# Beyond Capacity Credits: Adaptive Stress Period Planning for Evolving Power Systems


Jess Kuna, Gord Stephen, and Trieu Mai

*National Renewable Energy Laboratory*



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Contract No. DE-AC36-08GO28308

**Technical Report**
NREL/TP-6A40-89386
May 2024

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**Suggested Citation**
Kuna, Jess, Gord Stephen, and Trieu Mai. 2024. *Beyond Capacity Credits: Adaptive Stress Period Planning for Evolving Power Systems*. Golden, CO: National Renewable Energy Laboratory. NREL/TP-6A40-89386. https://www.nrel.gov/docs/fy24osti/89386.pdf.

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#  Abstract

This paper combines and applies concepts from several researchers to outline an alternative framework to plan power systems for resource adequacy needs, which we call Adaptive Stress Period Planning (ASPP). It first provides background information regarding least-cost planning objectives and the challenge of balancing an increasing need for model representation with computational intensity as power systems evolve in complexity. Next, it motivates the opportunity for a new paradigm by outlining challenges of frameworks in use today that rely on aggregate capacity heuristics (i.e., capacity credits and planning reserve margins). It then lays out the main process details of ASPP, which more directly represent spatial and temporal detail of power systems in a capacity expansion model to adaptively select risk periods. The paper concludes with a summary of the approach, its benefits, and opportunities for future work.

Acknowledgments

The authors would like to thank the following individuals for their contributions. Editing and communications support was provided by Emily Horvath. Helpful discussion, review, and comments were provided by Patrick Brown, Luke Lavin, Charalampos Avraam, Wesley Cole, Paul Denholm, Bethany Frew, Jaquelin Cochran (National Renewable Energy Laboratory), Gage Reber (U.S. Department of Energy), Derek Stenclik (Telos Energy), and Genevieve de Mijolla (Electric Power Research Institute). We also thank Patrick Gilman (U.S. Department of Energy) for supporting this work.

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# 1 Background

An important goal of electrical power system planning is to identify cost-effective strategies to ensure resource adequacy by balancing future power supply with projected demand. In practice, the planning exercise is primarily a task in identifying least-cost infrastructure investments to meet a defined resource adequacy criterion (often loss-of-load expectation). "Better" system designs meet the socially defined level of acceptable shortfall risk at a lower cost than alternative strategies, as illustrated in Figure 1a.

Solution quality is also a function of trade-offs of the modeling tools and methods that represent a system (as illustrated in Figure 1b). Tools often used for planning exercises, often called capacity expansion models (CEMs), vary widely in degree of power system representation (Cole et al. 2017). Generally, more detail leads to greater accuracy in capturing resource specifications and system interactions and thus higher-quality solutions. However, increased detail requires more data and increases computational burden. Planners therefore must balance model sophistication with computational intensity, striving to maximize solution quality within the bounds of the tool.

As a system increases in complexity, greater detail is often needed to retain acceptable solution quality. For example, dependence on interregional power transfers, a broader range of potential generation and storage investment options and configurations, and wide meteorological diversity across candidate variable renewable resource sites all complicate the portfolio selection process. Without adjustments to consider this increased complexity, planners risk designing systems with higher-than-necessary system costs or inaccurately estimated resource adequacy levels.

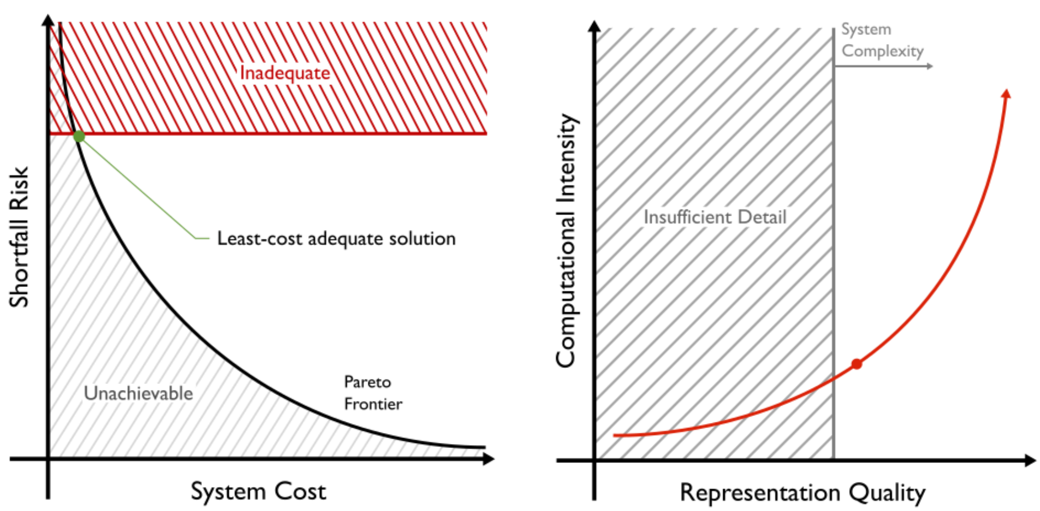


**Figure 1. a) Objective of the planning process; b) modeling trade-off impacting solution quality**

Historical frameworks for planning with respect to resource adequacy were based on available capacity and are largely still in use today (National Association of Regulatory Utility Commissioners [NARUC] 2023, North American Electric Reliability Corporation [NERC] 2020). In predominantly thermal systems, shortfall risk was assumed to be sufficiently low if enough generating capacity was installed relative to projected peak demand. In recent years, several technological and meteorological evolutions have introduced new considerations impacting resource availability and conditions of system risk. These include the growth of renewable, storage, flexible load resources, electrification, and extreme weather (Energy Systems Integration Group [ESIG] 2021). Considering these changes, methods to estimate aggregate capacity heuristics (i.e., capacity credits and planning reserve margins) evolved to retain the original capacity-based structure (ESIG 2023, NARUC 2023). However, challenges remain in balancing model fidelity with computing needs.

Several power system modelers are considering approaches to represent evolving considerations for resource adequacy in planning models without aggregate capacity heuristics (Bahl 2017, Li et al 2022, Teichgraeber 2021, Massachusetts Institute of Technology [MIT] 2022, Johnston 2019, Pfenninger 2018, Stephen 2023). The goal of these new methods is to simultaneously achieve improved computational efficiency and greater system representation, as illustrated by the blue line in Figure 2. As real-world systems increase in complexity, greater model detail is needed to retain the quality of the system representation (highlighted by the grey shaded area). Conventional planning methods, including those that rely on aggregate capacity heuristics, increase exponentially in computational complexity to retain quality (illustrated by the red line). Ultimately, new approaches that improve computational efficiency with greater model representation should produce higher-quality adequacy assessments and more cost-effective planning decisions.

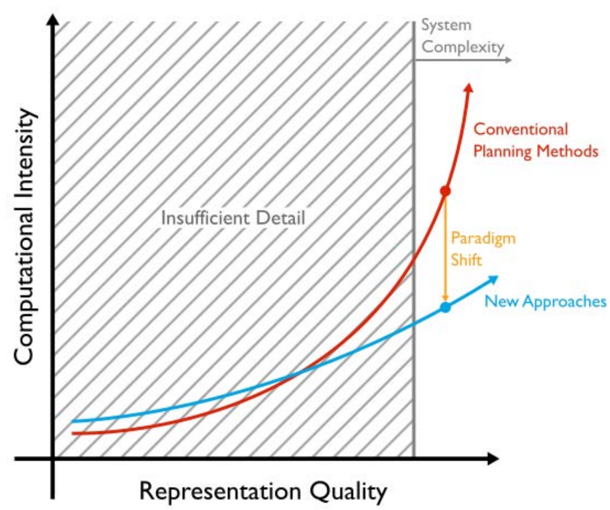


**Figure 2. The goal of the new paradigm is to achieve better computational performance at the levels of representation quality required to model modern power systems.**

This paper outlines the opportunity for and the main process details of an alternative modeling framework for power system planning, which we call Adaptive Stress Period Planning (ASPP). ASPP more directly represents temporal and spatial detail in a CEM while using an adaptive process to strategically select "stress periods." This allows for greater model representation during the most important times for planning. For example, each stress period in the planning model includes transmission network representation and time-sequenced resource dispatch. Importantly, this more efficiently considers interactions within resources and with load when identifying solution alternatives and captures energy limitations (or measures "energy adequacy")—two limitations often cited with respect to current aggregate capacity planning frameworks (ESIG 2023).

The report is organized as follows. Section 2 reviews the limitations of aggregate capacity frameworks that motivate the need for a paradigm shift. Section 3 synthesizes preceding work and elaborates upon considerations of the ASPP framework. Section 4 concludes with a summary of the approach, its benefits, and opportunities for future work.

# 2 Opportunities To Improve on Aggregate Capacity Frameworks

Challenges in balancing model representation quality and computational tractability when planning for evolving grid systems are driving researchers to explore alternatives to the aggregate capacity paradigm. This section describes those challenges by highlighting core elements of these frameworks, evolutions in the grid, and limitations of the core elements for those evolutions.

## 2.1 The aggregate capacity framework was created for thermal-based systems with relatively few spatial, temporal, or resource interaction effects to consider.

For this paper, we define aggregate capacity frameworks according to two core components:

1. **A (or multiple) resource adequacy target(s)** based on peak load or peak net load and a planning reserve margin (PRM), defined independently for an aggregate representation of space and time and for a particular resource portfolio (in megawatts [MW]).[1][2]
2. **Individual resource capacity contributions (accreditation),** defined independently for an aggregate representation of space and time and for a particular resource portfolio (in MW).

The outlines of these components came from the first resource adequacy planning processes, which were developed when most power systems consisted of primarily thermal generators (i.e., natural gas, coal, and nuclear) and relatively stable patterns of load (NARUC 2023, NERC 2020). Periods of greatest system risk occurred during periods of high load or when a generator was forced out.

A straightforward and sufficiently accurate way to conduct resource adequacy planning was simply to compare a sum of capacity contributions (initially nameplate capacity, then capacity credits) to the resource adequacy target in MW, as illustrated in Equation 1 and Figure 3.

$$\text{Sum of capacity contributions (MW)} \geq \text{peak demand} + \text{planning reserve margin (MW)}$$

**Equation 1. Simple aggregate capacity framework for resource adequacy assessment**

[1] Note that historically, most PRMs were static and not recalculated regularly, though the need to adjust PRM-based adequacy targets based on the system is well recognized (Reimers 2018; WECC 2020).
[2] Aggregate representation refers to how planning processes define resource adequacy targets and capacity contributions on an annual, seasonal, or in rare cases, a monthly, basis.

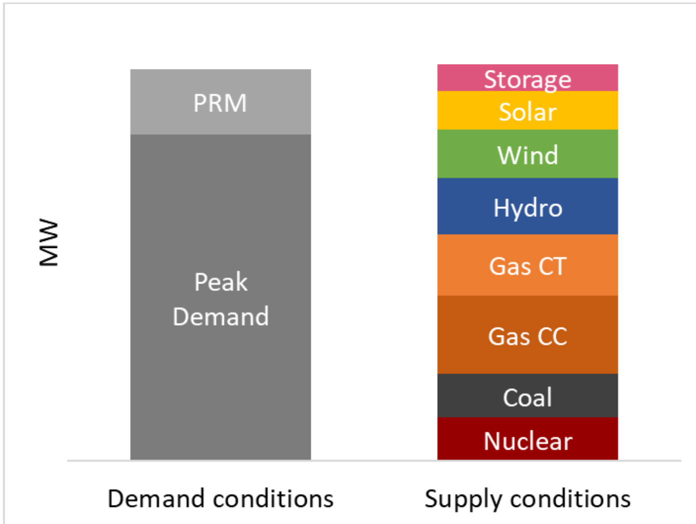


**Figure 3. Simple aggregate capacity framework for resource adequacy assessment**

As will be discussed next, several modifications have been made to details of the framework. Capacity accreditation was developed to fit wind, solar, and storage resources into a single aggregate value representing the resource's average contribution during periods of high shortfall risk. Detailed modeling techniques were introduced to aid calculations of capacity credits and PRM (Milligan and Parsons 1997; Madaeni et al. 2012). Most workflow processes rely on a combination of resource adequacy and capacity expansion models to identify new infrastructure, as illustrated below in Figure 4. Resource adequacy models are used to exogenously determine a system level reserve margin and individual resource capacity credits. These capacity values are then passed to a capacity expansion model where the contributions of existing resources are compared against a planning reserve margin and the most cost-effective new resources are identified to meet needs. While methods vary, the commonality across these frameworks is aggregate (often annual, seasonal, or monthly) targets and capacity credit heuristics.

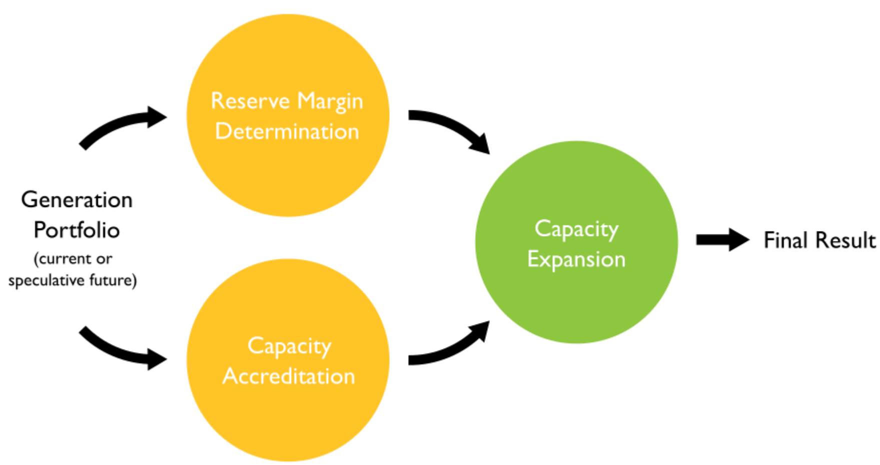


**Figure 4. Traditional capacity expansion framework with system needs and individual resource contributions precalculated.**

## 2.2 Modern developments require greater model detail which presents computational challenges.

Several evolutions of the grid have added sources of uncertainty and interactive effects that require greater modeling representation to accurately assess and plan for resource adequacy. Three important evolutions are 1) the introduction and growth of variable renewable energy (VRE), 2) the introduction and growth of energy storage resources, and 3) opportunities for interregional coordination via transmission.

**Assessing resource availability by location and time and system risk at all times.** The availability of resources such as solar and wind varies across time and geography. In turn, this has created new conditions for system risk. System risk is now not only a function of load variability and generator outages but also the interactive variation in resource profiles with one another and with load. Rather than risk occurring only if there are not enough thermal resources online to meet peak load, a shortfall event might occur any time of the day due to low renewable resource during high or low load hours. To capture interactive effects and ensure adequacy, it is important for planning tools to consider a resource's location, model more granular timescales, and test all time periods for potential risk (Carvallo et al. 2023).

**Chronological sequencing and grid economics.** Storage resources are limited in capacity and duration, and their availability in any period is a function of how much charging or discharging occurred during preceding periods from other system resources. In addition, the choice to charge or discharge is influenced by grid economics and the opportunity cost of charging or discharging at prices in preceding or projected future periods. As a result of these dependencies, system risk is increasingly impacted by interactive effects between resources and load. To represent this, planning models must capture chronological sequencing and grid economics (Stephen et al. 2022).

**Transmission networks and outages.** As penetrations of VRE grow and the grid becomes more weather dependent, geographically diverse resource mixes enabled by transmission and coordination become important to balance grid needs. When considering transmission, the amount and location of energy available from resources are influenced by congestion and outages on transmission lines. In turn, transmission limitations can also influence system risk. Bigger, connected systems exponentially increase interactive effects between resources and load. To take advantage of the opportunities of geographic resource diversity and accurately capture considerations for transmission and interregional coordination, models must incorporate sufficient spatial representation to capture transmission networks and outages (Carvallo et al. 2023).

## 2.3 Aggregate capacity frameworks are limited by the need to represent complex spatial, temporal, and resource interaction effects with reductive capacity contribution and adequacy target heuristics.

As noted previously, the two main elements of aggregate capacity frameworks (capacity contributions and resource adequacy targets) are defined individually for an aggregate representation of space and time and for a given portfolio of resources. For example, most planning processes define an annual or seasonal resource adequacy target and establish annual or seasonal capacity contributions for groups of resource types (solar, wind, and storage) in a region (NARUC 2023). The need to aggregate system interactions into single-dimensional heuristics creates challenges when trying to balance greater needs for model representation with computing. These challenges are described below.

**Information reduction requires estimation techniques and computing power.** Capacity credit and PRM calculations require methods and assumptions that inherently introduce potential for error. Several research papers and industry practitioners have concluded that these heuristics are sensitive to methodological details and often change from year to year and by planning entity (Jorgenson et al. 2021; ESIG 2023). These calculations also require multiple runs of a resource adequacy model. As the grid continues to evolve and interactive effects multiply, capacity credit calculations must adjust for new needs and compress more information. The challenge of achieving an accurate solution amid growing computational needs is recognized among researchers (Mills 2020), recently prompting a study to identify and prioritize methodological considerations according to computing effort and meaningful influence on assessments (Carvallo et al. 2023).

**Single-dimension heuristics do not capture interactive effects needed to test portfolio options.** The goal of resource adequacy planning processes is to determine the least-cost resource mix for meeting resource adequacy needs. To do this, capacity expansion processes must evaluate multiple combinations of resources, or “portfolio options.”

Because of interaction effects between resources and loads, capacity credits and planning reserve margin calculations are a function of the other resources in any given system or portfolio (Stephen et al. 2021). This means they change with each incremental resource considered for a portfolio. Capturing interaction effects requires a detailed representation of time and space, chronologically linking time, and connecting spatial elements with a network representation.

In aggregate capacity frameworks, this spatial and temporal representation is captured in a resource adequacy model, which is used to help calculate individual, aggregate capacity credits and planning reserve margins. However, the resource adequacy model captures interactions only of a single portfolio—it is not designed to consider multiple options of resources.

Conversely, spatial and temporal detail is inevitably lost when complete chronology is compressed into capacity credits, load duration curves, or representative days for use in a CEM, where portfolio options are evaluated. Thus, CEMs relying on these constructs do not explicitly capture portfolio interactions. This challenge is recognized and similarly described by ESIG’s New Design Principles for Capacity Accreditation in sections on disentangling portfolio effects and circularity (ESIG 2023).

**Solutions to portfolio challenges require exponential increase in computing needs.** To address the challenge of evaluating portfolio options that rely on system interactions, practitioners (Nelson and Heath 2021; NWPCC 2021; Dison 2023) have sought to populate multidimensional capacity credit lookup tables for use in capacity expansion exercises. These approaches require precomputing aggregate capacity heuristics under many alternative resource portfolios.

While producing a single capacity credit may require several runs of a resource adequacy model, calculating the capacity credits of one full portfolio may increase computing in multiplicative terms. Calculating capacity credits for interregional systems adds another dimension of scale to computing. The approach to precompute capacity credits for multiple portfolio options increases computing needs exponentially. For relatively small systems with few options available to expand, this approach may be tractable. For larger systems—particularly those considering interregional options—an aggregate capacity framework would likely require significant simplifications in model representation (e.g., number of investment alternatives considered, interregional transmission constraints, etc.) to feasibly run.

# 3 Adaptive Stress Period Planning: An Alternative Framework

In recent years, different planning paradigms have begun to emerge as alternatives to the aggregate capacity planning framework. This section compiles and supplements work from prior research into a single framework. It first presents ideas that address challenges identified in the previous section and then outlines practical considerations of such methods.

## 3.1 Alternatives to aggregate capacity heuristics

As described previously, a key underlying challenge of aggregate capacity frameworks is the need to compress spatial and temporal detail and related resource interaction effects into single-attribute capacity heuristics. Alternatively, a growing body of work eliminates aggregate capacity heuristics, instead directly representing operational attributes for each resource type in a CEM. Calliope (Pfenninger 2018) and SWITCH (Johnston 2019) are two examples of CEMs that eschew capacity credits in favor of simply enforcing energy and power balance constraints in each chronologically modeled operating period, with an operating reserve margin applied in each timestep to enforce sufficient surplus so that the resulting system is resource adequate.

Unfortunately, for all but the smallest systems, explicitly modeling every hour of the operating horizon—as would seemingly be required with this approach to guarantee the designed system is resource adequate—can require significant simplifications in other modeling dimensions to maintain computational tractability. To solve this problem, a diverse and growing body of literature has investigated the potential benefits of an iterative approach, where outputs from a reduced-chronology CEM are tested against a full-chronology operations model.

Earlier versions of this concept used automated adequacy assessments to adjust a traditional CEM's planning reserve margin (Frew et al. 2019), but later work improved on this to pass more information through the feedback loop and select new periods to explicitly model in subsequent iterations (Bahl 2017; Teichgraeber 2021; Li et al. 2022; Massachusetts Institute of Technology [MIT] 2022; Li et al. 2023).

These approaches all leverage the fact that only the most stressful periods in the planning horizon drive system adequacy requirements; once these are accounted for and mitigated against, the remaining periods are also covered.[3] Because not all periods checked in the assessment phase must be modeled in the investment optimization, planning tools can design cost-effective systems that are resource adequate under many years of operating conditions, despite being derived from much more compact computational problems. For example, Stephen (2023) describes applying this approach to design a large, multiregional, 100% wind/solar/storage power system that maintains resource adequacy under 7 years of hourly operating conditions, despite considering fewer than 1% of operating periods in the expansion problem. This approach also eliminates the requirement for speculative capacity credit precalculations under different

[3] Note this is the same logic behind traditional planning reserve margin constraints used in planning models—however, in that case, generating resources have uniform availability across the planning horizon, so there are no resource portfolio interactions and the period of greatest system stress is always the period with peak load.

resource portfolios, saving both computational cost as well as the need to make subjective choices in accreditation methodology.

This approach has several benefits. In the presence of storage resources, enforcing hourly constraints as an effective load adder (an “energy reserve margin”) ensures the system has sufficient energy, not just capacity, available to satisfy the reserve requirement (Hawaiian Electric Company 2021; Stephen 2021). A transmission network can also be modeled when not relying on single-attribute heuristics, allowing congestion between areas to be considered directly in the planning problem. Directly representing these constraints within an assessment or procurement model provides the optimization process with additional (less “compressed”) information that can more economically address adequacy constraints.

## 3.2 Process and method details

The general framework proposed is illustrated in Figure 5. It is a six-step iterative process:

1. Initialize the expansion decision process.
2. Assess the system’s resource adequacy.
3. Based on adequacy assessment results, identify times of system stress.
4. Augment the CEM based on identified stress periods.
5. Rerun the CEM to propose a better candidate resource portfolio.
6. Repeat Steps 2–5 until the candidate portfolio is assessed to be resource adequate; then select that portfolio.

Two modeling components are used in the process. First, a resource adequacy model (RAM) assesses system adequacy and identifies stress periods. Second, information about those stress periods is passed to a CEM to consider and make decisions about what resources to build to meet periods of inadequacy in the assessment phases.

The remainder of this section outlines each step in greater detail.

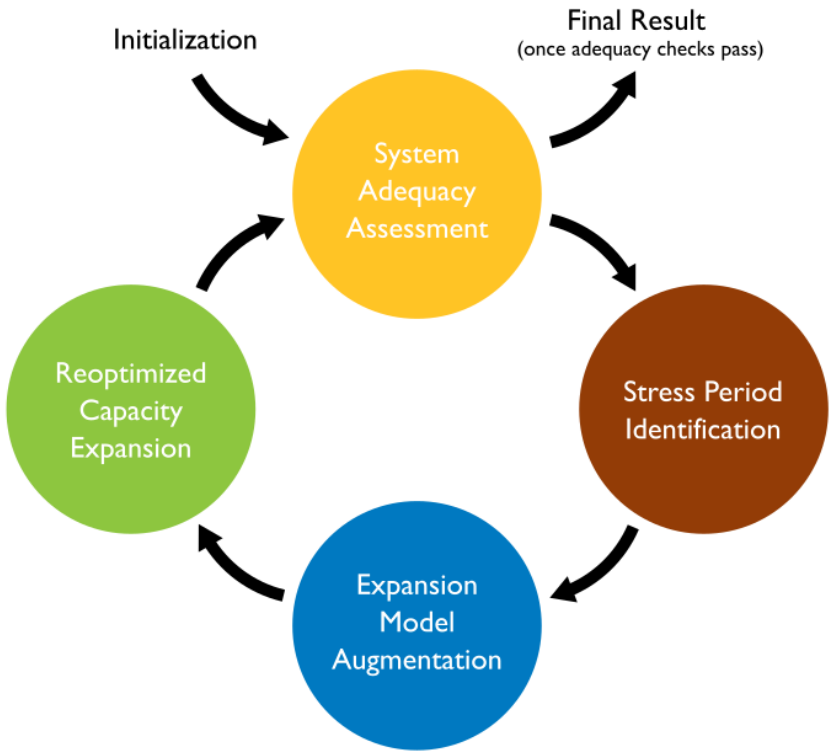


**Figure 5. Proposed general iterative framework.**

**Step 1: Initialization**

The first step in the process is to establish the parameters of the expansion decision. These key inputs include the following:

- What is the initial infrastructure state of the study system to which candidate investments will be added?
- Under what conditions (weather, economic activity, policy constraints, and so on) is the expanded system expected to operate?
- What are the probabilistic resource adequacy metrics and criteria (e.g., loss of load expectation [LOLE] = 0.1 event-day/year, normalized expected unserved energy [NEUE] = 1 part per million) (Electric Power Research Institute [EPRI] 2022) against which the system's performance should be measured? This will determine at what point the system can be considered resource adequate.

Once these have been determined, the existing resource portfolio and conditions under which it is expected to operate reliably are passed forward to Step 2. Note that this first step is performed only once.

**Step 2: System Adequacy Assessment**

Once an infrastructure buildout has been determined (either directly from the initial system state or in subsequent iterations as the result of a decision from the CEM), the portfolio's resource adequacy performance can be assessed and compared to the established adequacy criteria. If the assessment determines system adequacy matches its adequacy target (within some tolerance band), the process is complete, and the candidate portfolio becomes the final solution. If the candidate portfolio is inadequate relative to the criteria, the iteration process continues on to Step 3. Alternatively, if the portfolio exceeds the defined adequacy thresholds, the process may either terminate or continue iterating to eliminate unnecessary investments and reduce overall system costs.

In the stress period identification literature, the operations model used to test system performance is often not a dedicated RAM but rather an adjustment of the optimization based CEM with expansion decisions fixed and all time periods added. Using a dedicated RAM provides several benefits and is the recommended approach for this process. Class-leading RAMs are carefully designed for maximum computational performance and can usually evaluate adequacy risk across the operating horizon far faster than is possible with a one-shot optimization formulation, particularly as the size of the study system grows. Furthermore, this enhanced computational efficiency allows a dedicated RAM to quantify probabilistic adequacy risks—not just deterministic operating performance—which is necessary to comprehensively conclude a candidate system is in fact resource adequate according to the parameters described in Step 1.

The representational fidelity of the chosen RAM, including transmission disaggregation and generator operating constraints, should be carefully considered relative to the representation used in the capacity expansion step. The resource adequacy assessment may involve simulating hundreds or thousands of times more operating periods than are run in the CEM (before even considering probabilistic assessment), so some simplifications to achieve acceptable computational performance are necessary. However, if the RAM simplifies too many operating constraints, it may lose the ability to identify certain aspects of system stress and so fail to inform the CEM about those conditions—even if the CEM could have mitigated against them had it known they were an issue.

One possible solution may be to employ multiple parallel assessment models in this step, each screening for different kinds of operability challenges (e.g., energy and capacity adequacy versus flexibility challenges). Though it would be preferable for a single model to capture all factors holistically, there may be performance benefits to decomposing assessments in this way.

Conversely, if the RAM considers factors not modeled in the CEM, there must be other mechanisms (beyond simply reproducing the problematic time) applied in the model augmentation step to communicate the nature of such issues. Otherwise, the planning model will fail to recognize the issue and be unable to mitigate against it. For example, the RAM may identify problematic conditions arising from stochastically modeled forced thermal outages, even though the deterministic CEM considers those time periods to be adequate given the average availability of thermal generation. In that case, some supplementary signal (e.g. explicitly representing the outage condition, increasing an energy reserve margin, or producing an internal estimate of the probabilistic risk) would be required to make the RAM outcome actionable to the CEM.

Key consideration in this step:

- Given the system's previously determined adequacy criteria, is the candidate system resource adequate under the scenario(s) to be studied? If so, no new adequacy investments are required.

Workflow design decisions in this step:

- Are the (likely simplified) operating constraints captured by the chosen RAM(s) sufficient to identify relevant system stress conditions for the CEM?
- Can any risk factors considered by the RAM(s) but not explicitly represented in the CEM be communicated through other means?

**Step 3: Stress Period Identification**

If the system adequacy assessment concludes the system is in fact not adequate, as defined by the initialization step, the next step is to identify periods of greatest stress from the RAM to pass to the CEM. An inadequacy determination from the RAM implies the CEM's simplified temporal or spatial representation may be missing information about conditions that lead to adequacy events and requires iteration (discussed more below). If the expansion step knew about these conditions, it could make mitigating investments to design a system capable of operating with sufficiently low shortfall risk.

The key distinguishing feature of the decision process described here (relative to aggregate capacity frameworks used largely today) is that a complete time series of system risk is obtained from the adequacy assessment step and used to determine what information is most important to provide to the expansion decision step. For example, rather than modeling a limited number of typical days or time periods in the CEM, the RAM would flag a specific period of elevated system risk and provide the corresponding load, renewable output level, and other system conditions to the CEM to be considered directly.

The process for prioritizing which periods to include in the expansion step will vary between implementations of the framework, but a typical approach could involve ranking contiguous blocks of time (e.g., 24-hour days) based on risk metrics such as expected unserved energy (EUE), as observed in the previous adequacy assessment step. Though a day-long stress period is sufficient to capture operational details of diurnal storage, longer time blocks may be needed in systems with multi-day reliability events or otherwise stronger cross-day energy coupling because of long-duration or seasonal storage. Alternatively, storage-specific ranking metrics—such as deviations between expected (in the expansion model) and observed (in the adequacy model) storage state-of-charge evolution—could be used to capture key storage charging periods that may be temporally distant from shortfall events but still critical for system adequacy.

This step assumes the candidate system is inadequate as designed and needs more information about risky operating conditions to improve its future decisions. In some cases, however, the workflow may be iterating on the system design because it is overly adequate and investment levels can be reduced. In that case, no new stress periods need to be identified.

Workflow design decisions in this step:

- What are the criteria used for ranking stress periods (e.g., adequacy metrics, mismatched storage behavior)?
- How should the duration of a stress period be defined (e.g., day, multiple days, week)?

**Step 4: Capacity Expansion Model Augmentation**

Once the previous system design's adequacy has been assessed and operating periods have been ranked to reflect their importance for informing adequacy-aware expansion decisions, the next step is to update the expansion model to include the periods identified as most important.

How many such periods to add, and whether these should augment or replace stress periods identified in previous iterations, are factors that must be specified as part of the workflow design process. On one hand, adding many risk periods at once may reduce the total number of iterations required to achieve a resource-adequate system. On the other hand, many of the top stress periods from one iteration may share similar underlying drivers and so provide redundant investment signals to the expansion problem. In this case, adding fewer risk periods at once and building up the problem more incrementally may yield a smaller but more diverse set of stress conditions, at the cost of additional resource adequacy and capacity expansion runs (even if the individual CEM runs may be faster). The optimal selection strategy will likely depend on the diversity of risks facing the system as well as the relative computational performance of the RAM and CEM used in the process.

Other planning model parameters can also be adjusted in response to adequacy assessment results. For example, if the CEM includes operating reserve requirements or applies an energy reserve margin (ERM), the magnitude of those adequacy buffers may be adaptively adjusted in response to performance observations from the RAM (for example, increasing the ERM during already-modeled high-risk periods that are still causing adequacy issues). Alternatively, if the planning problem applies an internal adequacy constraint, such as an upper bound on estimated EUE, this constraint could be tightened or relaxed—or the internal estimator updated—to better align outcomes with the desired "true" adequacy metric measured by the RAM.

Workflow design decisions in this step:

- Should sets of stress periods identified in previous iterations be retained or replaced?
- How many "top" stress periods (as identified in the previous step) should be added to the expansion model at a time?
- Should the expansion problem's endogenous reliability criteria be (re)adjusted based on feedback from the adequacy assessment and/or stress period identification steps?

**Step 5: Capacity Expansion (Re)Optimization**

The CEM is formulated to select the new resources required to balance supply and demand in all time periods identified by the RAM. Among other factors, the model considers availability of candidate resources during stress periods and selects resources that meet overall system needs while minimizing total capital and operating costs.

This explicit representation of stress events eliminates the need for precomputed heuristics such as capacity credits and instead directly assesses potential investment contributions based on resource availability profiles and other explicitly modeled factors such as transmission congestion or chronological storage operations.

As discussed in Step 2, the level of fidelity represented in the planning model should be considered in concert with the representation available in the RAM. If operations in the CEM are substantially more detailed than the RAM, the iteration process may fail to identify important classes of operating conditions for the CEM to consider, even though the CEM is theoretically capable of mitigating those classes of issues. Similarly, if the CEM operations representation is substantially less detailed than the RAM, and no alternative way to signal those issues is available (e.g., parameter recalibration), the CEM will not be able to mitigate adequacy issues identified by the RAM—preventing the iteration process from terminating.

A concrete example of this is the chronological representation of long-duration or seasonal storage applied in the CEM. If a RAM (running with full storage chronology) is identifying energy adequacy challenges arising from an inability to charge interday storage resources, a CEM that considers only individual days of operations with periodic boundary conditions would be unable to reproduce these issues and would therefore be unable to mitigate the adequacy issues identified. In this situation, the CEM would need to be enhanced to use a "sparse" chronological storage representation that allows tracking and constraining the evolution of a storage device's charge state over an arbitrarily large number of time periods—while explicitly representing system operating conditions and dispatch decisions only for the set of time periods modeled (Kotzur et al. 2018; Gonzato et al. 2021).

**Step 6: Iterate and Finalize Result When Adequacy Is Achieved**

After an initial assessment of stress periods, CEM adjustment, and resource reselection, the adequacy of the updated candidate system can be reassessed to determine whether the new results are acceptable according to the chosen adequacy criteria. If the updated system adequacy is sufficiently close to the target, the process terminates, with the most recent system design reported as the final result. Otherwise, the RAM results are used to readjust the CEM, and the iteration process continues. The final result reports the types of technologies, sizing, and locations of new resource investments that together meet the system's preestablished performance criteria.

Relative to other heuristic-based approaches, designing a system to mitigate concrete adequacy risks provides a more economically efficient solution because resource investments can be sized to address specific events drawn from a large meteorological dataset rather than relying on preprocessed, reduced-form estimates of resource availability—which may not provide sufficiently detailed information to inform optimal investment decisions—during times of system need. Eliminating the need for preprocessed static availability estimates also presents computational savings, which can become substantial when attempting to accurately characterize adequacy contributions of individual resources in a high-dimensional decision space. Because the number of periods required for capturing adequacy needs is much smaller than the full operations horizon—and optimization problem complexity increases superlinearly relative to problem size—repeatedly solving several small planning problems can also be substantially more computationally efficient than solving a single, much larger planning problem.

# 4 Conclusions and Future Work

This paper describes the opportunity and method details for an alternative framework of power system planning for resource adequacy needs, called Adaptive Stress Period Planning (ASPP). The framework overcomes the challenges of compressing evolving spatial and temporal detail of modern power systems by identifying the most stressful periods and directly modeling detailed system interactions in a capacity expansion model. In doing so, it eliminates aggregate capacity heuristics (i.e., capacity credits and planning reserve margins) that add computational burden and challenge the ability to consider portfolio options in the planning process. The goal of this method is to achieve greater model representation within computing bounds so that the ultimate power system solution accurately models resource adequacy needs and achieves lower-cost solutions than are possible under current planning paradigms.

This paper is part of an ongoing body of research on the ASPP framework. Additional work is underway at NREL exploring applications of the ASPP framework in producing more robust, cost-effective, and computationally simpler power system planning solutions. Future work would be beneficial to further compare ASPP applications to aggregate capacity solutions.

Another key area for future work is to explore the appropriate tuning of workflow considerations and parameters for different levels of system complexity. As noted previously, technological evolutions in the grid have prompted the need for more detailed modeling of grid interactions, such as chronological operations for storage resources. Depending on the number of unique viable generator types and the size of a system, parameters in the ASPP framework can be tuned to include more detail with the trade-off of computing burden. Some parameters include the length of stress periods, the selection criteria for stress periods, and number of periods added per iteration. It would be useful to explore the sensitivity of solutions to various parameters within the context of a highly connected and complex system versus one with fewer interactive components. Like Carvallo et al. (2023), this could help prioritize model considerations and fit the framework to specific planning needs.

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