Application of Monte Carlo Simulation for the Probabilistic Assessment of Hydropower Generator Capacity Loss Due to Forced Outages

by John M. Bauer

B.S. in Renewable Energy Engineering, June 2014, Oregon Institute of Technology
M.S. in Engineering and Technology Management, August 2017,
Portland State University

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Cory Fagan
Professorial Lecturer of Engineering Management and Systems Engineering

The School of Engineering and Applied Science of The George Washington University certifies that John M. Bauer has passed the Final Examination for the degree of Doctor of Engineering as of July 11, 2025. This is the final and approved form of the Praxis.

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John M. Bauer

Praxis Research Committee:

Cory Fagan Professorial Lecturer in Engineering and Applied Science, Praxis Director

Daniyal Ali, Professorial Lecturer in Engineering and Applied Science, Committee Chair

Konstantinos Belesis, Professorial Lecturer in Engineering and Applied Science, Committee Member

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Dedication

This Praxis is dedicated to my family who have supplied unending support while embarking on this endeavor. To my wife Lauren and daughter Audrey, accomplishing this persistent goal was made possible by your encouragement, understanding and patience. To Marie, whose love and support is endless.

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Abstract of Praxis

Application of Monte Carlo Simulation for the Probabilistic Assessment of Hydropower Generator Capacity Loss Due to Forced Outages

The Bonneville Power Administration (BPA), the federal transmission and marketing agency for the 31-dam Federal Columbia River Power System (FCRPS), is preparing to join the Western Resource Adequacy Program (WRAP) as a binding participant in FY 2027. WRAP participation requires BPA to commit generation capacity for grid reliability seven months in advance, creating operational challenges for capacity planning across the multi-agency FCRPS system.

Forced outages present significant risks to BPA's capacity commitments, potentially resulting in lost revenue from marketable surplus capacity or costly capacity deficits. The current deterministic planning approach inadequately accounts for forced outage probabilities and limits BPA's ability to optimize capacity commitments while maintaining capacity obligations. This study develops a probabilistic Monte Carlo simulation model to forecast hydropower generator capacity loss due to forced outages, enabling more accurate capacity planning and revenue optimization.

The model utilizes five years of historical forced outage data (2019-2023) from FCRPS hydropower plants to predict capacity loss in 2024. Validation results demonstrate significant improvements over current deterministic methods. The probabilistic model achieved greater accuracy in forced outage capacity loss estimates, increased marketable surplus capacity for WRAP by over 50 MW, and established

capacity reserve levels that avoided potential capacity deficits. These improvements were validated despite 2024 experiencing anomalously high forced outage rates.

This research contributes to capacity planning methodologies for cooperative resource adequacy programs and provides practical benefits for WRAP's 22 utility members in advancing regional resource adequacy. The validated probabilistic assessment offers broader applications for the energy sector through its use of actual forced outage data and generator availability modeling. The model will support BPA's operational planning for seven-month forward-showing capacity commitments during critical summer and winter peak load periods in WRAP.

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List of Symbols

λ	Failure rate (lambda)
σ	Standard deviation (sigma)
σ^2	Variance (sigma squared)
μ	Repair rate (mu)
∞	Unbounded limit
e	Euler's number
i	Index representing a specific iteration
$E(x)$	Expected value of a probability distribution (also, μ)

List of Acronyms

BPA	Bonneville Power Administration
CAISO	California Independent System Operator
CCA	Community Choice Aggregators
CDF	Cumulative Distribution Function
CGS	Columbia Generating Station
CPUC	California Public Utilities Commission
DoE	Department of Energy
ESP	Energy Service Providers
FCRPS	Federal Columbia River Power System
FERC	Federal Energy Regulatory Commission
FOR	Forced Outage Rate
GADS	Generating Availability Data System
IOU	Investor-Owned Utility
ISO	Independent System Operator
IQR	Interquartile Range
LOLP	Loss of Load Probability
LOLE	Loss of Load Expectation
MAD	Mean Average Deviation
MTBF	Mean Time Between Failure
MTTR	Mean Time To Repair
MID-C	Northwest Mid-Columbia

NERC	North American Electric Reliability Corporation
NWPCC	Northwest Power and Conservation Council
NPP	Northwest Power Pool
OTS	Outage Tracking System
PDF	Probability Density Function
PMA	Power Marketing Authority
PRM	Planning Reserve Margin
SPP	Southwest Power Pool
SWEDE	Idaho and the Desert Southwest
USACE	U.S. Army Corps of Engineers
USBR	U.S. Bureau of Reclamation
WAPA	Western Area Power Administration
WFOF	Weighted Forced Outage Factor
WPP	Western Power Pool
WRAP	Western Resource Adequacy Program

Chapter 1—Introduction

1.1 Background

The Bonneville Power Administration (BPA) is a Federal agency within the Department of Energy (DoE) and the transmission and marketing arm of the Federal Columbia River Power System (FCRPS). The FCRPS is a highly coordinated bulk electric generation system comprised of 31 hydroelectric projects in the Columbia River Basin that are owned and operated by the U.S. Bureau of Reclamation (USBR) and the U.S. Army Corps of Engineers (USACE). The FCRPS also includes a 1GW nuclear power plant owned and operated by Energy Northwest. Figure 1-1 below is a map of the FCRPS, including both the U.S. and Canadian jurisdictions of the Columbia River Basin.

Figure 1-1. FCRPS Hydro-electric Power Plant Facilities (Columbia Basin Fish and Wildlife Authority, 2005)

BPA serves as the Power Marketing Authority (PMA) for the FCRPS. BPA markets FCRPS hydropower generation and transmits power from both federal and non-federal hydropower plants (Bureau of Reclamation, 2019). One of the greatest challenges facing BPA and the U.S. electric grid is ensuring enough generation and transmission capacity to reliably deliver electric energy to serve its load centers (Carvallo, 2021). The North American Electric Reliability Commission (NERC) defines resource adequacy as "the ability of supply-side and demand-side resources to meet the aggregate electrical demand" (NERC, 2023). Additionally, ensuring resource adequacy is the purpose of the Northwest Power Act which aims to deliver "adequate, efficient, economical and reliable power to the Pacific Northwest" (NWPCC, 2021b).

To comply with NERC reliability standards and the Northwest Power Act, the Western Power Pool (WPP) launched the Western Resource Adequacy Program (WRAP) in 2019. WRAP is a NERC approved resource adequacy program and was created collaboratively through regional utilities and public power partnerships to address resource adequacy concerns driven by an everchanging energy supply and demand landscape. The goal of WRAP is to leverage diverse regional resources to enhance resource adequacy and electric grid reliability for customers across the western U.S. Currently, WRAP participants include 22 public and private utilities sharing generation and transmission capacity throughout the western U.S. The program is administered by WPP and employs the Southwest Power Pool (SPP) as the technical program operator (WPP, 2024).

As the first regional resource adequacy program in the western U.S., WRAP's electric utility participants share capacity resources to address reliability uncertainty

during summer and winter peak loads. To do this, binding participants commit to generation capacity for power pooling seven months in advance of both summer and winter load peaks. WRAP is designed to support two regions in the western U.S. – Northwest Mid-Columbia (Mid-C), and Idaho through the desert Southwest (SWEDE). Currently BPA is participating in WRAP as a sharing participant to test its capabilities and preparedness. BPA is planning to join WRAP as a binding participant in the winter 2027-2028 season. As a shared participant, about 90% of BPA's WRAP loads are within the Mid-C, and about 10% are in the SWEDE. There are two binding seasons in WRAP, winter and summer shown in Table 1-1. As a binding participant, BPA will be required to provide capacity commitments for WRAP seven months in advance for both summer and winter load peak seasons.

WRAP Binding Season Timeframe	
Winter	November 1st through March 15th
Summer	June 1st through September 15th

Table 1-1. WRAP Binding Seasons

The benefits to BPA for participating include guaranteed resources to purchase capacity in the case of a deficit to meet load demands. Additionally, through bilateral agreements, energy deployments in the WRAP are settled at higher-than-market payments. BPA benefits by creating sales revenue from the power pool members at between 120% and 125% of the spot price – based on WRAP settlement calculations. Furthermore, failing to meet WRAP commitments could result in significant penalty charges under the WRAP tariff. These penalties are intended to incentivize the compliance of binding participants in the program.

BPA's successful marketing of power pool capacity depends on capacity planners' ability to accurately forecast FCRPS system-wide availability. The availability of FCRPS generation capacity includes planned and unplanned generation outages. After fulfilling generation and transmission capacity commitments and obligations to existing customers, BPA can allocate remaining resources to the WPP and WRAP, capitalizing on significant revenue opportunities. However, to be successful, capacity planners will need to account for the uncertainty of forced outages when committing power pool resources.

1.2 Research Motivation

Critical to BPA's success as a binding-participant in WRAP, is a forward-showing capacity commitment that meets its load obligations while optimizing its surplus in the power pool. The motivation for this research is to enable BPA to optimize available WRAP capacity commitments by accounting for the effect of forced outages on planned capacity. The determination of surplus capacity depends on quantifying and accounting for the uncertainty of forced outages. If BPA doesn't accurately forecast available capacity, the commitment made in WRAP may leave a shortage to meet current capacity obligations. This would be costly for BPA and necessitate purchasing capacity in day-ahead markets to meet its obligations, resulting in lost net revenue. Successful marketing of power pool capacity in the WRAP depends on capacity planners' ability to accurately forecast overall FCRPS system availability and commit to a forward showing capacity that accounts for the uncertainty of forced outages.

The development of a forecasting tool to predict the probability of reduced capacity due to forced outages will allow BPA to carry less MW reserve generation capacity and optimize its power pool commitment in WRAP.

1.3 Problem Statement

Forced outages reduce Bonneville Power Administration's planned capacity in the WRAP, and risk revenue loss of marketable power at 120-125% of the spot price.

BPA capacity planners use scheduled transmission and generation maintenance outages to forecast future available FCRPS capacity. The uncertainty of forced outages has the potential to reduce available planned capacity, and planners set aside reserves to account for this risk. Holding reserves limits BPA's marketable power and may have significant opportunity costs, especially in summer and winter peak load periods with high demand and premium energy prices. Optimizing the level of reserves and the amount of marketable surplus can help BPA capitalize on premium energy prices and increase revenue during periods of high demand.

1.4 Thesis Statement

A forced outage forecasting model is necessary for Bonneville Power Administration to both maintain capacity obligations and maximize revenue opportunities in the WRAP.

Forced outages are unplanned and reduce planned capacity. A forced outage simulation model will aid capacity planners in determining a system-wide available capacity that accounts for the uncertainty of reduced capacity due to unforeseen and

unplanned outages. A simulation of historical generation outages using Monte Carlo methods can model the probability of MW reductions of planned generation capacity due to forced outages (Scully et al., 1992). Using Monte Carlo simulation, capacity planners can optimize the MW generation capacity reserve based on risk appetite using a lost-capacity exceedance curve to maximize marketable energy in the WRAP's power pool.

1.5 Research Objectives

The research objective is to develop a probabilistic generation capacity forecasting model to predict the probability of forced outages for capacity planning at BPA. Currently, WRAP capacity planners estimate forced outages in the forward showing capacity plan that is deterministic, using a rolling five-year average lost capacity due to forced outages on the system. The research objectives for this praxis are:

- to develop a stochastic simulation using Monte Carlo methods and estimate the probability of generation capacity loss due to forced outages.
- to provide capacity planners with a lost generation capacity estimate that will aid in the optimization of capacity commitments to the WRAP power pool and align capacity commitments with risk tolerance.
- to determine whether Monte Carlo simulation provides improved capacity planning through optimized reserves based on the probability of forced outages.
- To determine whether Monte Carlo Simulation reduces the forecast error, compared to current methods for developing estimates based on a five-year average of generation capacity loss.

1.6 Research Questions and Hypotheses

There are four research questions and four hypotheses. The research questions (RQ) and hypotheses (H) are the following:

RQ1: How well does the random number from exponential distribution simulate the independent variables of MTBF and MTTR compared to historical actuals?

RQ2: How is generation capacity loss prediction accuracy improved by simulating the MTBF and MTTR of equipment failures due to forced outages?

RQ3: How does the Monte Carlo Simulation of forced outages help estimate reserve generation capacity?

RQ4: How does a Monte Carlo simulation of forced outages improve WRAP power pool revenues of surplus capacity?

H1: Historical five-year average MTBF and MTTR can be simulated as a random number from an exponential distribution to estimate WRAP capacity.

H2: Monte Carlo simulation of availability metrics MTBF and MTTR quantify the frequency and severity of forced outages to more accurately estimate the reduction of available capacity from a limited data set.

H3: The probability distribution of the Monte Carlo simulation defines statistical limits for estimated availability that provides a disciplined approach to setting reserve capacity.

H4: The probability distribution of the Monte Carlo simulation optimizes the generation capacity reserve to maximize marketable power.

1.7 Scope of Research

The scope of this research is focused on estimating generation capacity loss due to unplanned forced generation outages. The timeframe considered in this analysis is one year and specifically designed to align with WRAP's forward-showing capacity planning requirements. WRAP requires binding capacity commitments seven months in advance of both winter and summer peak load periods. The winter peak period spans five months (November through March), representing the longest continuous WRAP planning period. To encompass the complete planning cycle, the analysis scope must cover the seven-month advance commitment period plus the five-month winter peak duration, totaling twelve months. This timeframe directly supports WRAP's operational needs by providing forced outage estimates for the complete planning horizon.

Capacity planners currently account for lost generation capacity by using a five-year average generation capacity loss. This five-year estimate is used to commit power pool capacity for winter and summer load peaks as defined by WRAP. This research is conducted using historical forced outage data stored in BPA's outage tracking system (OTS) and encompassing twenty-one federal generation projects in the FCRPS that are owned and operated by either USBR or USACE.

1.8 Research Limitations

The analysis performed for this praxis is designed to estimate generation capacity loss due to forced generation outages, at twenty-one hydropower plants. The analysis performed for this praxis is designed to estimate system-wide generation capacity loss, as an average of each hydropower plant's unavailability due to forced outages. Additionally,

this praxis research uses generator max capacities in the analysis of forced outage generation capacity loss. In practice, operational capacity is dependent on water supply throughout the year. Capacity planners will use water supply forecasts along with the planning tools in this research to plan capacity commitments for WRAP that account for the uncertainty of generation capacity loss due to forced outages.

1.9 Organization of Praxis

This praxis comprises five chapters. Chapter 1 is the introduction, providing background and motivation, the problem statement, the thesis statement, and the research questions. Chapter 2 is the literature review, providing a review of existing research in generation capacity planning and forced outage predictive modeling. Chapter 3 details the data sources and the methodologies used in this praxis. Chapter 4 presents the results of the forced outage predictive model and details the model validation approach. Chapter 5 includes a discussion of the results, new contributions to the practice of generation capacity planning, and recommendations for future research.

Chapter 2—Literature Review

2.1 Introduction

As discussed in Chapter 1, this praxis is focused on predicting lost capacity probabilities due to unplanned forced generation outages. Forced generation outage predictions will aid BPA in the optimization of power marketing benefits in WRAP. This chapter consists of a literature review critical to understanding this praxis research. This literature review includes research regarding resource adequacy, capacity planning, and stochastic and predictive modeling, specifically with respect to electric grid operations.

2.2 Resource Adequacy in the Pacific Northwest

The Pacific Northwest is increasingly committing to unprecedented carbon-free electrical energy goals. With the passing of House Bill 2021, Oregon joins Washington, Idaho and California in commitment to 100% carbon-free energy. Furthermore, Oregon has committed to eliminating greenhouse gas emissions by 2040 (HB2021 Clean Energy, 2021). To meet these goals, utilities are decommissioning coal power plants that will reduce greenhouse gas emissions but create resource adequacy challenges for the entire region (NWPCC, 2021a). Added to the complexity is the need for not just clean energy sources, but reliable and dispatchable resources for peak demand – for which coal and LNG power plants have been relied upon. Utilities need to meet energy demand under all scenarios, not just average conditions, thus energy capacity is needed to meet peak demand in extreme conditions such as peak summer and winter loads.

Resource adequacy is critically important to ensure electric grid stability by maintaining the required supply of power generation to meet load obligations. Balancing

supply and demand across the bulk electric system requires bulk electric suppliers like BPA, as well as investor-owned load serving entities to ensure that planned capacity and available reserves are in place to serve load requirements. An additional challenge for utilities is the need to meet energy demand under all scenarios, not just average conditions (NERC, 2024a). In the Pacific Northwest, resource adequacy is studied and quantified by the Northwest Power and Conservation Council (NWPCC). NWPCC resource adequacy studies consider many different factors including hydrology, weather extremes, and potential disruptions to generation and transmission. Forced generation outages represent a significant uncertainty in capacity disruption and deficits to meet demand, especially in extreme demand situations (Ming et al., 2019). NWPCC's most recent study shows that demand for energy is already beginning to outpace supply (NWPCC, 2024).

Hydropower in the Pacific Northwest is not only carbon free but provides controllable energy output that can be deployed quickly, ramping up or down to meet changing energy demand. These attributes result in a greater regional reliance upon the Pacific Northwest's hydropower bulk electric system. To combat this emerging need for resource adequacy, the region has collectively worked together with the Northwest Power Pool (NWP), to create a regional resource adequacy program. More than twenty utilities, federal and investor-owned entities, are responsible for different parts of the grid called balancing authorities. Moreover, resource planning has historically been an independent process by each individual entity. The resource adequacy program will address the segmented nature of the region's power grid, to collectively define the region's energy needs, identify capacity deficits, and share in a power pooling effort through the WRAP,

ensuring that surplus energy serves power and capacity deficit areas within the power pool (WPP, 2024).

2.3 Resource Adequacy in other Regions

Resource adequacy has a critical role in utilities across the west. Outside of BPA's territory is the California Independent System Operator (CAISO) who is responsible for delivering wholesale electricity for most of California and portions of Nevada (CAISO, 2024). Additionally, the Desert Southwest is served by the Western Area Power Administration (WAPA) and the Southwest Power Pool (SPP). The Desert Southwest includes southern California, Arizona, New Mexico and a small part of SW Texas (WAPA, 2024).

Following the California Energy Crisis in 2001, the California Public Utilities Commission (CPUC) created a resource adequacy program for California. The objective of this program was to support the system reliability objectives of the CAISO while improving economic efficiency and assuring the lowest-cost energy for California consumers. Load-serving entities such as investor-owned utilities (IOUs), energy service providers (ESPs) and community choice aggregators (CCAs) are subject to the CPUC's resource adequacy obligation requirements. CPUC's RA program helps facilitate resource procurement and drives infrastructure investment by requiring that load-serving entities invest in capacity resources that are made available to the CAISO (CPCU, 2015).

The Desert Southwest is experiencing rapid load growth. Additionally, aging infrastructure and mandates for clean energy are causing resource retirements. This energy resource deficit is creating an urgent need for the desert Southwest to invest in

new energy resources to maintain reliability and resource adequacy. Meeting the growing energy needs of the Desert Southwest will depend on load serving entities' ability to procure and deploy new energy resources fast enough to serve loads. Doing this will require energy resource development to keep pace with demand. Maintaining reliability will depend on both maintaining existing generation capacity and new investments in solar energy development and energy storage. While load growth is a key component driving load serving entities' resource adequacy, uncertainty with climate change and extreme weather events create significant reliability risks. As the Desert Southwest's energy landscape transitions to meet the latest clean energy targets, its energy portfolio will depend on renewable energy sources, energy storage technologies and distributed energy resources. Because of the challenges of integrating variable resources and new energy technologies, this transition to clean energy in the Desert Southwest is one of the greatest challenges to grid reliability (Schlag et al., 2022).

Resource adequacy planners in the Desert Southwest are not the only ones facing these challenges. Load serving entities across the country are investing in grid modernization to improve availability and resource adequacy in a rapidly changing and uncertain energy landscape. Capacity planning continues to develop as resource adequacy evolves. The following sections of this praxis review the current state of capacity planning and best practices, define availability and reliability and discuss the main components of capacity planning – loss of load probability (LOLP), forced outage factor (FOF) and planning reserve margin (PRM).

2.4 Summary of Electric Grid Reliability

Wholesale power customers and the end-using public and private sectors depend on the availability and reliability of the wholesale bulk electric system to power our homes, drive industry and support communities. Despite significant risks, the U.S. grid, including generation and transmission, has very high reliability. On average U.S. electrical customers experience disruption to power supply fewer than two times per year a total outage duration of fewer than five hours. According to a recent U.S. Dept of Energy study, on average the U.S. electric grid has a 99.95% reliability (Denholm, 2024). Furthermore, most outages are not due to due to generator unit outages but instead are mostly caused by disruptions to the electrical distribution system, unrelated to the bulk electric system. In other words, most power outages occur in the local distribution systems of load serving entities.

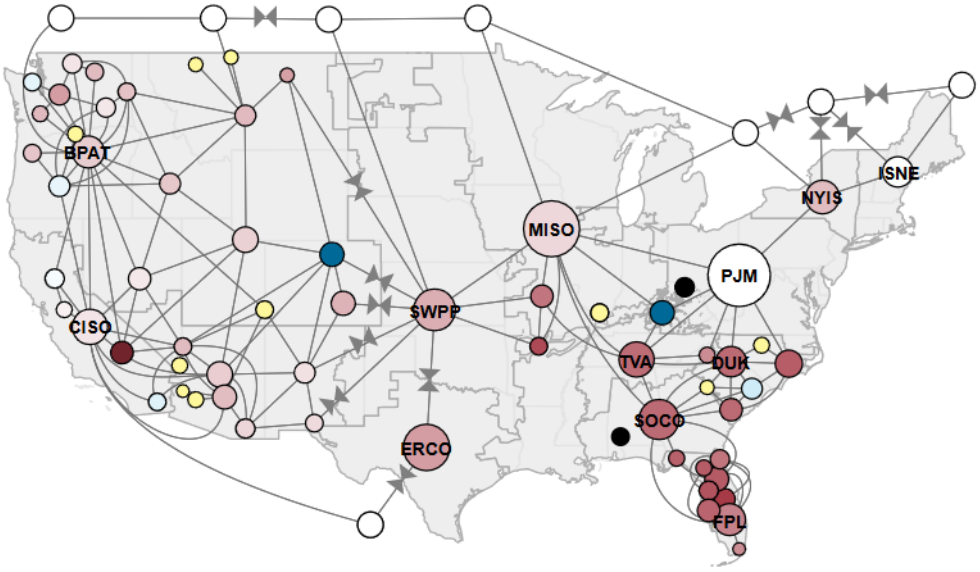

Figure 2-1. Balancing Authorities Interconnections (U.S. Energy Information Administration, 2025)

The U.S. electric grid is a highly coordination system that allows individual power generator units and transmission line failures to occur without affecting the larger grid system. This level of autonomy is accomplished through the coordination of multiple balancing authorities sharing transmission routes to serve load centers. The cooperation of balancing authorities in the U.S. electric grid allows flexibility to maintain energy generation and transmission to balance load despite unexpected outages (Denholm, 2024). Figure 2-1 is a map of the U.S. electric grid interconnections of balancing authorities across North America.

There is almost no contribution to power outages from the loss of generation units. This high reliability is achieved through resource sharing across all U.S. electric grid regions between balancing authorities. This interconnection is mainly due to a highly coordinated system in which power is pooled from areas with surplus capacity to areas with a deficit. As discussed earlier, this coordination is made possible through resource adequacy programs like WRAP and the participation of various independent system operators and load-serving entities of the bulk electric system. The WRAP region and its 22 load serving entities, including BPA, is shown in Figure 2-2.

Figure 2-2. WRAP Region (Northwest Power and Conservation Council, 2023)

2.5 Hydropower Forced Outages

Hydropower generation represents one of the most established renewable energy technologies, providing approximately 6.6% of U.S. electricity generation and significant grid flexibility services. However, the operational management of hydropower facilities faces unique challenges, particularly regarding forced outages of generating units. Unlike planned maintenance outages, forced outages introduce operational uncertainty that impacts system reliability, revenue generation and long-term asset management strategies. Recent hydropower market data indicates that "from 2019–2021, the average hydropower availability factor was stable at 79% for small units, 83% for medium-sized units and 78% for large units" (U.S. Department of Energy, 2022). These availability

factors reflect the combined impact of planned and unplanned outages on hydropower plants.

2.5.1 Generator Availability Data System (GADS)

The North American Electric Reliability Corporation (NERC) first developed the Generator Availability Daya System (GADS) in 1982 to support power generation outage data collection. Today, GADS is the primary source of generation outages for public and private utilities across North America. The GADS database stores operational information collected through mandatory reporting from thermal, coal, natural gas and hydropower generation facilities. Additionally, variable resource power plants such as wind and solar report to GADS. Through GADS, NERC collects generation outage events that are characterized by eight separate event types, including forced and planned outages. GADS data supports load serving entities' resource adequacy programs and capacity planning modeling. All conventional generators (including hydro power facilities) that are larger than 20MW must report outage information to GADS. The historical forced outage data used in this praxis research comes from BPA's internal outage tracking system (OTS), which is discussed in the next section. Outage data collected in OTS follows the GADS outage type standards.

GADS defines a generation outage as whenever a generating unit is not synchronized to the grid and not in a reserve shutdown state. FCRPS partner hydro projects report outages following NERC GADS standards and report monthly outage data to BPA. BPA tracks and provides performance indicator metrics that include forced

outage factor (FOF) and scheduled outage factor (SOF) for all FCRPS federal hydropower projects (NERC, 2024b).

2.5.2 BPA Outage Tracking System (OTS)

BPA's Outage Tracking System (OTS) is an internal BPA database for generation outage tracking and is separate from GADS. FCRPS project operators access OTS to input outage information that includes the generator unit affected and associated equipment, the time of the outage and the time (or estimated time if the outage is current) the unit returned or will return to service. The information recorded in OTS is delivered to transmission dispatchers from FCRPS project operators who are following the same GADS standards. In addition to tracking forced outages, OTS also tracks planned outages at FCRPS hydropower projects up to a ten-year horizon. OTS provides over 7 years of historical outage data, both planned and unplanned. OTS data is the primary data source used in this praxis for modeling the probability of future forced outages, used for capacity planning.

2.6 Capacity Planning BPA

Understanding capacity planning requires distinguishing between two fundamental utility concepts: energy and capacity. Energy represents the total quantity of electricity delivered to customers over time, typically measured in kilowatt-hours (kWh) or megawatt-hours (MWh). In contrast, capacity refers to the maximum amount of electricity that can be generated at any given moment, measured in megawatts (MW). Capacity planning is the strategic assessment of generation, transmission and distribution

resources necessary to reliably meet projected electricity demand while maintaining system adequacy and operational efficiency (Hobbs, 1995).

The Bonneville Power Administration published the Pacific Northwest Loads and Resources Study, commonly called the White Book. BPA's White Book is an annual publication that documents the latest projection of the federal system's loads and resources and the Northwest region's total retail loads, power supply obligations and resources for the upcoming 10-year period. BPA uses the White Book as a planning tool and data source for the Columbia River Treaty studies, providing a snapshot of the current load/resource balance. It specifically looks at current obligations, contracts and conservation, along with resource forecasts. Other studies that BPA produces look at loads and resources with a specific design intent. For example, rate case studies are designed to get to a load resource balance by including either augmentation or surplus sales that do not yet exist. Resource Program studies use fixed load forecasts to optimize resource selection in order to fill deficits (BPA, 2023).

The federal system analysis provides a deterministic analysis of federal firm loads and resources based on expected loads and varying water conditions. All analyses are based on agreements currently in place and represent BPA's total obligations and the current resource portfolio (physical and contractual resources available to serve load). BPA uses this analysis as input for Columbia River Treaty studies, data submittals and other studies. Other entities – the Northwest Power and Conservation Council, BC Hydro and Power Authority, Pacific Northwest Utilities Conference Committee, Pacific Northwest Coordination Agreement participants and individual customers – also access and use this analysis for various purposes. The result of the latest study shows that under

firm water conditions, the federal system has annual energy deficits throughout the 10-year study period, with the largest deficit near the end of the study period. Under median water conditions, however, the analysis shows annual energy surpluses across the study period (BPA, 2023).

The Pacific Northwest regional analysis provides a deterministic analysis of regional firm loads and resources. BPA, the Council, BC Hydro, PNUCC, PNCA and other entities use the study results as inputs for Treaty studies, data submittals and other analyses. Under firm water conditions, the region is projected to have annual energy surpluses until the third year of the study period (operating year 2027). After that, deficits increased considerably throughout the period. Under median water conditions, the analysis shows annual energy surpluses until the end of the study period (BPA 2023).

The types of available resources under firm conditions to meet the load for the federal system and the Pacific Northwest region in the Operating Year 2025 are shown in Figure 2-3. More than 80% of the energy and capacity available from the federal system comes from hydropower. The PNW regional analysis reveals that 43% of the energy comes from hydropower, as shown in Figure 2-4. While hydro supplies a significant share of the resources across the region, the above figures show the PNW region has a more diverse resource portfolio. At the same time, the federal system is highly dependent on hydro (BPA, 2023).

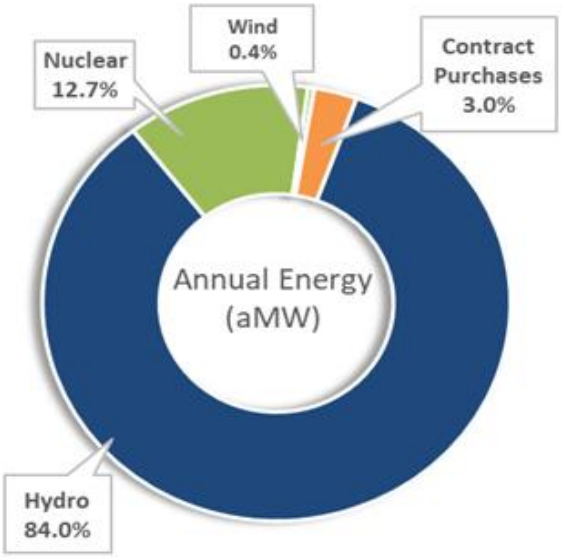

Figure 2-3. Federal System Firm Resource Mix for Annual Energy (BPA, 2023)

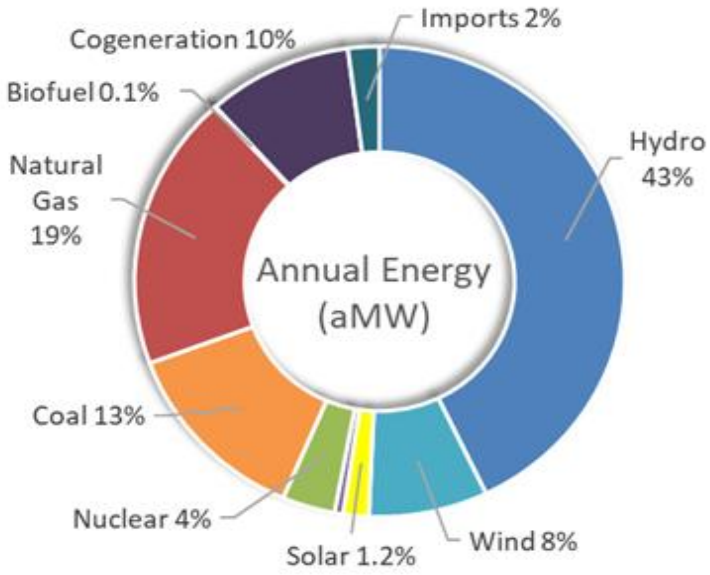

Figure 2-4. PNW Regional Firm Resource Mix for Annual Energy (BPA, 2023)

2.7 Reliability and Availability

Reliability measures system readiness at specific intervals, while availability measures the percentage of operability (Bargai & Shittu, 2021). Both offer insights into

electric grid stability and help identify areas of vulnerability. Reliability of the U.S. electric grid is the probability that the broader, coordinated bulk electric system will perform as intended without failure for any given period. In addition, reliability is used to measure the bulk electric system's ability to maintain functionality and performance, despite generation and transmission outages. NERC resource adequacy programs, such as WRAP are designed to improve electric grid reliability through coordinated pooling of capacity resources.

Reliability is essential for maintaining customer confidence and operational efficiency. Reliability modeling is used to predict system performance using interdisciplinary methods in probability, statistics and simulation. Reliability theory uses mathematical models and statistical techniques to estimate a system's or component's probability of failure (Ben-Daya et al., 2016). NERC provides GADS standards for outages and failure rates in their Data Reporting and Instructions manual (NERC, 2024b).

NERC defines factors and rates for a variety of system conditions shown in Figure 2-5. Failure rates like Weighted Forced Outage Factor (WFOF) are used to determine system or component failure probability. These NERC metrics are important for reliability analysis, as they provide insight into the frequency and likelihood of system or component failures. By understanding these metrics, BPA and other load serving entities can better predict maintenance needs, plan for replacements and improve overall system reliability.

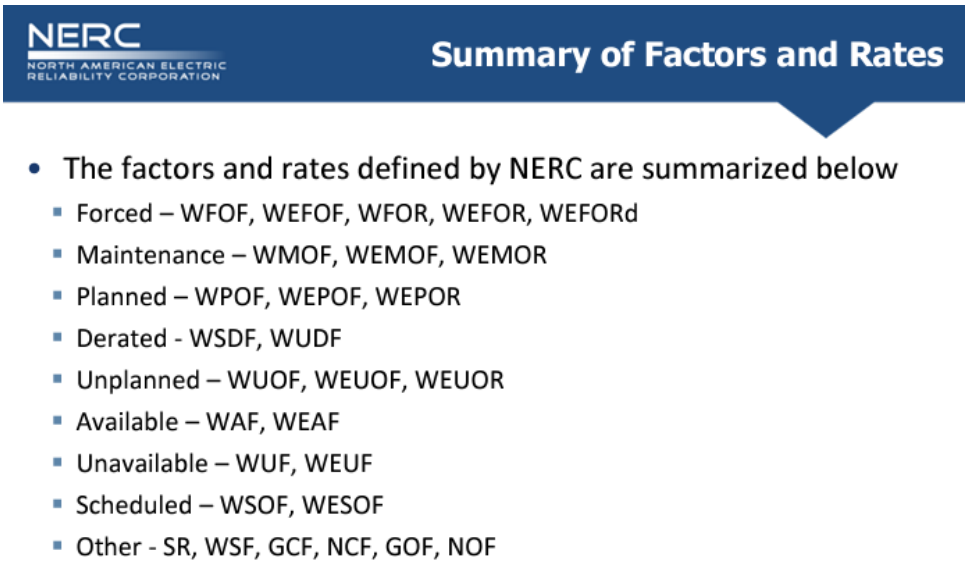

Figure 2-5. NERC Factors and Rates (NERC, 2024b)

Measuring availability with performance metrics, such as mean time between failures (MTBF) and the mean time to repair (MTTR) is common practice in industry. MTBF is calculated by dividing the total operation time by the number of failures as shown in Equation 1. MTBF is a key metric used in this praxis to define the average time duration between generation outages. MTBF and MTTF are often used interchangeably, however MTTF is typically used for non-repairable systems, while MTBF is used for repairable systems.

$$MTBF = \frac{Total\ Operational\ Time}{Number\ of\ Failures} \quad (1)$$

Equation 1. Mean Time Between Failure (MTBF)

$$MTTR = \frac{Total\ Repair\ Time}{Number\ of\ Repairs} \quad (2)$$

Equation 2. Mean Time To Repair (MTTR)

This praxis research uses MTBF and MTTR to develop a forced outage forecasting model used to determine lost generation capacity due to forced outages. Calculating MTBF and MTTR involves collecting historical data on failure events and using statistical methods to compute the average time to failure and between failures. In this praxis research, historical outage data comes from BPA's OTS database.

The availability metric is the percentage of time that a system or component is in an operational state, ready to perform its function at a certain point in time or interval. Availability is a metric used to measure the amount of time that a generating unit can be used for energy production. Availability is in part defined by an asset's uptime and downtime. These are random variables determined by failure time and repair time distributions. As mentioned earlier, availability can be determined for a specific singular point in time, or over a certain time interval. For the purposes of BPA capacity planning in the WRAP, this praxis will focus on estimating generation availability for a period of one year, or 8,760 hours.

The steady-state average proportion of time a system is operational over a given period $(0,\infty)$ determines the probabilistic, mean availability of a generating unit. Asymptotic average availability is shown in Equation 3, where $t_1 = 0$ and $t_2 = \infty$. Using asymptotic average availability, where uptimes are independent and share the same exponential distribution function $F(t)$, the average uptime is equal to MTBF. This same case is applied to downtimes, which is equal to MTTR and shown in Equation 2. Applying the ordinary renewal process to Equation 3, we get the commonly used formula for availability shown in Equation 4, where MTBF + MTTR is equal to the total time span (Ben-Daya et al., 2016).

$$A_{\infty} = A(0, \infty) \quad (3)$$

Equation 3. Asymptotic average interval availability

$$A_{\infty} = \frac{MTBF}{MTBF+MTTR} \quad (4)$$

Equation 4. Generator Operational Availability

Equation 4 determines the generator availability, meaning it is in an available state, ready for deployment. The FCRPS electric grid operates continuously and maintaining high availability is critical. Utilizing availability metrics such as MTBF and MTTR, capacity planners and system operators can improve electric availability. Equation 4 shows that availability and reliability are connected, with reliability improving through either longer MTBF or shorter MTTR. (Ben-Daya et al., 2016). Forced outage probabilities can enable BPA capacity planners to reduce capacity reserve and optimize the surplus capacity committed to the power pool. As discussed in Section 1.1, capacity is acquired in the power pool at 125% of the energy price. Capacity planning informed with forced outage probabilities may reduce BPA's required capacity reserve, resulting in more marketable capacity in the power pool.

2.8 Deterministic and Probabilistic Methods

Capacity planners in the power industry have used multiple methods for evaluating resource adequacy. As discussed in "*Probabilistic resource adequacy assessment of large interconnected systems,"* authors Bagen et al, discuss the two common approaches as deterministic and probabilistic. Deterministic approaches set a reserve margin based on the unavailability of generation capacity. What deterministic methods don't account for is the randomness of generator failures (Bagen et al., 2010). A

probabilistic approach to generation capacity forecasting has become more prevalent in the power and utility industry as the integration of variable resources such wind and solar present greater uncertainty (Zhang et al., 2022).

Sections 2.8.1 and 2.9 provide a review of methodologies for modeling forced outage probabilities for capacity planning. Model analysis can combine several analytical and computational techniques. A literature review of loss of load probabilities (LOLP) and loss of load expectations (LOLE) finds these are standard approaches for probabilistic determination of resource adequacy. A Monte Carlo simulation literature review identifies various successful applications in which forced outage probabilities are determined by a statistical analysis of thousands of simulations. This helpful approach utilizes confidence limits in the solution and can be tailored to risk tolerance. Additionally, Monte Carlo simulation can perform sensitivity analysis and provide a lost-capacity exceedance curve to inform capacity planners when including the uncertainty of forced outages in future capacity commitments (Ben-Daya et al., 2016).

2.8.1 LOLP and LOLE

Capacity planners in the power industry have used multiple methods for evaluating resource adequacy. As discussed in "*Probabilistic resource adequacy assessment of large interconnected systems,"* authors Bagen et al, discuss the two common approaches as deterministic and probabilistic. Deterministic approaches set a reserve margin based on the unavailability of generation capacity. What deterministic methods don't account for is the randomness of generator failures (Bagen et al., 2010). A probabilistic approach to load forecasting has become more prevalent in the power and

utility industry as the integration of variable resources such wind and solar present greater uncertainty (Zhang et al., 2022).

LOLP is a standard index used for electric grid reliability and is a measure of generation capacity reliability. LOLP is defined as the expected probability that available generation capacity is less than the expected load. For generation capacity planners wanting to quantify the impacts of forced outages on system availability, the LOLP is used to measure the probability for a single point, or an interval such as summer peak loads. (Almutairi et al., 2015). In the paper, *Optimal Sizing and Designing of Hybrid Renewable Energy Systems in Smart Grid Applications*, the LOLP is generally defined as the expected number of hours in a particular period when capacity deficiency occurs. During a loss of load period where generation capacity is deficient, the available generation does not meet load demand (Eltamaly et al., 2018).

NERC has published a resource for capacity planners, *Methods to Model and Calculate Capacity Contributions of Variable Generation for Resource Adequacy*. In this NERC guide, the LOLP calculation combines the load profiles and planned generator outage schedules with forced outage probabilities (NERC, 2011). This computation for LOLP includes the uncertainty of forced outages.

One limitation of the LOLP is that it only considers the number of hours in which generation is deficit relative to load demand. The LOLP calculation does not account for MTBF or the MTTR (NREL, 2011). Forced outages encompass a range of outage durations from hours to years. In a federal hydropower system that includes 31 operating facilities that vary in installed capacity from 6.8GW to 28MW, the frequency and duration of forced outage has wide variability of impact to LOLP. To account for the

uncertainty of forced outages a model should include the severity of the outage, which is the frequency and duration relative to its operational impact on the system.

In the paper, "*The effects of Uncertainties in Forced Outage Rates and Load Forecast on the Loss of Load Probabilities*," the authors summarize the standard method of calculating the LOLP into three steps. The first step to calculating the LOLP of a system of generating units is to compute the cumulative forced outage probability for the system using individual FOR of each generator. The second step uses the Capacity Outage Probability Table (COPT) to calculate the probability of Loss of Energy Expectation (LOEE) for each forecasted peak load. The third and final step is the summation of LOEE probabilities for all the forecasted load demand peaks (Wang, 1977). LOLE and LOEE are also common indices used in capacity planning to quantify resource adequacy and reliability and shown in Equations 5 and 6. LOLE is an expected value metric typically measured in days/year, though it can be calculated using other time units like hours/year depending on the analysis requirements (NERC, 2011).

$$LOLP = \sum_{k=1}^{K} Pk * t_{loss,k} \quad (5)$$

Equation 5. Loss of Load Probability

$$LOLE = E(x) = P_1X_1 + P_2X_2 \dots P_i \dots + P_nX_n \quad (6)$$

Equation 6. Loss of Load Expectation

2.9 Stochastic Simulation and Monte Carlo Methods

Monte Carlo simulations and Markov processes are used in a variety of reliability and resource adequacy modeling applications. Electric utilities have been utilizing probabilistic methods for determining resource adequacy for decades. Changes in the

energy landscape the electric power industry has adopted probabilistic modeling versus deterministic approaches. In addition, NERC standards are becoming increasingly focused on probabilistic methods and are including probabilistic methods in RA standards and best practices. When capacity planners determine reserve margins using a probabilistic approach, the reserve margin is based on the probability that some level of generation deficit renders the power system unable to meet demand (Bagen et al., 2010).

In the paper, *Using a Semi-Guided Monte Carlo Method for Faster Simulation of Forced Outages of Generating Units*, the authors determine the uptime and downtime of generating units using an unguided and semi-guided Markov process, in a two-state model. The results show that the semi-guided technique reduced computation time and reduced the number of required iterations (Scully et al., 1992). It is common for capacity planners to employ Multi-state Markov models to determine power system reliability. A two-state model of a generating unit would limit the unit to two states - a capacity of zero and full capacity. Generating units can exist in multi-states where the unit is generating at a derated capacity, as in the case of a fix blade Kaplan unit, or a transmission limitation that requires reduced generation. In the paper, *A Multi-State Markov Model for a Short-term Reliability Analysis of a Power Generating Unit*, the authors write that because a simple two-state model doesn't accurately characterize generators, the results of resource adequacy studies will be much less conservative using a multi-state model that can capture generation capacity between zero and full operational capacity (Lisnianski et al., 2012).

In the paper, *"Forced Generation Outage Investigations for the Northwest Power Pool"*, authors Brown, et al, explain that their analysis of data from almost 2,000

machine-years of hydroelectric generating unit operation, finds that while statistical testing indicates that neither exponential nor log-normal distributions adequately represent the true underlying distribution of outage duration data, the log-normal distribution provides sufficient accuracy for practical applications (Brown et al., 1960).

The probability of generator failure rates over time can be depicted in the bathtub curve shown in Figure 2-6, with three main failure periods: burn-in, useful life, and wear-out. In the burn-in period, failures from manufacturing and assembly result in a high initial failure rate that decreases over time. In the useful life period, failures become random, and a constant failure rate is assumed. Finally, the wear-out phase is characterized by an increasing failure rate as equipment ages beyond its useful life. The time to failure is a discrete random variable, *T*, with a cumulative distribution function (CDF) *F(t)*, shown in Equation 7. The reliability function *R(t)* is the probability of no failures before time *t*, shown in Equation 8. Finally, the hazard rate shown in Figure 2-6 as a function of time, is shown in Equation 10, where *f(t)* is the probability density function (PDF), shown in Equation 13 (Ben-Daya et al., 2016).

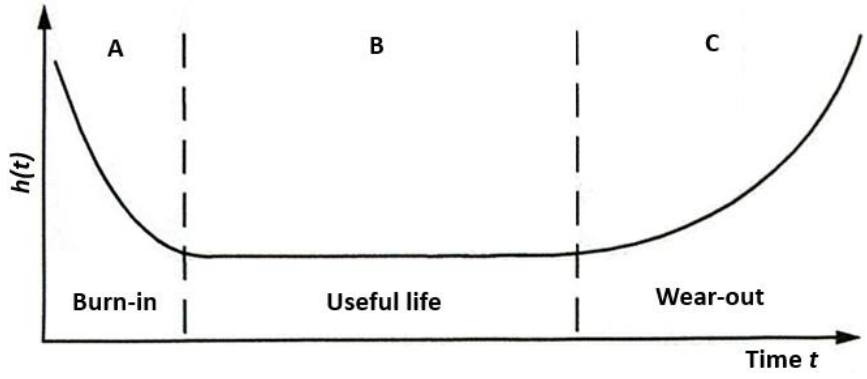

Figure 2-6. Bathtub Curve (Ben-Daya et al., 2016)

$$F(t) = \mathrm{P}(T \leq t) \tag{7}$$

Equation 7. Cumulative Distribution Function

$$R(t) = \mathrm{P}(T > t) = 1 - F(t), \quad t > 0 \tag{8}$$

Equation 8. Reliability Function

$$F(t) = 1 - \mathrm{e}^{-\lambda \mathrm{t}}, \quad 0 \leq t < \infty \tag{9}$$

Equation 9. Exponential Distribution

$$h(t) = \frac{f(t)}{R(t)} \tag{10}$$

Equation 10. Hazard Function

Forced Outage Rate (FOR) is the percentage of time that a generator is unexpectedly out of service due to forced outages. FOR is a key index for resource adequacy analysis. FOR is defined as the ratio of the downtime hours to the total number of hours the generator unit is in an operational state. The MTBF is the reciprocal of the constant failure rate where lambda is calculated using Equation 11 (Schneeweiss, 1984).

FOR, is represented by (λ) and the repair rate (μ). Failure rate represents how frequently equipment fails during its operational time, while repair rate indicates how quickly equipment is restored during downtime periods. Exponential distribution is commonly used in reliability engineering because it aligns with the constant failure rate assumption for generation equipment. This approach relies on the assumptions that generators are homogeneous components sharing identical failure rates (λ)and second, that failures are memoryless, meaning a generator's failure probability remains independent of its operational history (Billinton, 1996).

$$\lambda = \frac{1}{MTBF} \tag{11}$$

Equation 11. Generator Failure Rate

Additionally, the repair rate (μ) is assumed to be constant and is calculated by using equation 12, where MTTR is the reciprocal of the constant repair rate.

$$\mu = \frac{1}{MTTR} \tag{12}$$

Equation 12. Generator Repair Rate

The PDF for the failure rate (λ) and the repair rate (μ) are shown in Equations 13 and 14.

$$f(t, \lambda) = \lambda e^{-t/\lambda} \tag{13}$$

Equation 13. PDF of Failure Rate

$$f(t, \mu) = \mu e^{-t/\mu} \tag{14}$$

Equation 14. PDF of Repair Rate

This literature review found similar research conducted on the Canadian jurisdiction of the Columbia River basin, researching the application of Monte Carlo analysis to quantify the generation capacity loss due to forced outages. In this research, author Agrawal proposes a Monte Carlo analysis with multi-state Markov Chain methods. Agrawal argues that the multi-state approach improves the capture of generation capacity loss due to generator de-rates. In Agrawal's model, generator de-rates represent a third operational state, between operating at max capacity and no capacity as in a forced outage state (Agrawal, 2018).

2.10 Current Approach for BPA Capacity Planners

WRAP capacity planners at BPA commit to a power pool capacity seven months in advance of winter or summer peak load periods. FCRPS operating hydro projects update OTS with planned outages one year in advance and maintain the database with updated

and accurate schedules. Capacity planners use a deterministic approach, utilizing planned and unplanned outages in OTS to calculate system availability over summer and winter peak load time intervals. This accounting of system availability alone is insufficient and does not account for uncertainty.

An example of uncertainty with planned outages is when an operating project cancels, extends or postpones an outage after the capacity commitment to WRAP has been set. A capacity commitment set seven months in advance can have a significant amount of uncertainty and planners may rely heavily on reserves. In addition to emergent schedule changes to planned outages, capacity planners contend with the risk of unplanned or forced outages.

Currently no model or planning tool exists within BPA to quantify the probability of capacity reducing forced outages. Instead, capacity planners use 10 years of historical GADS outage data and average the capacity deficit due to forced outages during the summer and winter WRAP periods. They use the ten-year historical average to inform the necessary reserve requirements. The intent of this praxis is to develop a probabilistic forced outage forecasting model that will help optimize the planned MW generation capacity reserve. Optimized reserves allow more surplus capacity to be available and marketed in the power pool and reduce the risk of deficit capacity.

2.11 Summary and Conclusion

In summary, capacity planning primarily relies on LOLP and LOLE analysis. LOLP represents the probability that available generation capacity is less than demand and serves as a standard reliability index for electric grid adequacy assessment. While LOLP

provides valuable insights into generation capacity planning, its limitation lies in not capturing the frequency and duration characteristics of outages. Monte Carlo simulation offers a more comprehensive approach to availability modeling by enabling stochastic analysis of MTBF and MTTR. These simulations assume that generator failure and repair rates follow exponential distributions. This modeling approach depends on two key assumptions: 1) generator homogeneity, where all units of the same type share identical failure rates (λ) and 2) memoryless behavior, where a generator's failure probability remains independent of its forced outage history (Billinton, 1992).

The research methodology in this praxis differentiates from previous research by focusing on the probability of unavailable capacity due to forced outages using actual forced outage data from the FCRPS hydropower plants. Additionally, this praxis contributes to the body of knowledge based on the uniqueness of the FCRPS and the actual model build developed in this research to aid capacity planners at BPA and the 22 member utilities in WRAP. Finally, this analysis treats derated generators as a separate capacity planning consideration, avoiding the complexity of multi-state Markov Chain modeling. The analysis of five years of historical data reveals that observed generator derates are overwhelmingly, long-term conditions spanning the entire dataset period. These derates typically result from repairs that safely restore units to service but with lower operational capacity. Long-term derates can often be addressed through capital investments to restore generators to their original nameplate capacity. The proposed methodology requires accurate accounting of maximum generation capacity that reflects both long-term capacity changes from derates, as well as operational capacity variations due to water supply forecasts.

Chapter 3—Research Methodology

3.1 Introduction

This chapter provides a detailed overview of the methodology used in this praxis research. This praxis is focused on estimating generation capacity loss due to unplanned, forced generation outages. Forced generation outage estimates aid BPA capacity planners in the optimization of marketable capacity in WRAP and other future resource adequacy power-pooling markets. This chapter consists of an overview of the proposed model development. Section 3.2 is a statement of the problem and the proposed solution. Section 3.3 introduces the independent and dependent variables used in simulation. Section 3.4 describes the data sources used in this research. Section 3.5 is a detailed summary of the data collection. Section 3.6 discusses the required data preparation and quality control. Section 3.7 discusses the various data limitations encountered in the five-year historical data set used. Section 3.8 outlines data analysis steps followed in this research. Sections 3.9 and 3.10 describe the MATLAB model. Section 3.11 outlines and describes the validation methods used in this research. Section 3.12 discusses the hypotheses to be tested in this research. Finally, Section 3.13 provides a summary and conclusion.

3.2 Statement of the Problem and Proposed Solution

Availability forecasting is a coordinated effort, as the FCRPS comprises thirty-one federal hydroelectric dams owned and operated by the USBR and USACE (Bureau of Reclamation, 2019). Twenty-one are analyzed for WRAP purposes. Forced outages reduce Bonneville Power Administration's planned capacity in WRAP. Capacity commitments that don't account for forced outage probabilities risk losing revenue of

marketable power up to 120% of spot price. When a hydropower generator is forced out of service, this is an unplanned event that reduces the hydropower system availability. The time a hydropower generator is out of service is its unavailability. A Monte Carlo simulation for forced outage unavailability allows BPA to both maintain capacity obligations and maximize revenue opportunities in the WRAP. Maximizing revenue in the WRAP market depends on the amount of surplus BPA can commit. BPA's marketable surplus capacity is the remaining capacity after subtracting its load resource obligations, water resource obligations, treaty obligations, scheduled transmission outages, scheduled generation outages and unplanned forced generator outages. Forced outages represent significant uncertainty of available capacity – especially in WRAP's forward showing (seven months in advance) capacity commitment. WRAP capacity planners consider generation capacity loss due to both scheduled and forced generator outages in their capacity commitments. This research aims to provide a Monte Carlo simulation model that minimizes uncertainty in planned capacity through disciplined accounting of forced outage unavailability. The model will be used for operations planning to commit to power pool capacity seven months in advance for both summer and winter load peaks.

3.3 Relevant Variables

The generator outage data variables include the outage type (whether it is forced, planned, urgent, etc.), out of service time in hours and the return to service time in hours. The outage types for each logged outage in OTS follow the NERC Generator Availability Data System (GADS) standards for classification and reporting.

The Monte Carlo simulation has two independent variables, the MTBF and the MTTR. As discussed, MTBF is the mean time between failures in hours and MTTR is the mean time to repair in hours. This analysis uses average historical generator outage data in a five-year period, to estimate the next year's generation capacity loss due to forced outages. WRAP planners will use this yearly estimate to plan the bi-annual capacity commitment for both summer and winter peak loads.

MTBF and MTTR are determined by FCRPS operating project outage data entered into BPA's OTS database. As mentioned above, the historical data in OTS conforms to NERC GADS standards in terms of forced outage classification. Generator uptime and downtime are determined by MTBF and MTTR. MTBF is the generator's uptime, otherwise known as the available time, that the generator is synced to the grid. MTTR is the generator down time, which is the time the generator is not synced to the grid. The variables are obtained from the FCRPS outage data in PBA's OTS database. Figure 3-1 shows that the MTBF is the generator "uptime" where it is synced to the grid and operational. Additionally, the figure shows that the MTTR is the generator "downtime," in an outage state and not synced to the grid.

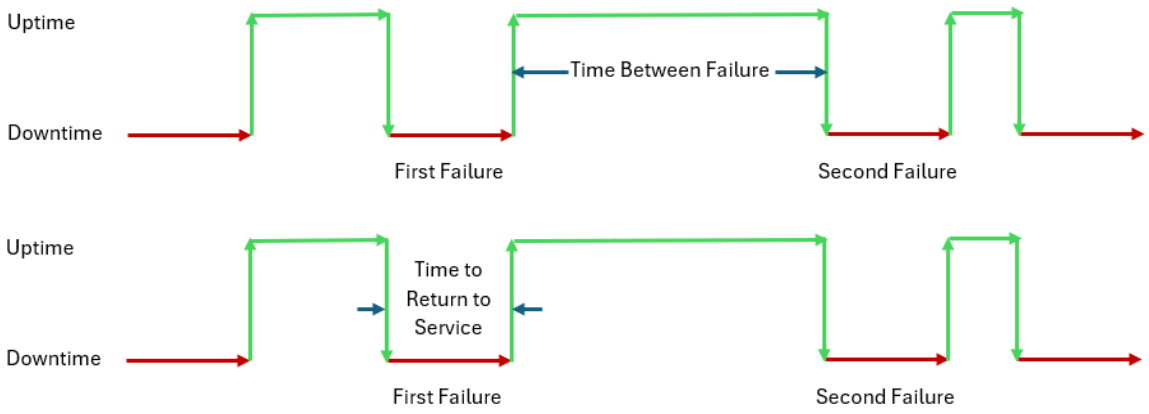

Figure 3-1. Uptime and Downtime

The inputs to the Monte Carlo simulation include the number of experiments and the random number of the exponential distribution for both MTBF and MTTR. The number of experiments for the model run is 10,000 and is discussed more in Section 3.9. The output of the simulation is the generator availability, shown in Equation 4 and is the ratio of the average uptime and the total span of time including the total hours the generator is in both operational and failure states.

$$Unavailability = 1 - \frac{MTBF}{MTBF+MTTR} \quad (15)$$

Equation 15. Generator Unavailability

Finally, the unavailability of the generating unit is shown in Equation 15. The generation loss due to forced outages is shown in Equation 16. Equation 16 is the method used to determine generation capacity loss due to forced outages. One issue to overcome, that is discussed in Section 3.5.1 is that a single hydropower plant may have multiple generators with different capacities. In these cases, the methodology used in this research organizes generators by capacity to determine average unavailability. The generation capacity loss is determined for each plant and when required, grouped by equal capacity generators. Generation capacity loss is then aggregated by generator capacity and by hydropower plant to determine overall system availability.

$$Capacity\ Loss_{FO} = Unavailability * Capacity \quad (16)$$

Equation 16. Generator Capacity Loss

3.4 Data Source

The data used in this praxis comes from BPA's outage tracking system (OTS) database, maintained by BPA and used by FCRPS federal partners as well as BPA

transmission. This data includes forced outages from all 31 hydro power plants across the FCRPS. MTBF and MTTR are variables determined from the outage data. The outage data includes the out of service and in service times for each forced outage. This Praxis research uses plant-specific outage information to estimate overall system availability. This research is approved by BPA; however, FCRPS outage data is BPA business sensitive and cannot be shared or published. Additionally, hydropower plant names are anonymized from the results and data tables to protect business sensitivity. Figure 3-2 is an example of the forced outage data format from OTS, using mock data for illustration.

3.5 Data Collection

The variable MTTR to is obtained from the "Out of Service Duration Hrs' shown as a column header in Figure 3-2 and is the downtime of the corresponding forced outage. The MTBF is the number of hours between the "In Service Time" of the previous forced outage and the "Out of Service Time" of the next forced outage, also shown in Figure 3-2. This data is pulled from the OTS database as a .csv file and the MTBF is calculated in Excel. The "Duration Days" and "Duration Hrs" are checked for correctness. In addition, outage data is continuously monitored for correctness of outage type and duration.

Due to the limited historical dataset spanning 2019-2023 and the age of the OTS database, some forced outages have recorded MTTR values without corresponding MTBF values. This occurs when the "Out of Service Time" precedes the data collection period, affecting only the historical dataset used for model training. Rather than artificially generating MTBF values, this analysis uses only observed historical values to maintain statistical integrity for validating exponential distribution. This results in a

slightly larger sample of MTTR observations compared to MTBF observations. This approach maintains the statistical integrity of the observed historical forced outage data.

OTS Status	Outage Ty	Out Of Service Time	In Service Time	Duration Days	Duration Hrs	Units
Returned to Service	Forced	9/4/2018	9/4/2018	0.572916667	13.75	1
Returned to Service	Forced	9/5/2018	9/6/2018	1.25625	30.15	2
Returned to Service	Forced	10/1/2018	10/2/2018	0.797222222	19.13333333	3
Returned to Service	Forced	10/4/2018	10/16/2018	11.60486111	278.5166667	4
Returned to Service	Forced	11/21/2018	12/26/2018	34.81180556	835.4833333	5
Returned to Service	Forced	11/23/2018	12/17/2018	24.50208333	588.05	6
Returned to Service	Forced	11/23/2018	11/29/2018	6.268055556	150.4333333	7
Returned to Service	Forced	11/26/2018	11/28/2018	2.288888889	54.93333333	8
Returned to Service	Forced	11/27/2018	12/6/2018	8.982638889	215.5833333	9
Returned to Service	Forced	1/1/2020	1/10/2020	9	216	10
Returned to Service	Forced	7/26/2018	11/10/2018	107.3381944	2576.116667	11
Returned to Service	Forced	8/16/2018	11/10/2018	86.47916667	2075.5	12
Returned to Service	Forced	9/1/2018	9/4/2018	2.994444444	71.86666667	13
Returned to Service	Forced	9/1/2018	9/12/2018	11.07013889	265.6833333	14
Returned to Service	Forced	9/4/2018	9/4/2018	0.572916667	13.75	15
Returned to Service	Forced	10/17/2018	10/17/2018	0.560416667	13.45	16
Returned to Service	Forced	10/16/2018	10/17/2018	1.440972222	34.58333333	17
Returned to Service	Forced	10/17/2018	10/17/2018	0.290972222	6.983333333	18
Returned to Service	Forced	10/18/2018	10/22/2018	3.8	91.2	19
Returned to Service	Forced	10/19/2018	10/19/2018	0.098611111	2.366666667	20
Returned to Service	Forced	10/20/2018	10/22/2018	1.543055556	37.03333333	21

Figure 3-2. OTS Outage Data

3.6 Data Preparation

The OTS database captures generator outages both scheduled and unplanned, across the FCRPS. OTS is at the center of outage coordination activities and processes at BPA. OTS was built in 2018 and contains seven years of outage data. Historical forced outage data from OTS encompasses all federal hydro generation projects in the FCRPS. Figure 1-1 shows the geographic area of the Columbia River Basin and the 31 FCRPS hydropower projects. For this Praxis research, this model is being designed for WRAP capacity planners who focus on specific hydropower plants. The 21 plants studied in this analysis are shown in Table 3-1 and represent the specific subset of FCRPS hydropower

plants that WRAP capacity planners currently use in their deterministic capacity planning approach.

Plants / Generators Used in WRAP Modeling				
Plant	# of Units	Range of Units	MW	Total MW
P1	5	1-5	121	605
P2	3	1-3	16	48
P3	4	1-4	107	428
P4	18	1-18	125	2250
	3	19-21	690	2070
	3	22-24	805	2415
P5	16	1-16	88	1408
	11	17-27	109	1199
P6	2	1-2	103	206
	1	3	259	259
P7	6	1-6	155	930
P8	6	1-6	155	930
P9	6	1-6	155	930
P10	3	1-3	103	309
	3	4-6	128	384
P11	14	1-14	80	1120
P12	16	1-16	155	2480
P13	14	1-14	81	1134
	8	15-22	92	736
P14	10	1-10	60	600
	8	11-18	77	616
P15	2	1-2	58	116
P16	2	1-2	46	92
P17	2	1-2	11.5	23
P18	2	1-2	14	28
P19	3	1-3	46	138
P20	2	1-2	17	34
P21	2	1-2	28	56

Table 3-1. Generators Used in WRAP Modeling

To demonstrate the improvement of the proposed Monte Carlo methodology over existing practices, this research maintains the same plant selection used by WRAP capacity planners. There are ten hydropower plants not considered by WRAP capacity planners and thus filtered out of the data set. The ten excluded FCRPS plants serve different operational purposes, primarily focused on irrigation and, to a lesser extent, recreation. These hydropower plants are not considered in WRAP capacity planning

because of their operational priorities. This approach to plant selection enables adoption by WRAP capacity planners, by using their established scope. BPA also markets the power from Columbia Generating Station (CGS), a 1GW nuclear facility that is also excluded from this analysis. CGS outages are filtered out for the dataset. For the 21 projects in this analysis, OTS outage schedule data is filtered for only forced outages and separated by project and individual generating units. There are 175 hydropower generators in this analysis, totaling 21,544MW of capacity.

Finally, when hydropower plants contain multiple generators with different nameplate capacities, these generators are grouped by capacity shown in Table 3-1. As an example, for a hydropower plant that has ten generators consisting of five 80MW units and five 100MW units, generators are grouped by capacity: Group 1 with 400MW total capacity (5 × 80MW) and Group 2 with 500MW total capacity (5 × 100MW). This grouping approach ensures consistency when calculating generation capacity loss.

3.7 Data Limitations

As discussed in Section 4.2, OTS contains only seven years of outage data and this has some limitations. For many of the smaller projects the frequency of outages is much lower and thus may have a small data set, making the determination of best fit for an underlaying distribution more difficult. Furthermore, many projects have had long-term outages that span the entirety or a large part of the five-year span of the data. This is significant for hydropower plants with large capacity generators that account for a larger percentage of overall, system-wide capacity. Figure 3-3 shows the projects studied in this

analysis and their capacities. The figure shows that the largest hydropower plant, P4, accounts for approximately 31% of the total system capacity.

Simulation directly addresses the challenge of limited historical data by providing an alternative source of modeling information, with the benefit of compensating for limited data availability (Morris et al., 2019). This capability is particularly useful with respect to forced generator outages in OTS, as the database is relatively new and has limited historical records.

Another limitation of the data is that some smaller plants in this analysis don't always have a forced outage on the hydropower generating units every year. This is the reasoning for using the average from a five-year data set. Section 4.7 describes the model validation approach, in which the five-year historical average, calendar years 2019-2023, is used to estimate calendar year 2024. A data limitation when doing this is that a single forced outage may be recorded for the entire year. The calculation for MTBF in this case is handled differently. When a hydropower generating unit only has a single forced outage in calendar year 2024, the starting point is unavailable.

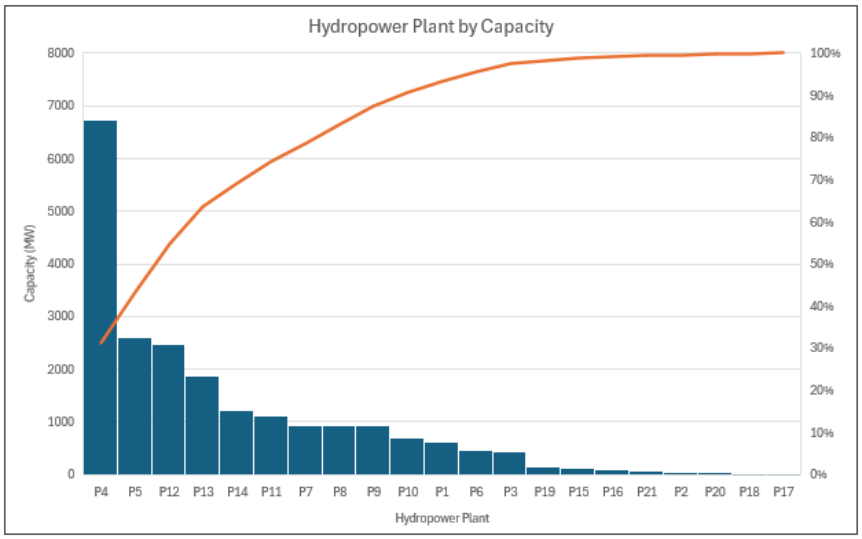

Figure 3-3. System Capacity

An additional limitation of the data set is the manual entry of forced outages. These are entered into OTS by plant operators, dispatchers, or the BPA outage group. Sometimes these are miscategorized. To avoid missing data and to ensure all historical forced outages are included in the data set, filtering for forces outages requires both the selected outage type and the outage description, which would indicate that the outage was forced and unplanned. This required additional filtering for key words. These words include “forced”, “F/O” and “FOOS”.

The last data limitation to discuss is the complexity of generator capacity. For example, there is name plate capacity and operational capacity. A hydropower generator’s max capacities can change. One example is when a repair to a turbine blade necessitates a fixed position. The power curve and max capacity will no longer match the name plate capacity. There are many examples of repairs to equipment that keep the hydropower generators safely operating until a major capital project begins for a complete overhaul. This repair often comes at a cost to operational efficiencies or a reduction of capacity. It is important for this model to be updated with the latest hydropower generator max capacity. In the paper, “*A Systematic Comparison of Operating Reserve Methodologies”* the authors argue that power system operators must proactively establish reserve capacity levels to address potential supply-demand mismatches caused by forecasting inaccuracies and unexpected generator failures (Ibanez et al, 2014). Capacity planners should work with system operators to ensure WRAP capacity commitments are based on correct assumptions for max capacities,

Finally, data errors existed in the database for the outage duration in hours. These errors were corrected by multiplying the duration in days by 24 hours. This praxis

research aims to support an important work problem with BPA. In anticipation of building a Monte Carlo simulation to estimate the generation capacity loss, several quality control and reporting processes have been created to quickly catch and correct hydropower generator forced outage errors.

3.8 Data Analysis Steps

This section details the steps followed in this research and describes the analysis performed to evaluate and answer the research questions posed. Using five years of historical forced outage data collected from OTS for years 2019 -2023, capacity planners at BPA use the years average hydropower generator unavailability due to forced outages, to estimate the next year's generation capacity loss. Generation capacity loss is calculated as shown in Equation 16. This is the current approach capacity planners are taking to estimate yearly generation capacity loss from forced outages. This research compares the results of different approaches to estimating the annual generation capacity loss resulting from forced outages, using the same historical data.

The Monte Carlo method simulates 10,000 availabilities based on the independent variables MTBF and MTTR, which are averages from the five-year (2019 – 2023) data set. To simulate the independent variables, a best fit distribution is tested using the exponential distribution. The results section describes this analysis, and it is found that the exponential distribution will work well as the underlying distribution in the simulation of random variables. In the MATLAB script MTBF and MTTR are random numbers generated from exponential distribution. By using Monte Carlo simulation, availability and unavailability are estimated from 10,000 random simulations. The current

approach by capacity planners uses the much smaller historical, five-year data set. The Monte Carlo simulation estimates the availability for each hydropower plant generator, using each of the 10,000 simulations. The formula is shown in Equation 17 below. After running the Monte Carlo analysis, not only can we use the availability from the entire simulation shown in Equation 18, but we can perform some statistical analysis, create probability distributions and compare estimated availability.

$$A(i) = \frac{uptime\ (i)}{downtime\ (i) + \ uptime\ (i)} \tag{17}$$

Equation 17. Simulated Availability (i)

$$A = \frac{sum\ (uptime)}{sum(uptime) + sum(downtime)} \tag{18}$$

Equation 18. Simulated Availability

After determining an estimated availability from 10,000 simulations, MATLAB creates an array of the10,000 availabilities, from each simulated random MTBF and MTTR variables. A probability distribution is created from the 10,000 availabilities and the expected value is determined. The expected value is used as an estimate for availability and used to calculate generation capacity loss. A probability distribution is created for the discrete variable, availability. The probability distribution is a mutually exclusive list of all possible outcomes, with each simulated availability's respective probability of occurrence, *P(x). P(x)* is calculated for every estimate and shown in Equation 19. *X*P(x)* is the availability estimate times its probability. The expected value is equal to the sum of the probabilities *P(x).* Using Equation 20 below, the expected value is determined (Gupta et al., 2019).

$$P(x) = \frac{Frequency}{Total} \tag{19}$$

Equation 19. Probability, P(x)

$$\mu = E(x) = \sum_{i=1}^{k} x_i p(x_i) \quad (20)$$

Equation 20. Expected Value, E(x)

$$\sigma^2 = Var(X) = \sum_{i=1}^{k} (x - \mu)^2 p(x_i) \quad (21)$$

Equation 21. Variance, Var(x)

$$\sigma = \sqrt{Var(x)} \quad (22)$$

Equation 22. Standard Deviation

After the expected value is calculated from the probability distribution, the next step taken identifies outliers. Outliers are identified and removed from the data set using the interquartile range IQR method. The IQR creates an upper and lower bound and removes extreme events that can provide poor availability estimates. After outliers are removed a new availability estimate is determined, using the 50th percentile or P50. Actual hydropower generation capacity loss has a 50% probability to exceed this estimate and likewise a 50% probability that it will be less than this estimate. This is compared to the simulated availability estimate, the average five-year historical availability estimate, the expected value estimate of the entire 10,000 availability simulations and finally, the P50 estimate after outliers are removed. Using the interquartile range (IQR) method, outliers are removed. The IQR is calculated using Equation 23, the third quartile minus the first quartile (Gupta et al., 2019).

$$IQR = Q_3 - Q_1 \quad (23)$$

Equation 23. Interquartile Range

The IQR measures the range of simulated availability outcomes, relative to the middle 50% of the 10,000 simulated availabilities that lie between the upper and lower quartiles. To use the IQR to identify outliers in the simulated generator availabilities we

use the values for Quartile 1 and Quartile 3 to calculate a lower and upper bound. The lower bound and upper bound formulas are shown in Equations 24 and 25. Simulated availability below the lower bound and above the upper bound are considered outliers (Ben-Daya, 2016).

$$Lower\ Bound = Q_1 - (1.5 * IQR) \quad (24)$$

Equation 24. IQR Lower Bound

$$Upper\ Bound = Q_3 + (1.5 * IQR) \quad (25)$$

Equation 25. IQR Upper Bound

3.9 Monte Carlo Simulation Parameters

The selection of 10,000 simulations follows standard Monte Carlo practice for achieving statistical convergence while maintaining computational efficiency (Ballio & Guadagnini, 2004). The adequacy of 10,000 simulations is validated by the results shown in Table 4-5 of Section 4.3.1. The simulated system-wide unavailability differs by only 0.3% from the historical 5-year average unavailability calculated from the same independent variables. This demonstrates that 10,000 iterations provide sufficient precision without requiring more simulations.

Additionally, 10,000 simulations support the methodology used in this praxis research by enabling robust statistical analysis including probability distribution generation, outlier removal using the IQR method, and expected value determination. Finally, 10,000 simulations are practical for computational requirements and operational implementation by WRAP capacity planners.

3.10 Model Build

The Monte Carlo analysis is simulated using MATLAB script. Based on an exponential distribution for MTBF and MTTR, 10,000 simulations using a random number generator function simulates availability over one year, which is 8760 hours of operational timespan. Each hydropower plant is characterized by the average MTBF and MTTR. These are calculated for each generating unit across 21 hydropower plants using the five-year forced outage data set.

Figure 3-4 shows the script to run the simulation. Simulated MTTR represents the total hours the unit is in a forced outage state. There is no overlap with a forced outage state and any other state. Therefore, MTTR represents the downtime of the generating unit and MTBF represents the total hours the unit is in not in a forced outage state. Likewise, for MTBF, there is no overlap with a forced outage state and any other state. Therefore, MTBF represents the uptime of the generating unit.

The model's MATLAB script is shown below. The simulation is defined by "number_of_runs" which is equal to 10,000. The 'for-end' loop is simulated 10,000 times, generating uptime and downtime histories. The MTBF is determined by the hours between failures for each generating unit by hydroelectric power plant. The MTBF / 8760 represents the MTBF in percentage of hours per year. MTTR / 8760 represents the mean time to repair in percentage of hours per year. The model's transfer equation is the availability formula describing the system-wide availability of the 21 hydropower plants studied (Hamsa, 2024).

$$A(i) = \frac{Up\ Time(i)}{\left(Up\ Time(i) + Down\ Time\ (i)\right)} \tag{26}$$

Equation 26. Availability A(i) in MATLAB

$$A = \frac{sum(Up\ Time)}{Time\ Span} \tag{27}$$

Equation 27. Availability in MATLAB

```
% Number of simulations for all simulated availabilities is 10,000
Number_Of_Runs = 10000

% MTBF is the mean time between failures, MTTR the mean time to repair
% Hours per year

MTBF=5379.557576/8760
MTTR=115.1181159/8760

% Up_time and Down_time. use zeros( ) function to create array with zeros

Up_Time = zeros(Number_Of_Runs,1);
Down_Time = zeros(Number_Of_Runs,1);

% for-end loop is repeated for i, 1 to 10,000
% Down_Time_Hist and Up_Time_Hist are the simulated time histories
% A = availability
% ramdom number generator from exp distribution using Matlab function
% exprnd()

for i=1:Number_Of_Runs
    Up_Time_Hist=exprnd(MTBF);
    Down_Time_Hist=exprnd(MTTR);
    Up_Time(i)=Up_Time_Hist;
    Down_Time(i)=Down_Time_Hist;
    A(i)=Up_Time(i)/(Up_Time(i)+Down_Time(i));
end

% Availavility is the simulated availability
% Unavailability is 1 - availability

Time_Span=(sum(Up_Time)+sum(Down_Time));
disp(Time_Span);
Availability=sum(Up_Time)/Time_Span
Unavailability=1-Availability
```

Figure 3-4. MATLAB Script

This MATLAB function generates a random number from exponential distribution. The exprnd(MTBF) function simulates uptime and generates a random number from the exponential distribution with the historical MTBF. Likewise, the exprnd(MTTR) function simulates downtime and generates a random number from the exponential distribution

with the historical MTTR. An array is created in MATLB with 10,000 simulated availabilities (Gilat, 2025).

3.11 Validation Method

The validation approach has two parts. The Monte Carlo simulation is validated by comparing the results of the current planning method using five-year actual availability averages and the simulated estimates. The simulated estimates are evaluated for how well the simulation accounts for the uncertainty of generation capacity loss due to forced outages. The lost generation forecast results are compared to the actual lost generation in the historical data set and evaluated for accuracy. The mean absolute deviation error (MAD) is used to measure the accuracy of lost generation predictions of the five-year estimates and shown in Equation 28. MAD is selected over percentage-based metrics to avoid division errors when availability or unavailability is zero.

$$MAD = \frac{\sum_{t=1}^{n} |A_t - F_t|}{n} \quad (28)$$

Equation 28. Mean Absolute Deviation

The second validation method used in this praxis employs hold-out validation, using out-of-sample testing with a five-year historical data set (years 2019 through 2023) to estimate the total generation capacity loss in calendar year 2024. Hydropower generator forced outage data is collected from OTS for calendar year 2024 and filtered the same way as the test data. MTBF and MTTR are calculated for the same 175 generators across 21 hydropower plants.

To evaluate the accuracy of generation capacity loss estimates, calendar year 2024 actual forced outage unavailability and generation capacity loss is compared to the

estimates of the five- year simulation, five-year average, expected value and the P50 estimate with outliers removed. This analysis uses the mean absolute deviation error (MAD) to identify the estimate with the best accuracy and lowest MAD. The results of the MAD between the actual generation capacity loss and the estimate are averaged across all hydropower plants.

Additionally, to assess model robustness across different operational scenarios, the methodology was tested against 2025 year-to-date forced outage data with scenario analysis. This approach was selected over testing prior years or reducing the historical window because it provides true out-of-sample validation while maintaining current industry practice. BPA capacity planners currently use a 5-year average for their deterministic approach, which this research replicates to demonstrate methodology improvements. Four scenarios were evaluated: actual 2025 year-to-date capacity loss and three projections representing 50%, 100%, and 150% increases to account for potential additional forced outages through year-end.

3.12 Hypothesis Testing

The hypotheses to be tested are as follows:

H1: Historical five-year average MTBF and MTTR can be simulated as a random number from an exponential distribution to estimate WRAP capacity.

H2: Monte Carlo simulation of availability metrics MTBF and MTTR quantify the frequency and severity of forced outages to more accurately estimate the reduction of available capacity from a limited data set.

H3: The probability distribution of the Monte Carlo simulation defines statistical limits for estimated availability that provides a disciplined approach to setting reserve capacity.

H4: The probability distribution of the Monte Carlo simulation optimizes the generation capacity reserve to maximize marketable power.

3.13 Summary and Conclusion

Hydropower generator forced outages present a large uncertainty in capacity planning. The methodology used in this praxis research will provide a data driven model using historical forced outage data to estimate lost generation capacity due to unplanned forced generation outages. Accurate estimates of generation capacity loss from forced outages will aid BPA capacity planners in the optimization of marketable generation capacity in WRAP and other future RA power-pooling markets. The Monte Carlo analysis is simulated using MATLAB script. Based on an exponential distribution for MTBF and MTTR, 10,000 random number simulation from an exponential distribution simulates availability over one year. Each hydropower plant is characterized by the average MTBF and MTTR. These are calculated for each generating unit, across 21 hydropower plants using the five-year forced outage data set.

The Monte Carlo simulation of historical forced outages is evaluated for accuracy using the MAD metric for the prediction of calendar year 2024 actual generation capacity loss. Quantifying the uncertainty of forced outages allows BPA to both maintain capacity obligations and maximize revenue opportunities in the WRAP. This solution will minimize uncertainty in planned capacity through disciplined accounting of forced outage

probabilities and allow for power-pool capacity planning seven months in advance for both summer and winter load peaks.

Finally, the probabilistic reserve capacity methodology proposed in Section 3.8 uses the IQR method to eliminate extreme events. The P50 unavailability provides a baseline for capacity commitments, while the expected value serves as the upper planning boundary. The reserve requirement is calculated as the difference between expected unavailability generation capacity loss and P50 unavailability generation capacity loss, creating a risk buffer proportional to actual system uncertainty.

Chapter 4—Results

4.1 Introduction

This praxis is focused on predicting lost capacity probabilities due to unplanned forced generation outages. This chapter provides a detailed overview of the model results. Section 4.2 outlines the initial data analysis to determine if the exponential distribution is sufficient for representing generator unit failure rates in model simulation. Section 4.3 discusses the simulation results. Section 4.4 discusses the IQR and method for removing outliers in the simulated availability data set. Section 4.5 discusses the probability distribution and expected value of the simulated availability. Section 4.6 is the model results, showing the comparison of availability estimates of the five-year historical forced outage data set. Section 4.7 discusses results of the simulation validation, which estimates generation capacity loss for calendar year 2024 based on estimates from the five-year data set. Results of the estimation error using MAPE is presented. Finally, section 4.8 through 4.9 presents the hypothesis test results.

4.2 Preliminary Analysis

After creating a complete data set, the first step taken in data analysis was to test the hypothesis that the exponential distribution was suitable as an underlying distribution for generator unit outage simulation. The MTBF was calculated for each hydropower generator forced outage, by plant and by generator. The variables MTBF and MTTR for each generator are plotted and analyzed for fitness. The fit of the distribution is validated using R^2 values. The results are shown in Table 4-1. The most significant reason for low R^2 values is the lack of forced outage data at some hydropower projects. Other reasons

include long-term outages spanning the majority, or whole, of the five-year data set, generator conditions and other operational conditions.

Plant	Unit	MTTF	MTTR	Plant	Unit	MTTF	MTTR	Plant	Unit	MTTF	MTTR	Plant	Unit	MTTF	MTTR
P1	1	0.9643	0.662	P5	7	0.9991	0.901	P10	1	0.8725	0.883	P13	7		
	2				8	0.9924	0.9412		2	0.8494	0.7816		8	0.951	0.9603
	3	0.6992	0.9999		9	0.7942	0.8251		3	0.9843	0.9322		9	0.9878	0.9346
	4	0.9845	0.9999		10	0.6942	0.6907		4	0.9458	0.9047		10	0.7367	0.8819
	5		0.9741		11	0.5975	0.6077		5	0.9565	0.7173		11	0.5812	0.8774
P2	1	0.9827	0.9962		12	0.8907	0.9222		6	0.9361	0.9836		12	0.579	0.9671
	2	0.9254	0.9919		13	0.9295	0.9234	P11	1	0.8712	0.7254		13	0.8739	0.9669
	3	0.8477	1		14	0.9778	0.5693		2	0.9523	0.6733		14		
P3	1	0.9179	0.879		15	0.9778	0.5693		3	0.7725	0.6315		15	0.9927	0.9459
	2	0.9853	0.9817		16	0.78	0.9773		4	0.881	0.7775		16	0.93	0.9789
	3	0.9459	0.8622		17	0.8333	0.8725		5	0.8551	0.8584		17	0.8871	0.9693
	4	0.9721	0.9058		18	0.8539	0.9187		6	0.9019	0.9085		18	0.8214	0.9491
P4	1	0.9615	0.949		19	0.7804	0.9614		7	0.9066	0.9653		19		
	2	0.8345	0.9566		20	0.9996	0.9919		8	0.947	0.9002		20		
	3	0.9128	0.8847		21	0.6352	0.8968		9	0.9871	0.7939		21	0.9434	0.9692
	4	0.6584	0.72		22	0.7711	0.9999		10	0.9085	0.6578		22	0.9675	0.9366
	5	0.9155	0.8566		23	0.8779	0.8847		11	0.962	0.6638	P14	1	0.9455	0.8841
	6	0.9046	0.9421		24	0.6152	0.6616		12	0.8894	0.655		2	0.9448	0.8611
	7				25	0.9432	0.9674		13	0.9826	0.911		3	0.9616	0.9282
	8				26	0.9432	0.9674		14	0.9323	0.9064		4	0.9902	0.8684
	9	0.6218	0.8657		27	0.8656	0.8031	P12	1	0.9296	0.9263		5	0.8188	0.9498
	10			P6	1	0.7868	0.8445		2	0.9293	0.9857		6	0.982	0.9363
	11	0.894	0.9485		2	0.9301	0.9339		3	0.8208	0.9531		7	0.9335	0.9727
	12				3	0.9672	0.9474		4	0.9594	0.8467		8	0.9942	0.9919
	13			P7	1	0.656	0.8845		5	0.8961	0.953		9	0.9989	0.8419
	14	0.9625	0.9928		2	0.9673	0.9505		6				10	0.9079	0.9418
	15				3	0.7722	0.913		7				11	0.9	0.9181
	16	0.7575	0.9529		4	0.9643	0.9541		8	0.9442	0.9666		12	0.9111	0.9844
	17	0.5433	0.8279		5	0.7401	0.999		9	0.9668	0.966		13	0.7646	0.8358
	18	0.5957	0.8482		6	0.879	0.8812		10	0.7787	0.6649		14	0.8357	0.7737
	19	0.851	0.7817	P8	1	0.9444	0.8273		11	0.9282	0.751		15	0.9683	0.7276
	20	0.9162	0.8941		2	0.9524	0.7303		12	0.9262	0.6817		16	0.9434	0.9328
	21	0.8449	0.8605		3	0.9206	0.9894		13	0.8008	0.7297		17	0.9734	0.9402
	22	0.9658	0.7276		4	0.8526	0.9615		14	0.9627	0.9872		18	0.8799	0.9428
	23	0.9094	0.873		5	0.9512	0.9998		15	0.9219	0.7677	P15	1	0.9936	1
	24	0.951	0.9692		6	0.8301	0.9756		16	0.9232	0.9565		2	0.9881	0.7287
P5	1	0.89	0.9781	P9	1	0.9126	0.9776	P13	1	0.6639	0.8132	P16	1	0.948	0.9818
	2	0.9849	0.9303		2	0.8353	0.8726		2	0.774	0.9998		2	0.8448	0.9536
	3	0.9934	0.9526		3	0.8384	0.8688		3			P17	1	0.9993	0.9989
	4	0.9553	0.9632		4	0.8697	0.9651		4	0.9863	0.9829		2	0.9948	0.9998
	5	0.9913	0.9432		5	0.851	0.9774		5	0.9624	0.8452	P18	1		
	6	0.8596	0.9868		6	0.8936	0.897		6				2		
				P20	1	0.9146	0.9107	P21	1	0.7489	0.9708	P19	1	0.9511	0.8063
					2	0.9629	0.9389		2	0.7783	0.9807		2		
													3	0.8116	0.9738

Table 4-1. R-squared Values to Determine Exponential Fit

4.3 Model Results

This praxis is focused on predicting lost capacity probabilities due to unplanned forced generation outages. This section provides a detailed review of the results of the

Monte Carlo simulation. The Matlab script shown in Figure 3.5 simulates the variables of MTBF and MTTR 10,000 times using a random number, exponential distribution generator. The MTBF and MTTR variables determine the simulated availability using the historical outage data from 2019-2023. These availabilities are plant level, unless the plant has generators of varying max capacities. In this case the simulated availability is by grouped of generators, by order of generator capacity.

The unavailability is 1 – the availability and both are shown in Table 4-3. To determine the generation capacity loss due to forced outages the unavailability times the total MW capacity of the generator or group of generators calculates generation capacity loss. The total simulated lost generation capacity due to forced outages is the summation lost generation capacity across the system of 21 hydropower projects.

4.3.1 Monte Carlo Simulation Results

Table 4-2 summarizes the Monte Carlo simulation results. Based on five years of historical forced outages, the simulation models a total yearly generation capacity loss of 1,327.42 MW. The total capacity of the 21 hydropower plants is 21,544 MW. The simulated percentage of generation capacity loss due to forced outages over the 8,760 hours of operation is 6.16%.

Monte Carlo Simulation Lost Generation Capacity Summary Table (2019 - 2023)	
Total simulated lost generation due to forced outages	1,327.42 MW
Total capacity of WRAP system of generators	21,544 MW
Total capacity of WRAP system of generators	6.16%

Table 2-2. Simulation Results Summary Table

Forced Outage and Lost Generation Capacity Table: Simulated with 5 Years of Historical Outage Data (2019-2023)									
Plant	# of Units	Range of Units	MW	Total MW	MTTF	MTTR	Availability	Unavailability	Lost Gen due to FO
P1	5	1-5	121	605	14849.23788	37.78928571	0.997520784	0.002479216	1.499925622
P2	3	1-3	16	48	4065.692593	285.380303	0.934623636	0.065376364	3.138065486
P3	4	1-4	107	428	4887.160345	25.80107527	0.994577003	0.005422997	2.321042623
P4	18	1-18	125	2250	4683.803797	430.6390741	0.91444875	0.08555125	192.4903132
	3	19-21	690	2070	3838.2	314.1222222	0.925628916	0.074371084	153.9481441
	3	22-24	805	2415	5379.557576	115.1181159	0.978893863	0.021106137	50.97132044
P5	16	1-16	88	1408	3072.054851	31.3614094	0.990156502	0.009843498	13.85964493
	11	17-27	109	1199	3163.738667	39.83783784	0.987477642	0.012522358	15.01430768
P6	2	1-2	103	206	6580.940741	15.96060606	0.997624677	0.002375323	0.48931656
	1	3	259	259	7223.54	24.16388889	0.99665342	0.00334658	0.866764101
P7	6	1-6	155	930	3262.412925	65.7829932	0.980399135	0.019600865	18.22880474
P8	6	1-6	155	930	3117.87119	558.0264286	0.848141378	0.151858622	141.2285183
P9	6	1-6	155	930	5259.727193	125.8136752	0.976699747	0.023300253	21.66923501
P10	3	1-3	103	309	3911.144444	25.05444444	0.993689641	0.006310359	1.949900888
	3	4-6	128	384	4920.212121	282.8348485	0.945810823	0.054189177	20.80864397
P11	14	1-14	80	1120	3548.131235	111.6597032	0.969575408	0.030424592	34.07554252
P12	16	1-16	155	2480	3418.221766	437.0787982	0.88696456	0.11303544	280.3278916
P13	14	1-14	81	1134	6867.066981	227.5807292	0.968648502	0.031351498	35.55259818
	8	15-22	92	736	4100.9275	2117.638372	0.660243182	0.339756818	250.061018
P14	10	1-10	60	600	5644.964052	155.5262712	0.972089537	0.027910463	16.7462776
	8	11-18	77	616	5715.951361	205.775731	0.965057692	0.034942308	21.52446192
P15	2	1-2	58	116	2907.140278	1860.294118	0.617296087	0.382703913	44.39365392
P16	2	1-2	46	92	5100.590909	23.72916667	0.995276372	0.004723628	0.434573814
P17	2	1-2	11.5	23	6494.913333	255.8083333	0.962351711	0.037648289	0.865910649
P18	2	1-2	14	28	4440.041667	251.9935185	0.946758893	0.053241107	1.490750994
P19	3	1-3	46	138	5050.223077	106.5784314	0.979068156	0.020931844	2.888594523
P20	2	1-2	17	34	6443.807692	111.4142857	0.983075243	0.016924757	0.575441724
P21	2	1-2	28	56	5009.415385	61.09666667	0.987786007	0.012213993	0.683983599

Table 4-3. Simulated Availability, Unavailability, Generation Capacity Loss Results

These simulation results are compared to the current methodology that capacity planners use to account for forced outages in capacity planning. The uncertainty of the generation capacity loss due to forced outages is currently determined by averaging the unavailability of historical forced outages in the same five-year data set 2019 - 2023. Table 4-4 shows the simulation results compared to the average availability method currently used. The comparison in Table 4-5 shows that the Monte Carlo simulation results predict 65.55MW more in yearly generation capacity loss.

Simulated and Average Availability and Unavailability Comparison							
Plant	# of Units	Range of Units	Total MW	5-year Average Availability	5-year Simulated Availability	5-year Average Unvailability	5-year Simulated Unvailability
P1	5	1-5	605	0.997461596	0.997520784	0.002538404	0.002479216
P2	3	1-3	48	0.93441151	0.934623636	0.06558849	0.065376364
P3	4	1-4	428	0.994748366	0.994577003	0.005251634	0.005422997
P4	18	1-18	2250	0.915799416	0.91444875	0.084200584	0.08555125
	3	19-21	2070	0.92435023	0.925628916	0.07564977	0.074371084
	3	22-24	2415	0.979049152	0.978893863	0.020950848	0.021106137
P5	16	1-16	1408	0.989894553	0.990156502	0.010105447	0.009843498
	11	17-27	1199	0.987564574	0.987477642	0.012435426	0.012522358
P6	2	1-2	206	0.99758059	0.997624677	0.00241941	0.002375323
	1	3	259	0.996665994	0.99665342	0.003334006	0.00334658
P7	6	1-6	930	0.980234639	0.980399135	0.019765361	0.019600865
P8	6	1-6	930	0.848193153	0.848141378	0.151806847	0.151858622
P9	6	1-6	930	0.976638618	0.976699747	0.023361382	0.023300253
P10	3	1-3	309	0.993634863	0.993689641	0.006365137	0.006310359
	3	4-6	384	0.945640535	0.945810823	0.054359465	0.054189177
P11	14	1-14	1120	0.969490142	0.969575408	0.030509858	0.030424592
P12	16	1-16	2480	0.886629125	0.88696456	0.113370875	0.11303544
P13	14	1-14	1134	0.976918977	0.968648502	0.023081023	0.031351498
	8	15-22	736	0.740266981	0.660243182	0.259733019	0.339756818
P14	10	1-10	600	0.973187392	0.972089537	0.026812608	0.027910463
	8	11-18	616	0.965250724	0.965057692	0.034749276	0.034942308
P15	2	1-2	116	0.609791355	0.617296087	0.390208645	0.382703913
P16	2	1-2	92	0.995369304	0.995276372	0.004630696	0.004723628
P17	2	1-2	23	0.96210652	0.962351711	0.03789348	0.037648289
P18	2	1-2	28	0.946293344	0.946758893	0.053706656	0.053241107
P19	3	1-3	138	0.979332454	0.979068156	0.020667546	0.020931844
P20	2	1-2	34	0.983003736	0.983075243	0.016996264	0.016924757
P21	2	1-2	56	0.987950592	0.987786007	0.012049408	0.012213993

Table 4-4. 5-year Simulated and 5-year Average Availability Comparison Table

Simulated and Average Lost Generation Capacity Comparison					
Plant	# of Units	Range of Units	Total MW	5 Year Simulated Lost Gen	5 Year Avg Lost Gen
P1	5	1-5	605	1.499925622	1.535734274
P2	3	1-3	48	3.138065486	3.148247541
P3	4	1-4	428	2.321042623	2.247699355
P4	18	1-18	2250	192.4903132	189.4513129
	3	19-21	2070	153.9481441	156.5950245
	3	22-24	2415	50.97132044	50.59629823
P5	16	1-16	1408	13.85964493	14.22846977
	11	17-27	1199	15.01430768	14.9100755
P6	2	1-2	206	0.48931656	0.498398365
	1	3	259	0.866764101	0.863507577
P7	6	1-6	930	18.22880474	18.38178556
P8	6	1-6	930	141.2285183	141.180368
P9	6	1-6	930	21.66923501	21.72608487
P10	3	1-3	309	1.949900888	1.966827275
	3	4-6	384	20.80864397	20.87403447
P11	14	1-14	1120	34.07554252	34.17104138
P12	16	1-16	2480	280.3278916	281.1597699
P13	14	1-14	1134	35.55259818	26.17388014
	8	15-22	736	250.061018	191.1635023
P14	10	1-10	600	16.7462776	16.08756459
	8	11-18	616	21.52446192	21.40555421
P15	2	1-2	116	44.39365392	45.26420287
P16	2	1-2	92	0.434573814	0.426023999
P17	2	1-2	23	0.865910649	0.871550029
P18	2	1-2	28	1.490750994	1.503786361
P19	3	1-3	138	2.888594523	2.852121321
P20	2	1-2	34	0.575441724	0.577872988
P21	2	1-2	56	0.683983599	0.674766828
Total Lost Gen				1327.420663	1259.860738
Total Lost Gen %				0.061614401	0.058478497

Table 4-5. 5-year Simulated and 5-year Average Generation Capacity Loss Table

The time that a generator is available is referred to as “Up-Time” and is represented by the variable MTBF. This variable is the amount of time, in hours between the end of

the generator's last failure and the beginning of the next failure. Likewise, the time the generator is inoperable due to a forced outage resulting from equipment failure is its "Down-Time," represented by MTTR, which is the duration of the outage, in hours. The model creates 10,000 simulated "Up-Times" and 10,000 simulated "Down-Times". For each simulated Up-Time and Down-Time, there is a simulated availability, A. The formula for each simulated availability is shown in Equation 26. Availability is the amount of time the generator is operating or available to operate, divided by the total amount of time, which for this analysis is 8,760 hours. The model's simulated availability is the sum of the 10,000 simulated Up Times divided by the total time span, which is the sum of the 10,000 simulations of both Up Time and Down Time, this is shown in Equation 27.

The simulated availabilities shown in Table 4-4 are determined by using Equation 27 from the simulated variables. The simulated availability for each generator is calculated using simulated Up Times and Down Times, which are generated random numbers from exponential distribution.

4.4 Removing Outliers from Simulated Availabilities

The scatter plots of the simulated generator availabilities indicate outliers exist. Removing the outliers may lead to a more useful prediction of unavailability due to forced outages. The scatter plots are shown below. Using the interquartile range (IQR) method, outliers are removed. The IQR is calculated using Equation 23. As discussed in Section 3.8, the IQR measures the range of simulated availability outcomes, relative to the middle 50% of the 10,000 simulated availabilities, that lie between the upper and

lower quartiles. To use the IQR to identify outliers in the simulated generator availabilities we use the values for Quartile 1 and Quartile 3 to calculate a lower and upper bound. The lower bound and upper bound formulas are shown in Equations 24 and 25. Data points that fall below the lower bound and above the upper bound are considered outliers (Ben-Daya, 2016).

Table 4-6 shows the calculated 1st and 3rd quartiles, IQR and the lower and upper bounds for the 10,000 simulated availabilities of each generating unit. Because the simulated availability and calculated variables are simulated randomly in exponential distribution, removing the outliers improves accuracy by reducing variance. Using the upper and lower bounds as fences, outliers are removed from the simulated availability. Once the outliers are removed the median, or P50, value is used as the estimated generator availability and compared to the simulated availability without removing outliers.

Two hydropower projects had a negative lower bound and no data points were removed. A negative lower bound is expected when there is a large number of simulated generator availabilities close to zero. This is evidenced by looking at the scatter plots for the projects with negative lower bounds, shown below. A negative lower bound can also be an indication the exponential distribution may not be the best fit for the historical outage data used to simulate MTBF and MTTR.

Plant	# of Units	Range of Units	1st Quarter	3rd Quarter	IQR	Up Bound	Lwr Bound
P1	5	1-5	0.9925833	0.9991689	0.0065856	1.0090473	0.9827049
P2	3	1-3	0.8302081	0.9774162	0.1472081	1.1982283	0.609396
P3	4	1-4	0.983553	0.9981679	0.0146149	1.0200903	0.9616306
P4	18	1-18	0.7805964	0.969708	0.1891116	1.2533755	0.4969289
	3	19-21	0.8056105	0.9735306	0.1679201	1.2254107	0.5537304
	3	22-24	0.9390868	0.9928514	0.0537647	1.0734985	0.8584398
P5	16	1-16	0.9708521	0.9967716	0.0259195	1.0356508	0.931973
	11	17-27	0.9621185	0.9957233	0.0336048	1.0461305	0.9117113
P6	2	1-2	0.992979	0.9992168	0.0062378	1.0085736	0.9836222
	1	3	0.9898639	0.9988649	0.009001	1.0123664	0.9763624
P7	6	1-6	0.9420231	0.9933539	0.0513308	1.0703501	0.8650268
P8	6	1-6	0.648185	0.9448082	0.2966233	1.3897431	0.2032501
P9	6	1-6	0.9330053	0.9923081	0.0593027	1.0812621	0.8440513
P10	3	1-3	0.9809512	0.9978839	0.0169327	1.0232829	0.9555521
	3	4-6	0.8541809	0.981185	0.1270041	1.1716911	0.6636747
P11	14	1-14	0.9144347	0.9893877	0.0749529	1.1018171	0.8020053
P12	16	1-16	0.7265824	0.9592319	0.2326495	1.3082062	0.3776081
P13	14	1-14	0.9113222	0.989284	0.0779617	1.1062266	0.7943796
	8	15-22	0.3992713	0.8547154	0.4554441	1.5378815	-0.283895
P14	10	1-10	0.920964	0.9904032	0.0694392	1.094562	0.8168052
	8	11-18	0.9056921	0.9882214	0.0825293	1.1120153	0.7818982
P15	2	1-2	0.3515546	0.8293237	0.4777692	1.5459775	-0.365099
P16	2	1-2	0.985752	0.998469	0.012717	1.0175444	0.9666765
P17	2	1-2	0.898293	0.9873128	0.0890198	1.1208424	0.7647633
P18	2	1-2	0.8552726	0.9814134	0.1261408	1.1706247	0.6660613
P19	3	1-3	0.9388333	0.9928002	0.0539668	1.0737504	0.8578831
P20	2	1-2	0.9513423	0.9942728	0.0429305	1.0586686	0.8869465
P21	2	1-2	0.9650179	0.9958769	0.0308589	1.0421653	0.9187295

Table 4-6. IQR Lower and Upper Bounds

Figure 4-1. Simulated Availability Outliers

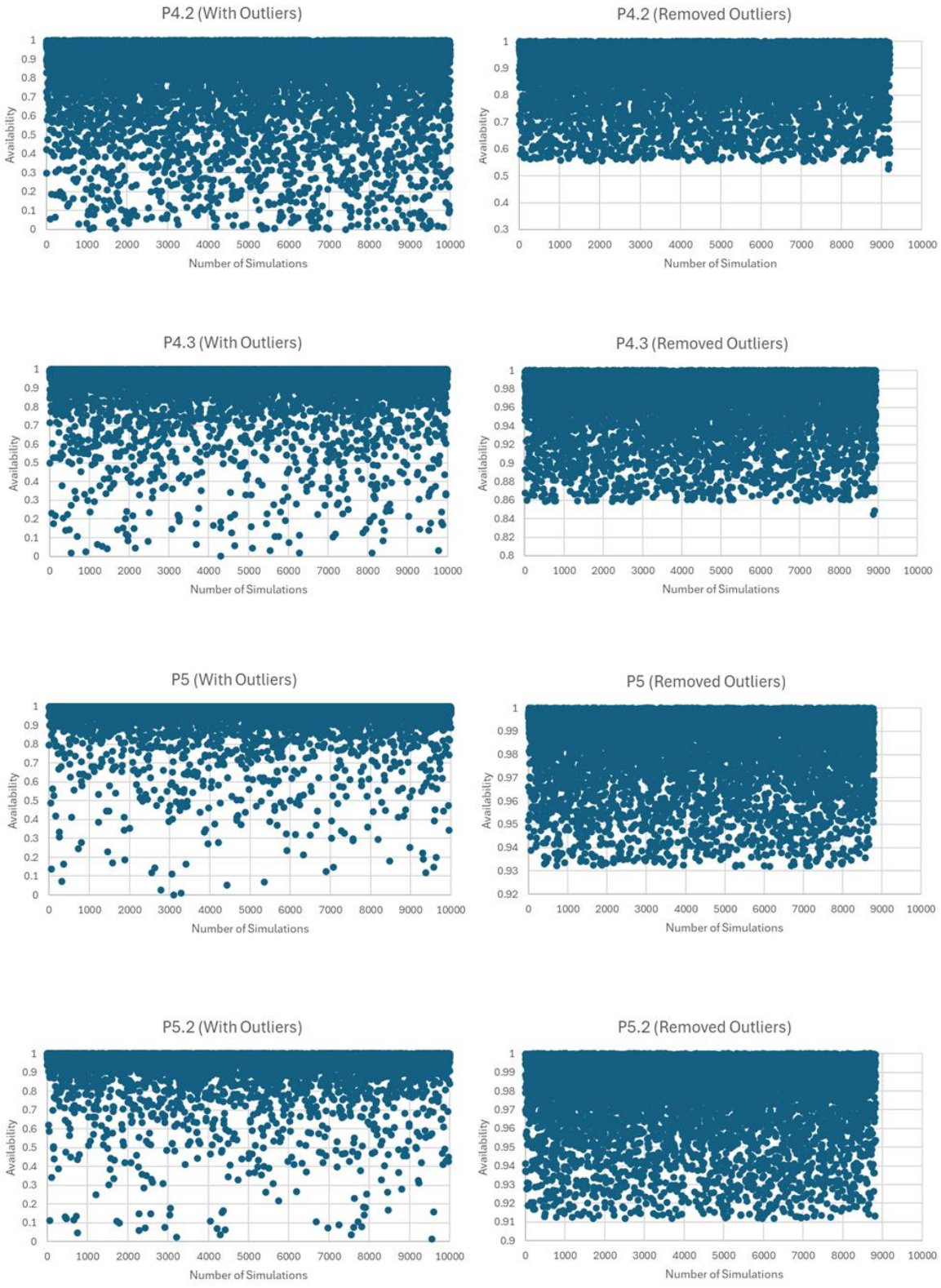

Figure 4-2. Simulated Availability Outliers

Figure 4-3. Simulated Availability Outliers

Figure 4-4. Simulated Availability Outliers

Figure 4-5. Simulated Availability Outliers

Figure 4-6. Simulated Availability Outliers

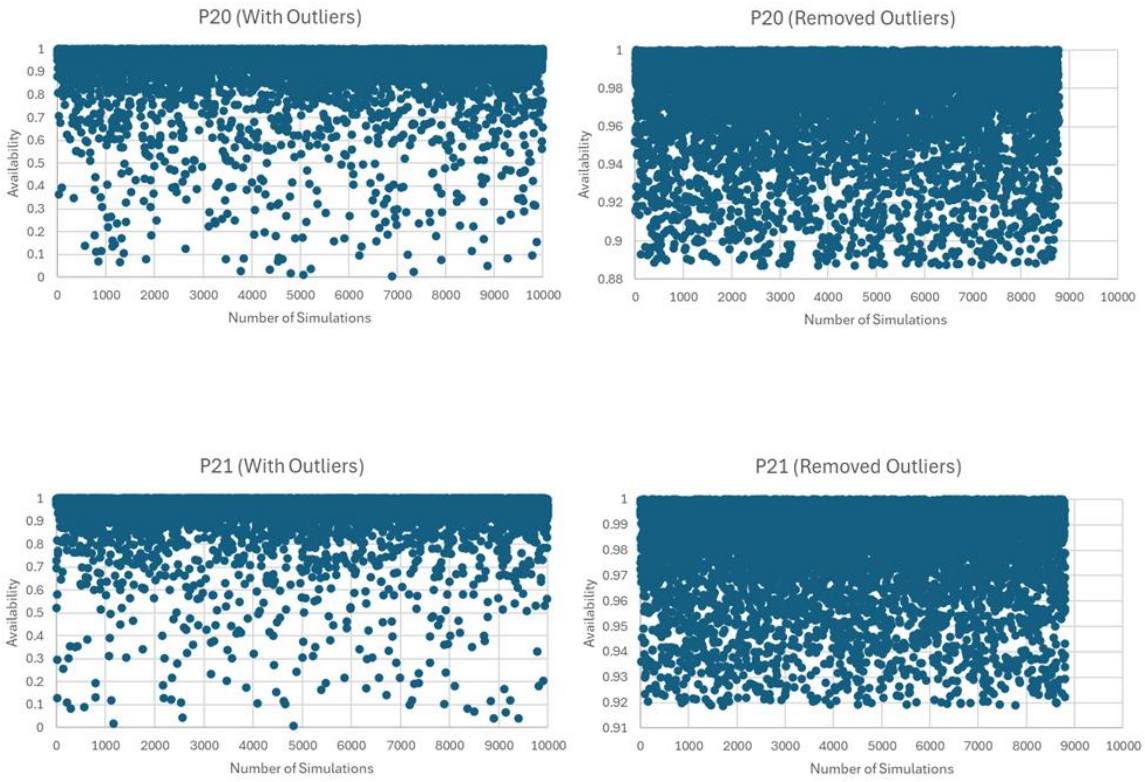

Figure 4-7. Simulated Availability Outliers

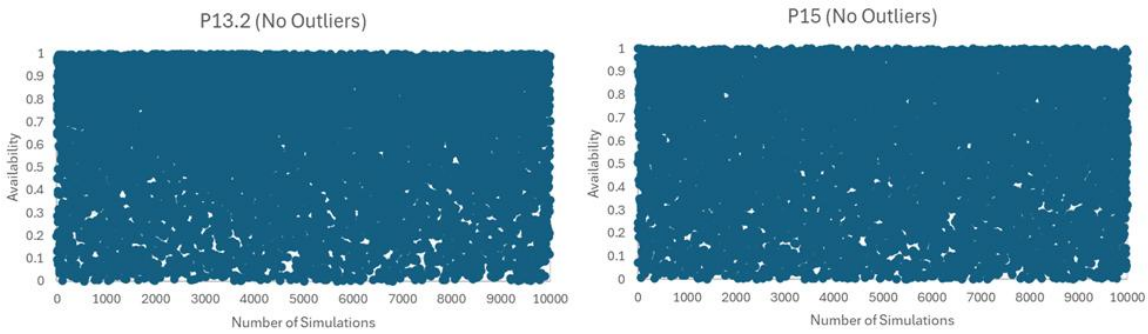

Figure 4-8. Simulated Availability No Outliers

Plant	# of Units	Range of Units	# of Outliers Removed
P1	5	1-5	1204
P2	3	1-3	968
P3	4	1-4	1188
P4	18	1-18	853
	3	19-21	804
	3	22-24	1058
P5	16	1-16	1197
	11	17-27	1176
P6	2	1-2	1237
	1	3	1219
P7	6	1-6	1176
P8	6	1-6	490
P9	6	1-6	1133
P10	3	1-3	1210
	3	4-6	985
P11	14	1-14	1088
P12	16	1-16	719
P13	14	1-14	1063
	8	15-22	0
P14	10	1-10	321
	8	11-18	1098
P15	2	1-2	0
P16	2	1-2	1139
P17	2	1-2	1131
P18	2	1-2	1028
P19	3	1-3	1154
P20	2	1-2	1236
P21	2	1-2	1206

Table 4-7. Number of Outliers Removed

The outliers were removed using the IQR method and the number of outliers in 10,000 simulated availabilities at each project is shown in Table 4-7. Hydropower plants P13 and P15, shown in Table 4-7 are the two hydropower projects with negative lower bounds. With the new availabilities for each project, the P50 or median value is used as the forecasted availability, shown in Table 4-8. The P50 value is chosen as a realistic estimate, meaning the actual generator availability has a 50% chance of being higher or

lower. With the P50 availability, capacity planners have a reasonable point of reference for determining acceptable risk.

P50 Availability and Forced Outage Generation Capacity Loss							
Plant	# of Units	Range of Units	MW	Total MW	Availability Outliers Removed	Unavailability Outliers Removed	Lost Gen due to FO
P1	5	1-5	121	605	0.998048562	0.001951438	1.180620201
P2	3	1-3	16	48	0.945984545	0.054015455	2.592741829
P3	4	1-4	107	428	0.995691241	0.004308759	1.844148945
P4	18	1-18	125	2250	0.928352513	0.071647487	161.2068446
	3	19-21	690	2070	0.936555272	0.063444728	131.3305863
	3	22-24	805	2415	0.982977281	0.017022719	41.10986561
P5	16	1-16	88	1408	0.992426243	0.007573757	10.66384983
	11	17-27	109	1199	0.990104657	0.009895343	11.86451635
P6	2	1-2	103	206	0.998145083	0.001854917	0.382112962
	1	3	259	259	0.997446834	0.002553166	0.661270053
P7	6	1-6	155	930	0.984487989	0.015512011	14.42617009
P8	6	1-6	155	930	0.86150791	0.13849209	128.7976438
P9	6	1-6	155	930	0.981664928	0.018335072	17.05161734
P10	3	1-3	103	309	0.995046131	0.004953869	1.53074567
	3	4-6	128	384	0.955315207	0.044684793	17.15896065
P11	14	1-14	80	1120	0.97546248	0.02453752	27.48202259
P12	16	1-16	155	2480	0.88643413	0.11356587	281.6433568
P13	14	1-14	81	1134	0.974429387	0.025570613	28.99707504
	8	15-22	92	736	0.662460648	0.337539352	248.4289629
P14	10	1-10	60	600	0.977812418	0.022187582	13.31254918
	8	11-18	77	616	0.971736628	0.028263372	17.41023736
P15	2	1-2	58	116	0.618685631	0.381314369	44.23246681
P16	2	1-2	46	92	0.99631095	0.00368905	0.339392608
P17	2	1-2	11.5	23	0.969405436	0.030594564	0.703674983
P18	2	1-2	14	28	0.956376966	0.043623034	1.221444938
P19	3	1-3	46	138	0.983333189	0.016666811	2.300019903
P20	2	1-2	17	34	0.98677373	0.01322627	0.449693168
P21	2	1-2	28	56	0.990308774	0.009691226	0.542708644

Table 4-8. P50 Availability

4.5 Probability Distribution and Expected Value

The expected value is calculated from the 10,000 availability simulations, as an estimate for availability. 1 – expected value of generator availability is the expected unavailability and is used to calculate generation capacity loss for comparison. As discussed in Section 3.8, a probability distribution is created for simulated availability.

The calculated expected value (mean), variance and standard deviation are shown in Table 4-9 and the unavailability and generation capacity loss are shown in Table 4-10.

Plant	# of Units	EV	Variance	σ (Stdev)
P1	5	0.98778885	0.002193901	0.046839098
P2	3	0.86074025	0.034764959	0.186453637
P3	4	0.97676476	0.00470541	0.068595994
P4	18	0.83341836	0.041294679	0.203210923
	3	0.84642406	0.038555897	0.196356555
	3	0.93448196	0.015407309	0.124126182
P5	16	0.96320569	0.007766341	0.088126848
	11	0.95522885	0.009855019	0.099272449
P6	2	0.98798668	0.002379443	0.048779534
	1	0.9836447	0.00316969	0.0563
P7	6	0.93769604	0.014503437	0.120430217
P8	6	0.75855325	0.059686067	0.244307321
P9	6	0.93099199	0.016638196	0.128989133
P10	3	0.97469124	0.00484507	0.069606537
	3	0.87739512	0.029995998	0.173193527
P11	14	0.916425	0.020044131	0.141577299
P12	16	0.80148413	0.048287257	0.219743617
P13	14	0.91574504	0.019946552	0.141232263
	8	0.61077487	0.078323997	0.279864247
P14	10	0.92222257	0.018486146	0.135963768
	8	0.91029122	0.021198039	0.145595464
P15	2	0.58017547	0.080440667	0.283620639
P16	2	0.97920913	0.003893801	0.062400331
P17	2	0.90466567	0.023319579	0.152707493
P18	2	0.8775546	0.030227498	0.17386057
P19	3	0.93364763	0.016511787	0.128498198
P20	2	0.94428483	0.013152707	0.114685252
P21	2	0.957004861	0.009803341	0.099011824

Table 4-9. EV, Variance and σ of Simulated Availability

Plant	# of Units	Total MW	EV Availability	Unavailability	EV Gen Loss
P1	5	605	0.98778885	0.01221115	7.38774575
P2	3	48	0.86074025	0.13925975	6.684468
P3	4	428	0.97676476	0.02323524	9.94468272
P4	18	2250	0.83341836	0.16658164	374.80869
	3	2070	0.84642406	0.15357594	317.9021958
	3	2415	0.93448196	0.06551804	158.2260666
P5	16	1408	0.96320569	0.03679431	51.80638848
	11	1199	0.95522885	0.04477115	53.68060885
P6	2	206	0.98798668	0.01201332	2.47474392
	1	259	0.9836447	0.0163553	4.2360227
P7	6	930	0.93769604	0.06230396	57.9426828
P8	6	930	0.75855325	0.24144675	224.5454775
P9	6	930	0.93099199	0.06900801	64.1774493
P10	3	309	0.97469124	0.02530876	7.82040684
	3	384	0.87739512	0.12260488	47.08027392
P11	14	1120	0.916425	0.083575	93.604
P12	16	2480	0.80148413	0.19851587	492.3193576
P13	14	1134	0.91574504	0.08425496	95.54512464
	8	736	0.61077487	0.38922513	286.4696957
P14	10	600	0.92222257	0.07777743	46.666458
	8	616	0.91029122	0.08970878	55.26060848
P15	2	116	0.58017547	0.41982453	48.69964548
P16	2	92	0.97920913	0.02079087	1.91276004
P17	2	23	0.90466567	0.09533433	2.19268959
P18	2	28	0.8775546	0.1224454	3.4284712
P19	3	138	0.93364763	0.06635237	9.15662706
P20	2	34	0.94428483	0.05571517	1.89431578
P21	2	56	0.957004861	0.042995139	2.407727784

Table 4-10. Expected Value Generation Capacity Loss

4.6 Final results

Table 4-11 shows the simulations' results, comparing the estimated lost generation capacity. BPA capacity planners' current approach to estimating generation capacity loss is the five-year average from historical data shown in Table 4-11. The current approach (2019-2023 average generator availability) is compared to generation capacity loss estimates calculated from the unavailability determined by the following:

1. Monte Carlo simulation availability estimate
2. Expected value (μ) availability estimate of 10,000 (simulated availabilities)

3. Average availability estimate (simulated availabilities with outliers removed)

4. P50 availability estimate (simulated availabilities with outliers removed)

The total estimated generation capacity loss across 21 hydropower plants and the percentage total generation capacity loss are tabulated at the bottom of Table 4-11.

Generation Capacity Loss (Simulated and Historical Actuals)							
Plant	# of Units	Total MW	Historical 5 Year Average Availability	Simulated 5 Year Average Availability	EV Availability Simulated 5 Year Average	Outliers Removed Mean Availability	Outliers Removed P50 Availability
P1	5	605	1.535734274	1.499925622	7.38774575	2.093912628	1.180620201
P2	3	48	3.148247541	3.138065486	6.684468	4.224119573	2.592741829
P3	4	428	2.247699355	2.321042623	9.94468272	3.254792768	1.844148945
P4	18	2250	189.4513129	192.4903132	374.80869	262.4099263	161.2068446
	3	2070	156.5950245	153.9481441	317.9021958	210.8122716	131.3305863
	3	2415	50.59629823	50.97132044	158.2260666	70.56326536	41.10986561
P5	16	1408	14.22846977	13.85964493	51.80638848	19.1322994	10.66384983
	11	1199	14.9100755	15.01430768	53.68060885	21.23992295	11.86451635
P6	2	206	0.498398365	0.48931656	2.47474392	0.668614942	0.382112962
	1	259	0.863507577	0.866764101	4.2360227	1.202189592	0.661270053
P7	6	930	18.38178556	18.22880474	57.9426828	25.40356734	14.42617009
P8	6	930	141.180368	141.2285183	224.5454775	193.1588955	128.7976438
P9	6	930	21.72608487	21.66923501	64.1774493	29.78582302	17.05161734
P10	3	309	1.966827275	1.949900888	7.82040684	2.700263371	1.53074567
	3	384	20.87403447	20.80864397	47.08027392	28.61042533	17.15896065
P11	14	1120	34.17104138	34.07554252	93.604	46.6190711	27.48202259
P12	16	2480	281.1597699	280.3278916	492.3193576	379.6118485	281.6433568
P13	14	1134	26.17388014	35.55259818	95.54512464	49.67714646	28.99707504
	8	736	191.1635023	250.061018	286.4696957	286.4700801	248.4289629
P14	10	600	16.08756459	16.7462776	46.666458	22.92536605	13.31254918
	8	616	21.40555421	21.52446192	55.26060848	28.51596946	17.41023736
P15	2	116	45.26420287	44.39365392	48.69964548	48.69971288	44.23246681
P16	2	92	0.426023999	0.434573814	1.91276004	0.608081222	0.339392608
P17	2	23	0.871550029	0.865910649	2.19268959	1.151713843	0.703674983
P18	2	28	1.503786361	1.490750994	3.4284712	2.039512208	1.221444938
P19	3	138	2.852121321	2.888594523	9.15662706	4.009434237	2.300019903
P20	2	34	0.577872988	0.575441724	1.89431578	0.777226086	0.449693168
P21	2	56	0.674766828	0.683983599	2.407727784	0.923569771	0.542708644
Total Lost Gen Capacity			1260.535505	1328.104647	2528.275385	1747.289021	1208.865299
Total Lost Gen %			5.85%	6.16%	11.74%	8.11%	5.61%

Table 4-11. Final Lost Generation Capacity Comparison Table

The five-year lost generation capacity simulation and estimation results are compared to the actual average generation capacity loss that occurred in CY 2019-2023 in the historical data set, shown in Table 4-11. The mean absolute deviation error (MAD) is used to measure the accuracy of lost generation capacity predictions. Table 4-12 shows the results of the actual generator forced outage unavailability occurring in CY 2024.

Plant	Total MW	2024 Lost Gen	Availability	Unavailability
P1	605	22.28301523	0.96316857	0.03683143
P2	48	0.016438356	0.999657534	0.000342466
P3	428	13.21050729	0.969134329	0.030865671
P4	2250	20.89549389	0.990713114	0.009286886
	2070	600.2675341	0.710015684	0.289984316
	2415	853.4373606	0.646609789	0.353390211
P5	1408	17.28322652	0.987724981	0.012275019
	1199	44.03363784	0.963274697	0.036725303
P6	206	0.91437474	0.995561288	0.004438712
	259	1.873492466	0.992766438	0.007233562
P7	930	3.149540548	0.996613397	0.003386603
P8	930	164.778313	0.822819018	0.177180982
P9	930	116.6941111	0.874522461	0.125477539
P10	309	9.74737537	0.968455096	0.031544904
	384	15.44280373	0.959784365	0.040215635
P11	1120	23.45541041	0.979057669	0.020942331
P12	2480	355.3018302	0.856733133	0.143266867
P13	1134	13.65148701	0.987961652	0.012038348
	736	185.2599186	0.748288154	0.251711846
P14	600	435.6977193	0.273837135	0.726162865
	616	62.94706753	0.897813202	0.102186798
P15	116	0.743977918	0.993586397	0.006413603
P16	92	0	1	0
P17	23	0.013127644	0.999429233	0.000570767
P18	28	1.147754521	0.959008767	0.040991233
P19	138	0.070015781	0.999492639	0.000507361
P20	34	0.504961129	0.985148202	0.014851798
21	56	0.087259507	0.998441795	0.001558205
Total Generator Capacity Loss		2962.907754		
% Total System Capacity		13.75%		

Table 4-12. Actual Average Generation Capacity Loss CY 2024 Table

Table 4-13 shows the results of the actual generator capacity loss occurring in CY 2024, compared to the five-year historical and simulated generator capacity loss results. The lost generator capacity percentage is based on the total modeled, system capacity of 21,544 MW.

Plant	# of Units	Total MW	2024 Lost Gen		Historical 5-year Average Gen Loss	Simulated 5-Year Gen Loss	EV Availability Simulated	Outliers Removed Mean Availability	Outliers Removed P50 Availability
P1	5	605	22.28301523		1.535734274	1.499925622	7.38774575	2.093912628	1.180620201
P2	3	48	0.016438356		3.148247541	3.138065486	6.684468	4.224119573	2.592741829
P3	4	428	13.21050729		2.247699355	2.321042623	9.94468272	3.254792768	1.844148945
P4	18	2250	20.89549389		189.4513129	192.4903132	374.80869	262.4099263	161.2068446
	3	2070	600.2675341		156.5950245	153.9481441	317.9021958	210.8122716	131.3305863
	3	2415	853.4373606		50.59629823	50.97132044	158.2260666	70.56326536	41.10986561
P5	16	1408	17.28322652		14.22846977	13.85964493	51.80638848	19.1322994	10.66384983
	11	1199	44.03363784		14.9100755	15.01430768	53.68060885	21.23992295	11.86451635
P6	2	206	0.91437474		0.498398365	0.48931656	2.47474392	0.668614942	0.382112962
	1	259	1.873492466		0.863507577	0.866764101	4.2360227	1.202189592	0.661270053
P7	6	930	3.149540548		18.38178556	18.22880474	57.9426828	25.40356734	14.42617009
P8	6	930	164.778313		141.180368	141.2285183	224.5454775	193.1588955	128.7976438
P9	6	930	116.6941111		21.72608487	21.66923501	64.1774493	29.78582302	17.05161734
P10	3	309	9.74737537		1.966827275	1.949900888	7.82040684	2.700263371	1.53074567
	3	384	15.44280373		20.87403447	20.80864397	47.08027392	28.61042533	17.15896065
P11	14	1120	23.45541041		34.17104138	34.07554252	93.604	46.6190711	27.48202259
P12	16	2480	355.3018302		281.1597699	280.3278916	492.3193576	379.6118485	281.6433568
P13	14	1134	13.65148701		26.17388014	35.55259818	95.54512464	49.67714646	28.99707504
	8	736	185.2599186		191.1635023	250.061018	286.4696957	286.4700801	248.4289629
P14	10	600	435.6977193		16.08756459	16.7462776	46.666458	22.92536605	13.31254918
	8	616	62.94706753		21.40555421	21.52446192	55.26060848	28.51596946	17.41023736
P15	2	116	0.743977918		45.26420287	44.39365392	48.69964548	48.69971288	44.23246681
P16	2	92	0		0.426023999	0.434573814	1.91276004	0.608081222	0.339392608
P17	2	23	0.013127644		0.871550029	0.865910649	2.19268959	1.151713843	0.703674983
P18	2	28	1.147754521		1.503786361	1.490750994	3.4284712	2.039512208	1.221444938
P19	3	138	0.070015781		2.852121321	2.888594523	9.15662706	4.009434237	2.300019903
P20	2	34	0.504961129		0.577872988	0.575441724	1.89431578	0.777226086	0.449693168
P21	2	56	0.087259507		0.674766828	0.683983599	2.407727784	0.923569771	0.542708644
Total Lost Gen Capacity			2962.907754		1260.535505	1328.104647	2528.275385	1747.289021	1208.865299
Total Lost Gen %			13.75%		5.85%	6.16%	11.74%	8.11%	5.61%

Table 4-13. Generation Capacity Loss Comparison Table Including CY 2024

4.7 Model Validation

The validation approach has two parts. The Monte Carlo simulation of the five-year historical data MTBF and MTTR is validated by comparing the results to the results of the current planning method, using actual availability averages of the same data set. The simulated estimates are evaluated for how well the simulation accounts for the uncertainty of generation capacity loss due to forced outages, compared to the historical averages. The mean absolute deviation error (MAD) is used to measure the accuracy of lost generation estimations of the five-year estimates.

In the second step of validation, The Monte Carlo simulation of the five-year historical data's MTBF and MTTR is validated by comparing the results to the results of CY 2024. Likewise, the simulated estimates are evaluated for how well the simulation accounts for the uncertainty of generation capacity loss due to forced outages, compared to the actuals of CY 2024 that are not in the historical five-year average data set. The mean absolute deviation error (MAD) is used to measure the accuracy of lost generation capacity estimations compared to CY 2024 actuals.

	Generation Capacity Loss (Simulated and Historical Actuals)					
	2024 Actual Availability	Historical 5-year Average	Simulated 5-Year Average Availability	EV Availability Simulated 5 Year Average	Outliers Removed Mean Availability	Outliers Removed P50 Availability
Total Lost Gen Capacity	2962.907754	1260.535505	1328.104647	2528.275385	1747.289021	1208.865299
Total Lost Gen Capacity %	13.75%	5.85%	6.16%	11.74%	8.11%	5.61%

Table 4-14. Actual Average System-Wide Generation Capacity Loss CY 2024 Table

4.7.1 Validation Results: Gen Capacity Loss Five-year Historical Actuals

Generation capacity loss for the simulated and five-year actual average availability for years 2019-2023 is shown in tables 4-15 and 4-16. The generation capacity loss error

is shown in the MAD calculation. The estimate using the simulated availability of the 10,000 simulations, from the five-year actual forced outage MTBF and MTTR, has the lowest average absolute deviation. However, the generation capacity loss estimate for the overall system was closest to the five-year average actuals when using the P50 estimate with outliers removed.

Gen Capacity Loss	Absolute Error			
Historical 5-year Average Gen Loss	Simulated 5-Year Gen Capacity Loss	EV Availability Simulated	Outliers Removed Mean Availability	Outliers Removed P50 Availability
1.535734274	0.035808653	5.852011476	0.558178354	0.355114073
3.148247541	0.010182056	3.536220459	1.075872032	0.555505712
2.247699355	0.073343268	7.696983365	1.007093413	0.40355041
189.4513129	3.039000335	185.3573771	72.95861337	28.24446823
156.5950245	2.646880372	161.3071713	54.21724712	25.26443815
50.59629823	0.375022205	107.6297684	19.96696712	9.486432624
14.22846977	0.368824835	37.57791871	4.903829638	3.56461994
14.9100755	0.104232172	38.77053335	6.329847448	3.045559159
0.498398365	0.009081805	1.976345555	0.170216576	0.116285403
0.863507577	0.003256524	3.372515123	0.338682016	0.202237524
18.38178556	0.15298082	39.56089724	7.021781783	3.955615468
141.180368	0.048150263	83.3651095	51.9785275	12.38272422
21.72608487	0.056849858	42.45136443	8.059738154	4.674467529
1.966827275	0.016926386	5.853579565	0.733436096	0.436081604
20.87403447	0.065390506	26.20623945	7.736390851	3.715073821
34.17104138	0.095498864	59.43295862	12.44802971	6.689018786
281.1597699	0.831878256	211.1595877	98.45207857	0.483586945
26.17388014	9.378718042	69.3712445	23.50326632	2.823194906
191.1635023	58.8975157	95.3061934	95.30657781	57.26546058
16.08756459	0.658713016	30.57889341	6.837801459	2.775015408
21.40555421	0.118907702	33.85505427	7.110415247	3.995316857
45.26420287	0.870548952	3.435442609	3.435510006	1.031736056
0.426023999	0.008549814	1.486736041	0.182057222	0.086631391
0.871550029	0.00563938	1.321139561	0.280163814	0.167875046
1.503786361	0.013035367	1.924684839	0.535725847	0.282341423
2.852121321	0.036473202	6.304505739	1.157312917	0.552101418
0.577872988	0.002431265	1.316442792	0.199353097	0.128179821
0.674766828	0.009216771	1.732960956	0.248802943	0.132058184
MAD	2.783323443	45.27642427	17.38405416	6.171953239

Table 4-15. Mean Absolute MW Deviation, Historical Average

Generation Capacity Loss (Simulated and Historical Actuals)				
Historical 5 Year Average Availability	Simulated 5 Year Average Availability	EV Availability Simulated 5 Year Average	Outliers Removed Mean Availability	Outliers Removed P50 Availability
1260.535505	1328.104647	2528.275385	1747.289021	1208.865299
A - F	-67.56914164	-1267.739879	-486.7535164	51.67020583

Table 4-16. Forecast Error, Historical Average

4.7.2 Validation Results: Generation Capacity Loss CY 2024 Actuals

Generation capacity loss for the simulated and actual CY 2024 average availability for years 2019-2023 is shown in tables 4-17 and 4-18. The generation capacity loss error is shown in the MAD calculation. The MAD error metric is relatively close in comparison to all estimates. In comparison to CY 2024 actual availability, the estimate using the simulated availability of the 10,000 simulations, from the five-year actual forced outage MTBF and MTTR, also has the lowest average absolute deviation. Additionally, when comparing simulated estimates to the five-year average, the generation capacity loss estimate for the overall system was closest to the CY 2024 actuals when using the simulated availability of the 10,000 simulations.

Generation Capacity Loss (Simulated and Historical Actuals)					
2024 Actual Availability	Historical 5 Year Average Availability	Simulated 5 Year Average Availability	EV Availability Simulated 5 Year Average	Outliers Removed Mean Availability	Outliers Removed P50 Availability
2962.907754	1260.535505	1328.104647	2528.275385	1747.289021	1208.865299
A-F	1702.372249	1634.803108	434.6323698	1215.618733	1754.042455

Table 4-17. Forecast Error, CY 2024

Gen Capacity Loss	Absolute Error			
2024 Lost Gen Capacity	Simulated 5-Year Gen Capacity Loss	EV Availability Simulated	Outliers Removed Mean Availability	Outliers Removed P50 Availability
22.28301523	20.74728096	20.78308961	14.89526948	20.1891026
0.016438356	3.131809185	3.121627129	6.668029644	4.207681217
13.21050729	10.96280793	10.88946466	3.265824568	9.95571452
20.89549389	168.555819	171.5948193	353.9131961	241.5144324
600.2675341	443.6725096	446.31939	282.3653383	389.4552625
853.4373606	802.8410624	802.4660402	695.211294	782.8740953
17.28322652	3.054756754	3.423581589	34.52316196	1.849072884
44.03363784	29.12356233	29.01933016	9.646971014	22.79371488
0.91437474	0.415976374	0.42505818	1.56036918	0.245759798
1.873492466	1.009984889	1.006728365	2.362530234	0.671302873
3.149540548	15.23224501	15.07926419	54.79314225	22.2540268
164.778313	23.59794502	23.54979475	59.76716449	28.38058248
116.6941111	94.96802623	95.02487609	52.5166618	86.90828808
9.74737537	7.780548095	7.797474481	1.92696853	7.047111999
15.44280373	5.431230749	5.365840243	31.63747019	13.1676216
23.45541041	10.71563097	10.62013211	70.14858959	23.16366068
355.3018302	74.14206036	74.97393861	137.0175274	24.31001821
13.65148701	12.52239312	21.90111117	81.89363763	36.02565945
185.2599186	5.903583708	64.80109941	101.2097771	101.2101615
435.6977193	419.6101547	418.9514417	389.0312613	412.7723533
62.94706753	41.54151332	41.42260562	7.686459054	34.43109807
0.743977918	44.52022495	43.649676	47.95566756	47.95573496
0	0.426023999	0.434573814	1.91276004	0.608081222
0.013127644	0.858422386	0.852783005	2.179561946	1.138586199
1.147754521	0.356031841	0.342996474	2.280716679	0.891757688
0.070015781	2.78210554	2.818578742	9.086611279	3.939418457
0.504961129	0.07291186	0.070480595	1.389354651	0.272264957
0.087259507	0.587507321	0.596724092	2.320468277	0.836310264
MAD	80.16300459	82.7608043	87.82734944	82.82388839

Table 4-18. Mean Absolute MW Deviation, CY 2024

4.7.3 Additional Out-of-Sample Testing: CY 2025 Analysis

Out-of-sample testing using CY 2025 forced outage data provides additional model testing and improves the robustness of testing. This approach combines interim model assessment using actual YTD data with sensitivity analysis using projected scenarios.

This approach for more testing maintains alignment with current industry practice as BPA capacity planners currently use a 5-year average for their deterministic approach. Maintaining the full 5-year historical data set best demonstrates the improvements the probabilistic Monte Carlo simulation provides over existing deterministic methods. Reducing the historical dataset to enable additional out-of-sample testing years was considered but rejected to preserve practical value to BPA, and also due to limited sample sizes of forced outage events. As shown in Table 5-1, the number of actual forced outages per generator over the five-year period ranges from only 9 to 187 events across the 175 generators studied. Reducing the historical dataset would further reduce the limited data availability, particularly given that some hydropower plants don't experience forced outages every year.

To address the challenge of incomplete 2025 data (~7.5 months), scenario analysis was employed to project capacity loss increases of 50%, 100%, and 150% for the remainder of the year. The scenario approach improves model evaluation by testing the methodology across multiple capacity loss conditions rather than relying on a single additional year of data. These scenarios test the methodology under varying operational conditions. The analysis uses four scenarios based on actual 2025 year-to-date forced outage data to project future generation capacity loss. Table 4-19 shows generator unavailability and generation capacity loss for the CY 2025 year-to-date period of ~7.5 months by hydropower plant.

Table 4-20 compares the generation capacity loss increase scenarios for CY 2025, increasing by 50% from the current year-to-date generation capacity loss of approximately 1,503 MW. As shown in Table 4-21, 10 current forced outages are

scheduled to return to service in the fourth quarter of 2025. Additionally, 57% of current outages originated in CY 2024. This carryover of long-duration outages from the previous year provides justification for the scenario ranges tested. The three projection scenarios include a 50% increase (2,254.7 MW total), 100% increase (3,006.3 MW) and 150% increase (3,757.9 MW). Scenarios analysis helps show the advantages of probabilistic versus deterministic approaches, by leveraging the Expected Value from the Monte Carlo simulation's full probability distribution.

Additional Out-of-Sample Testing: CY 2025 Analysis				
Plant	Total MW	Availability	Unavailability	Gen Capacity Loss
P1	605	0.999486	0.000514	0.31097
P2	48	1	0	0
P3	428	0.999887	0.000113	0.048364
P4	2250	0.997475	0.002525	5.68125
P5	2070	0.776619	0.223381	462.39867
P6	2415	0.998239	0.001761	4.252815
P7	1408	0.926321	0.073679	103.740032
P8	1199	0.965221	0.034779	41.700021
P9	206	0.999622	0.000378	0.077868
P10	259	1	0	0
P11	930	0.999261	0.000739	0.68727
P12	930	0.848078	0.151922	141.28746
P13	930	0.999368	0.000632	0.58776
P14	309	0.997607	0.002393	0.739437
P15	384	1	0	0
P16	1120	0.999554	0.000446	0.49952
P17	2480	0.814366	0.185634	460.37232
P18	1134	0.999226	0.000774	0.877716
P19	736	0.776095	0.223905	164.79408
P20	600	0.811953	0.188047	112.8282
P21	616	0.998479	0.001521	0.936936
P22	116	0.993943	0.006057	0.702612
P23	92	1	0	0
P24	23	1	0	0
P25	28	0.99871	0.00129	0.03612
P26	138	0.99636	0.00364	0.50232
P27	34	1	0	0
P28	56	0.998237	0.001763	0.098728
Total Generation Capacity Loss				1503.160469

Table 4-19. Additional Out of Sample Testing, CY 2025

	2025 YTD	50% Scenario	100% Scenario	150% Scenario
	Gen Capacity Loss	Gen Capacity Loss	Gen Capacity Loss	Gen Capacity Loss
P1	0.31097	0.466455	0.62194	0.777425
P2	0	0	0	0
P3	0.048364	0.072546	0.096728	0.12091
P4	5.68125	8.521875	11.3625	14.203125
P5	462.39867	693.598005	924.79734	1155.996675
P6	4.252815	6.3792225	8.50563	10.6320375
P7	103.740032	155.610048	207.480064	259.35008
P8	41.700021	62.5500315	83.400042	104.2500525
P9	0.077868	0.116802	0.155736	0.19467
P10	0	0	0	0
P11	0.68727	1.030905	1.37454	1.718175
P12	141.28746	211.93119	282.57492	353.21865
P13	0.58776	0.88164	1.17552	1.4694
P14	0.739437	1.1091555	1.478874	1.8485925
P15	0	0	0	0
P16	0.49952	0.74928	0.99904	1.2488
P17	460.37232	690.55848	920.74464	1150.9308
P18	0.877716	1.316574	1.755432	2.19429
P19	164.79408	247.19112	329.58816	411.9852
P20	112.8282	169.2423	225.6564	282.0705
P21	0.936936	1.405404	1.873872	2.34234
P22	0.702612	1.053918	1.405224	1.75653
P23	0	0	0	0
P24	0	0	0	0
P25	0.03612	0.05418	0.07224	0.0903
P26	0.50232	0.75348	1.00464	1.2558
P27	0	0	0	0
P28	0.098728	0.148092	0.197456	0.24682
Total Cap Loss	1503.160469	2254.740704	3006.320938	3757.901173

Table 4-20. Generation Capacity Loss in CY 2025: Scenarios

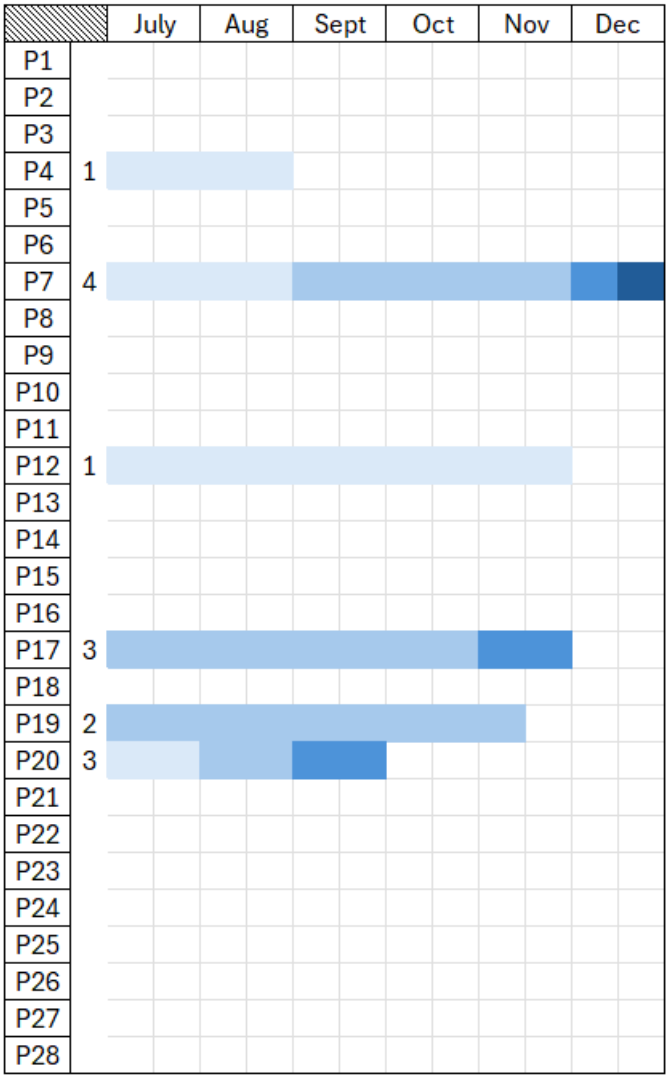

Table 4-21. Current Forced Outages in Second Half of CY 2025

The MAD error analysis is summarized in Tables 4-22 through 4-25 (detailed tables in Appendix C). The MAD error is very consistent, and close in comparison across all scenarios. Finally, this analysis enables testing of the Expected Value reserve sizing approach across multiple operational scenarios (50%, 100%, and 150% increase in generation capacity loss). This is shown in Section 4.10 and demonstrates the benefits of probabilistic Monte Carlo simulation for risk-based capacity planning.

Summary Table: Generation Capacity Loss and MAD					
2025 YTD Unavailability	Historical 5 Year Average Availability	Simulated 5-Year Gen Loss	EV Availability Simulated	Outliers Removed Mean Availability	Outliers Removed P50 Availability
1503.160469	1260.535505	1328.104647	2528.275385	1747.289021	1208.865299
MAD	41.20378206	43.83385769	55.36780839	46.38441506	42.6833297

Table 4-22. Current Forced Outages 2025 Generation Capacity Loss

Summary Table: Generation Capacity Loss and MAD (50% Incease)					
50% Increase Unavailability	Historical 5 Year Average Availability	Simulated 5-Year Gen Loss	EV Availability Simulated	Outliers Removed Mean Availability	Outliers Removed P50 Availability
2254.740704	1260.535505	1328.104647	2528.275385	1747.289021	1208.865299
MAD	65.5895572	64.21766013	67.56794259	63.06311497	63.06713215

Table 4-23. 50% Increase in 2025 Generation Capacity Loss

Summary Table: Generation Capacity Loss and MAD (100% Incease)					
100% Increase Unavailability	Historical 5 Year Average Availability	Simulated 5-Year Gen Loss	EV Availability Simulated	Outliers Removed Mean Availability	Outliers Removed P50 Availability
3006.320938	1260.535505	1328.104647	2528.275385	1747.289021	1208.865299
MAD	91.8588625	90.28197273	90.13061481	86.52678026	89.2480201

Table 4-24. 100% Increase in 2025 Generation Capacity Loss

Summary Table: Generation Capacity Loss and MAD (150% Incease)					
150% Increase Unavailability	Historical 5 Year Average Availability	Simulated 5-Year Gen Loss	EV Availability Simulated	Outliers Removed Mean Availability	Outliers Removed P50 Availability
3757.921173	1260.535505	1328.104647	2528.275385	1747.289021	1208.865299
MAD	118.1281678	116.551278	116.3999201	112.7960856	115.5400288

Table 4-25. 150% Increase in 2025 Generation Capacity Loss

4.8 Hypothesis Test Results

This praxis research focuses on developing lost generation capacity estimates due to unplanned, forced generation outages. The motivation for this research is to enable

BPA to accurately account for the lost generation capacity due to forced outages in WRAP capacity planning. As discussed in Chapter 1, the development of the WRAP power-pooling market began in 2020. By 2023 the RA program achieved NERC approval. BPA has been participating since 2024. By 2027 BPA's forward-showing capacity commitments will be binding, meaning there will be penalties for not fulfilling capacity commitments when they are called upon in the power pool. The forecasting tool developed in this praxis research aims to improve BPA's estimated generation capacity loss due to forced outages for capacity planning in the WRAP.

Forced outages reduce Bonneville Power Administration's planned capacity in the Wrap and risk revenue loss of marketable power at 120-125% of the spot price.

The research objectives for this praxis are:

- to develop a Monte Carlo simulation using historical forced outage data to estimate lost generation capacity due to forced outages.
- to provide capacity planners with a simulated estimate of the generation capacity loss due to forced outages as a baseline to align capacity commitments with risk tolerance.
- to determine whether Monte Carlo simulation provides improved capacity planning through optimized reserves based on the Monte Carlo simulation of forced outages.

RQ1: How well does the random number from exponential distribution simulate the independent variables of MTBF and MTTR compared to historical actuals?

RQ2: How is generation capacity loss prediction accuracy improved by simulating the MTBF and MTTR of equipment failures due to forced outages?

RQ3: How does the Monte Carlo Simulation of forced outages help estimate reserve generation capacity?

RQ4: How does a Monte Carlo simulation of forced outages improve WRAP power pool revenues of surplus capacity?

4.9 Hypothesis 1 Test Results

This Praxis research tests the following hypotheses:

H1: *Historical five-year average MTBF and MTTR can be simulated as a random number from an exponential distribution to estimate WRAP capacity.*

The Monte Carlo simulation of the independent availability variables MTBF and MTTR aims to improve BPA's estimated generation capacity loss due to forced outages for capacity planning in the WRAP. In this praxis research, the MTBF is the average time in hours, that a system or component takes to fail – it is the metric used for repairable systems. The MTTR is the average time to repair to an operational state in hours.

This research determines the exponential distribution is validated as a reasonable fit to the independent variables of MTBF and MTTR of 175 hydropower generators across 21 hydropower plants. The MTBF and MTTR variables are historical actuals from a five-year data set (2019 – 2023). The historical MTBF and MTTR data is fit to the exponential distribution and validated by the R^2 value. The results are shown in Table 4-1. The MTBF and MTTR of each individual generator is analyzed to fit to the exponential distribution. System-wide, across all 175 generators, the average R^2 value for MTBF is 0.886. and MTTR is 0.891. The two main reasons for lower R^2 values for some generators' MTBF and MTTR is a small sample or even no sample, of forced outages in

the data set. The other is long duration outages and major equipment failures. In a few cases generators have been in a forced outage state beyond the five-year data set and the availability is 0. Shown in Table 4-19, the simulated availability is the forecasted availability, whose MAD error to historical actuals is very low – less than 1 percent.

Plant	# of Units	Historical 5-year Average Availability	Simulated Availability	|A-F|
P1	5	0.997461596	0.997520784	0.000059188
P2	3	0.93441151	0.934623636	0.000212126
P3	4	0.994748366	0.994577003	0.000171363
P4	18	0.915799416	0.91444875	0.001350667
	3	0.92435023	0.925628916	0.001278686
	3	0.979049152	0.978893863	0.000155289
P5	16	0.989894553	0.990156502	0.000261949
	11	0.987564574	0.987477642	0.000086933
P6	2	0.99758059	0.997624677	0.000044086
	1	0.996665994	0.99665342	0.000012573
P7	6	0.980234639	0.980399135	0.000164496
P8	6	0.848193153	0.848141378	0.000051774
P9	6	0.976638618	0.976699747	0.000061129
P10	3	0.993634863	0.993689641	0.000054778
	3	0.945640535	0.945810823	0.000170288
P11	14	0.969490142	0.969575408	0.000085267
P12	16	0.886629125	0.88696456	0.000335435
P13	14	0.976918977	0.968648502	0.008270474
	8	0.740266981	0.660243182	0.080023799
P14	10	0.973187392	0.972089537	0.001097855
	8	0.965250724	0.965057692	0.000193032
P15	2	0.609791355	0.617296087	0.007504732
P16	2	0.995369304	0.995276372	0.000092933
P17	2	0.96210652	0.962351711	0.000245190
P18	2	0.946293344	0.946758893	0.000465549
P19	3	0.979332454	0.979068156	0.000264299
P20	2	0.983003736	0.983075243	0.000071508
P21	2	0.987950592	0.987786007	0.000164585
MAD of Availability Estimate =			0.941304902	

Table 4-26. MAD of Simulated Availability Estimates

4.9.1 Hypothesis 2 Test Results

H2: *Monte Carlo simulation of availability metrics MTBF and MTTR quantify the frequency and severity of forced outages to more accurately estimate the reduction of available capacity from a limited data set.*

The Monte Carlo simulation of the independent availability variables MTBF and MTTR improve BPA's generation capacity loss prediction accuracy for WRAP generation capacity planning. The five-year historical forced outage data for the years 2019-2023 contains 1,119 forced generator outages for the 21 hydropower plants in this praxis research. The number of forced outages by each hydropower plant are shown in Figure 4-1 below.

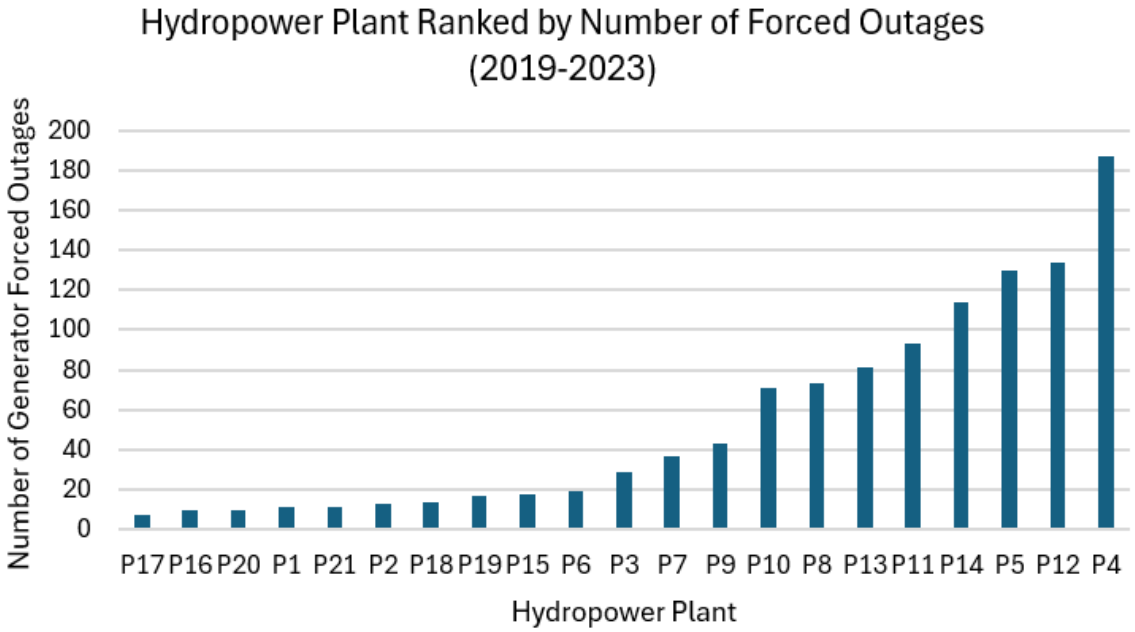

Figure 4-9. Number of Forced Outages by Hydropower Plant

The number of actual forced outages in the five-year data set ranges from 9 to 187. Using Monte Carlo simulation for 10,000 data point for both MTBF and MTTR allows more data and statistical analysis for quantifying the uncertainty of forced outage

generation capacity loss. The simulation estimates are validated by the MAD from both the five-year average generation capacity loss and the actual CY 2024 forced outage data summarized in Figure 4-1. The CY 2024 actuals are not in the historical data set and are used for measuring forecast accuracy.

Table 4-17 shows the results of the forecast error when estimating CY 2024. The current approach BPA capacity planners use is a rolling five-year average for generation capacity loss. The actual generation capacity loss in CY 2024 was 2,962.91 MW of a 21,544 MW total max capacity of the twenty-one hydropower projects used in WRAP capacity planning. The five-year rolling average estimate was 1,259.86 MW, underestimated by 1,703 MW for the calendar year. Using the Mont Carlo simulation and probability distribution of the 10,000 simulations yields an expected value of 2,525.87 MW. This estimate is much closer to the actual generation capacity loss. The CY 2024 actual generation capacity loss was more than the simulated expected value estimate by 437 MW.

CY 2024 had some outlier generator availabilities and unexpected failures. Hydropower plant P14 forced out of service, 10 of its 18 generators for most or all of 2024 due to a common mode failure. Several other hydropower plants had one or more generator units out of service for major repairs. The MTTR has also been extended, due primarily to supply chain disruptions. However, rising costs, labor shortages due to hiring freezes, deferred resignation and reduction in force measures and other constraints, are likely to be future impactful drivers to a longer MTTR than seen in past failures.

4.9.2 Hypothesis 3 Test Results

H3: *The probability distribution of the Monte Carlo simulation defines statistical limits for estimated availability that provides a disciplined approach to setting reserve capacity.*

The Monte Carlo simulation of forced outages improves the current method of a rolling five-year outage. By simulating 10,000 availabilities, a system-wide availability is calculated and a probability distribution determined. This allows capacity planners to develop a data informed generation capacity reserve, when the historical data is limited.

Table 4-15 shows the MAD error between the five-year rolling average actual generation capacity loss and the forecasted estimate. The simulated availability using all 10,000 simulated availabilities has the lowest MAD error across 21 hydropower plants. The P50 estimate using the simulated 10,000 availabilities with outliers removed (as shown in figures 4-1 through 4-8) has the smallest error of the total estimated capacity loss, to the five-year rolling average. Table 4-18 shows the MAD error between the CY 2024 actual generation capacity loss and the forecast. Again, the simulated availability using all 10,000 simulated availabilities has the lowest MAD error across 21 hydropower plants. The expected value of the probability distribution for the 10,000 simulations is calculated using formula 16. The expected value estimate was the closest to the CY 2024 actual generation capacity loss.

This research shows that the Monte Carlo simulation improves the ability to plan capacity reserves. Using the P50 estimate as the lower bound and the expected value as the upper bound, capacity reserves can be calculated as the MW difference, shown in Table 4-20. The MW difference is 1319.41 MW. Table 4-21 shows the capacity reserve

spread across the calendar year and Table 4-22 shows the capacity reserve, weighted by the summer and winter load peaks for WRAP. To show adding capacity reverses to the P50 estimates meets or exceeds the expected values, the capacity reserve of 146.60 MW is extended to non-peak months as shown in Table 4-23. The theoretical sum of monthly reserve capacity is 1,759.24 MW. Added to the P50 capacity estimate of 1,208.86 MW, the total is 2,968.11 MW. The results show that reserve-setting methodology was effective under anomalous conditions, leaving a small remaining buffer of 5.2 MW.

2024 Actual Availability	EV Availability Simulated 5 Year Average	Outliers Removed P50 Availability
2962.907754	2528.275385	1208.865299
Total 2024 Capacity Reserve (MW)		1319.410085

Table 4-27. Capacity Reserve

Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
109.95	109.95	109.95	109.95	109.95	109.95	109.95	109.95	109.95	109.95	109.95	109.95

Table 4-28. 12-month Capacity Reserve

Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
146.40	146.40	146.40			146.40	146.40	146.40	146.40		146.40	146.40

Table 4-29. 9-month WRAP Capacity Reserve

Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
146.40	146.40	146.40	146.40	146.40	146.40	146.40	146.40	146.40	146.40	146.40	146.40

Table 4-30. Theoretical Reserve

4.9.3 Hypothesis 4 Test Results

H4: *The probability distribution of the Monte Carlo simulation optimizes the generation capacity reserve to maximize marketable power.*

From BPA's power marketing perspective, the marketable surplus is the available capacity – less operational obligations – less scheduled outages – less forced outages and – less reserve capacity. A portion of marketable, surplus capacity is used to commit to WRAP. This simplified formula will be used to answer research question four.

RQ4: How does a Monte Carlo simulation of forced outages improve WRAP power pool revenues of surplus capacity?

The marketable surplus is increased by the MW difference between the historical average and P50 estimates for generation capacity. Estimating generation capacity loss with the P50 of the 10,000 simulations versus the historical average increased marketable surplus capacity by 51.67 MW as shown in Table 4-17. The value of the marketable capacity saved is potential revenue earned, whether that's revenue from WRAP or another current or future market opportunity for BPA's surplus.

The cost of being deficit in terms of MW capacity is determined by the same process in hypothesis 3. Table 4-24 shows the generation capacity reserve as the MW difference between the expected value estimate and the historical five-year average estimate. The generation capacity reserve is 1267.74 MW. Table 4-25 shows the generation capacity reserve spread across the nine months of peak loads for WRAP. The theoretical sum of monthly reserve capacity shown in Table 4-27, is 1,690.32 MW. Adding the theoretical sum of 1,690.32 to the generation capacity loss calculated from the historical five-year average availability of 1,260.53 MW, yields a total of 2,950.85 MW. In CY 2024 the

actual generation capacity loss due to forced outages was 2,962.91 MW. Sizing generation capacity reserves using the lost generation capacity estimate from the historical five-year average availability, leaves a 12 MW deficit. This is above the design limit when stress tested by the actuals for CY 2024.

2024 Actual Availability	EV Availability Simulated 5 Year Average	Historical 5 Year Average Availability
2962.907754	2528.275385	1260.535505
Total 2024 Capacity Reserve (MW)		1267.739879

Table 4-31. Capacity Reserve (Historical 5 Year Average)

Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
105.64	105.64	105.64	105.64	105.64	105.64	105.64	105.64	105.64	105.64	105.64	105.64

Table 4-32. 12-month Capacity Reserve (Historical 5 Year Average)

Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
140.86	140.86	140.86			140.86	140.86	140.86	140.86		140.86	140.86

Table 4-33. 9-month WRAP Capacity Reserve (Historical 5 Year Average)

Table 4-34. Theoretical Reserve

4.10 Reserve Sizing Testing: Second Data Set, 2025

To test the expected value reserve sizing methodology on a second independent dataset, this analysis applies the two-tiered approach using the P50 estimate and the Expected Value of the full probability distribution. The scenarios developed in section

4.7.3 address the partial year of forced outages in 2025. Using all three CY 2025 scenarios (50%, 100%, and 150% generation capacity loss increases) tests the reserve methodology in different forced outage conditions based on 7.5 months of actual out-of-sample data. The reserve sizing methodology demonstrates effectiveness for the 50% scenario (2,254.7 MW capacity loss), resulting in a 713.4 MW reserve buffer remaining. However, the 100% (3,006.3 MW) and 150% (3,757.9 MW) scenarios show the methodology's limitations, resulting in respective deficits of 38.2 MW and 789.8 MW. This deficit demonstrates the need for additional extreme event modeling using distributions like Gumbel for more extreme scenarios, as discussed in future research recommendations.

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Chapter 5—Discussion and Conclusions

5.1 Introduction

This praxis is focused on estimating lost generation capacity due to forced outages. Critical to BPA's success in WRAP, is a forward-showing capacity commitment that meets its load obligations while optimizing its surplus capacity in the power pool. The motivation for this research is to enable BPA to optimize available WRAP capacity commitments by accounting for generation capacity loss due to forced outages. The thesis statement guides the research, the development of research questions and hypotheses:

A predictive model for forced outage capacity loss is necessary for Bonneville Power Administration to both maintain capacity obligations and maximize revenue opportunities in the WRAP.

Determining capacity commitments to WRAP depends on quantifying and accounting for the uncertainty of forced outages. Accurately estimating availability ensures that BPA's capacity obligations are met and a capacity deficit is avoided. A capacity deficit is a shortage of capacity to meet load obligations. A position of deficit capacity requires purchasing power in real-time markets to fulfill obligations. This is especially important to avoid in WRAP as this market supplies power in seasonal periods of peak demand, where MWh prices are high. Successful marketing surplus capacity in the WRAP depends on accurate availability estimates that quantify the generation capacity loss of forced outages well before the occur. The current method for estimating capacity loss is a five-year rolling average of generation capacity loss from unavailable generators due to an unplanned outage.

This praxis research aims to improve forced outage capacity loss, with stochastic simulation and Monte Carlo analysis. No modeling tool exists within BPA to estimate generator unavailability by simulation of the independent variables of MTBF and MTTR. Through the research questions posed in this praxis, the following objective has been achieved:

- Develop a stochastic simulation using Monte Carlo methods to more accurately estimate the generation capacity reduction due to forced outages and optimize capacity reserves based on the expected value of availability probabilities.

5.2 Generation and Generation Capacity

Table 2 shows the 21 hydropower plants that are studied in this analysis and each generator's corresponding MW capacity. It is important to stress that though those MW capacities were used to test the simulation model and develop the generation capacity loss for validation, in practice max generation is not just dependent on the generator's name plate capacity, but its fuel supply. Capacity planners use streamflow forecasts that are converted to a generator's MW output based on flow rate, head and turbine efficiency. For every hydropower plant in Table 2, capacity planners use flow rate to calculate MW output. In practice, capacity planners would use the forecasting tool developed in this praxis with a MW capacity for each generator based on water supply forecasts. Additionally, A hydropower generator's max capacities can change, as discussed in Chapter 3. Certain repairs to the turbine or generator can reduce efficiency, change the power curve and limit the generator's maximum name plate capacity. It is important for generator max capacities to be updated for planning WRAP capacity commitments.

5.3 Discussion of Hypothesis 1

H1: *Historical five-year average MTBF and MTTR can be simulated as a random number from an exponential distribution to estimate WRAP capacity.*

The hypothesis that the independent availability variables MTBF and MTTR can be simulated as random numbers in an exponential distribution is validated by the R^2 correlation coefficients shown in Table 4-1, of the historical forced outage data. For all 175 generators, the average R^2 value for MTBF is 0.886. and MTTR is 0.891.

Plant	Number of Forced Outages	Number of Generators
P1	11	5
P2	13	3
P3	29	4
P4	187	24
P5	130	27
P6	19	3
P7	37	6
P8	73	6
P9	43	6
P10	71	6
P11	93	14
P12	134	16
P13	81	22
P14	114	18
P15	18	2
P16	9	2
P17	6	2
P18	14	2
P19	17	3
P20	9	2
P21	11	2

Table 5-1. Actual Number of Forced Outages Per Generator (2019-2023)

Plant	# of Units	Historical 5-year Average Availability	Simulated Availability	Outliers Removed P50 Availability
P1	5	0.997461596	0.997520784	0.998048562
P2	3	0.93441151	0.934623636	0.945984545
P3	4	0.994748366	0.994577003	0.995691241
P4	18	0.915799416	0.91444875	0.928352513
	3	0.92435023	0.925628916	0.936555272
	3	0.979049152	0.978893863	0.982977281
P5	16	0.989894553	0.990156502	0.992426243
	11	0.987564574	0.987477642	0.990104657
P6	2	0.99758059	0.997624677	0.998145083
	1	0.996665994	0.99665342	0.997446834
P7	6	0.980234639	0.980399135	0.984487989
P8	6	0.848193153	0.848141378	0.86150791
P9	6	0.976638618	0.976699747	0.981664928
P10	3	0.993634863	0.993689641	0.995046131
	3	0.945640535	0.945810823	0.955315207
P11	14	0.969490142	0.969575408	0.97546248
P12	16	0.886629125	0.88696456	0.88643413
P13	14	0.976918977	0.968648502	0.974429387
	8	0.740266981	0.660243182	0.662460648
P14	10	0.973187392	0.972089537	0.977812418
	8	0.965250724	0.965057692	0.971736628
P15	2	0.609791355	0.617296087	0.618685631
P16	2	0.995369304	0.995276372	0.99631095
P17	2	0.96210652	0.962351711	0.969405436
P18	2	0.946293344	0.946758893	0.956376966
P19	3	0.979332454	0.979068156	0.983333189
P20	2	0.983003736	0.983075243	0.98677373
P21	2	0.987950592	0.987786007	0.990308774
Average Availability		0.944194944	0.941304902	0.946188742
Average Unvailability		0.055805056	0.058695098	0.053811258

Table 5-2. Actual and Simulated Availability

One limitation with this validation test is the size of the historical forced outage data. Table 5-1 shows the small data set and limitations to a meaningful R^2 value. With only a five-year data set. To further validate this hypothesis, the five-year average forced

outage availability from historical actuals is compared to the availability estimates from the random numbers generated from exponential distribution. The forecast error using MAD is less than 1% and is shown in table 4-19. The simulated P50 availability estimate with outliers removed, is shown in Table 5-2 below. Despite the data limitations, the validation shows an acceptable error between the actual and simulated availability.

5.4 Discussion of Hypothesis 2

H2: *Monte Carlo simulation of availability metrics MTBF and MTTR quantify the frequency and severity of forced outages to more accurately estimate the reduction of available capacity from a limited data set.*

The hypothesis testing attempts to show that the Monte Carlo simulation of the independent availability variables MTBF and MTTR improve BPA's generation capacity loss prediction accuracy for WRAP generation capacity planning. To validate this hypothesis CY 2024 actual generation capacity loss is estimated using the five-year historical forced outage data for years 2019-2023 and the simulated availability using average MTBF and MTTR from the same data set. The results are shown in Table 4-13. Forced outage capacity loss spiked in 2024 to approximately 2,963 MW. The five-year average historical actual generation capacity loss is 1260.5. The main drivers for the 2024 decrease in availability are three year-long generator outages at two plants and the loss of ten generators at one other plant. These failures have an unusually long MTTR. Despite the slightly more accurate generation capacity loss estimate using the simulated availabilities to predict generation capacity loss in 2024, no estimate was a good predictor of CY 2024 actuals. The expected value of the simulated availabilities is the exception

and a benefit to the Monte Carlo simulation in establishing capacity reserves. This is discussed in the hypothesis 3 discussion, section 5.6.

5.5 Discussion of Hypothesis 3

H3: *The probability distribution of the Monte Carlo simulation defines statistical limits for estimated availability that provides a disciplined approach to setting reserve capacity.*

The Monte Carlo simulation of forced outages improves the current method of a rolling five-year average unavailability due to forced outages, by utilizing the expected value of the probability distribution. By simulating 10,000 availabilities, an expected value determined from the probability distribution, allows capacity planners to develop a reserve generation capacity to absorb outlier capacity loss due to forced outages.

Table 4-20 shows the estimated generation capacity loss compared to the actual loss in CY 2024. The P50 estimate is the median value for availability of the 10,000 simulations with outliers removed. The P50 availability was used to determine the generation capacity loss estimate, while the expected value availability from the probability distribution provides an upper limit to determine MW reserves. This approach determines the reserve sizing upper bound based on the expected value of the probability distribution. The methodology's effectiveness was validated during the anomalous 2024 operating year, which experienced significantly higher forced outage rates than historical averages. Despite these anomalous conditions, the probabilistic reserve sizing left only 5.2 MW of unused reserve capacity, demonstrating that the model avoided a potentially costly deficit.

5.6 Discussion of Hypothesis 4

H4: *The probability distribution of the Monte Carlo simulation optimizes the generation capacity reserve to maximize marketable power.*

Quantifying the uncertainty of generation capacity loss from forced outages is a key factor in forecasting marketable surplus in WRAP. As shown in hypothesis test 4, the marketable surplus is increased by the MW difference between the historical average and P50 estimates for generation capacity loss. Estimating the generation capacity loss in CY 2024 with the P50 estimate of the simulated availability, allows an additional 51.67 MW to be planned capacity in WRAP. Furthermore, marketed capacity in WRAP is sold at premium prices, between 120 and 125% of the spot price.

As discussed, CY 2024 saw an increase in generation capacity loss due to forced outages not captured in any estimate. Equally important to maximizing available surplus, is minimizing the deficit. A deficit market position requires BPA to purchase energy to meet its load obligations. Forced purchases to meet WRAP commitments for high peak periods reduces net revenues. Using a generation capacity loss estimate from the historical average availability, leaves capacity reserves deficit by 12 MW when sizing for CY 2024.

5.7 Discussion of Extended Validation Results

The extended 2025 analysis demonstrates the Monte Carlo methodology's effectiveness across multiple independent datasets. The prediction accuracy assessment (Section 4.7.3) and reserve sizing analysis (Section 4.10) confirm the approach works reliably for normal-to-moderate operational scenarios while identifying realistic

limitations for extreme conditions. This additional testing strengthens confidence in the methodology's practical utility for BPA's immediate WRAP implementation needs.

5.8 Conclusion

The objective of this research is to help BPA quantify the uncertainty of generation capacity loss due to forced outages. Simulating availability using Monte Carlo analysis improves BPA’s ability to quantify the uncertainty of generation capacity loss. This praxis research improves capacity loss estimates and forecasted reserve requirements. The hypotheses are confirmed, and the validation results confirm the methodology's practical value. The small remaining buffer of 5.2MW indicates efficient reserve sizing under uncertainty. This outcome validates the assumption that probability distributions from Monte Carlo simulations can effectively capture real-world forced outage uncertainty and support risk-based capacity planning decisions.

5.9 Implementation

This praxis research is intended to address important capacity planning challenges in WRAP. In practice, WRAP capacity commitments are forward showing and are required seven months in advance of the summer and peak load periods. Referring to Table 4-27, capacity commitments will need to be planned in March for the winter peak loads and October for the summer peak loads. The simulation and analysis can be performed seven months ahead of the capacity planning deadline. Forced outage capacity loss is estimated over a period of one year, which is long enough to encompass the seven months of advance and the length of the planning period.

5.10 Contributions

This praxis research supports resource adequacy, reliability and compliance in the region by offering a disciplined, data driven approach to quantify the uncertainty of generation capacity loss, not only to BPA but regional partners for resource adequacy.

This research is not only novel for its timely contribution to a new resource adequacy program in the Northwest, but further contributions come from a unique position within BPA. This research uses actual forced outage data for its out-of-sample validation, which adds a unique benefit in its practical application to support the needs of the region. Additionally, this research provides the broader electric utility industry with an innovative, probabilistic capacity reserve-sizing methodology that improves upon existing deterministic methods. Finally, this praxis research addresses a literature gap by providing probabilistic capacity planning for resource adequacy markets.

5.11 Future Research

Future research can address the limitations discussed in Section 1.8. Future research includes incorporating water supply estimates for developing realistic operational capacity – specifically in WRAP capacity planning periods. Additionally, the capacity sizing approach has limitations in very extreme, “black swan” events. Valuable future research includes developing a reserve sizing methodology using the Gumbel distribution for extreme events. Finally, further research using the Weibull distribution when a constant failure rate cannot be assumed.

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Appendix A

Appendix A shows a snapshot of the 10,000 simulated availabilities. The binary column identifies the outlier from the IQR method. Hydropower plant names are masked.

H	I	J	K	L	M	N	O	P	Q	R	S
HydropowerPlantAvailabilitySimulation											
P4	P4	P4	P4	P5	P5	P6	P6	P7	P7	P8	P8
Number	Text	Number	Text	Number	Text	Number	Text	Number	Text	Number	Text
0.9806	0	0.8924	0	0.9529	0	0.7960	1	0.9411	0	0.7664	1
0.7214	0	0.9955	0	0.9840	0	0.9518	0	0.9792	0	0.9956	0
0.9934	0	0.9792	0	0.8463	1	0.9971	0	0.9945	0	0.9923	0
0.9058	0	0.9688	0	0.9974	0	0.9661	0	0.9696	0	0.9998	0
0.8859	0	0.7272	0	0.8927	0	0.9958	0	0.9944	0	0.9993	0
0.9783	0	0.9614	0	0.7161	1	0.9982	0	0.9821	0	0.9987	0
0.9842	0	0.9817	0	0.9935	0	0.9892	0	0.9994	0	0.9873	0
0.9968	0	0.4232	1	0.9939	0	0.9937	0	0.9372	0	0.9924	0
0.9501	0	0.8288	0	0.4987	1	0.9997	0	0.9886	0	0.9973	0
0.8767	0	0.9915	0	0.9825	0	0.9991	0	0.9936	0	0.9976	0
0.9816	0	0.6937	0	0.9828	0	0.9925	0	0.9963	0	0.9935	0
0.9724	0	0.9913	0	0.9460	0	0.9000	1	0.9819	0	0.8773	1
0.4266	1	0.9531	0	0.9864	0	0.9936	0	0.9870	0	0.9966	0
0.9829	0	0.9108	0	0.8678	0	0.9988	0	0.9946	0	0.9998	0
0.9682	0	0.9869	0	0.9986	0	0.9992	0	0.9983	0	0.9993	0
0.9905	0	0.9873	0	0.9697	0	0.9973	0	0.9875	0	0.9967	0
0.8515	0	0.9666	0	0.9847	0	0.9969	0	0.9565	0	0.9964	0
0.8330	0	0.8830	0	0.9600	0	0.9999	0	0.9999	0	0.9992	0
0.7944	0	0.9998	0	0.9901	0	0.9967	0	0.9368	0	0.9968	0
0.9219	0	0.8633	0	0.9975	0	0.9912	0	0.9986	0	0.9995	0
0.7858	0	0.9733	0	0.9786	0	0.9814	0	0.9889	0	0.9830	1
0.9766	0	0.8802	0	0.9968	0	0.9955	0	0.9682	0	0.9996	0
0.9255	0	0.7293	0	0.9725	0	0.9024	1	0.9979	0	0.9872	0
0.5965	0	0.5811	0	0.9864	0	0.9806	0	0.9938	0	0.9921	0
0.7606	0	0.9144	0	0.8541	1	0.9763	0	0.9950	0	0.9984	0
0.9202	0	0.9471	0	0.9670	0	0.9996	0	0.9712	0	0.9990	0
0.7511	0	0.9264	0	0.9701	0	0.9939	0	0.9947	0	0.9994	0
0.9854	0	0.9898	0	0.9931	0	0.9703	0	0.9836	0	0.9972	0
0.9925	0	0.9917	0	0.9960	0	0.9639	0	0.9977	0	0.9988	0
0.8370	0	0.9619	0	0.9633	0	0.9896	0	0.9972	0	0.9997	0
0.5155	0	0.9421	0	0.9910	0	0.9995	0	0.9972	0	0.9998	0
0.6964	0	0.9776	0	0.9910	0	0.9992	0	0.9998	0	0.9982	0
0.9797	0	0.4747	1	0.9980	0	0.9992	0	0.9867	0	0.9993	0
0.9630	0	0.8901	0	0.9794	0	0.9953	0	0.9047	1	0.9942	0
0.6543	0	0.9835	0	0.9861	0	0.9899	0	0.9840	0	0.9993	0
0.8183	0	0.7069	0	0.8049	1	0.9541	0	0.9972	0	0.9996	0

Table A-1. Simulated Availabilities

Appendix B

Appendix B is Figure 3-2 showing an example of the forced outage data format from OTS, using mock data for illustration.

OTS Status	Outage Ty	Out Of Service Time	In Service Time	Duration Days	Duration Hrs	Units
Returned to Service	Forced	9/4/2018	9/4/2018	0.572916667	13.75	1
Returned to Service	Forced	9/5/2018	9/6/2018	1.25625	30.15	2
Returned to Service	Forced	10/1/2018	10/2/2018	0.797222222	19.13333333	3
Returned to Service	Forced	10/4/2018	10/16/2018	11.60486111	278.5166667	4
Returned to Service	Forced	11/21/2018	12/26/2018	34.81180556	835.4833333	5
Returned to Service	Forced	11/23/2018	12/17/2018	24.50208333	588.05	6
Returned to Service	Forced	11/23/2018	11/29/2018	6.268055556	150.4333333	7
Returned to Service	Forced	11/26/2018	11/28/2018	2.288888889	54.93333333	8
Returned to Service	Forced	11/27/2018	12/6/2018	8.982638889	215.5833333	9
Returned to Service	Forced	1/1/2020	1/10/2020	9	216	10
Returned to Service	Forced	7/26/2018	11/10/2018	107.3381944	2576.116667	11
Returned to Service	Forced	8/16/2018	11/10/2018	86.47916667	2075.5	12
Returned to Service	Forced	9/1/2018	9/4/2018	2.994444444	71.86666667	13
Returned to Service	Forced	9/1/2018	9/12/2018	11.07013889	265.6833333	14
Returned to Service	Forced	9/4/2018	9/4/2018	0.572916667	13.75	15
Returned to Service	Forced	10/17/2018	10/17/2018	0.560416667	13.45	16
Returned to Service	Forced	10/16/2018	10/17/2018	1.440972222	34.58333333	17
Returned to Service	Forced	10/17/2018	10/17/2018	0.290972222	6.983333333	18
Returned to Service	Forced	10/18/2018	10/22/2018	3.8	91.2	19
Returned to Service	Forced	10/19/2018	10/19/2018	0.098611111	2.366666667	20
Returned to Service	Forced	10/20/2018	10/22/2018	1.543055556	37.03333333	21

Table B-1. OTS Data

Appendix C

Appendix C includes the data tables supporting the additional out-of-sample validation using actual year-to-date 2025 forced outage data.

Generation Capacity Loss CY 2025 Scenarios				
	2025 YTD	50% (Back-loaded)	100%(Current Pace)	150% (Front-loaded)
Plant	Availability	Availability	Availability	Availability
P1	0.999486	0.999229	0.998972	0.998715
P2	1	1	1	1
P3	0.999887	0.9998305	0.999774	0.9997175
P4	0.997475	0.9962125	0.99495	0.9936875
P5	0.776619	0.6649285	0.553238	0.4415475
P6	0.998239	0.9973585	0.996478	0.9955975
P7	0.926321	0.8894815	0.852642	0.8158025
P8	0.965221	0.9478315	0.930442	0.9130525
P9	0.999622	0.999433	0.999244	0.999055
P10	1	1	1	1
P11	0.999261	0.9988915	0.998522	0.9981525
P12	0.848078	0.772117	0.696156	0.620195
P13	0.999368	0.999052	0.998736	0.99842
P14	0.997607	0.9964105	0.995214	0.9940175
P15	1	1	1	1
P16	0.999554	0.999331	0.999108	0.998885
P17	0.814366	0.721549	0.628732	0.535915
P18	0.999226	0.998839	0.998452	0.998065
P19	0.776095	0.6641425	0.55219	0.4402375
P20	0.811953	0.7179295	0.623906	0.5298825
P21	0.998479	0.9977185	0.996958	0.9961975
P22	0.993943	0.9909145	0.987886	0.9848575
P23	1	1	1	1
P24	1	1	1	1
P25	0.99871	0.998065	0.99742	0.996775
P26	0.99636	0.99454	0.99272	0.9909
P27	1	1	1	1
P28	0.998237	0.9973555	0.996474	0.9955925
Avg Availability	0.960503821	0.940755732	0.921007643	0.901259554

Table C-1. Availabilities 2025 Scenarios

Generation Capacity Loss CY 2025 Scenarios			
	50% Scenario	100% Scenario	150% Scenario
Plant	Unavailability	Unavailability	Unavailability
P1	0.000771	0.001028	0.001285
P2	0	0	0
P3	0.0001695	0.000226	0.0002825
P4	0.0037875	0.00505	0.0063125
P5	0.3350715	0.446762	0.5584525
P6	0.0026415	0.003522	0.0044025
P7	0.1105185	0.147358	0.1841975
P8	0.0521685	0.069558	0.0869475
P9	0.000567	0.000756	0.000945
P10	0	0	0
P11	0.0011085	0.001478	0.0018475
P12	0.227883	0.303844	0.379805
P13	0.000948	0.001264	0.00158
P14	0.0035895	0.004786	0.0059825
P15	0	0	0
P16	0.000669	0.000892	0.001115
P17	0.278451	0.371268	0.464085
P18	0.001161	0.001548	0.001935
P19	0.3358575	0.44781	0.5597625
P20	0.2820705	0.376094	0.4701175
P21	0.0022815	0.003042	0.0038025
P22	0.0090855	0.012114	0.0151425
P23	0	0	0
P24	0	0	0
P25	0.001935	0.00258	0.003225
P26	0.00546	0.00728	0.0091
P27	0	0	0
P28	0.0026445	0.003526	0.0044075

Table C-2. Unavailability 2025 Scenarios

Generation Capacity Loss CY 2025 Scenarios				
	2025 YTD	50% Scenario	100% Scenario	150% Scenario
Plant	Availability	Availability	Availability	Availability
P1	0.999486	0.999229	0.998972	0.998715
P2	1	1	1	1
P3	0.999887	0.9998305	0.999774	0.9997175
P4	0.997475	0.9962125	0.99495	0.9936875
P5	0.776619	0.6649285	0.553238	0.4415475
P6	0.998239	0.9973585	0.996478	0.9955975
P7	0.926321	0.8894815	0.852642	0.8158025
P8	0.965221	0.9478315	0.930442	0.9130525
P9	0.999622	0.999433	0.999244	0.999055
P10	1	1	1	1
P11	0.999261	0.9988915	0.998522	0.9981525
P12	0.848078	0.772117	0.696156	0.620195
P13	0.999368	0.999052	0.998736	0.99842
P14	0.997607	0.9964105	0.995214	0.9940175
P15	1	1	1	1
P16	0.999554	0.999331	0.999108	0.998885
P17	0.814366	0.721549	0.628732	0.535915
P18	0.999226	0.998839	0.998452	0.998065
P19	0.776095	0.6641425	0.55219	0.4402375
P20	0.811953	0.7179295	0.623906	0.5298825
P21	0.998479	0.9977185	0.996958	0.9961975
P22	0.993943	0.9909145	0.987886	0.9848575
P23	1	1	1	1
P24	1	1	1	1
P25	0.99871	0.998065	0.99742	0.996775
P26	0.99636	0.99454	0.99272	0.9909
P27	1	1	1	1
P28	0.998237	0.9973555	0.996474	0.9955925
Avg Availability	0.960503821	0.940755732	0.921007643	0.901259554

Table C-3. Generation Capacity Loss 2025 Scenarios

Generation Capacity Loss (Simulated and Historical Actuals)									
Plant	# of Units	Total MW	2025 YTD Average Actual Availability		Historical 5 Year Average Availability	Simulated 5 Year Average Availability	EV Availability Simulated 5 Year Average	Outliers Removed Mean Availability	Outliers Removed P50 Availability
P1	5	605	0.31097		1.535734274	1.499925622	7.38774575	2.093912628	1.180620201
P2	3	48	0		3.148247541	3.138065486	6.684468	4.224119573	2.592741829
P3	4	428	0.048364		2.247699355	2.321042623	9.94468272	3.254792768	1.844148945
P4	18	2250	5.68125		189.4513129	192.4903132	374.80869	262.4099263	161.2068446
	3	2070	462.39867		156.5950245	153.9481441	317.9021958	210.8122716	131.3305863
	3	2415	4.252815		50.59629823	50.97132044	158.2260666	70.56326536	41.10986561
P5	16	1408	103.740032		14.22846977	13.85964493	51.80638848	19.1322994	10.66384983
	11	1199	41.700021		14.9100755	15.01430768	53.68060885	21.23992295	11.86451635
P6	2	206	0.077868		0.498398365	0.48931656	2.47474392	0.668614942	0.382112962
	1	259	0		0.863507577	0.866764101	4.2360227	1.202189592	0.661270053
P7	6	930	0.68727		18.38178556	18.22880474	57.9426828	25.40356734	14.42617009
P8	6	930	141.28746		141.180368	141.2285183	224.5454775	193.1588955	128.7976438
P9	6	930	0.58776		21.72608487	21.66923501	64.1774493	29.78582302	17.05161734
P10	3	309	0.739437		1.966827275	1.949900888	7.82040684	2.700263371	1.53074567
	3	384	0		20.87403447	20.80864397	47.08027392	28.61042533	17.15896065
P11	14	1120	0.49952		34.17104138	34.07554252	93.604	46.6190711	27.48202259
P12	16	2480	460.37232		281.1597699	280.3278916	492.3193576	379.6118485	281.6433568
P13	14	1134	0.877716		26.17388014	35.55259818	95.54512464	49.67714646	28.99707504
	8	736	164.79408		191.1635023	250.061018	286.4696957	286.4700801	248.4289629
P14	10	600	112.8282		16.08756459	16.7462776	46.666458	22.92536605	13.31254918
	8	616	0.936936		21.40555421	21.52446192	55.26060848	28.51596946	17.41023736
P15	2	116	0.702612		45.26420287	44.39365392	48.69964548	48.69971288	44.23246681
P16	2	92	0		0.426023999	0.434573814	1.91276004	0.608081222	0.339392608
P17	2	23	0		0.871550029	0.865910649	2.19268959	1.151713843	0.703674983
P18	2	28	0.03612		1.503786361	1.490750994	3.4284712	2.039512208	1.221444938
P19	3	138	0.50232		2.852121321	2.888594523	9.15662706	4.009434237	2.300019903
P20	2	34	0		0.577872988	0.575441724	1.89431578	0.777226086	0.449693168
P21	2	56	0.098728		0.674766828	0.683983599	2.407727784	0.923569771	0.542708644
Total Lost Gen Capacity			1503.160469		1260.535505	1328.104647	2528.275385	1747.289021	1208.865299
Total Lost Gen %			6.98%		5.85%	6.16%	11.74%	8.11%	5.61%

Table C-4. Generation Capacity Loss 2025 Scenarios

Generation Capacity Loss (Simulated and Historical Actuals)									
Plant	# of Units	Total MW	2025 YTD 50% Increase of Unavailability		Historical 5 Year Average Availability	Simulated 5 Year Average Availability	EV Availability Simulated 5 Year Average	Outliers Removed Mean Availability	Outliers Removed P50 Availability
P1	5	605	0.466455		1.535734274	1.499925622	7.38774575	2.093912628	1.180620201
P2	3	48	0		3.148247541	3.138065486	6.684468	4.224119573	2.592741829
P3	4	428	0.072546		2.247699355	2.321042623	9.94468272	3.254792768	1.844148945
P4	18	2250	8.521875		189.4513129	192.4903132	374.80869	262.4099263	161.2068446
	3	2070	693.598005		156.5950245	153.9481441	317.9021958	210.8122716	131.3305863
	3	2415	6.3792225		50.59629823	50.97132044	158.2260666	70.56326536	41.10986561
P5	16	1408	155.610048		14.22846977	13.85964493	51.80638848	19.1322994	10.66384983
	11	1199	62.5500315		14.9100755	15.01430768	53.68060885	21.23992295	11.86451635
P6	2	206	0.116802		0.498398365	0.48931656	2.47474392	0.668614942	0.382112962
	1	259	0		0.863507577	0.866764101	4.2360227	1.202189592	0.661270053
P7	6	930	1.030905		18.38178556	18.22880474	57.9426828	25.40356734	14.42617009
P8	6	930	211.93119		141.180368	141.2285183	224.5454775	193.1588955	128.7976438
P9	6	930	0.88164		21.72608487	21.66923501	64.1774493	29.78582302	17.05161734
P10	3	309	1.1091555		1.966827275	1.949900888	7.82040684	2.700263371	1.53074567
	3	384	0		20.87403447	20.80864397	47.08027392	28.61042533	17.15896065
P11	14	1120	0.74928		34.17104138	34.07554252	93.604	46.6190711	27.48202259
P12	16	2480	690.55848		281.1597699	280.3278916	492.3193576	379.6118485	281.6433568
P13	14	1134	1.316574		26.17388014	35.55259818	95.54512464	49.67714646	28.99707504
	8	736	247.19112		191.1635023	250.061018	286.4696957	286.4700801	248.4289629
P14	10	600	169.2423		16.08756459	16.7462776	46.666458	22.92536605	13.31254918
	8	616	1.405404		21.40555421	21.52446192	55.26060848	28.51596946	17.41023736
P15	2	116	1.053918		45.26420287	44.39365392	48.69964548	48.69971288	44.23246681
P16	2	92	0		0.426023999	0.434573814	1.91276004	0.608081222	0.339392608
P17	2	23	0		0.871550029	0.865910649	2.19268959	1.151713843	0.703674983
P18	2	28	0.05418		1.503786361	1.490750994	3.4284712	2.039512208	1.221444938
P19	3	138	0.75348		2.852121321	2.888594523	9.15662706	4.009434237	2.300019903
P20	2	34	0		0.577872988	0.575441724	1.89431578	0.777226086	0.449693168
P21	2	56	0.148092		0.674766828	0.683983599	2.407727784	0.923569771	0.542708644
Total Lost Gen Capacity			2254.740704		1260.535505	1328.104647	2528.275385	1747.289021	1208.865299
Total Lost Gen %			10.47%		5.85%	6.16%	11.74%	8.11%	5.61%

Table C-5. 50% Gen Capacity Comparison

Generation Capacity Loss (Simulated and Historical Actuals)									
Plant	# of Units	Total MW	2025 YTD 100% Increase of Unavailability		Historical 5 Year Average Availability	Simulated 5 Year Average Availability	EV Availability Simulated 5 Year Average	Outliers Removed Mean Availability	Outliers Removed P50 Availability
P1	5	605	0.62194		1.535734274	1.499925622	7.38774575	2.093912628	1.180620201
P2	3	48	0		3.148247541	3.138065486	6.684468	4.224119573	2.592741829
P3	4	428	0.096728		2.247699355	2.321042623	9.94468272	3.254792768	1.844148945
P4	18	2250	11.3625		189.4513129	192.4903132	374.80869	262.4099263	161.2068446
	3	2070	924.79734		156.5950245	153.9481441	317.9021958	210.8122716	131.3305863
	3	2415	8.50563		50.59629823	50.97132044	158.2260666	70.56326536	41.10986561
P5	16	1408	207.480064		14.22846977	13.85964493	51.80638848	19.1322994	10.66384983
	11	1199	83.400042		14.9100755	15.01430768	53.68060885	21.23992295	11.86451635
P6	2	206	0.155736		0.498398365	0.48931656	2.47474392	0.668614942	0.382112962
	1	259	0		0.863507577	0.866764101	4.2360227	1.202189592	0.661270053
P7	6	930	1.37454		18.38178556	18.22880474	57.9426828	25.40356734	14.42617009
P8	6	930	282.57492		141.180368	141.2285183	224.5454775	193.1588955	128.7976438
P9	6	930	1.17552		21.72608487	21.66923501	64.1774493	29.78582302	17.05161734
P10	3	309	1.478874		1.966827275	1.949900888	7.82040684	2.700263371	1.53074567
	3	384	0		20.87403447	20.80864397	47.08027392	28.61042533	17.15896065
P11	14	1120	0.99904		34.17104138	34.07554252	93.604	46.6190711	27.48202259
P12	16	2480	920.74464		281.1597699	280.3278916	492.3193576	379.6118485	281.6433568
P13	14	1134	1.755432		26.17388014	35.55259818	95.54512464	49.67714646	28.99707504
	8	736	329.58816		191.1635023	250.061018	286.4696957	286.4700801	248.4289629
P14	10	600	225.6564		16.08756459	16.7462776	46.666458	22.92536605	13.31254918
	8	616	1.873872		21.40555421	21.52446192	55.26060848	28.51596946	17.41023736
P15	2	116	1.405224		45.26420287	44.39365392	48.69964548	48.69971288	44.23246681
P16	2	92	0		0.426023999	0.434573814	1.91276004	0.608081222	0.339392608
P17	2	23	0		0.871550029	0.865910649	2.19268959	1.151713843	0.703674983
P18	2	28	0.07224		1.503786361	1.490750994	3.4284712	2.039512208	1.221444938
P19	3	138	1.00464		2.852121321	2.888594523	9.15662706	4.009434237	2.300019903
P20	2	34	0		0.577872988	0.575441724	1.89431578	0.777226086	0.449693168
P21	2	56	0.197456		0.674766828	0.683983599	2.407727784	0.923569771	0.542708644
Total Lost Gen Capacity			3006.320938		1260.535505	1328.104647	2528.275385	1747.289021	1208.865299
Total Lost Gen %			13.95%		5.85%	6.16%	11.74%	8.11%	5.61%

Table C-6. 100% Gen Capacity Comparison

Generation Capacity Loss (Simulated and Historical Actuals)									
Plant	# of Units	Total MW	2025 YTD 150% Increase of Unavailability		Historical 5 Year Average Availability	Simulated 5 Year Average Availability	EV Availability Simulated 5 Year Average	Outliers Removed Mean Availability	Outliers Removed P50 Availability
P1	5	605	0.777425		1.535734274	1.499925622	7.38774575	2.093912628	1.180620201
P2	3	48	0		3.148247541	3.138065486	6.684468	4.224119573	2.592741829
P3	4	428	0.12091		2.247699355	2.321042623	9.94468272	3.254792768	1.844148945
P4	18	2250	14.203125		189.4513129	192.4903132	374.80869	262.4099263	161.2068446
	3	2070	1155.996675		156.5950245	153.9481441	317.9021958	210.8122716	131.3305863
	3	2415	10.6320375		50.59629823	50.97132044	158.2260666	70.56326536	41.10986561
P5	16	1408	259.35008		14.22846977	13.85964493	51.80638848	19.1322994	10.66384983
	11	1199	104.2500525		14.9100755	15.01430768	53.68060885	21.23992295	11.86451635
P6	2	206	0.19467		0.498398365	0.48931656	2.47474392	0.668614942	0.382112962
	1	259	0		0.863507577	0.866764101	4.2360227	1.202189592	0.661270053
P7	6	930	1.718175		18.38178556	18.22880474	57.9426828	25.40356734	14.42617009
P8	6	930	353.21865		141.180368	141.2285183	224.5454775	193.1588955	128.7976438
P9	6	930	1.4694		21.72608487	21.66923501	64.1774493	29.78582302	17.05161734
P10	3	309	1.8485925		1.966827275	1.949900888	7.82040684	2.700263371	1.53074567
	3	384	0		20.87403447	20.80864397	47.08027392	28.61042533	17.15896065
P11	14	1120	1.2488		34.17104138	34.07554252	93.604	46.6190711	27.48202259
P12	16	2480	1150.9308		281.1597699	280.3278916	492.3193576	379.6118485	281.6433568
P13	14	1134	2.19429		26.17388014	35.55259818	95.54512464	49.67714646	28.99707504
	8	736	411.9852		191.1635023	250.061018	286.4696957	286.4700801	248.4289629
P14	10	600	282.0705		16.08756459	16.7462776	46.666458	22.92536605	13.31254918
	8	616	2.34234		21.40555421	21.52446192	55.26060848	28.51596946	17.41023736
P15	2	116	1.75653		45.26420287	44.39365392	48.69964548	48.69971288	44.23246681
P16	2	92	0		0.426023999	0.434573814	1.91276004	0.608081222	0.339392608
P17	2	23	0		0.871550029	0.865910649	2.19268959	1.151713843	0.703674983
P18	2	28	0.0903		1.503786361	1.490750994	3.4284712	2.039512208	1.221444938
P19	3	138	1.2558		2.852121321	2.888594523	9.15662706	4.009434237	2.300019903
P20	2	34	0		0.577872988	0.575441724	1.89431578	0.777226086	0.449693168
P21	2	56	0.24682		0.674766828	0.683983599	2.407727784	0.923569771	0.542708644
Total Lost Gen Capacity			3757.901173		1260.535505	1328.104647	2528.275385	1747.289021	1208.865299
Total Lost Gen %			17.44%		5.85%	6.16%	11.74%	8.11%	5.61%

Table C-7. 150% Gen Capacity Comparison

Generation Loss	Absolute Error				
2025 YTD Unavailability	Historical 5 Year Average Availability	Simulated 5-Year Gen Loss	EV Availability Simulated	Outliers Removed Mean Availability	Outliers Removed P50 Availability
0.31097	1.224764274	1.188955622	7.07677575	1.782942628	0.869650201
0	3.148247541	3.138065486	6.684468	4.224119573	2.592741829
0.048364	2.199335355	2.272678623	9.89631872	3.206428768	1.795784945
5.68125	183.7700629	186.8090632	369.12744	256.7286763	155.5255946
462.39867	305.8036455	308.4505259	144.4964742	251.5863984	331.0680837
4.252815	46.34348323	46.71850544	153.9732516	66.31045036	36.85705061
103.740032	89.51156223	89.88038707	51.93364352	84.6077326	93.07618217
41.700021	26.7899455	26.68571332	11.98058785	20.46009805	29.83550465
0.077868	0.420530365	0.41144856	2.39687592	0.590746942	0.304244962
0	0.863507577	0.866764101	4.2360227	1.202189592	0.661270053
0.68727	17.69451556	17.54153474	57.2554128	24.71629734	13.73890009
141.28746	0.107092004	0.058941741	83.2580175	51.8714355	12.48981623
0.58776	21.13832487	21.08147501	63.5896893	29.19806302	16.46385734
0.739437	1.227390275	1.210463888	7.08096984	1.960826371	0.79130867
0	20.87403447	20.80864397	47.08027392	28.61042533	17.15896065
0.49952	33.67152138	33.57602252	93.10448	46.1195511	26.98250259
460.37232	179.2125501	180.0444284	31.9470376	80.76047155	178.7289632
0.877716	25.29616414	34.67488218	94.66740864	48.79943046	28.11935904
164.79408	26.36942228	85.26693798	121.6756157	121.6760001	83.63488286
112.8282	96.74063541	96.0819224	66.161742	89.90283395	99.51565082
0.936936	20.46861821	20.58752592	54.32367248	27.57903346	16.47330136
0.702612	44.56159087	43.69104192	47.99703348	47.99710088	43.52985481
0	0.426023999	0.434573814	1.91276004	0.608081222	0.339392608
0	0.871550029	0.865910649	2.19268959	1.151713843	0.703674983
0.03612	1.467666361	1.454630994	3.3923512	2.003392208	1.185324938
0.50232	2.349801321	2.386274523	8.65430706	3.507114237	1.797699903
0	0.577872988	0.575441724	1.89431578	0.777226086	0.449693168
0.098728	0.576038828	0.585255599	2.308999784	0.824841771	0.443980644
MAD	41.20378206	43.83385769	55.36780839	46.38441506	42.6833297

Table C-8. YTD MAD 2025 Scenarios

Generation Loss	Absolute Error				
2025 YTD 50% Increase of Unavailability	Historical 5 Year Average Availability	Simulated 5-Year Gen Loss	EV Availability Simulated	Outliers Removed Mean Availability	Outliers Removed P50 Availability
0.466455	1.069279274	1.033470622	6.92129075	1.627457628	0.714165201
0	3.148247541	3.138065486	6.684468	4.224119573	2.592741829
0.072546	2.175153355	2.248496623	9.87213672	3.182246768	1.771602945
8.521875	180.9294379	183.9684382	366.286815	253.8880513	152.6849696
693.598005	537.0029805	539.6498609	375.6958092	482.7857334	562.2674187
6.3792225	44.21707573	44.59209794	151.8468441	64.18404286	34.73064311
155.610048	141.3815782	141.7504031	103.8036595	136.4777486	144.9461982
62.5500315	47.639956	47.53572382	8.86942265	41.31010855	50.68551515
0.116802	0.381596365	0.37251456	2.35794192	0.551812942	0.265310962
0	0.863507577	0.866764101	4.2360227	1.202189592	0.661270053
1.030905	17.35088056	17.19789974	56.9117778	24.37266234	13.39526509
211.93119	70.750822	70.70267174	12.6142875	18.7722945	83.13354623
0.88164	20.84444487	20.78759501	63.2958093	28.90418302	16.16997734
1.1091555	0.857671775	0.840745388	6.71125134	1.591107871	0.42159017
0	20.87403447	20.80864397	47.08027392	28.61042533	17.15896065
0.74928	33.42176138	33.32626252	92.85472	45.8697911	26.73274259
690.55848	409.3987101	410.2305884	198.2391224	310.9466315	408.9151232
1.316574	24.85730614	34.23602418	94.22855064	48.36057246	27.68050104
247.19112	56.02761772	2.869897984	39.27857568	39.2789601	1.237842859
169.2423	153.1547354	152.4960224	122.575842	146.316934	155.9297508
1.405404	20.00015021	20.11905792	53.85520448	27.11056546	16.00483336
1.053918	44.21028487	43.33973592	47.64572748	47.64579488	43.17854881
0	0.426023999	0.434573814	1.91276004	0.608081222	0.339392608
0	0.871550029	0.865910649	2.19268959	1.151713843	0.703674983
0.05418	1.449606361	1.436570994	3.3742912	1.985332208	1.167264938
0.75348	2.098641321	2.135114523	8.40314706	3.255954237	1.546539903
0	0.577872988	0.575441724	1.89431578	0.777226086	0.449693168
0.148092	0.526674828	0.535891599	2.259635784	0.775477771	0.394616644
MAD	65.5895572	64.21766013	67.56794259	63.06311497	63.06713215

Table C-9. 50% MAD 2025 Scenarios

Generation Loss	Absolute Error				
2025 YTD 100% Increase of Unavailability	Historical 5 Year Average Availability	Simulated 5-Year Gen Loss	EV Availability Simulated	Outliers Removed Mean Availability	Outliers Removed P50 Availability
0.62194	0.913794274	0.877985622	6.76580575	1.471972628	0.558680201
0	3.148247541	3.138065486	6.684468	4.224119573	2.592741829
0.096728	2.150971355	2.224314623	9.84795472	3.158064768	1.747420945
11.3625	178.0888129	181.1278132	363.44619	251.0474263	149.8443446
924.79734	768.2023155	770.8491959	606.8951442	713.9850684	793.4667537
8.50563	42.09066823	42.46569044	149.7204366	62.05763536	32.60423561
207.480064	193.2515942	193.6204191	155.6736755	188.3477646	196.8162142
83.400042	68.4899665	68.38573432	29.71943315	62.16011905	71.53552565
0.155736	0.342662365	0.33358056	2.31900792	0.512878942	0.226376962
0	0.863507577	0.866764101	4.2360227	1.202189592	0.661270053
1.37454	17.00724556	16.85426474	56.5681428	24.02902734	13.05163009
282.57492	141.394552	141.3464017	58.0294425	89.4160245	153.7772762
1.17552	20.55056487	20.49371501	63.0019293	28.61030302	15.87609734
1.478874	0.487953275	0.471026888	6.34153284	1.221389371	0.05187167
0	20.87403447	20.80864397	47.08027392	28.61042533	17.15896065
0.99904	33.17200138	33.07650252	92.60496	45.6200311	26.48298259
920.74464	639.5848701	640.4167484	428.4252824	541.1327915	639.1012832
1.755432	24.41844814	33.79716618	93.78969264	47.92171446	27.24164304
329.58816	138.4246577	79.52714202	43.11846432	43.1180799	81.15919714
225.6564	209.5688354	208.9101224	178.989942	202.731034	212.3438508
1.873872	19.53168221	19.65058992	53.38673648	26.64209746	15.53636536
1.405224	43.85897887	42.98842992	47.29442148	47.29448888	42.82724281
0	0.426023999	0.434573814	1.91276004	0.608081222	0.339392608
0	0.871550029	0.865910649	2.19268959	1.151713843	0.703674983
0.07224	1.431546361	1.418510994	3.3562312	1.967272208	1.149204938
1.00464	1.847481321	1.883954523	8.15198706	3.004794237	1.295379903
0	0.577872988	0.575441724	1.89431578	0.777226086	0.449693168
0.197456	0.477310828	0.486527599	2.210271784	0.726113771	0.345252644
MAD	91.8588625	90.28197273	90.13061481	86.52678026	89.2480201

Table C-10. 100% MAD 2025 Scenarios

Generation Loss	Absolute Error				
2025 YTD 150% Increase of Unavailability	Historical 5 Year Average Availability	Simulated 5-Year Gen Loss	EV Availability Simulated	Outliers Removed Mean Availability	Outliers Removed P50 Availability
0.777425	0.758309274	0.722500622	6.61032075	1.316487628	0.403195201
0	3.148247541	3.138065486	6.684468	4.224119573	2.592741829
0.12091	2.126789355	2.200132623	9.82377272	3.133882768	1.723238945
14.203125	175.2481879	178.2871882	360.605565	248.2068013	147.0037196
1155.996675	999.4016505	1002.048531	838.0944792	945.1844034	1024.666089
10.6320375	39.96426073	40.33928294	147.5940291	59.93122786	30.47782811
259.35008	245.1216102	245.4904351	207.5436915	240.2177806	248.6862302
104.2500525	89.339977	89.23574482	50.56944365	83.01012955	92.38553615
0.19467	0.303728365	0.29464656	2.28007392	0.473944942	0.187442962
0	0.863507577	0.866764101	4.2360227	1.202189592	0.661270053
1.718175	16.66361056	16.51062974	56.2245078	23.68539234	12.70799509
353.21865	212.038282	211.9901317	128.6731725	160.0597545	224.4210062
1.4694	20.25668487	20.19983501	62.7080493	28.31642302	15.58221734
1.8485925	0.118234775	0.101308388	5.97181434	0.851670871	0.31784683
0	20.87403447	20.80864397	47.08027392	28.61042533	17.15896065
1.2488	32.92224138	32.82674252	92.3552	45.3702711	26.23322259
1150.9308	869.7710301	870.6029084	658.6114424	771.3189515	869.2874432
2.19429	23.97959014	33.35830818	93.35083464	47.48285646	26.80278504
411.9852	220.8216977	161.924182	125.5155043	125.5151199	163.5562371
282.0705	265.9829354	265.3242224	235.404042	259.145134	268.7579508
2.34234	19.06321421	19.18212192	52.91826848	26.17362946	15.06789736
1.75653	43.50767287	42.63712392	46.94311548	46.94318288	42.47593681
0	0.426023999	0.434573814	1.91276004	0.608081222	0.339392608
0	0.871550029	0.865910649	2.19268959	1.151713843	0.703674983
0.0903	1.413486361	1.400450994	3.3381712	1.949212208	1.131144938
1.2558	1.596321321	1.632794523	7.90082706	2.753634237	1.044219903
0	0.577872988	0.575441724	1.89431578	0.777226086	0.449693168
0.24682	0.427946828	0.437163599	2.160907784	0.676749771	0.295888644
MAD	118.1281678	116.551278	116.3999201	112.7960856	115.5400288

Table C-11. 150% MAD 2025 Scenarios