the Resource Adequacy Initiative for a Decarbonized Future Project can be found in www.epri.com/resource-adequacy

4 REFERENCES

[1] G. Hering and J. Stanfield, "'You have to rethink these old ways': Parting advice from CAISO's retiring CEO," 25 September 2020. [Online]. Available: https://www.spglobal.com/marketintelligence/en/news-insights/latest-news-headlines/you-have-to-rethink-these-old-ways-parting-advice-from-caiso-s-retiring-ceo-60481529.

[2] Redefining Resource Adequacy Task Force, "Redefining Resource Adequacy," Energy Systems Integration Group, Reston, VA, 2021.

[3] EPRI, "Resource Adequacy for a Decarbonized Future: A Summary of Existing and Proposed Resource Adequacy Metrics (3002023230)," Palo Alto, CA, 2022.

[4] EPRI, "EPRI Resource Adequacy for a Decarbonized Future Case Study: Texas (3002027838)," 2023.

[5] S. Murphy, L. Lavin and J. Apt, "Resource adequacy implications of temperature-dependent electric generator availability," *Applied Energy,* vol. 262, p. 114424, 2020.

[6] EPRI, "Strategic and Flexible System Planning - 2016 Update: Deliverable Flexibility and Flexibility in Resource Adequacy (3002008379)," EPRI, Palo Alto, CA, 2016.

[7] EPRI, "Flexibility Methods and Guidelines: Assessing Operational Flexibility in Systems with High Penetrations of Variable Generation – 2019 Update (3002016257)," 2020.

[8] US Energy Information Administration, "Short Term Energy Outlook, March 2023," US DOE, Washington, DC, 2023.

[9] Z. Zhang and Z. Chen, "Optimal wind energy bidding strategies in real-time electricity market with multi-energy sources," *IET Renewable Power Generation,* vol. 13, no. 13, pp. 2383-2390, 2019.

[10] NPCC, "Reliability Assessment for Summer 2023," NPCC, New York, NY, 2023.

[11] V. Henze, "Global Energy Storage Market to Grow 15-Fold by 2030," 12 October 2022. [Online]. Available: https://about.bnef.com/blog/global-energy-storage-market-to-grow-15-fold-by-2030/.

[12] EPRI, "Energy Storage Technologies," 2022. [Online]. Available: https://storagewiki.epri.com/index.php/Energy_Storage_101/Technologies.

[13] U.S. Energy Information Administration, "Form EIA-860 detailed data with previous form data (EIA-860A/860B)," 2022. [Online]. Available: https://www.eia.gov/electricity/data/eia860/.

[14] EPRI, "Energy Storage System Taxonomy of Operating Behaviors: 2nd Edition (3002025652)," EPRI, Palo Alto, CA, 2022.

[15] ENTSO-e, "ERAA Annex 2 - Methodology," ENTSO-e, Brussels, 2022.

[16] G. Stephen, T. Joswig-Jones, S. Awara and D. Kirschen, "Impact of Storage Dispatch Assumptions on Resource Adequacy and Capacity Credit," in *2022 17th International*

Conference on Probabilistic Methods Applied to Power Systems (PMAPS), Manchester, 2022.

[17] F. Zeng, "Future Grid Reliability Study - Phase 1 Assumptions," ISO-NE, Holyoake, MA, 2021.

[18] NPCC, "NPCC 2022 Long Range Adequacy Overview," NPCC, New York, NY, 2022.

[19] NY-ISO, "2020 Reliability Needs Assessment," NY-ISO, Renssalaer, NY, 2020.

[20] EPRI, "Utility Battery Energy Storage System (BESS) Handbook: A Handbook for Utility Project Managers and Engineers Involved in the Life Cycle of BESS Projects (3002025748)," EPRI, Palo Alto, CA, 2022.

[21] EPRI, "BESS Failure Event Database," 2022. [Online]. Available: https://storagewiki.epri.com/index.php/BESS_Failure_Event_Database.

[22] ISO New England, "Installed Capacity Requirement (ICR) Reference Guide," ISO-NE, Holyoake, MA, 2021.

[23] HECO, "Grid Needs Assessment & Solution Evaluation Methodology," HECO, Honolulu, HI, 2022.

[24] EPRI, "EPRI Resource Adequacy for a Decarbonized Future Case Study: Southwest Power Pool (3002027836)," 2023.

[25] EPRI, "EPRI Resource Adequacy for a Decarbonized Future Case Study: Western US (3002027834)," 2023.

[26] M. Mann, S. Babinec and V. Putsche, "Energy Storage Grand Challenge: Energy Storage Market Report," National Renewable Energy Lab, Golden, CO, 2020.

[27] EPRI, "Long-Term Planning Considerations for Hybrid Renewable- Plus-Storage Resources (3002019611)," EPRI, Palo Alto, CA, 2021.

[28] Bipartisan Policy Center, "Inflation Reduction Act Summary - Energy and Climate Provisions," Bipartisan Policy Center, Washington, DC, 2023.

[29] V. Durvasulu, C. Murphy and P. Denholm, "Evaluating Utility-Scale PV-Battery Hybrids in Operational Models for the Bulk Power System," National Renewable Energy Laboratory, Golden, CO, 2021.

[30] IHA, "2022 Hydropower Status Report," International Hydropower Association, London, 2022.

[31] H. Ritchie, M. Roser and P. Rosado, "Energy," 2022. [Online]. Available: https://ourworldindata.org/energy.

[32] ENTSO-e, "Hydropower Modelling - New database complementing PECD," ENTSO-e, Brussels, 2019.

[33] G. Iotti, "Hydropower Modelling in Mid-Term Adequacy Forecasts," Politecnico Di Milano, Milan, 2020.

[34] Energy Education, "Pondage," 2015. [Online]. Available: https://energyeducation.ca/encyclopedia/Pondage.

[35] B. Stoll, J. Andrade, S. Cohen, G. Brinkman and C. Brancucci Martinez-Anido, "Hydropower Modelling Challenges," National Renewable Energy Laboratory, Golden, CO, 2017.

[36] E. Blom, "Including Hydropower in Large Scale Power System Models," KTH Royal Institute of Technology, Stockholm, 2019.

[37] EPRI, "Cavitation Pitting Mitigation in Hydraulic Turbines, Volume 1: Guidelines and Recommendations," EPRI, Palo Alto, CA, 1986.

[38] M. Bonnet, A. Witt, K. Steward, H. Boualem and M. Mobley, "The Economic Benefits of Multipurpose Reservoirs in the United States - Federal Hydropower Fleet," Oak Ridge National Laboratory, Oak Ridge, TN, 2015.

[39] C. Holder, G. Schellenberg, C. R. Donnelly and R. Ahsan, "Dealing with Sediment: Effects of Dams and Hydropower Generation," Hydro Review, 22 February 2017. [Online]. Available: https://www.hydroreview.com/world-regions/north-america/dealing-with-sediment-effects-on-dams-and-hydropower-generation/.

[40] EPRI, "Hydropower Perspectives on Climate Change Technical Update (3002025853)," EPRI, Palo Alto, CA, 2022.

[41] S. Gebre, N. Timalsina and K. Alfredsen, "Some Aspects of Ice-Hydropower Interaction in a Changing Climate," Energies, Trondheim, 2014.

[42] AEMO, "2021 Inputs and Assumptions Workbook," 10 December 2021. [Online]. Available: https://aemo.com.au/-/media/files/major-publications/isp/2021/2021-inputs-and-assumptions-workbook.xlsx?la=en.

[43] ENTSO-e, "European Resource Adequacy Assessment 2021 - Annex 3: Methodology," ENTSO-e, Brussels, 2021.

[44] EPRI, "Distributed Energy Resources and Flexible Demand in Resource Adequacy (3002019286)," Palo Alto, CA, 2021.

[45] R. Hledik, A. Faruqui, T. Lee, J. Higham and T. Lee, "The National Potential for Load Flexiblity: Value and Market Potential Through 2030," The Brattle Group, Cambridge, MA, 2019.

[46] European Commission DG Energy, "Impact Assessment Study on Downstream Flexibility, Price Flexibility, Demand Response & Smart Metering," DG Energy, European Commission, Brussels, 2016.

[47] IEA, "Global Hydrogen Review," 2022. [Online]. Available: https://iea.blob.core.windows.net/assets/c5bc75b1-9e4d-460d-9056-6e8e626a11c4/GlobalHydrogenReview2022.pdf.

[48] ENTSO-e, "European Resource Adequacy Assessment - Annex 3: Methodology," ENTSO-e, Brussels, 2021.

[49] California Public Utilities Commission, "Unified Resource Adequacy and Integrated Resource Plan Inputs and Assumptions - Guidance for Production Cost Modeling and Network Reliability Studies," CPUC, San Francisco, CA, 2019.

[50] AEMO, "Demand Side Participation Forecast Methodology: Estimating Existing and Future Demand Side Participation in the National Electricity Market," AEMO, Sydney, 2020.

[51] EPRI, "Resource Adequacy with Distributed Resources (3002021210)," 2021.

[52] EPRI, "Accounting for Demand Response and Distributed Generation in Resource Adequacy (3002024371)," Palo Alto, CA, 2022.

[53] EPRI, "Demand Flexibility for Grid Reliability and Resilience: Planning Tool Integration of Demand Flexibility – Phase 2 (3002028252)," 2023.

[54] EPRI, "Distributed Resource Integration Framework: A Reference Model for Characterizing Projects and Relating Programs that Integrate Demand Response and Distributed Energy Resources," Palo Alto, CA, 2009.

[55] EPRI, "Data Collection Guide: EPRI Resource Adequacy Assessment Framework (3002027831)," 2023.

[56] CPUC, *Decision Revising Net Energy Metering Tariffs and Subtariffs,* San Francisco, CA, 2022.

[57] S. Wigness, "What is NEM 3.0 and How Will it Impact California Solar Owners?," Solar.com, 4 May 2022. [Online]. Available: https://www.solar.com/learn/nem-3-0-proposal-and-impacts-for-california-homeowners/.

[58] B. Heath and J. Lawhorn, "Stochastic generator availability modeling on very large transmission network systems," in *International Conference on Probabilistic Methods Applied to Power Systems (PMAPS)*, Beijing, China, 2016.

[59] New York Independent System Operator, "Central East Voltage Collapse and Stability Limits for Marcy South Series Capacitors All Requirements I/S - Report #: CE-16," Albany, NY, 2016.

[60] EPRI, "EPRI Resource Adequacy for a Decarbonized Future Case Study: Midcontinent (3002027837)," 2023.

[61] EPRI, "EPRI Resource Adequacy for a Decarbonized Future Case Study: Northeastern US and Canada (3002027835)," 2023.

[62] NERC, "2013 Special Reliability Assessment: Accommodating an Increased Dependence on Natural Gas for Electric Power. Phase II: A Vulnerability and Scenario Assessment for the North American Nulk Power System," NERC, Atlanta, GA, 2013.

[63] EPRI, "Natural Gas Networks and Hydraulic Modeling: Basic Needs for Gas Data Sets (3002024649)," EPRI, Palo Alto, CA, 2022.

[64] A. Schwele, C. Ordoudis, J. Kazempour and P. Pinson, "Coordination of Power and Natural Gas Systems: Convexification Approaches for Linepack Modeling," in *IEEE PES Powertech*, Milan, 2019.

[65] ISO, "https://www.iso.org/obp/ui/#iso:std:iso:16818:ed-1:v1:en," ISO, 2008. [Online]. Available: https://www.iso.org/obp/ui/#iso:std:iso:16818:ed-1:v1:en.

[66] J. Schmidt, K. Gruber, M. Klingler, C. Klockl, L. Ramirez Camargo, P. Regner, O. Turkovska, S. Wehrle and E. Wetterlund, "A new perspective on global renewable energy systems: why trade in energy carriers matters," *Energy & Environmental Science,* vol. 12, pp. 2022-2029, 2022.

[67] Y. Li, H. Chen, X. Zhang, C. Tan and Y. Ding, "Renewable energy carriers: Hydrogen or liquid air/nitrogen," *Applied Thermal Engineering,* vol. 30, pp. 1985-1990, 2010.

[68] F. Orecchini and A. Santiangeli, "Beyond smart grids - The need of intelligent energy networks for a higher global efficiency through energy vectors integration," *International Journal of Hydrogen Energy,* vol. 36, pp. 8126-8133, 2011.

[69] EIA, "Hydrogen for refineries is increasingly provided by industrial suppliers," 2016. [Online]. Available: https://www.eia.gov/todayinenergy/detail.php?id=24612.

[70] Office of Energy Efficiency & Renewable Energy, "Hydrogen Production: Natural Gas Reforming," [Online]. Available: https://www.energy.gov/eere/fuelcells/hydrogen-production-natural-gas-reforming#:~:text=In%20steam%2Dmethane%20reforming%2C%20methane,for%20the%20reaction%20to%20proceed.

[71] ENTSO-E, "Potential of P2H2 technologies to provide system services," ENTSO-e, Brussels, 2021.

[72] Energy+Environmental Economics, "Long-Run Resource Adequacy under Deep Deacrbonization Pathways for California," Energy and Environmental Economics, San Francisco, CA, 2019.

[73] M. Hogan and D. Littell, "Get What You Need: Reclaiming Consumer-Centric Resource Adequacy," The Regulatory Assistance Project, Montpelier, VT, 2020.

[74] PJM Resource Adequacy Planning Department, "2021 Load Forecast Supplement," PJM, Valley Forge, PA, 2021.

[75] National Grid ESO, "FES Modeling Methods 2021," Warwick, 2021.

[76] PJM Planning Division, "Grid of the Future: PJM's Regional Planning Perspective," PJM, Valley Forge, PA, 2022.

[77] Duke Energy, "2021 Integrated Resource Plan: Stakeholder Workshop #3," Duke Energy, Valley Forge, PA, 2021.

[78] WECC, "Impact of High Distributed Resources," WECC, Salt Lake City, UT, 2022.

[79] ERCOT, "Report on the Capacity, Demand and Reserves (CDR) in the ERCOT Region, 2021-2030," ERCOT, Austin, TX, 2020.

[80] Eurelectric, "CHP as Part of the Energy Transition," Brussels, 2014.

[81] DOE Alternative Fuels Data Center, "Hydrogen Production and Distribution," 2019. [Online]. Available: https://afdc.energy.gov/fuels/hydrogen_production.html.

[82] J. Bard, N. Gerhardt, P. Selzam, M. Beil, M. Wiemer and M. Buddensiek, "The Limitations of Hydrogen Blending in the European Gas Grid - study on the use, limitations and cost of hydrogen blending," Fraunhofer IEEE, Kassel, 2022.

[83] I. Saedi, S. Mhanna and P. Mancarella, "Integrated electricity and gas system modelling with hydrogen injections and gas composition tracking," *Applied Energy,* vol. 303, 2021.

[84] Z. Fan, H. Sheerazi, A. Bhardwaj, A.-S. Corbeau, K. Longobardi, A. C. Vidal, A.-K. Merz, C. M. Woodall, M. Agrawal and J. Friedmann, "Hydrogen Leakage: A Potential Risk for the Hydrogen Economy," 5 July 2022. [Online]. Available: https://www.energypolicy.columbia.edu/publications/hydrogen-leakage-potential-risk-hydrogen-economy/.

[85] US DOE Hydrogen and Fuel Cell Technologies Office, "Thermodynamic and Economic Modeling of Boil-off Losses in Liquid Hydrogen Handling Processes," US DOE Hydrogen and Fuel Cell Technologies Office;, Washington DC, 2017.

[86] Duke Energy Indiana, "Duke Energy Indiana Integrated Resouce Plan," Charlotte, NC, 2021.

[87] ISO New England, *Developing a GridView Flexible Electric Vehicle Charging Model: Future Grid Reliability Study,* Holyoke, MA, 2021.

[88] S. Murphy, F. Sowell and J. Apt, "A time-dependent model of generator failures and recoveries captures correlated events and quantifies temperature dependence," *Applied Energy,* vol. 253, no. 1, 2019.

[89] WESC, " Calculation of effective forced outage rate of offshore wind (DWW100) and offshore wind plus battery (DWW100 + Lie400)," 2016.

[90] C. T. Clack, "Modeling Solar Irradiance and Solar PV Power Output to Create a Resource Assessment Using Linear Multiple Multivariate Regression," *Journal of Applied Meteorology and Climatology,* vol. 56, no. 1, pp. 109-125, 2017.

[91] NREL, "System Advisor Model (SAM)," [Online]. Available: https://sam.nrel.gov/photovoltaic.html.

[92] EPRI, "Distributed Resource Integration Framework: A Reference Model for Characterizing Projects and Relating Programs that Integrate Demand Response and Distributed Energy Resources," Palo Alto, 2009.

[93] EPRI, "Distributed Resource Integration Framework: A Reference Model for Characterizing Projects and Relating Programs that Integrate Demand Response and Distributed Energy Resources (1020313)," Palo Alto, CA, 2009.

[94] IEA, "Distributed PV capacity growth by segment, 2007-2024," Paris.

[95] H. e. a. Hersbach, "The ERA5 global reanalysis," *Quarterly Journal of the Royal Meteorological Society,* vol. 146, no. 730, pp. 1999-2049, 2020.

[96] J. Olouson, "ERA5: The new champion of wind power modelling?," *Renewable Energy,* vol. 126, pp. 322-331, 2018.

[97] H. e. a. Hazim, "Review on Optimization Techniques of PV/Inverter Ratio for Grid-Tie PV Systems," *Applied Sciences,* vol. 13, no. 5, p. 3155, 2023.

[98] The World Bank, "Concentrating Solar Power: Clean Power on Demand 24/7," The World Bank, Washington, DC, 2020.

[99] EPRI, "Energy Storage Economics," 2022. [Online]. Available: https://storagewiki.epri.com/index.php/Energy_Storage_101/Economics#Introduction_to_Grid_Services.

[100] J. Mashal and T. Sloane, "A battery for hire: AC vs. DC coupling for solar + energy storage projects," 13 April 2018. [Online]. Available: https://blog.fluenceenergy.com/energy-storage-ac-dc-coupled-solar.

[101] U.S. Department of Energy, "Pumped Storage Hydropower," 2016. [Online]. Available: https://www.energy.gov/eere/water/pumped-storage-hydropower.

[102] G. Stephen, "Probabilistic Resource Adequacy Suite (PRAS) v0.6 Model Documentation," National Renewable Energy Laboratory, Golden, CO, 2021.

[103] Dominion Energy, "Natural Gas and Electric Market Coordination. Electric Gas Coordination Senior Task Force.," 2021. [Online]. Available: https://www.pjm.com/-/media/committees-groups/task-forces/egcstf/2021/20211105/20211105-item-02-dominion-energy-presentation.ashx.

[104] M. T. Baumhof, E. Raheli, A. G. Johnsen and J. Kazempour, "Optimization of Hybrid Power Plants: When Is a Detailed Electrolyzer Model Necessary?," 2023.

[105] T. Bowen, I. Chernyakhovskiy and P. L. Denholm, "Grid-Scale Battery Storage - Frequently Asked Questions," National Renewable Enery Laboratory, Golden, CO, 2019.

[106] AEMO, "ESOO and Reliability Forecast Methodology Document," Australian Energy Market Operator, Sydney, 2022.

[107] AEMO, "ISP Methodology," AEMO, Sydney, 2021.

[108] D. Graf, J. Marschewski, L. Ibing, D. Huckebrink, M. Fiebrandt, G. Hanau and V. Bertsch, "What drives capacity degradation in utility-scale battery energy storage systems? The impact of operating strategy and temperature in different grid applications," *Journal of Energy Storage,* p. 47, 2021.

[109] X.-Z. Yuan, C. Song, A. Platt, N. Zhao, H. Wang, K. Fatih and D. Jang, "A review of all-vanadium redox flow battery durability: Degradation mechanisms and mitigation strategies," *International Journal of Energy Research,* vol. 43, 2019.

[110] B. Xu, "The role of modeling battery degradation in bulk power system optimizations," *MRS Energy & Sustainability,* vol. 9, pp. 198-211, 2022.

[111] EPRI, "Exploring the Trade-Offs between Solar + Storage Hybrid Plants and Standalone Configurations (3002024033)," EPRI, Palo Alto, CA, 2022.

[112] M. Bolinger, W. Gorman, J. Rand, S. Jeong, R. H. Wiser, J. Seel and C. Warner, "Hybrid Power Plants: Status of Operating and Proposed Plants, 2022 Edition," Lawrence Berkeley National Laboratory, Berkeley, CA, 2022.

[113] Elia Group, "Adequacy and Flexibility for Belgium 2022 - 2032," Elia Group, Brussels, 2021.

[114] G. M. Freeman, J. Apt and J. Moura, "What causes natural gas fuel shortages at U.S. power plants?," *Energy Policy,* vol. 147, 2020.

[115] C. M. Correa Posada, Optimal Sectúrity-Constrained Model for the Integrated Power and Natural-Gas System, Madrid: Universidad Ponitificia Comillas de Madrid, PhD Thesis, 2015.

[116] IRENA, "Hydrogen from Renewable Power - Technology Outlook for the Energy Transition," IRENA, Abu Dhabi, 2018.

[117] P. Alstone, J. Potter, M. A. Piette, P. Schwartz, M. A. Berger, L. N. Dunn, S. J. Smith, M. D. Sohn, A. Aghajanzadeh, S. Stensson, J. Szinai, T. Walter, L. McKenzie, L. Lavin, B. Scheniderman, A. Mileva, E. Cutter, A. Olson, J. Bode, A. Ciccone and A. Jain, "2025 California Demand Response Potential - Charting California's Demand Response Future: Final Report on Phase 2 Results," Laurence Berkeley National Laboratory, CA, 2017.

[118] M. Mann, S. Babinec and V. Putsche, "Energy Storage Grand Challenge: Energy Storage Market Report," National Renewable Energy Lab, Golden, 2020.

[119] AEMO, "ISP Methodology," Australian Energy Market Operator, 2021.

[120] M. Christian, "Hydropower Perspectives on Climate Change Technical Update," EPRI, Palo Alto, 2022.

[121] W. S. Parker, "Reanalyses and Observations: What's the Difference?," *Bulletin of the American Meteorological Society,* vol. 97, no. 9, pp. 1565-1572, 2016.

[122] New York ISO, "2022 Reliability Needs Assessment (RNA): Appendicies," Rensselaer, NY, 2022.

[123] EIA, *Today in Energy: About 25% of U.S. power plants can start up within an hour,* 2020.

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