Probabilistic Planning Methods: A Review of Methods Available to Transmission Planners

Executive Summary

Prepared for MISO

August 2025

Energy+Environmental Economics

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Table of Contents

Introduction

The electricity industry is undergoing significant economic, policy, and technological transformations. Policies to drive greenhouse gas emissions reductions, coupled with technological progress, have led to substantial growth in renewable energy, as well as increased electrification of end uses in transportation, buildings, and industry. System planners are also facing unprecedented large load interconnection requests from data centers and industrial customers, whose magnitude and location are characterized by varying degrees of certainty. Additionally, extreme weather events are growing in both impact and frequency, increasing the importance of system resilience. These changes present opportunities for a cleaner, more resilient grid, but they also introduce profound challenges for transmission planning, which must now contend with an ever-increasing level of uncertainty and complexity. Despite this growing complexity, maintaining system reliability remains crucial, necessitating a move beyond traditional transmission planning approaches, which historically have primarily leveraged deterministic evaluation methods.

In this context, probabilistic methods are being explored as a valuable tool within transmission planning for navigating uncertainty and ensuring a resilient and cost-effective grid. Probabilistic planning methods enable transmission planners to systematically account for variability and risk, offering a deeper understanding of potential outcomes and their likelihoods. Unlike deterministic methods, which produce a single, fixed outcome, probabilistic approaches account for uncertainty and produce a range of possible outcomes which each have an associated likelihood. These methods are crucial for effectively addressing inputs that may have a substantial range of uncertainty, allowing for a comprehensive assessment of potential outcomes that influence grid reliability and investment decisions.

The importance of evaluating new methods is underscored by the unique challenges currently facing transmission planners. With diverse resource mixes, varied state-level policies, and vast geographic footprints, transmission planners and system operators must balance competing priorities, including implementation feasibility and stakeholder accessibility, while addressing the increasing complexity of its transmission network. Probabilistic methods have the potential to provide a structured approach to incorporating these various factors, offering valuable insights that improve decision-making and foster better stakeholder engagement.

This white paper builds a foundation by examining current industry practices, along with a comprehensive exploration of probabilistic planning methods within the transmission planning process, detailing applications of these methods across power flow modeling, production cost analysis, and capacity expansion planning. Through real-world case studies and best practices, we illustrate how these methods can be effectively implemented to address key sources of uncertainty, such as outage & contingency risks, economic and policy variability, climate and weather impacts, and shifts in resource mix and demand.

What is the Purpose of this White Paper?

Significant investments in the transmission system are expected in the coming decades; however, planners are facing increased complexity and uncertainty when trying to identify least-regret plans and the optimal timing for these investments. Increased reliability risks during times of correlated outages, weather dependence of renewable generation resources, higher demand-side uncertainty, frequency and intensity of extreme weather, and varying levels of policy ambition are all sources of uncertainty that must be considered.

This white paper seeks to provide transmission planners and their stakeholders with a comprehensive understanding of probabilistic planning methods and their potential applications in transmission planning. The goal is to outline actionable steps to enhance transmission planning processes, ensuring they remain robust and adaptable in the face of increasing uncertainty. Key areas of focus include reliability planning, economic transmission planning, and resource (capacity) expansion planning, while examining the potential integration of probabilistic techniques to complement existing deterministic frameworks

Through evaluation of probabilistic methods, transmission planners can position themselves as leaders in innovative transmission planning, ensuring that the grid remains reliable, resilient, and economically optimized in the face of growing uncertainty. This white paper establishes a framework for decision-makers, offering a detailed overview of existing and emerging probabilistic methods as well as actionable insights and recommendations.

Why is Planning for Uncertainty Important?

Transmission investments often require a much longer lead time relative to other assets, resulting in an even greater degree of uncertainty that must be considered during a typical transmission planning horizon. On average, the build time for a transmission line exceeds 10 years,[1] and planners often look more than 20 years into the future to ensure that the long-term needs of their system are met.[2] Effectively planning for key sources of near-term and long-term uncertainty requires methods which incorporate technological, policy, and economic uncertainty that could impact transmission system investments, as well as ensuring that the system continues to be reliable across a broad range of weather conditions.

Addressing uncertainty has always been central to system planning; however, the acceleration of electrification-driven demand growth and integration of renewable generation resources over the last decade has led to an increase in both the scope and complexity of transmission planning. Uncertainty driven by economic and policy changes as well as weather, climate change, contingencies and correlated outage risks must be understood and planned for to maintain a cost-effective and reliable electric system.

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[1] IEA - Average lead times to build new electricity grid assets in Europe and the United States, 2010-2021

[2] FERC Order 1920 requires that long-term planning for regional transmission facilities be conducted over a 20-year period: https://www.ferc.gov/news-events/news/ferc-strengthens-order-no-1920-expanded-state-provisions.

Additionally, transmission infrastructure projects require significant capital expenditure, so system planners prioritize the identification of least-regret investments which provide the most value across a wide range of possible future uncertainties. A lengthy planning horizon, coupled with significant capital outlay, requires planners to identify transmission investments that perform well across a diverse set of futures, which maximizes the benefits relative to the required investment. By understanding the range of and impacts of uncertainties, planners can minimize risks, maximize benefits, and ensure plans are both flexible and adaptable to meet long-term system needs.

Project Overview

E3 conducted a comprehensive review of deterministic and probabilistic methods and their applications in Power Flow, Production Cost, and Capacity Expansion modeling. The literature review examined existing and emerging methods across ISO, RTO, and utility planning processes, as well as methods in use or under exploration in academia and industry. E3 also held a series of interviews with experts and thought leaders across North America, including planning departments, academic researchers, and other industry practitioners, to discuss methods for addressing uncertainty. These topics were further discussed during a two-day symposium, jointly held by MISO and E3 in November 2024, with MISO's stakeholders and other experts from across the industry. The findings of the research, interviews, and the symposium are summarized within this executive summary and the accompanying ***Technical Report***. All references and sources supporting the methods and approaches discussed in this Executive Summary are detailed in the Technical Report.

Overview of Modeling Frameworks

Model Types

Before introducing methods for addressing uncertainty, it is important to provide a brief overview of the distinct interrelated modeling frameworks that are commonly used in transmission planning. In general, quantitative transmission planning methods and processes can be categorized in one of three key modeling frameworks: Power Flow, Production Cost, and Capacity Expansion. The following section describes each of these modeling frameworks in more detail and provides additional context, describing the tools and evolving methods that system planners use to make informed decisions to address uncertainty.

In the section ***Industry Practices and Emerging Methods to Address Uncertainty,*** we also examine the deterministic and probabilistic methods that can supplement or be incorporated into these frameworks to more effectively capture a greater range of outcomes and uncertainty. In addition to examining methods to address key sources of uncertainty within an individual modeling framework, this assessment also identifies ways in which advanced analytical techniques can enhance the coordination between modeling frameworks. We discuss these applications in greater detail in ***Enhanced Linkages Between Power Flow and Production Cost Models.***

Power Flow

Power Flow "cases" typically are an examination of a specific snapshot in time, at the hourly granularity, of electric flows across the system respecting the physics of AC power flows (i.e. including active and reactive power flow balances). These studies simulate specific grid conditions to determine if power flows on transmission lines or voltages at nodes and substations meet specific reliability standards. The models are used to perform contingency analysis, voltage stability, short circuit analysis, and assess optimal power flow characteristics.

AC Power Flow models are a complex system of mixed linear and non-linear (trigonometric) equations which represent the phase angles and voltage magnitudes used to calculate active and reactive power flows through transmission systems. The analyses provide planners with a detailed, granular assessment of relevant reliability metrics; however, a key constraint of Power Flow modeling is computational complexity. The substantial number of components within power systems that interact with each other, and the iterative techniques needed to solve convergence on the system limit most Power Flow models to a system representation during a singular moment in time. To minimize the inherent limitations due to computational requirements, "snapshots" are evaluated to capture a range of possible "high stress" system conditions such as periods of summer or winter peak demand.

A task frequently faced by planners is how to efficiently choose the most appropriate period to evaluate within a Power Flow model that best represents high-stress conditions on the system. The higher volumes of weather-dependent generation, as well as increases in the frequency and intensity of extreme weather events, are challenging the conventional approach of assessing winter or summer peaks. There have been a variety of efforts to solve this problem, which we discuss in greater detail in the ***Coordination Between Modeling Frameworks*** subsection and in the emerging methods evaluated in the accompanying research materials.

Production Cost

Production Cost models are typically software-based tools that can perform unit commitment and security-constrained economic dispatch while optimizing system operational (production) costs over a given timeframe — typically simulating hourly operations over an entire year. These models are often used to evaluate market congestion, assess bulk system impacts under broad federal or state policy changes, or measure the economic benefits of potential transmission upgrade options. Underpinning these models is a simplified representation of the transmission network using DC power flows, which is informed by the system topology developed in the (AC) Power Flow modeling. This simplified representation of DC-optimized power flows results in much lower computational requirements than that of the AC Power Flow models, which allows for a chronological (8,760-hour) evaluation of the bulk system across many years. The tradeoff of the simplified DC-optimized topology is a less granular representation of the power flows on the system and, as a result, Production Cost models are used primarily to conduct economic studies, while Power Flow models are used to evaluate transmission system reliability.

System planners often use scenario analysis within Production Cost models to capture a wide range of economic and policy uncertainty. For example, planners may examine multiple future scenarios to evaluate the impacts of fuel price forecasts on system dispatch and resulting congestion. Scenario analysis can also be used to assess broader system changes, such as different load forecasts or changes in future resource portfolios.

Production Cost models can evaluate a range of economic metrics, including total system operating costs and congestion on the transmission network. These modelscan be used to identify how the operations of a given portfolio change under different economic conditions, or can be used to explore potential cost savings from alleviating transmission constraints through new or upgraded infrastructure, among other use cases. As previously mentioned in the Power Flow subsection, snapshots from the Production Cost modeling may also be used to identify periods of high congestion, which can be further evaluated from a transmission reliability perspective within the Power Flow modeling framework.

Capacity Expansion

The extended lead times of transmission investments are also increasingly requiring system planners to conduct long-term analyses which account for projected changes in loads and generation portfolios over time. Planned and announced additions and retirements, as well as generation interconnection queues, are used to provide initial information about the new generation resources added within the system. However, an interconnection queue typically only includes resources that may be added in the near-term, such as the next 5 years. To evaluate plausible generator expansion plans over a longer time horizon (e.g. 10–30 years), system planners use Capacity Expansion models to identify least-cost portfolios of generation resources that meet key system constraints, such as planning reserve margin targets under increasing load and regulatory requirements, including renewable portfolio standards and decarbonization targets.

Because of the lengthy time horizon evaluated in Capacity Expansion models, these models often simplify the level of operational complexity —by only including transmission constraints at the zonal level, and/or only simulating operations and dispatch over a representative sample of days.

Key Sources of Uncertainty in Transmission Planning

There are numerous uncertainties facing the electricity industry today. For the purposes of this examination, we have categorized the following major sources of uncertainty relevant to transmission planning: Outage and Contingency Risk, Weather-Related Variability, and Future Uncertainty.

Outage and Contingency Risk

Outage-related uncertainty is one of the most critical challenges facing modern grids. Planners are increasingly trying to address the risks of simultaneous correlated outages and extended outage durations, which can significantly impact reliability.

Moreover, the growing integration of distributed energy resources (DERs) and the use of more advanced fault monitoring and control devices add additional layers of uncertainty. While these technologies help improve the speed and precision of outage responses, they also introduce new risks related to coordination and control across distributed systems. As a result, traditional approaches to managing outages must be expanded to consider these new variables.

Probabilistic methods can be used to assess outage risks by considering both the probability and severity of events, providing a more comprehensive picture of the grid's vulnerability. Unlike deterministic frameworks, which focus on the impacts of a fixed number of failures (e.g. N-1, N-1-1, etc.), probabilistic methods can help planners prioritize system upgrades and interventions based on identified risks across a wider range of potential contingencies.

Weather-Related Variability

The transition to a cleaner energy system is driving a growing reliance on variable renewable energy resources, such as wind and solar. Additionally, growing investments in electrification of building end uses like space heating is also leading to higher weather sensitivity on the demand side. As a result, this rapidly evolving system is becoming more influenced by fluctuations in weather conditions.

Planners are seeing an increased frequency of conditions that pose both operational challenges and reliability risks. In addition to traditional weather events that drive peak demand, as the share of renewable resources on their systems increase, system planners are facing additional challenges, such as coincident evening load peaks coupled with solar roll-off or the unpredictability of cloud cover. Weather conditions can cause dramatic fluctuations in renewable generation on sub-hourly timescales, and operators are placing increasing value on system flexibility across both generation and transmission in order to rapidly respond to changes in supply. In future scenarios with highly decarbonized systems, reliability risks can also be influenced by periods of winter weather that result in both high levels of heating demand and extended lulls in renewable generation (i.e. Dunkelflaute), leading to sustained high net load.

The increasing frequency and intensity of extreme weather events driven by climate change also pose significant challenges for transmission planning. Hurricanes, heatwaves, wildfires, and other events can disrupt generation and transmission infrastructure, while also influencing demand patterns.

To effectively accommodate the changing dynamics of the grid, system planners need new tools to enhance their assessments of the impact of changing weather conditions on the bulk electric system. While deterministic methods are evolving to assess weather variability, they are limited in their ability to measure the wide range of weather conditions and their resulting influence on the state of the grid. Here, probabilistic methods have the potential to more effectively quantify the variability of weather conditions and their potential impacts on electric system reliability and planning.

Future Uncertainty

Future uncertainties play a significant role when planning the future of the electricity grid. Costs of future technologies and fuels, future policies, economic conditions, and the locations of new resource additions all have profound impacts on how to identify the most cost-effective investments in electric generation and transmission. Quantifying the value and cost-effectiveness of new transmission presents a challenge when these uncertainties cannot be effectively captured in mathematical models or probability distributions — for example, the likelihood of a future federal or state policy being enacted is inherently subjective and does not lend itself to a discrete probability function. Historically, system planners addressed these 'non-quantifiable uncertainties' by utilizing different scenarios to assess a wide range of potential futures, and by deterministically varying key inputs.

Figure 1 provides an illustrative overview of key sources of uncertainty and how their magnitude increases with duration of the planning horizon. System planners are faced with the problem of identifying least-regrets investments for an uncertain and volatile future. Therefore, it is essential to evaluate whether current planning frameworks adequately address uncertainties and to determine if these frameworks need further enhancements in the face of a changing electric grid.

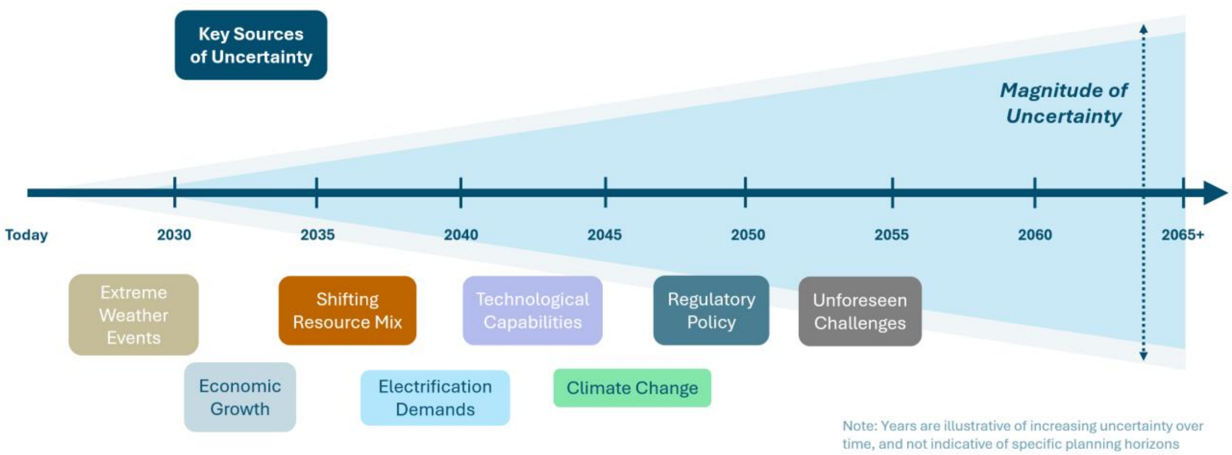

Figure 1: Planning Uncertainties vs Time

Key Sources of Uncertainty within Modeling Frameworks

Power Flow, Production Cost, and Capacity Expansion modeling frameworks each address many different categories of uncertainty. ***Table 1*** serves as a primer to introduce each source of uncertainty, how it can be addressed, and which modeling framework(s) are typically used to address this uncertainty. The table represents sources of uncertainty, mapped across models, which include categories currently being captured in industry (best practices) as well as future applications, with opportunities for further probabilistic or deterministic assessment.

	Modeling Framework		
Category of Uncertainty	**Power Flow**	**Production Cost**	**Capacity Expansion**
Outage and Contingency			
Generation Outages	✓	✓	Outage and contingency assessment is related to capacity expansion modelling, but typically addressed in Resource Adequacy assessments
Outage Events & Failure Rates	✓	✓	
Weather Related Variability			
Peak Demand	✓	✓	Weather variability and its impact on load and renewable generation is related to capacity expansion modelling, but typically addressed through ELCCs and Resource Adequacy assessments
Renewable Output	✓	✓	
Extreme Weather Events	✓	✓	
Future Climate Change		✓	✓
Future Uncertainty			
Economic and Policy Drivers for Demand	✓	✓	✓
Future Clean Energy/Emissions Policy		✓	✓
Fuel Prices		✓	✓
Locations of Future Resources	✓	✓	✓
Resource Costs			

Table 1: Key Sources of Uncertainty in Transmission Planning

Industry Practices and Emerging Methods to Address Uncertainty

Throughout this work, E3 has characterized existing and emerging methods for characterizing and evaluating key sources of uncertainty under three high-level categories: Deterministic, Probabilistic, and Hybrid.

Deterministic Methods

Deterministic methods have long been the foundation of transmission planning. These approaches involve analyzing fixed input scenarios to produce specific outputs, providing a straightforward and transparent framework for evaluating system reliability and economic outcomes. Deterministic methods excel in identifying system needs under well-defined conditions, making them suitable for regulatory compliance and straightforward planning exercises. For example, Capacity Expansion models are typically deterministic in nature — using a specific, defined set of inputs, the model will always yield the same portfolio. The same can be said for Power Flow models which deterministically examine AC transmission flows in great detail, typically for a single hour under a very specific set of system conditions. Often, multiple sets of inputs are run through deterministic models to identify the “sensitivity” of the modeled outcome to changes in system conditions. Scenario planning for future uncertainty is a good example of this approach, where multiple “futures” are examined to evaluate portfolios under different economic and policy conditions, the likelihood of which is not knowable.

However, the deterministic approach may fall short in addressing the inherent uncertainty of modern power systems. By focusing on a limited set of predefined scenarios, deterministic models can fail to capture the full spectrum of possible outcomes, particularly those associated with low-probability, high-impact events. Furthermore, deterministic methods are ill-equipped to account for the dynamic interdependencies between various factors, such as weather variability (and associated load/generation correlation), climate change, and evolving policy landscapes.

Probabilistic Methods

Probabilistic planning methods enable transmission planners to systematically account for variability and risk, offering a deeper understanding of potential outcomes and their likelihoods. Unlike deterministic methods, which rely on fixed inputs to produce consistent and repeatable outputs, probabilistic approaches incorporate randomness and variability to assess a range of possible scenarios.

Probabilistic planning represents a paradigm shift in how transmission systems are evaluated and designed. Unlike deterministic methods, probabilistic approaches incorporate randomness and variability into the modeling process, enabling planners to quantify risks and evaluate a broader range of potential outcomes. This capability is particularly valuable for addressing low-probability, high-impact events, which can have significant implications for grid reliability and investment decisions.

For example, probabilistic models can simulate thousands of scenarios to assess the likelihood of system failures, enabling planners to identify vulnerabilities and prioritize investments accordingly. These models also provide insights into the economic and reliability tradeoffs of different planning decisions, helping stakeholders make informed choices that balance cost, risk, and performance.

As previously mentioned, E3 conducted interviews with system planners (ISOs/RTOs and utilities) across the country, as well as academics and industry practitioners, to gather feedback about the degree to which probabilistic methods have been explored and implemented in planning processes. Deterministic methods coupled with scenario planning broadly remain the industry standard for addressing uncertainty in transmission planning. The overarching theme from our interviews as well as discussions during our symposium indicated that widespread adoption of probabilistic methods for transmission planning remains in its infancy; however, there is an appetite for methods that better capture uncertainty.

Many planners have explored some degree of probabilistic applications to increase the robustness of their planning processes, yet adoption remains limited in part due to implementation challenges. Common barriers limiting the transition from deterministic to probabilistic approaches include: data and computational requirements, staffing limitations and time constraints, the length of current planning processes, stakeholder acceptance, and the lack of commercially available tools. Despite these initial challenges, a hybrid approach emerged as a widely suggested possible first step to implementation — shaping model inputs using probabilistic methods may enhance existing deterministic frameworks.

It is clear that the transition to adopting probabilistic methods will be a gradual one and will require a balanced approach to ensure that the additional insights and benefits offered by such methods outweigh the incremental level of effort and associated implementation "costs".

Hybrid Methods

We have also defined a category of "Hybrid" methods, which include both deterministic and probabilistic elements. For example, many hybrid approaches rely on probabilistic or statistical methods to pre- or post-process the outputs of a deterministic model. By doing so, system planners may gain additional insights about the uncertainty they're evaluating, which would otherwise not be possible using only deterministic methods. Hybrid approaches allow a bridge to some of the benefits of full probabilistic methods while mitigating key implementation challenges, including high computational requirements, extended planning cycle times, stakeholder and regulatory acceptance, and the lack of commercially available tools. Hybrid methods may also rely on machine learning or other methods to "predict" the likelihood of events based on training on correlations within datasets, even if those relationships are not causal. An example of a hybrid approach may include performing a regression analysis to identify correlations between weather, renewable generation, and loads to better identify sets of conditions to examine in a Power Flow model run.

Coordination Between Modeling Frameworks

In practice, transmission planning models are often siloed, where data and results from one model are not coordinated with other modeling efforts of the same system. Through our research and interviews, we found industry participants who have taken initial steps toward linking tools; however, the degree of coordination varies significantly across systems and planning processes. One example of such a linkage is examining system dispatch over all hours of the year in a Production Cost model and using those outputs to identify the "snapshots" that warrant further examination of transmission system reliability in a Power Flow model.

The Production Cost model leverages a simplified representation of the transmission system (DC Power Flow) which was informed by the system topology developed in the AC Power Flow model. This simplified representation allows planners to evaluate many more hours than in a Power Flow model to identify periods that represent challenging system conditions. Once identified, these snapshot hours can be re-evaluated in detail in the Power Flow model to assess system reliability.

This linkage creates a type of feedback-loop between the modeling frameworks, where one process informs another, giving planners a more robust toolset for understanding and addressing uncertainty. In addition to addressing key sources of uncertainty within individual modeling frameworks, this white paper also explores ways in which advanced analytical techniques can enhance the coordination between modeling frameworks. The Chronological AC Power Flow Automated Generation (C-PAGE) method, using Application Programming Interfaces (APIs) to automate communication between tools, and the SERVM/TransCARE linkage demonstration, represent examples of opportunities for coordination and enhanced linkages. We describe these examples in more detail in the attached Technical Appendix in sections: *Linkages Between Modeling Frameworks, Study Recommendation (Enhanced Linkages Between Power Flow and Production Cost Models)*, *Weather-Related Variability (C-PAGE Method and Case Study)*, and *Outage and Contingency (SERVM + TransCare Linkage Method and Case Study)*. For precise references, see pages 14, 18, 39-40, and 43-44.

There are also many other opportunities to capture linkages between models that are beyond the scope of this work. Key examples include, but are not limited to:

- Representation of chronological system dispatch within capacity expansion
- Co-optimized generation and transmission planning
- Generator placement for future resource portfolios

It is also important to note that there are inherent tradeoffs with introducing additional complexity to capture linkages between modeling frameworks. Balancing these tradeoffs and capturing the most critical interactions to ensure a cost-effective and reliable system are the subject of Integrated System Planning.[3] Integrated system planning (ISP) utilizes a cohesive set of data, processes, and models to integrate generation and customer resource planning with transmission and distribution system planning. This approach contrasts with traditionally siloed planning processes, and this integration can be critical to making the right investments, in the right places and at the right times.

Reliability Models and Analyses

As previously mentioned, transmission reliability models evaluate whether the grid can operate securely and reliably under a wide range of conditions. They assess the ability of the system to meet demand while respecting thermal, voltage, and stability limits of transmission infrastructure. There are numerous software packages that simulate specific grid conditions to determine if transmission systems meet specific reliability standards — however, detailed assessment of each would be beyond the scope of this report. For the purposes of this study and to simplify discussion, we will broadly categorize this class of reliability tools as Power Flow models. These Power Flow models provide the basis for examining steady state (normal) and dynamic (sudden changes or faults) operating conditions.

Reliability analyses are generally structured around system “snapshots” that represent periods of elevated system stress. Typical snapshots may include Summer Peak Load, Winter Peak Load, and Spring Loads with High Renewable Outputs, each reflecting credible future system states that present different challenges to the transmission network, while providing robust insights into system performance and reliability. Through power flow modeling, planners evaluate the ability of the bulk power system to generate and deliver electricity reliably across the transmission network while meeting demand under a range of stressed operating conditions. Although a snapshot approach has historically provided excellent insights into reliability and stability under challenging operating conditions, the diversity of system challenges is increasing due to a number of factors, such as increased renewable penetration and changes in the magnitude and frequency of extreme weather. In the Technical Appendix section: *Technical Review – Power Flow Modeling* (page 23), we discuss several potential methods which provide system planners with additional means to address

[3] More discussion exploring the opportunities for Integrated System Planning can be found in E3’s 2024 and 2025 white papers Integrated System Planning - Holistic Planning for the Energy Transition, Foundations of Integrated Planning: Defining a Framework For Comprehensive Energy System Planning, Integrated Planning Guidebook: A Practical Coordination Framework for Electricity Planners

uncertainty within the Power Flow modeling framework. This research informs our recommendations, which can be found in the ***Overview of Findings*** section.

Economic Models and Analyses

To evaluate the long-term economic and market efficiency performance of the transmission system, transmission planners often rely on a class of economic planning tools known as Production Cost models.

The extended planning horizon for transmission development necessitates numerous assumptions to account for a wide range of potential future outcomes. These assumptions carry significant uncertainty, such as evolving economic conditions and associated load growth, clean energy policies, technology adoption, and the future siting and cost of new resources, among others. In the Technical Appendix section: *Technical Review – Production Cost Modeling* (page 41), we discuss several potential methods which provide system planners with additional means to address uncertainty within the Production Cost modeling framework. We also provide recommendations and insights into methods which can provide enhanced linkages between the Power Flow and Production Cost frameworks to enable a more dynamic approach to Power Flow modeling in the Technical Appendix section: Study Recommendation – *Enhanced Linkages Between Power Flow and Production Cost Models* (page 18). These findings are introduced in the next section, Overview of Findings.

Overview of Findings

Recommendations

E3 developed a comprehensive review of existing and emerging probabilistic methods, with a focus on their potential to improve current planning processes. Based on our findings, we have outlined four key recommendations that can be practically implemented by transmission planning entities in the near term. These recommendations aim to enhance ability to address uncertainty and improve its capacity to identify projects that deliver the greatest value to the overall system.

Study Recommendations

1. **Enhance the linkages between Power Flow and Production Cost Models**
2. **Pre-process inputs using probabilistic methods to characterize uncertainty**
3. **Adopt enhanced methods for assessing the economic cost of uncertainty**
4. **Adopt stochastic scenario evaluation and risk assessment**

1. Enhance the Linkages Between Power Flow and Production Cost Models

E3 recommends enhancing the linkages between Power Flow and Production Cost frameworks. In practice, transmission planning models are often siloed, where data and results from one model are not coordinated with other modeling efforts of the same system. E3 believes that improved coordination between models can be realized by using Production Cost model outputs in an iterative process to inform the inputs and snapshots used in Power Flow models. There are several tools and methods available that would allow system planners to use Production Cost models to identify periods of high system stress that warrant further examination in detailed Power Flow models.

We propose an enhancement of existing processes to create formal linkages between the models to enable a more dynamic approach to Power Flow modeling and streamline the data processing requirements. Linkages can include methods to share data back and forth between the Production Cost and Power Flow models by leveraging Application Programming Interfaces (APIs) or custom integration tools developed using Python (or other languages). Additionally, some embedded production cost and power flow models exist that can automate portions of this coordination, such as encoord's SAInt.[4]

Reduced computational requirements of Production Cost models relative to Power Flow models can provide improved snapshot identification by evaluating system conditions at an hourly granularity across many years. In most cases, current Production Cost modeling frameworks use a single weather year; however, it is relatively easy to extend this framework by leveraging time series of temporally coincident weather data.[5] Many years of weather, load, generation, and outages can be evaluated at the hourly level providing system planners with a wide range of system operating conditions that warrant further exploration. Further, most production cost models have the capability to incorporate Monte Carlo or other probabilistic approaches to randomly select weather and outage and contingency patterns. Through coordination, millions of potential system states can be created for further evaluation with significantly reduced user intervention. This approach allows planners to identify and zoom into challenging periods in Production Cost and run those probabilistically across several hours using Power Flow.

Test cases have been successful on several systems, including NYISO, ISO-NE and TVA; however, some degree of manual intervention is typically required when the model has difficulty solving. Case studies and methods implementing these linkages can be found in the Technical Appendix in sections: *Study Recommendation (Enhanced Linkages Between Power Flow and Production Cost Models), Weather Related Variability (C-PAGE Method and Case Study) and Outage and Contingency (SERVM + TransCare Linkage Method and Case Study)*. For precise references, see pages 18, 39-40 and 43-44.

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[4] https://www.encoord.com/resources/blog/saint-3.5

[5] ESIG - Weather Dataset Needs for Planning and Analyzing Modern Power Systems

2. Pre-Process Inputs Using Probabilistic Methods to Characterize Uncertainty

As previously discussed, factors that are limiting the transition from deterministic to probabilistic approaches include computational requirements, planning cycle time constraints, stakeholder or regulator acceptance, or lack of commercially available tools. Our research, interviews, and panel discussions also revealed a common theme: due to these challenges, the transition to fully adopting probabilistic methods is likely to be gradual. As an intermediate step, E3 suggests using probabilistic methods to shape modeling inputs to capture a more comprehensive representation of uncertainties.

Robust data-driven processes can help system planners to capture the range of uncertainty in input variables within Power Flow modeling. For example, historical data can be leveraged to determine variable renewable energy dispatch levels that represent credible system conditions, which are then studied to ensure reliable system performance. These conditions span a wide range of operating states—including light load, summer and winter peaks—and help identify scenarios that are both plausible and stressful to the system. E3 considers these approaches to be robust, as they effectively capture a substantial range of uncertainty, enhance the down-selection process, and strengthen the overall planning process. While this represents only one of several methods to incorporate uncertainty through pre-processing, system planning methods may benefit from similar practices for other inputs.

A wide range of statistical methods are available to quantify the variability of load, outages, and generation in response uncertainty such as weather conditions or component failure rates. This offers system planners the flexibility to choose methods that balance their needs to accurately capture uncertainty with practical constraints, such as staffing or complexity. A subset of probabilistic methods which can be used to pre-process inputs are described below; however, stochastic applications are vast, and therefore this list is not exhaustive.

+ **Stratified Sampling** is a method used by EPRI which extends Monte Carlo simulation by dividing time-series system load and renewable output into sub-populations—to generate dispatch scenarios that capture both average system conditions and low-probability, high-impact events. The approach ensures that scenarios with a low probability of occurrence will not get lost in the "average" scenarios, which occur more frequently on the system.
+ **Slicing and Latin-Hypercube Sampling** is an approach which uses an intelligent sampling method to find a small number of hourly cases representative of a full calendar year to account for seasonal and diurnal variability of renewable generation. This method uses joint cumulative distribution functions to down-sample to reduce the problem size and derive the appropriate scenarios, which are representative of variability in the specified input variable (generation, load, etc.) across an entire year.
+ **K-Means Clustering** is a machine learning algorithm used to classify data points into clusters based on their similarities. This algorithm is well suited to applications in weather pattern analysis (heatwaves, cold, high/low wind), extreme event detection (storms), categorizing renewable generation patterns (diurnal solar cycles, seasonal wind generation), and as a pre-processing data classification step in forecasting.

In addition to these methods, which warrant further exploration, machine learning (ML) applications offer potential value, such as applying AI-based predictive capabilities to assess outages and extreme weather scenarios, as well as supporting down-selection processes to identify the most relevant scenarios for Production Cost modeling. Although use cases for machine learning and the predictive capabilities of AI are nascent within transmission planning, E3 believes the fast-growing capabilities in this space may have many applications for transmission planning in the future, some of which are characterized in the Technical Appendix. For more detail, see sections: *Study Recommendation – Pre-Processing Using Probabilistic Methods (k-Means Clustering), Weather Related Variability – Statistical Weather Prediction (Numerical Weather Prediction and Global Climate Change Models) and Weather Related Variability – C-Page (Intelligent Sampling Method)*. For precise references, see pages 19, 36 and 39.

3. Adopt Enhanced Methods for Assessing the Economic Cost of Uncertainty

E3 recommends the adoption of metrics and methods which weigh the societal cost of "unreliability" or interruption against the incremental cost of investment. This approach uses methods that evaluate the tradeoff between incremental investment cost of transmission (to achieve a higher degree of reliability) to the cost of interruption. These methods quantify the impacts of transmission projects using probabilistic (or well defined deterministic) reliability assessments and interruption cost metrics such as Value of Lost Load (VOLL) or Expected Energy Not Served (EENS).

Economic Cost of Uncertainty is effective in identifying which projects provide the greatest reliability enhancement across a portfolio of potential alternatives, while incorporating a wide range of uncertainties such as weather impacts and outage risk. Comparability across many investment alternatives, while understanding the range of possible outcomes, is a key feature of this approach. Metrics such as Reliability Indices or Benefit/Cost ratios provide quantitative measures for assessing the economic benefit attributed to a higher degree of reliability. These indices are typically represented as a function of capital cost and provide system planners with specific, repeatable calculations that enable comparison across multiple scenarios.

When using this approach, it's important for planners to ensure that economic criteria and thresholds are well defined to ensure the appropriate benefits and risks are captured. For example, diversity of geography may present challenges when applying a single unitized value for VOLL or EENS. Planners must consider the values attributed to each region—the societal cost of interruption may be much higher in areas with critical loads (hospitals, communication infrastructure, industrial processes, etc.), compared to the cost of interruption in other settings. Additionally, when using this framework, care must be taken to explore tradeoffs in outcomes. We recommend that planners look at specific consequences and impacts of events, as there will be areas that need to meet a higher level of performance because the system can't withstand the consequences. Additionally, when assessing societal cost, tail or downside risk will also require further consideration. As an example, which scenario is worse for the system: a single $100bn event or 100 individual $1bn events? The expected value may be the same, but they each carry different considerations.

We explore these methods and considerations in three case studies in more detail in the Technical Appendix in sections: *Outage and Contingency Risk (GARPUR Norway Long-Term Case Study), Economic Cost of Unreliability (ERCOT PRA Framework Case Study),* and *Economic Cost of*

Unreliability (BC Hydro Vancouver Island Reinforcement Case Study). For precise references, see pages 32, 47 and 48.

4. Adopt Stochastic Scenario Evaluation and Risk Assessment

Our research revealed another common theme across all interviewed industry participants that suggested scenario analysis will remain the foundational tool for addressing long-term uncertainty. This approach primarily relies on deterministic methods which are evaluated across multiple, discrete scenarios. Industry practice involves modeling or evaluating boundary conditions, allowing planners to assume that all potential outcomes within these limits are accounted for. While this demonstrates the effectiveness of scenario planning, there are opportunities to improve the process by helping planners more efficiently identify credible base and edge cases. Evaluating additional scenarios helps planners build confidence when similar outcomes are observed. However, several industry stakeholders indicated that it may become difficult to justify the workforce, time, and processes needed for full utilization or exploration. Based on this feedback, E3 recommends enhancing, rather than replacing, existing processes using stochastic evaluation methods and/or out-of-model risk assessments.

Methods that improve scenario selection, increase comparability across scenarios, and incorporate thresholds to trigger scenario re-evaluations offer valuable opportunities to enhance planning approaches. We recommend three methods, which can improve scenario planning processes while retaining most of the current planning frameworks.

+ **Down-Selection of Scenarios:** Several methods can help system planners identify credible edge cases, which ensures that the most appropriate range of uncertainty is captured without the computational and staffing demands required to run every scenario. These methods leverage statistical or probabilistic approaches to describe the range of uncertainty across key input variables, to help system planners understand boundaries and select an optimized portfolio of scenarios.
+ **Stochastic Portfolio Risk Evaluation:** This is a method that requires limited effort and model and data requirements, yet it can improve the robustness of portfolio planning. This class of methods accounts for uncertainty by considering a range of possible futures and their associated probability of occurring, as opposed to a single scenario. The approach is unique because it can quantify the distributions of total system costs for each future and assign conditional probabilities to each future to determine the likelihood of each combination of outcomes. Results interpretation and visualization (such as the range of impact across scenarios for each input variable) is a key step to inform decision-making that is often underperformed.
+ **Out-of-Model Risk Assessment:** This method is used to improve long-term planning practices and outcomes through vulnerability assessment to identify which uncertainties pose the greatest risk. Performance measures (probabilistic, hybrid, or qualitative) are used to evaluate the effectiveness of decision options, and a vulnerability assessment is performed to identify uncertainties that pose the highest risk. These methods are designed to be continuously updated over long time horizons in response to new information and use signposts to establish thresholds for monitored variables that trigger re-evaluation.

We explore these methods and considerations in three case studies in more detail in the Technical Report in sections: *Weather Related Variability (C-PAGE method)*, *Future Uncertainty (Stochastic Portfolio Risk Evaluation and TVA 2019 IRP Case Study)* and *Future Uncertainty (Robust and Adaptive Planning)*. For precise references, see pages 39, 56 and 64.

Conclusion

Decarbonization policies, the accelerated integration of renewable energy resources, rising electrification demands, and the growing frequency and severity of extreme weather events—combined with unprecedented large-load interconnection requests and a heightened emphasis on system resilience—are fundamentally reshaping the electric grid. These dynamics create significant opportunities to transition toward a cleaner, more resilient system. However, they also introduce profound challenges for transmission planning, which must increasingly operate under higher levels of uncertainty, greater complexity, and evolving reliability requirements.

In response to these transformative dynamics, transmission planning methodologies must adapt to account for a broader range of uncertainties. At the same time, system planners must ensure that investment decisions—often characterized by long lead times—reflect a “least-regrets” approach, balancing flexibility, cost-effectiveness, and system resilience. This requires the adoption of methods which incorporate advanced scenario analysis, probabilistic modeling, and adaptive planning frameworks to guide infrastructure development under conditions of persistent uncertainty and accelerated change. This whitepaper outlines opportunities for the application of probabilistic planning methods that can support transmission planners in addressing these challenges.

Specifically, we offer four key recommendations for implementation of methods that layer probabilistic rigor onto existing processes:

1. Enhance the linkages between Power Flow and Production Cost Models
2. Pre-process inputs using probabilistic methods to characterize uncertainty
3. Adopt enhanced methods for assessing the economic cost of uncertainty
4. Adopt stochastic scenario evaluation and risk assessment

One pathway to align planning practices with emerging grid needs—while enhancing transparency, comparability, and stakeholder confidence—could take the form of a phased implementation of these recommendations through a hybrid approach that enhances, rather than replaces, existing planning frameworks. Additional details regarding these recommendations and other methods under exploration are provided in the Technical Report.

Technical Report

The following section of this report details the findings of our research and provides an in-depth assessment of categories of uncertainty, modeling frameworks, and existing, emerging, and probabilistic methods. In this Report, we provide detailed, actionable recommendations that are intended to support system planners by improving the methods used to address uncertainty across the Power Flow, Production Cost, and Capacity Expansion frameworks.

Probabilistic Planning Methods:

Review of Methods Available to Transmission Planners

Prepared on behalf of the Midcontinent Independent System Operator (MISO)

August 2025

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Energy+Environmental Economics

Table of Contents

Acronyms

Acronym	Definition
AC	Alternating Current
ACEP	Adaptive Co-optimized Expansion Planning
APC	Adjusted Production Cost
CEM	Capacity Expansion Modeling
CLL	Composite Load Level
C-PAGE	Chronological AC Power Flow Automated Generation
DC	Direct Current
DCS	Dynamic Contingency Selection
DOE	US Department of Energy
EENS	Expected Energy Not Served
ELCC	Effective Load Carrying Capacity
EPRI	Electric Power Research Institute
EUE	Expected Unserved Energy
GARPUR	Generally Accepted Reliability Principle with Uncertainty Modeling
GCM	Global Climate Change Model
ISO/RTO	Independent System Operator / Regional Transmission Organization

Acronym	Definition
JHSMINE	Johns Hopkins Stochastic Multi-stage Integrated Network Expansion
LOLE	Loss of Load Expectation
MC	Monte Carlo
MCP	Measure, Correlate, Predict
ML	(Generative) Machine Learning
NERC	North American Electric Reliability Corporation
NOAA/NCEP	National Oceanic and Atmospheric Administration / National Centers for Environmental Prediction
NWP	Numerical Weather Prediction
PCM	Production Cost Modeling
PFM	Power Flow Modeling
PNNL	Pacific Northwest National Laboratory
RMAC	Reliability Management Approach and Criterion
VOLL	Value of Lost Load

Project Overview

Project Overview

+ **MISO engaged E3 to outline the opportunities to employ probabilistic methods to address uncertainty in key elements of transmission planning frameworks:**
+ **Significant investments in the transmission system are expected in the coming decades; at the same time, planning for uncertainty is increasing in both importance and complexity due to several factors, such as:**
  - Increased weather dependence of generation resources, i.e., variable renewables
  - Higher demand-side uncertainty as data centers and electrification lead to shifts in the magnitude and timing of demand
  - Increases in the frequency and intensity of extreme weather due to climate change
  - Varying levels of policy ambition
+ **E3 conducted a comprehensive review of deterministic and probabilistic methods and their applications in Power Flow, Production Cost and Capacity Expansion modelling**
  - E3 performed an extensive literature review of existing and emerging methods across ISO/RTO planning processes as well as methods in use or under exploration in academia and industry, supplemented by interviews with key experts
  - E3 and MISO also co-hosted a 2-day symposium with experts and thought leaders across North America, including with ISO/RTO and utility planning departments, academic researchers, and other industry practitioners, to discuss methods for addressing uncertainty
+ **This research has also been summarized in a white paper; the slides herein serve as an appendix to the white paper**

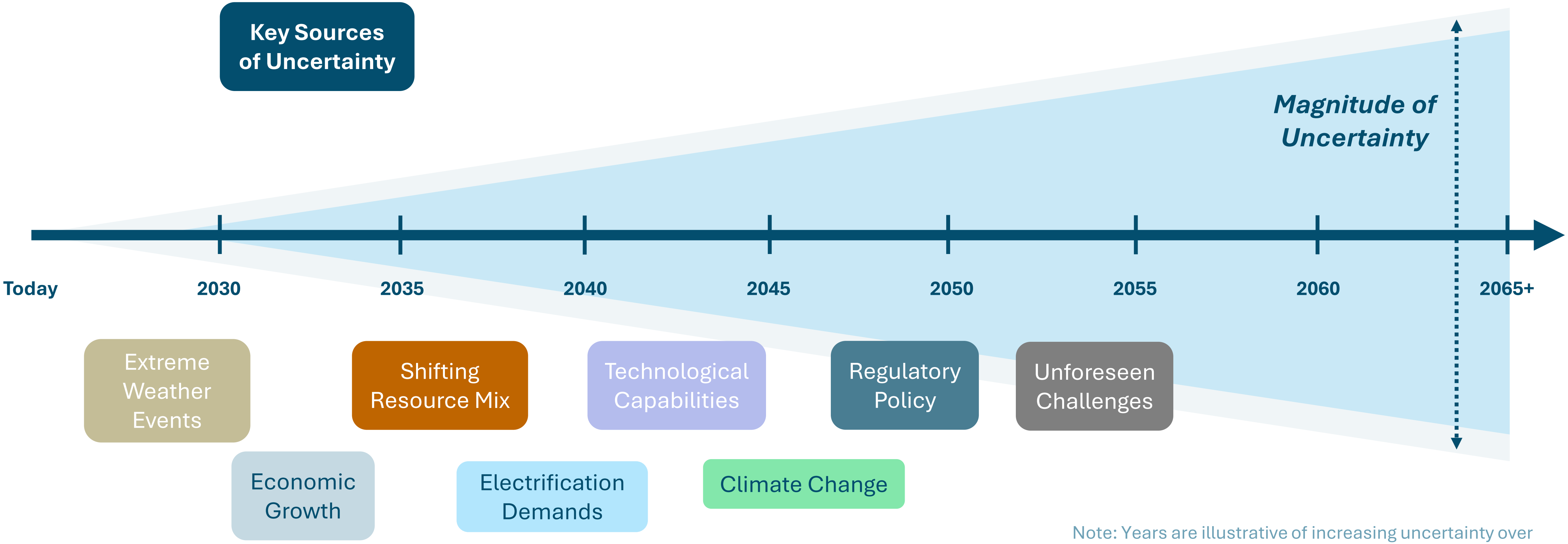
Why is Planning for Uncertainty Important?

Why is Planning for Uncertainty Important?

- **Over the past several decades, the electricity industry and its transmission systems have experienced significant economic, policy, and technological transformations. More changes are to come but their nature and magnitude is highly uncertain**
- **States, utilities and organizations are actively pursuing pathways to decarbonize, and maintaining system reliability is crucial as dependence on electrification continues to grow**
  - Considering economic, policy, and technology outcomes over a multi-decade time horizon is becoming increasingly important
- **System planners already address uncertainty, but the sources of uncertainty and their complexity are increasing**
  - Addressing increased uncertainty across economic and policy changes as well as weather and climate impacts to outages, loads and generation are key to maintaining a robust and reliable electric system
- **Affordability and least-regrets investments are central to transmission planners and stakeholders**
  - Planning for uncertainty gives transmission planners crucial information to maintain reliability and resiliency while maximizing the economic benefits and minimizing system costs
  - Transmission investment occurs over a much longer lead time relative to other assets, so greater uncertainty exists during the transmission planning horizon

Economic and Policy Uncertainty

Long-term power system planning necessitates that planners make decisions under *deep uncertainty*
This is a challenge exacerbated by the *rapid economic, policy, and technological transformations*



Note: Years are illustrative of increasing uncertainty over time, and not indicative of specific planning horizons

Addressing Uncertainty in Transmission Planning Processes

Methods for Characterizing Uncertainty

Throughout this work, E3 categorizes methods for characterizing and evaluating key sources of uncertainty as ***Deterministic, Probabilistic, or Hybrid***

+ **Deterministic:** Deterministic methods are defined as methods in which, for a given set of inputs, the method will always yield the same set of outputs; in other words, there is no randomness introduced anywhere in the calculation process
  - Example(s): A capacity expansion model is a deterministic model; for a specific set of inputs, the model will always yield the same portfolio.
  - A power flow model deterministically examines transmission flows under key system "snapshots", to N-1
  - Often, multiple sets of inputs are run through deterministic models to identify the "sensitivity" of the modeled outcome to changes in system conditions.
  - Example: MISO examines multiple "Futures" with its capacity expansion model to evaluate the resulting portfolios under different economic and policy conditions, the likelihood of which is not knowable.
+ **Probabilistic:** Probabilistic methods introduce at least one component of randomness into their calculation process; for a given set of inputs, the method may or may not yield the same set of outputs
  - Example: A loss-of-load probability (resource adequacy) model is a probabilistic model; for a specific portfolio, the model may or may not identify a loss-of-load event. When run over many simulations, the model can yield a likelihood of a loss-of-load event.
+ **Hybrid:** Our research identified many methods that rely on probabilistic or statistical methods to pre- or post-process the outputs of a deterministic model; we have defined these as "Hybrid" methods throughout the deck
  - Example(s): MISO performs a regression analysis on renewable and load correlations to identify sets of conditions to examine in its power flow snapshots
  - These methods may also rely on machine learning or other methods to "predict" the likelihood of events based on training on correlations within datasets, even if those relationships are not causal

Modeling Framework Overview

+ Power Flow

- System operators develop a series of Power Flow models which contain a detailed representation of the transmission network and are used to perform reliability assessments needed to fulfill various NERC and Tariff compliance obligations. These models also inform topology of production cost models used for economic planning studies
- AC Power Flow modeling is computationally intensive due to the large number of components within power systems that interact with each other, and the iterative techniques needed to solve convergence on the system
- To minimize computational requirements, “Snapshot” periods are evaluated which assess “high stress” periods such as summer and winter peak demand; Power Flow studies simulate specific grid conditions to determine if power flows on transmission lines or voltages at nodes/buses meet specific reliability standards

+ Production Cost

- Production Cost models are used for market congestion studies, assessment of bulk system impacts under broad federal or state policy changes, and to measure the economic benefits of potential transmission upgrade options
- These models leverage a simplified representation of the transmission network (DC power flow) which is informed by the system topology developed in the **Power Flow** (AC) modeling
- Computational requirements of the DC optimized power flow modeling is much lower than the AC Power Flow models allowing for a chronological (8,760 hour) evaluation of the bulk system across many years; snapshots from the Production Cost modeling can be used to identify periods of high congestion which can be further evaluated for reliability within the **Power Flow** modeling framework

+ Capacity Expansion

- Capacity Expansion models are used to identify future resource portfolios, and evaluate all possible combinations of both existing and new resources to reach an optimal, least-cost plan
- They can be used to examine least-cost portfolios under a range of load forecasts, fuel prices and renewable penetration, among other variables
- Future portfolios can then be assessed in both a **Power Flow** model to ensure the transmission system can reliably support new generators and in a **Production Cost** model to assess the impacts of new generators on system dispatch and congestion

Key Sources of Uncertainty in Transmission Planning Processes

	Modeling Framework		
Category of Uncertainty	**Power Flow**	**Production Cost**	**Capacity Expansion**
Outage and Contingency			
Generation Outages	✓	✓	Outage and contingency assessment is related to capacity expansion modelling, but typically addressed in Resource Adequacy assessments
Outage Events & Failure Rates	✓	✓	
Weather Related Variability			
Peak Demand	✓	✓	Weather variability and its impact on load and renewable generation is related to capacity expansion modelling, but typically addressed through ELCCs and Resource Adequacy assessments
Renewable Output	✓	✓	
Extreme Weather Events	✓	✓	
Future Climate Change		✓	✓
Future Uncertainty			
Economic and Policy Drivers for Demand	✓	✓	✓
Future Clean Energy/Emissions Policy		✓	✓
Fuel Prices		✓	✓
Locations of Future Resources	✓	✓	✓
Resource Costs		✓	✓

Sources of uncertainty across models include categories currently being captured in industry “best practices” as well as future applications with opportunities for probabilistic or deterministic assessment

Industry Practice in Planning for Uncertainty

- **In addition to the literature review, E3 conducted interviews with system planners (ISOs/RTOs and utilities) across the country as well as academics and industry practitioners, and jointly hosted a 2-day symposium with MISO to discuss these topics**
- **Deterministic methods coupled with scenario planning broadly remains the industry standard for addressing uncertainty in transmission planning; however, many transmission planners see value in adopting probabilistic methods to address uncertainty**
  - The overarching theme from our discussions indicated that widespread adoption of probabilistic methods for transmission planning remains in its infancy
  - Many ISO/RTOs have explored some degree of probabilistic applications to increase the robustness of their planning processes, however adoption to date remains narrowly focused on certain key applications
  - Most planners identified refinement of inputs in their models using probabilistic methods as a possible first step in adoption
- **Many describe similar challenges to implementation; common themes that are limiting the transition from deterministic to probabilistic approaches include:**
  - Data, computational and infrastructure requirements
  - Workforce limitations and time constraints
  - Existing lengthy planning processes leave little room for additional analysis
  - Stakeholder and regulator acceptance
  - Lack of commercially available tools (many tools are research based or custom developed)
  - Internal advocacy for adoption of new methods is limited and would be required for any major shift

Linkages between Modeling Frameworks

- In addition to examining methods to address key sources of uncertainty within an individual modeling framework, this assessment also identifies ways in which advanced analytical techniques can enhance the coordination between modeling frameworks
- For example, a production cost model examines system dispatch over all hours of the year; the outputs of a production cost model may be used in an iterative process to identify the "snapshots" that warrant further examination of transmission system reliability in a power flow model (e.g., C-PAGE method documented in Chronological AC Power Flow Automated Generation)
- There are many other opportunities to capture linkages between models that are beyond the scope of this work; key examples include but are not limited to:
  - **Representation of chronological system dispatch within capacity expansion** | While production cost models capture chronological system dispatch over an entire year, many capacity expansion modeling frameworks examine system dispatch over representative or "sample" days intended to capture different seasonal conditions over the course of a year. By doing so, the investment decisions in a capacity expansion model are better able to capture operational considerations such as ensuring sufficient flexibility exists to integrate variable renewable energy.
  - **Co-optimized generation and transmission planning** | Information from nodal production cost modeling and/or power flow models can be used to identify key transmission constraints that may impact the selection and placement of generation; capacity expansion frameworks can incorporate the costs of transmission upgrades such that generation and transmission investments are co-optimized.
  - **Generator placement for future resource portfolios |** Capacity expansion modeling is typically conducted at a zonal or regional level; these resource portfolios need to be mapped to specific locations on the transmission system when performing power flow modeling or nodal production cost modeling. Information about the Interconnection Queue, headroom on transmission elements, siting and permitting constraints, and other factors can be used to "intelligently" site generators at specific locations.
- There are inherent tradeoffs with integrating additional complexity to capture linkages between modeling frameworks; balancing these tradeoffs and capturing the most critical interactions to ensure a cost-effective and reliable system are the subject of Integrated System Planning

For more discussion of opportunities for Integrated System Planning, see E3's 2024 white paper: Integrated System Planning: Holistic Planning for the Energy Transition

Study Recommendations

Study Recommendations

Methods to Address Uncertainty in Planning Processes

High Value Applications of Probabilistic Methods:

1. **Enhance the Linkages Between Power Flow and Production Cost Models**
   - Reduce manual intervention and/or computational intensity required to iterate between Production Cost and Power Flow analyses
   - Improve methods used to identify the hours that represent challenging conditions for transmission system reliability and grid stability
   - Develop an enhanced modeling approach where a smaller subset of snapshots, representative of challenging system conditions, are identified in the DC PCM run and further evaluated in a full AC power flow model run
2. **Pre-Process Inputs Using Probabilistic Methods to Characterize Uncertainty**
   - The transition to full adoption of probabilistic methods will likely be a gradual one, so an intermediate step in adoption would be to use probabilistic methods to shape modeling inputs to capture a greater range of uncertainty
   - A wide range of statistical methods are available to quantify the variability of load, outages and generation in response to weather conditions. Weather year and temperature data is correlated and used across all weather-dependent technology and load models
   - Sampling techniques may also be leveraged to allow system planners to develop "average" system conditions as well as low probability, high impact conditions
3. **Adopt Enhanced Methods for Assessing the Economic Cost of Uncertainty**
   - Implement methods that evaluate the tradeoff between incremental investment cost of transmission (for a higher degree of reliability) and the societal cost of interruption
   - Assess societal costs for transmission projects using a Probabilistic Reliability Assessment (PRA) and interruption cost metrics such as VOLL
   - Metrics such as reliability indices (change in EUE divided by capital cost) or Benefit/Cost ratios provide quantitative calculations for assessing the economic benefit from reduced losses and/or unserved energy
4. **Adopt Stochastic Scenario Evaluation and Risk Assessment**
   - This class of methods accounts for uncertainty by considering a range of possible futures and their associated probability of occurring, as opposed to a single Scenario.
   - Can be used to quantify the distributions of total system costs for each future, or conditional probabilities can be assigned to each future to determine of the likelihood of each combination of outcomes
   - Additionally, out of model risk management methodologies can be used to improve long-term planning practices and outcomes. Performance measures (probabilistic, hybrid or qualitative) are used to evaluate the effectiveness of decision options, and a vulnerability assessment is performed to identify uncertainties that pose the highest risk. These methods are designed to be continuously updated over long-time horizons in response to new information and uses signposts to establish thresholds for monitored variables that trigger re-evaluation.

Applicability of Recommendations

Legend
- Enhanced Linkages between Modelling Frameworks
- Economic Cost of Uncertainty
- Pre-Processing Using Statistical Methods
- Stochastic Scenario Evaluation

	Modeling Framework		
Category of Uncertainty	**Power Flow**	**Production Cost**	**Capacity Expansion**
Outage and Contingency			
Generation Outages			Outage and contingency assessment is related to capacity expansion modelling, but typically addressed in Resource Adequacy assessments
Outage Events & Failure Rates			
Weather Related Variability			
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Renewable Output			
Extreme Weather Events			
Future Climate Change			
Future Uncertainty			
Economic and Policy Drivers for Demand			
Future Clean Energy/Emissions Policy			
Fuel Prices			
Locations of Future Resources			
Resource Costs			

Sources of uncertainty across models include categories currently being captured in industry "best practices" as well as future applications with opportunities for probabilistic or deterministic assessment

Study Recommendation

Enhance the Linkages Between Power Flow and Production Cost Models

E3 recommends enhancing linkages between Power Flow and Production Cost frameworks

+ **The approach links transmission reliability assessments with production cost (PCM) studies, enabling planners to identify high-stress operating periods from PCM results and develop power flow cases that reflect those operating conditions. The goal is to improve the robustness of the down selecting process for creating power flow cases that are representative of stressed operating conditions**
  - In practice, transmission planning is still multi-step and not coordinated across frameworks. Improved coordination can be realized using production cost model outputs in an iterative process, to identify the "snapshots" that warrant further examination in a power flow model.
  - Test cases have been successful on small systems including NYISO, ISO-NE and TVA; however, some degree of manual intervention was typically required when the model has difficulty solving
+ **Reduced computational requirements of production cost relative to power flow can provide several benefits for snapshot identification:**
  - Evaluation of system conditions at an hourly granularity across many years
  - Most production cost models have the capability to incorporate Monte Carlo or other probabilistic approaches to randomly selecting weather and outage & contingency patterns
  - Millions of potential system states can be created for further evaluation with reduced user intervention
  - Planners may identify and zoom into challenging periods in production post and run those probabilistically across several hours using Power Flow
+ **Creating linkages between the models enables a more dynamic approach to power flow modeling, and streamlines the data processing**
  - Linkages can include automated methods to hand data back and forth between the PCM and PFM using Application Programming Interfaces (APIs), custom automation tools using Python (or other languages) and modification of PFM input files. Some embedded PCM/PFM models also exist such as encoord's SAInt.
+ **Examples of case studies and methods implementing these linkages include:**
  - ***Electric Power Research Institute TVA SERVM + TransCARE Linkage Study:*** Assessed generation adequacy and transmission component failures using Monte Carlo simulations. Users were able to test any number of snapshots based on user-defined criteria and considered a wide range of weather and loads
  - ***Department of Energy PLEXOS-TARA Coupling*** to assess impacts of grid enhancing technologies (GETs). The linkage allowed PLEXOS to monitor as many high-voltage transmission flowgates as possible while allowing TARA to fill in the gaps at lower voltages in the study area. Round-trip modeling was necessary because the new flowgates identified will shift the dispatch in PLEXOS and potentially reveal new important flowgates
  - ***PNNL's C-PAGE Tool*** is used to convert system dispatch from a production cost model into time-sequenced power flow runs. Allows for the convergence of production cost models with power flow cases to improve power flow modeling practices. Can significantly reduce runtime and allow system planners to assess the solutions of thousands of chronological power flow cases

Study Recommendation

Pre-Process Inputs Using Probabilistic Methods to Characterize Uncertainty

E3 recommends pre-processing inputs using probabilistic methods to characterize uncertainty

+ **The transition to full adoption of probabilistic methods will likely be a gradual one, so an intermediate step in adoption would be to use probabilistic methods to shape modeling inputs to capture a greater range of uncertainty**
  - A wide range of statistical methods are available to quantify the variability of load, outages and generation in response to weather conditions. Weather year and temperature data is correlated and used across all weather-dependent technology and load models

+ **Examples of case studies and methods used to pre-process inputs using probabilistic methods include:**
  - ***Stratified Sampling*** is an approach to probabilistically develop dispatch scenarios which capture uncertainty in weather-correlated renewable generation output and economic load growth, as well as generation & transmission component performance. The input data was divided into sub-populations or "strata" which were assumed to be homogeneous (i.e., similar system conditions). Multiple strata ensured that scenarios which have a low probability of occurrence won't get lost in the "average" scenarios which occur more frequently on the system. Monte Carlo sampling was then used to define the number of dispatch scenarios in each strata. This approach allowed system planners to capture average scenarios as well as low probability, high impact scenarios.
  - ***Slicing and Latin-Hypercube Sampling*** is an approach uses an intelligent sampling method to find a small number of hourly cases representative of a full calendar year to account for seasonal and diurnal variability of renewable generation. This method uses a joint cumulative distribution functions to down sample to reduce the problem size and derive the appropriate scenarios which are representative of variability in the specified input variable (generation, load, etc.) across an entire year. This approach was used in used in by PNNL the C-PAGE case study to reduce the problem size of the power flow scenarios and ensure that the appropriate level of variability was captured. Stratified Sampling is an extension/application of Latin-Hypercube Sampling.
  - ***K-Means Clustering*** is a machine learning algorithm used to classify data points into k clusters based on their similarities. The algorithm iteratively assigns data points to the nearest cluster center, using a mathematical distance measure, with the objective of minimizing the sum of distances between data points and the assigned cluster. This algorithm is well suited to applications in weather pattern analysis (heatwaves, cold, high/low wind), extreme event detection (storms), categorizing renewable generation patterns (diurnal solar cycles, seasonal wind generation) and as a pre-processing data classification step in forecasting. The ERCOT PRA case study used Monte Carlo sampling with K-means clustering, selecting eight clusters using the Elbow method (indicates ideal number of clusters).
  - ***Stochastic Load and Renewable Generation*** refers to a wide range of methods used to quantify the variability of load and resource production in response to weather conditions. Approaches use fundamental statistics-based correlation methods such as regressions or moving averages, however Monte Carlo is the most common and well-established. Historical data is used to develop generation or load profiles as a function of probability of occurrence and can also be used to quantify expected generation during expected events or over a long-term average.

Study Recommendation

Adopt Enhanced Methods for Assessing the Economic Cost of Uncertainty

E3 recommends adoption of metrics and methods which balance the Value of Lost Load (VOLL) against the incremental cost of investment

+ **The approach uses methods that evaluate the tradeoff between incremental investment cost of transmission (for a higher degree of reliability) and the cost of interruption**
  - Additional metrics such as reliability indices (Δ EUE / capital cost) or Benefit/Cost ratios provide quantitative calculations for assessing the economic benefit from reduced losses and/or unserved energy. These methods assess societal costs for transmission projects using probabilistic (or well defined deterministic) reliability assessment and interruption cost metrics such as Value of Lost Load (VOLL), Expected Energy Not Served (EENS), among others.
  - These additional methods capture a greater range of uncertainty and assign specific, and measurable economic criteria which can be directly compared to the cost of alternative investments
+ **Economic criteria and thresholds must be well defined to ensure the appropriate benefits and risks are captured**
  - Diversity of geography may present challenges when defining a single unitized value for VOLL or EENS. Planners must consider the values attributed to each region – example, a higher value in areas with critical loads
  - Expected value vs. tail or downside risk is also worth considering. As an example, what scenario is worse for the system? 1x $100bn event or 100 x $1bn events? Expected value may be the same, but the impacts and risks may differ
  - Planners should look at specific consequences and impacts of events – there will be areas that need to meet a higher level of performance because the system can't withstand the consequences
+ **Examples of case studies and methods implementing the Economic Cost of Uncertainty:**
  - ***GARPUR RMAC Norway*** study compared two transmission alternatives in Southwest Norway. Assessed societal costs (using energy not served) for each alternative using probabilistic reliability assessment and interruption cost metrics. Higher security of supply did not defend higher investment costs. The lower cost alternative reduced investment costs by 25% (€110mm), while expected interruption costs increased by €5mm. Strict compliance in N-1 resulted in earlier investments in infrastructure, and probabilistic methods indicated investment could be deferred .
  - ***ERCOT Probabilistic Reliability Assessment (PRA)*** case study evaluated three fictional transmission investments using both production cost and power flow analysis. Conducted an 8,760-hour production cost simulation using 4 weather patterns to generate >35k scenarios. 8 clusters were selected (8 base cases) and reliability assessments in power flow were performed for 342 extreme events. A reliability index was calculated to enable comparison across scenarios measured change in Expected Unserved Energy as a function of capital cost. The study was effective in identifying which project provided the greatest reliability enhancement per million dollars invested, while incorporating weather uncertainty.
  - ***BC Hydro Vancouver Island Transmission Reinforcement.*** Study objective was to measure the reliability improvement and transmission loss reduction of several investment alternatives. EENS and peak transmission losses were calculated for hourly for a 10-year period, and unitized interruption and transmission loss costs were assigned. Estimated project cost for each alternative was compared to the incremental economic improvement EENS and losses to select the best alternative.

Study Recommendation

Adopt Stochastic Scenario Evaluation and Risk Assessment

E3 recommends enhancing the industry-standard approach to scenario evaluation in long-range planning using stochastic or out-of-model risk methodologies

+ **Scenario planning broadly remains the industry standard for addressing long-term uncertainty in transmission planning**
  - E3 received consistent feedback across all interviewed industry participants that suggested scenario analysis will remain the foundational tool for addressing long-term uncertainty.
  - Industry practice involves modeling or evaluating boundary conditions, allowing planners to assume that all potential outcomes within these limits are accounted for. While this demonstrates the effectiveness of scenario planning, there are opportunities to improve the process by helping planners more efficiently identify their 'Base Case' and credible 'Edge Cases'.
  - Evaluating additional scenarios helps planners build confidence when similar outcomes are observed. However, it becomes difficult to justify the manpower, time, and processes needed for full utilization or exploration. All interviewed jurisdictions highlighted the challenges related to the computational demands and the time required from planning teams to run each scenario.
+ **E3 recommends enhancing, rather than replacing existing processes using stochastic evaluation methods and/or out-of-model risk assessments. Methods to improve scenario selection, increase comparability across scenarios, as well as the adoption of thresholds to trigger the re-evaluation scenarios all represent opportunities to enhance planning approaches.**
  - ***Down Selection of Scenarios.*** Several methods exist to help system planners identify credible edge cases which ensures that the most appropriate range of uncertainty is captured without the computational and staffing demands required for running every scenario. These methods leverage statistical or probabilistic approaches to describing the range of uncertainty across key input variables to help system planners understand boundaries and select an optimized portfolio of scenarios.
  - ***Stochastic Portfolio Risk Evaluation*** is considered a widely accessible method that requires limited effort, model and data requirements, yet it can substantially improve the robustness of portfolio planning. This class of methods accounts for uncertainty by considering a range of possible futures and their associated probability of occurring, as opposed to a single Scenario. The approach is unique because it can be used to quantify the distributions of total system costs for each future or conditional probabilities can be assigned to each future to determine the likelihood of each combination of outcomes. Results interpretation and visualization (such as the range of impact across scenarios for each input variable) is a key step to inform decision-making that is often under-performed. The 2019 TVA IRP offers an example of a visualization that clearly shows the impact of each input variable across scenarios.
  - ***Out-of-Model Risk Assessment*** can be used to improve long-term planning practices and outcomes through vulnerability assessment to identify which uncertainties pose the greatest risk. Performance measures (probabilistic, hybrid or qualitative) are used evaluate the effectiveness of decision options and a vulnerability assessment is performed to identify uncertainties that pose the highest risk. These methods are designed to be continuously updated over long-time horizons in response to new information and uses signposts to establish thresholds for monitored variables that trigger re-evaluation.
+ **Examples of case studies and methods used for stochastic scenario evaluation and risk assessment include:**
  - ***Stratified Sampling*** and ***Slicing & Latin Hypercube Sampling*** (both discussed on previous slide) represent methods to assist planners in understanding the distributions of outcomes and ensuring that the edge cases represent credible boundary conditions. Down sampling is not limited to these methods, many statistical approaches can be used to understand the width of the distribution and reduce the number of scenarios requiring evaluation.
  - ***Stochastic Portfolio Risk Evaluation*** accounts for uncertainty by considering a range of possible futures and their associated probability of occurring, as opposed to a single Scenario. Monte Carlo analysis and Probability Trees are a common framework. The approach allows planners to quantify the distributions of total system costs and environmental outcomes. Idaho Power, CEI South, Pacificorp, TVA and AES Indiana have all implemented a variation of this framework in their long-term planning processes.
  - ***Robust and Adaptive Planning*** is an uncertainty and risks management methodology employed **out-of-model** to improve long-term planning. Involves a vulnerability assessment to identify uncertainties that pose the highest risk and a monitoring plan to identify new information regarding key uncertainties. Signposts establish thresholds for monitored variables which trigger re-evaluation. A probabilistic extension of this framework uses sequential Monte Carlo analysis to extend the sampling strategies. ConEdison's 2021 Climate Resiliency Plan leveraged this approach.

Technical Review of Methods to Address Uncertainty

Technical Review

Power Flow Modeling

Energy+Environmental Economics

Power Flow Modeling

Common Approaches to Addressing Uncertainty Across Industry

+ Contingency & Outages

- The bare minimum planning requirement across NERC members requires study of impacts across P0 through P7 planning events (normal system operations, single contingency and multiple contingency conditions) defined in the TPL-001-5 transmission system planning performance requirements.
- The common approach in industry to plan for outages and contingencies includes detailed power system studies, using models which are designed to align with system topology at a high degree of accuracy. Complex evaluations of AC power flows across bulk electric system elements are assessed, and typically also include tie lines to neighboring systems.
- Lines are screened for line loading across emergency, normal, and safe loading limits, and where applicable, voltages are screened against emergency and normal limits which allows planners to identify of critical contingencies based on risk thresholds. All screening is aimed at minimizing disruption and maintaining grid stability during unexpected transmission line failures.
- Transmission value is concentrated in only a few challenging hours, so system planners also evaluate scenarios which can be characterized as high-value periods that are dominated by transmission congestion. Historically, summer or winter peaks have been prioritized by system planners, however increasing renewable penetration and weather uncertainty is leading to increased focus on additional non-peak scenarios.
  - Examples of additional scenarios evaluated could include summer twilight (solar roll-off), extended periods of low wind generation (dunkelflaute), reverse transmission flows (import vs. export) and periods of extremely high renewable output (curtailment requirements).

+ Weather Related Variability

- There is considerable overlap between the contingency scenarios discussed above and the inherent weather-related variability which led to periods of challenging conditions. Planners evaluate the impacts of high and low renewable output, system characteristics under extreme weather conditions such as major storms, or periods of high demand due to heat waves and cold snaps.
- Power Flow modelling is extremely complex and computationally expensive, so system planners will evaluate snapshot hours (scenarios) which may be representative of challenging system conditions that are likely to be faced across a distribution of weather years. The problem system planners face is correctly identifying the hours which truly represent worst-case conditions that challenge grid stability.
- Production Cost Modeling using DC power flows is much less computationally expensive, yet it relies on system topology developed for the Power Flow model. The degree of system component details is much lower in PCM compared to PFM, but the lower complexity allows the evaluation of entire weather years. The identification of hours representative of high system stress in PCM followed by evaluation in PFM is becoming an increasingly common practice among system planners. This “feedback loop” across models allows planners greater accuracy in capturing high-stress periods across the broad distribution of weather variability.

Addressing Uncertainty within Power Flow

Outage and Contingency Risk

		Power Flow			
Source of Uncertainty	**Details**	**NERC TPL Standard**	**Monte Carlo**	**Contingency Enumeration**	**Dynamic Contingency Selection**
Outage and Contingency					
Outage Events & Failure Rates	**Technique**	**Deterministic**	**Probabilistic**	**Probabilistic**	**Probabilistic**
	Overview of Method	Evaluation of loss of largest source under multiple system conditions, Also called N-1-1 multiple contingency analysis, and evaluates a transmission network's reliability after sequential disruptions occur.	Method based on simulating many random trials of system conditions, tabulating the results and interpreting the results as probabilities of the various events and outcomes. Each trial simulates a potential system state with a combination of operational or failed components.	Moving deeper into second order contingencies to check for cascading failures. A method that enumerates (iterates through) system contingencies based on their potential impact on system stability and ranks each contingency in terms of severity using a performance index	Leverages Bayesian updating scheme to adjust failure rates by incorporating new data over time, refining predictions based on past performance and observed conditions. Combines historical failure data with recent factors (component age, weather impact, and operational stress) to improve accuracy in failure predictions
	Workflow	Involves running power flow model for a contingency or set of key contingencies; Evaluation of P1 through P7 contingencies in addition to Extreme Event Scenarios	Involves running power flow model over many different outage conditions. Each random trial represents a different system state, and each component has its own probabilistic model.	Reduces the scope to the most critical contingencies. Analyzes the most severe N-1 contingencies and proceeds until no significant reliability issues are identified. Severity is measured using reliability indices.	A discarding method that allows operators to eliminate less critical contingencies using a user-defined residual risk threshold. Can be combined with economic assessment for the tradeoff between VOLL and cost of investment
	Models Used	PSS/E, TARA, many commercially available tools	NH2 (Brazil), MECORE (BC Hydro). Some custom application in EPRI TransCARE, PSS/E,	Key contingency selection approach in TransCARE and PSS/E	Custom ML algorithms
	Data Needs	System topology, load forecasts, known outages	Historical failure rates, component data (system topology)	Historical failure rates, component data	Load, weather, and generation and historical failure probabilities
	Existing Case Studies or Applications	NERC Planning Standard Well documented, common practice	Limited availability outside of research and research grade tools due to the massive computational complexities for solving a full system	Functionality built into existing models	Most application limited to short-term. GARPUR RMAC Norway study explores long-term. No commercial tools exist

Outage and Contingency Risk

Monte Carlo (and Markov Chain)

Method Overview:

+ **Monte Carlo** simulation is based on simulating many random trials of system conditions, tabulating the results and interpreting the results as probabilities of the various events and outcomes involved.
  - Each trial represents a different system state, determined by randomly extracting an outcome for the component reliability models of the system (i.e., it is assumed that each component is characterized by a probabilistic model).
  - Contingency selection involves randomly selecting outages for system components based on predefined probability distributions. Distributions may be defined using failure rates and repair times from historical data.
  - The results of numerous trials are used to estimate the likelihood of system failures and other reliability metrics. The number of trials is independent of system size; however, most practical applications range from 1,000-10,000 iterations[1], before remedial actions.
+ **Markov Chain Monte Carlo** simulations generate dependent samples from a desired distribution, rather than independent observations (random trials) leveraged in typical Monte Carlo simulations. Markov models can be more computationally efficient for large-scale power systems, however on a large-scale power system the calculations still may be too large to consider.

Inputs:

+ Component reliability data such as failure rates, time-to-repair, and system load forecasts.
+ Historical data from sources like NERC's GADS and TADS databases to model failure probabilities.

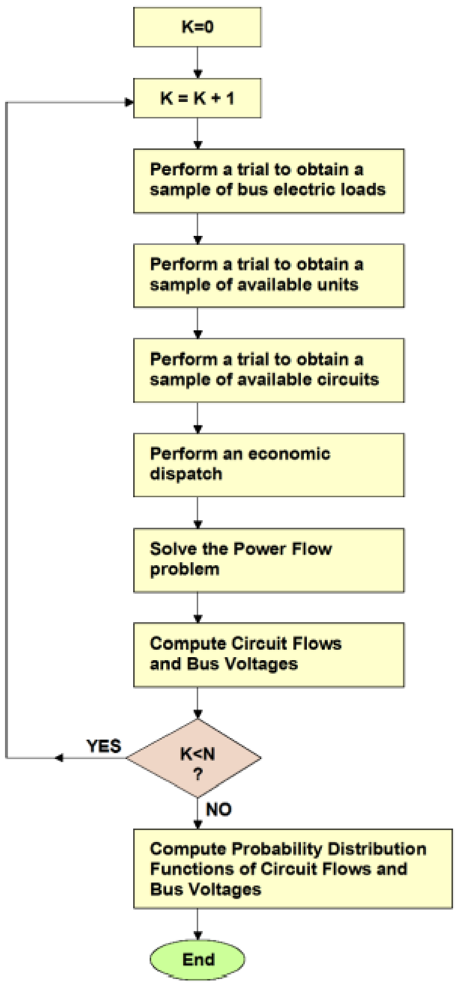
Tools Used:

+ Limited availability outside of research grade tools, but some functionality built some Power Flow tools such as EPRI TransCARE, PSS/E, however these primarily rely on contingency enumeration. NH2 (CEPEL Brazil) and MECORE (BC Hydro) offer functionality but are not commercially available or have not been used in the US.

Key Takeaways:

+ **Computational Issues:** Typical Monte Carlo analysis requires 1,000-10,000 iterations for most practical applications. In Markov Chain analysis, a system with n components, each with 2 states (up or down) will result in a total of 2^n states. For example, if n = 2000, then the number of states ($\sim 1.148 \times 10^{602}$) may be too large to consider. This is further complicated when remedial actions are evaluated
+ **Modeling Challenges:** It is challenging to model failure/repair processes associated with generators and transmission, as well as system load variations over time, effects of weather on failure/repair processes, and remedial actions
+ **Tool Availability:** Commercially available tools primarily rely on contingency enumeration. Custom code or research grade tools have been used to assess MC applications for contingency assessment

Monte Carlo Flow Chart



Source: *EISPC White Paper: Incorporation of Risk Analysis into Planning Processes*
1 – *Monte Carlo Simulations in Load Flow Calculations*

Outage and Contingency Risk

Contingency Enumeration

Method Overview:

- **Contingency Enumeration is** a method that enumerates system contingencies based on their potential impact on system stability and ranks each contingency in terms of severity using a performance index
  - Contingencies are selected based on the N-k criterion (N-1, N-2), where "k" represents the number of simultaneous failures
  - The Process begins by analyzing the most severe N-1 contingencies and proceeds until no significant reliability issues are identified
  - Severity is measured using reliability indices such as overload violations, voltage violations, loss of load, and expected unserved energy (EUE)

Inputs:

- Historical failure rates (NERC's GADS and TADS) & Component data (voltage ratings, thermal limits, and protection settings)

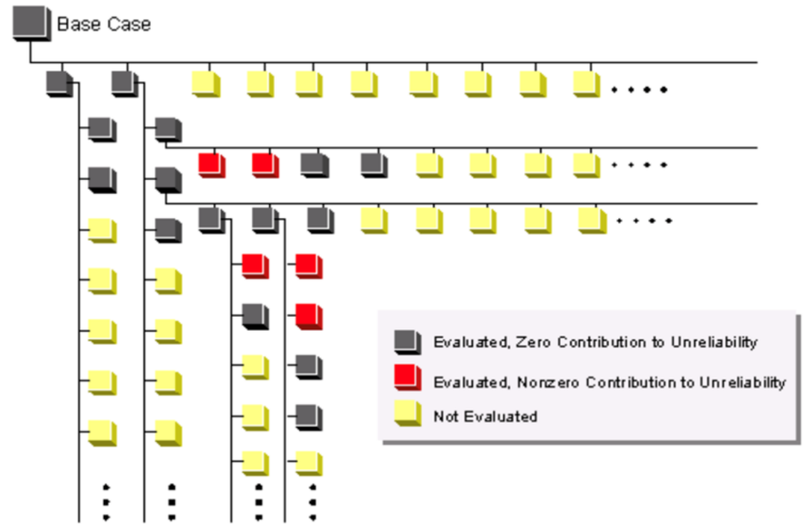
Tools Used:

- EPRIs TransCARE and Siemens PSS/E use contingency enumeration as an embedded contingency selection method.
- Post-processing tools (e.g., python or MATLAB-based) are often applied to automate contingency list generation, analyze protection and event data, perform critical event analysis, summarize simulations, and rank contingencies based on security metrics like load loss and cascade frequency

Key Takeaways:

- Effective for identifying critical outages that can be overlooked in deterministic methods. Computationally expensive for large systems, especially at higher N-k levels.
- May overlook rare, events with severe impacts. Focuses mainly on most-likely events based on predefined criteria

EPRI Wind-chime Contingency Enumeration Scheme



Wind-chime Enumeration[1] begins with a "Base Case" and all first-level contingencies are enumerated and ranked in decreasing order of severity. Second outage-level contingencies are obtained from each contingency in level one by having one more component on outage and then ranked in the same way.

The procedure continues until it reaches the predefined contingency depth level . In each outage level, the reliability evaluation starts from the highest ranked contingencies in terms of severity.

If the evaluation results of several successive contingencies show zero contribution to system unreliability, it is reasonable to conclude that the remaining contingencies in this level do not need to be investigated since they are considered to affect system reliability less severely.

Source: *EISPC White Paper: Incorporation of Risk Analysis into Planning Processes*

1- *A Comprehensive Approach for Bulk Power System Reliability Assessment*

Outage and Contingency Risk

Case Study: TVA Reliability Study

The study focused on assessing whether adding two new transmission lines (AEP 765 kV and AECI 500 kV) would improve the reliability of the TVA bulk transmission system

Approach:

+ Built-in functionality of contingency enumeration in TransCARE was used to generate a set of N-1 and N-2 contingencies, evaluating both single and double outages of transmission lines, transformers and generating units
+ Outage probabilities were informed by historical data from NERC's GADS and TADS, which provided failure rates and restoration times for the relevant components.
+ The tool systematically tested these contingencies across the study area's high-voltage network (161 kV and above), focusing on two specific zones affected by the proposed tie-lines.

Key Outcomes:

+ ***System Problem Approach:*** Evaluated specific system issues like voltage violations and overload frequency at individual circuits and buses.
+ ***Capability Approach:*** Measured overall system reliability, including probability of load loss and Expected Unserved Energy (EUE)
+ The analysis showed no significant reliability improvement from adding either of the proposed tie-lines

Number of Contingencies analyzed

Sr. No.	Study Case	Number of Contingencies
1	Base case-No tie lines	169,770
2	With765 KV Rockport-Paradise tie case	189,636
3	With 500 KV Lagoon Creek tie case	240,337

Sample Results from the Capability Approach

Index	Base Case	With the 500KV Tie	With the 765KV Tie
PROBABILITY OF LOAD LOSS -	0.01	0.01	0.01
FREQUENCY OF LOAD LOSS - (OCC/YEAR)	9.34	9.34	9.33
DURATION OF LOAD LOSS - (HRS/YEAR)	91.63	91.65	91.62
DURATION OF LOAD LOSS - (HRS/OCC)	9.81	9.81	9.82
EXPECTED UNSERVED ENERGY - (MWH/YEAR)	2423.54	2423.75	2423.34
EXPECTED UNSERVED ENERGY-(MWH/OCC)	259.18	259.17	259.26
EXPECTED UNSERVED DEMAND - (MW/YEAR)	249.85	249.86	249.78
EXPECTED UNSERVED DEMAND-(MW/OCC)	26.72	26.72	26.72
ENERGY CURTAILMENT-(MWH/ANNUALMWH)	5.2E-07	5.2E-07	5.2E-07
POWER INTERRUPTION - (MW/PEAK MW)	0.0005	0.0005	0.0005
CONTINGENCIES CAUSING LOAD LOSS:	1391	2258	1408

Outage and Contingency Risk

GARPUR RMAC Dynamic Contingency Selection (DCS)

Method Overview:

- The ***Generally Accepted Reliability Principle with Uncertainty Modeling*** (GARPUR) ***Reliability Management Approach and Criterion*** (RMAC) framework applies probabilistic risk assessment to identify and rank transmission contingencies from real-time to long-term planning. Each timeframe employs custom methods to manage risk based on system conditions.
  - Initial applications have been for **Real-Time** (operational risk assessment) using Dynamic Contingency Selection (DCS) and a Discarding Principle to prioritize high-risk contingencies based on live conditions.
  - **Long-Term** applications have been studied to compare grid expansion alternatives to ensure high security of supply in South-West Norway over a 40-year horizon
  - Similar methods could potentially be employed to identify high-impact contingencies and/or congested elements as part of the flowgate identification process.
- The Long-Term (planning scale) application of the framework utilizes macro scenarios and Monte Carlo simulations to model demand and production variability for zonal-to-nodal contingency analysis.
- The fundamental approach to the Long-Term application of the RMAC method was combining a ***probabilistic reliability assessment*** with an ***economic assessment*** of performance which was measured through interruption cost
  - **Reliability Assessment:** Custom tools were used for system response simulation and failure rates, which were adjusted with a Bayesian[1] updating scheme
  - **Economic Assessment:** A framework was used to calculate the societal cost of unserved energy. Long-term load flow scenarios using forecasted load-duration curves allow for the estimation of interruption cost metrics

Inputs and Tools:

- Significant Historical data collection is required and planning scenarios, including seasonal load profiles and outage schedules, as well as macro-level zonal scenarios with aggregated demand and supply data.
- GARPUR RMAC framework uses custom built tools and generated algorithms

Key Takeaways:

- **Effectively identifies high-risk contingencies and dynamically reduces unnecessary calculations**. ML models enhance real-time flexibility, with DCS primarily optimized for real-time, but adaptable for mid- and long-term planning.
- **Strict compliance to N-1 increases costs** Incremental investment cost for a higher degree of reliability may exceed the societal cost of interruption
- **No commercial tools are available** Tools need to be developed by experts who both understand the subject matter, approach and requisite programming skills
- **Current Real-time applications are limiting**. DCS method could be applied to bridge the gap between operational and long-term planning

Source: The GARPUR Project Results ; GARPUR – Results From Near Real-Life Pilot Testing

1 – Bayesian Updating Scheme

Outage and Contingency Risk

GARPUR RMAC DCS: Realtime Analysis

Method Overview:

+ The GARPUR RMAC framework applies probabilistic risk assessment to identify and rank transmission contingencies across real-time, mid-term, and long-term planning. Each timeframe employs tailored methods to manage risk based on system conditions.
  - **Real-Time:** Uses Dynamic Contingency Selection (DCS) and a Discarding Principle to prioritize high-risk contingencies based on live conditions.
  - **Mid-Term:** Employs parallel simulations and stochastic optimization to plan outage schedules over months.
  - **Long-Term:** Utilizes macro scenarios and Monte Carlo simulations to model demand and production variability for zonal-to-nodal contingency analysis.

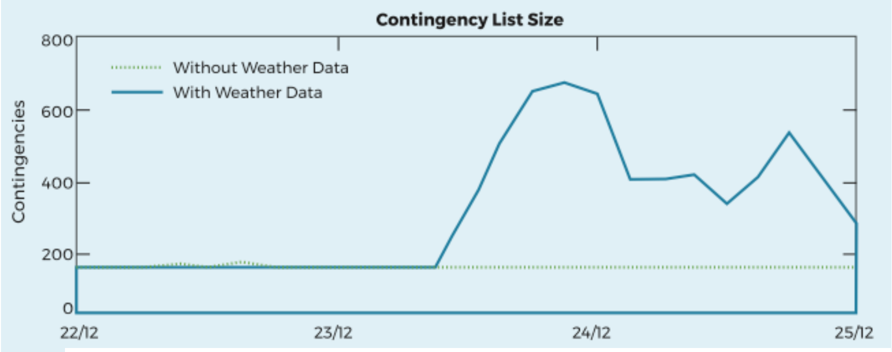
Inputs and Tools:

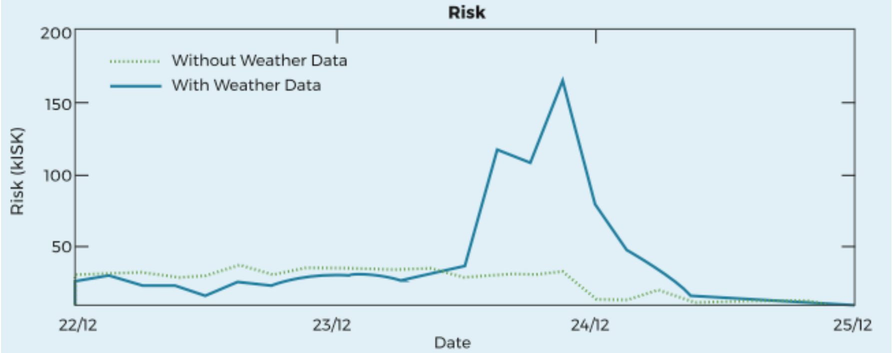
+ Inputs vary depending on horizon being evaluated, however real-time leverages current operational data, including weather conditions, load levels, and generation availability.
+ Mid-Term and Long-Term focus on historical data and planning scenarios, including seasonal load profiles and outage schedules, as well as macro-level zonal scenarios with aggregated demand and supply data.
+ Across all scenarios, the GARPUR RMAC framework uses custom built tools and generated algorithms

Key Takeaways:

+ **Effectively identifies high-risk contingencies and dynamically reduces unnecessary calculations**. ML models enhance real-time flexibility, with DCS primarily optimized for real-time, but adaptable for mid- and long-term planning.
+ **Current Real-time operational applications are limiting**. DCS method could be applied to bridge the gap between operational and long-term planning

RMAC Method: Dynamic Contingency Selection





Outage and Contingency Risk

Case Study: GARPUR RMAC Iceland (Short-Term)

The Icelandic power system served as a proof of concept for the EU RMAC real-time reliability assessment framework

Approach:

+ The study assessed if real-time Dynamic Contingency Selection could improve reliability by dynamically adjusting contingency lists to prioritize high-risk N-1 contingencies in response to changing conditions.

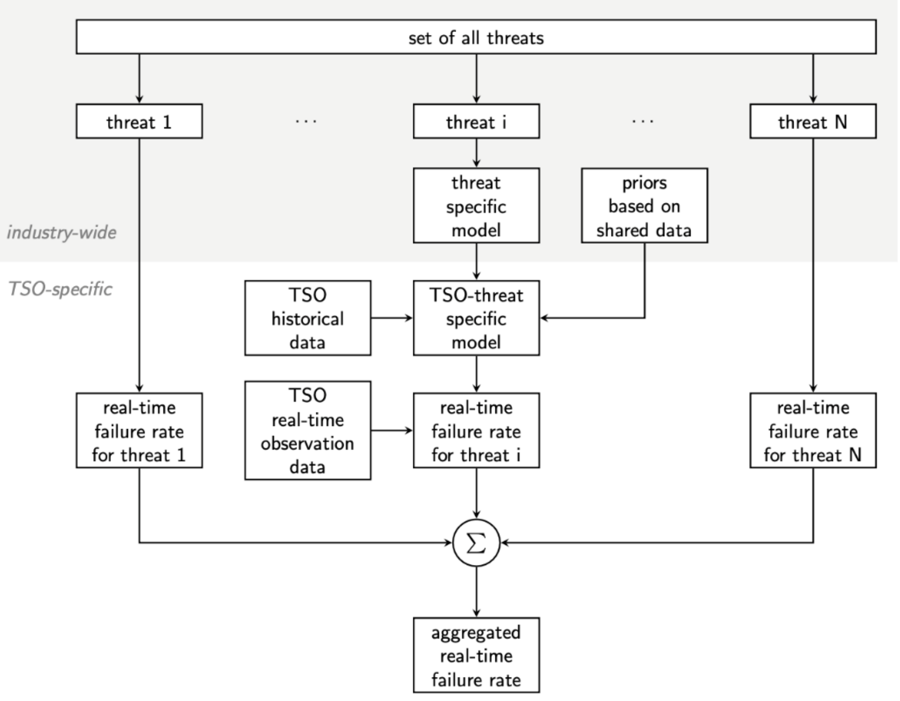
+ Threat-based dynamic models were selected to calculate contingency failure rates. These models differ from other (i.e., state-based) models as they focus on a specific threat such as wind, lightning, earthquake etc. Different threats then can be aggregated to a single failure rate metric in real-time.
    - Failure rate models were built using historic outage data and 10 years of Icelandic weather data.
    - For example, wind-dependent models were trained on 8 years (2005-2012) and tested on 2 years (2013-2015) to be incorporated in the algorithms.
    - The study focused on N-1 contingencies, continuously adjusting the list based on real-time weather data, load forecasts, and historical threat- based failure probabilities.
    - A discarding principle was applied to filter out low-risk contingencies, keeping the list manageable while focusing on critical events.

Key Outcomes:

+ The reliability assessment outputs key parameters, including assessed and residual risk (in kISK/hour) estimating interruption costs for the next hour, with residual risk as an error margin.
    - Other outputs include the number of contingencies assessed, probability of a contingency within the hour, computation time, and indicators of significant state changes

+ Reducing the residual risk target affects both accuracy and contingency set size.
    - A lower target improves accuracy but requires assessing more contingencies, while a higher target reduces computational load at the cost of precision. Optimal targets should balance accuracy and resource constraints

Framework of Threat-Based Failure Rate Models



Framework addresses integration in real-time application

This application of GARPUR RMAC have been focused on real-time reliability risks
Similar methods could potentially be employed to identify high-impact contingencies and/or congested elements as part of the flowgate identification process.

Outage and Contingency Risk
Case Study: GARPUR RMAC Norway (Long-Term)

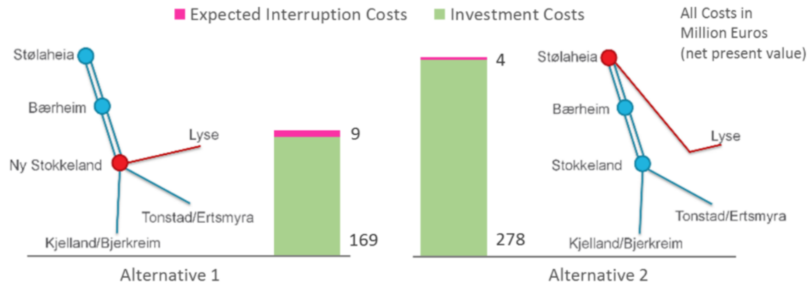
Approach:

+ **The study compared two grid expansion alternatives to ensure high security of supply in South-West Norway**
  - The societal costs for each alternative were estimated using probabilistic reliability assessment and interruption cost metrics.
  - The approach used a framework for calculating the cost of energy not served (value of lost load) to assess the societal costs for each expansion alternative
+ **The study used in-house tools which evaluate system response simulation and failure rates which were adjusted with a Bayesian updating scheme (estimating probability using a prior distribution).**
+ **Long-term load-flow scenarios were created which used forecasted load duration curves**
  - Load flow scenarios allowed for the estimation of interruption costs across the grid expansion cases

Key Outcomes:

+ ***Investment cost for increased reliability were compared to the societal costs of interruption***
+ **Different investment alternatives compared to typical N-1** approaches may be chosen when using probabilistic reliability assessment. This resulted in significant estimated societal cost savings
+ **Higher security of supply did not defend higher investment costs**
  - The cheaper alternative ***reduced investment costs by 25% or €110 million***, while expected ***interruption costs increased by €5 million***
  - Strict compliance with N-1 resulted in earlier investments in transmission infrastructure. annual savings of about 7 million Euros were estimated using the probabilistic methodology
+ **No commercial tools were available,** significant work was required to develop custom tools for data collection and handling, as well as for assessment
  - Monte Carlo simulation was the primary method for system response simulation, and improvements to computational efficiency were recommended

Norway RMAC Study Results



The study found that the positive benefits of higher security in Alternative 2 did not outweigh its larger investment cost

Bayesian-Updated Failure Rates

- **Bayesian Inference is a method of statistical inference used to calculate a probability using a prior distribution.**
- **This approach adjusts failure rates by incorporating new data over time, refining predictions based on past performance and observed conditions**
- **Initial failure rates are updated using Bayesian inference, which combines historical failure data with recent observations, accounting for factors like component age, weather impact, and operational stress to improve accuracy in failure predictions**

Addressing Uncertainty within Power Flow

Weather Related Variability

		Power Flow		
Source of Uncertainty	**Details**	**Extreme Event**	**Representative Weather Year**	**Stratified Sampling Using Monte Carlo**
Weather Related Variability				
Extreme Weather Events & Renewable Output	**Technique**	**Deterministic**	**Deterministic**	**Probabilistic**
	Overview of Method	Evaluating the ability of the electric system to respond to weather conditions by stress testing with extreme weather scenarios. Commonly used framework by system planners to choose "snapshot" hours	Evaluating the system's performance over periods of high stress that are representative of conditions that could occur within a typical weather (i.e., winter or summer peak). Analysis of multiple weather years are used to identify the distribution of renewable output. The derived distribution is used to inform what conditions are evaluated in the power flow case	Primarily academic method developed by EPRI method to probabilistically create dispatch scenarios which capture uncertainty due to variation in renewable output, weather related load variability and transmission component performance
	Workflow	Weather impacts to load and generation can be drawn from data on comparable historical events. "Snapshot" hours are chosen which are representative of challenging system conditions due to weather/load patterns or extreme events.	Comprehensive weather impacts to load and generation can be evaluated by selecting hourly or "snapshots" which represent conditions that correlate with a high system stress period. Due to the complexity of PFM, "snapshots" are representative hours that are evaluated at a high degree of detail.	The input data is divided into sub-populations, and it is assumed that each is homogeneous. Data is divided ensure that scenarios which have low probability of occurring will still be captured in one of the strata and won't get lost in the entire population
	Models Used	Pre-processing or identified hours from PCM results	PSS/E, TARA, many commercially available tools	EPRI Stratified Sampling Monte Carlo model
	Data Needs	Extreme event correlated load/generation	Complete weather year and correlated load/generation	Probability distributions for load and renewable generation
	Existing Case Studies or Applications	NREL Evaluation of Xcel Energy's 2030 Colorado Preferred Plan	Common modeling practice	EPRI Research

Addressing Uncertainty within Power Flow

Weather Related Variability (Continued)

Source of Uncertainty	Details	Power Flow: Stochastic Production	Power Flow: Statistical Weather Prediction	Power Flow: Composite Load Level (CLL)	Power Flow: Chronological AC Power Flow Automated Generation (C-PAGE)
Weather Related Variability					
Extreme Weather Events & Renewable Output	Technique	Probabilistic	Deterministic or Probabilistic	Probabilistic	Probabilistic
	Overview of Method	Seasonal variation in generation (or load) is aggregated into a profile detailing generation as a function of probability of occurrence.	Simple methods such as Measure Correlate-Predict (MCP) are used for filling gaps in location specific load and resource generation data. Extremely complex Numerical Weather Prediction (NWP) and Global Climate (GCM) models are to mathematically describe atmospheric processes	Composite load levels detail chronologically correlated plant-level renewable generation and bus-level load for specified weather conditions.	C-PAGE is used to convert system dispatch from a Production Cost (PCM) model into time-sequenced Power Flow (PFM) model runs for a reliability study. Tool allows for convergence of PCM with PFM
	Workflow	Historical data is used to build probability distributions that can be assessed in many ways to yield a quantification of weather-related variability across a wide set of weather conditions.	Correlations between existing measurements at a renewable resource site and a nearby site with a complete dataset are established through statistical models such as linear or moving average.	Coincident historical data is used to establish a high-resolution probability distribution for generation and load. Outputs are generated for specified weather conditions, referred to as Composite Load Levels (CLL)	As a first step an AC convergence process occurs between the DC power flow in the PCM and the PFM. To achieve this system topologies are aligned, line losses are equal and voltage violations are mitigated. Power flow cases are selected which are representative of the full year using slicing and Latin-Hypercube sampling
	Models Used	Monte Carlo, Probability Trees	MCP (common statistical models) NWP (NOAA, NCEP)	EPRI CLL	PNNL C-PAGE
	Data Needs	Historical load and renewable generation data	Ranges from site specific to highly detailed observations across many stations	Weather correlated plant/bus-level load and generation	Production cost model outputs, system topology, seasonality across generation types
	Existing Case Studies or Applications	NREL Evaluation of Xcel Energy's 2030 Colorado Preferred Plan	MCP commonly used in wind site assessment. NWP used for weather forecasting and climate change	EPRI SPP CLL Demonstration	C-PAGE WECC Transmission Expansion Case Study (2024 DOE NTP Study)

Probabilistic | Deterministic | Explored in More Detail | Case Study

Weather Related Variability

Stratified Sampling Using Monte Carlo

Method Overview:

- **EPRI's approach to probabilistically develop dispatch scenarios which capture variability due to:**
  - Variation in renewable output, weather related load variability, uncertainty in economic load growth and generation/transmission component performance
- **The input data is divided into sub-populations, and it is assumed that each sub-population is homogeneous. (i.e., that data points in a sub-population have similar system conditions).**
  - The data is divided into multiple strata to ensure that scenarios which have low probability of occurring will still be captured in one of the strata and won't get lost in the entire population
  - The entire population is dominated by "average" scenarios occurring more frequently on the system.
- ***Monte Carlo*** sampling is used to produce a user-defined number of dispatch scenarios in each strata

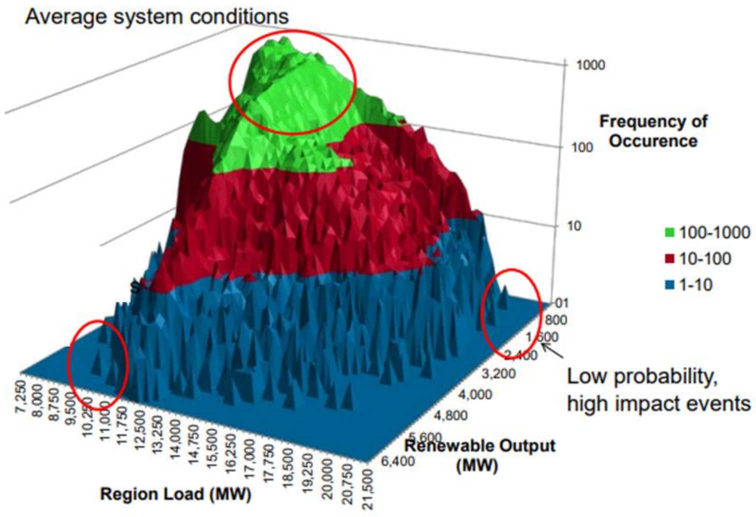
Inputs and Tools:

- Time series data of system load, renewable output, and hydro output (if available), historical performance of generating units and transmission components
- No commercially available tools. The method is an extension/application of Latin Hypercube sampling

Key Takeaways:

- Dispatch scenarios created using Monte Carlo sampling system planners to capture average scenarios as well as low probability, high impact scenarios
- Methodology also has applications for producing deeper contingencies (beyond N-1) for reliability evaluation using Monte Carlo
- Method has not been tested on a realistic system and should primarily be considered academic at this point. An application for the method was used by EPRI in 2020 for shade and sun stratum (vegetation cover) on a solar installation owned by Georgia Power Company

Stratified View in Monte Carlo Simulation



Monte Carlo weather simulations for weather variability can be adapted for use in power flow modeling, production cost modeling, and capacity expansion planning

Weather Related Variability

Statistical Weather Prediction

Several methods can be used to assess gaps in existing weather data used in power system planning. These methods range from relatively simple correlation exercises to extremely complex mathematical representations of atmospheric processes

Method Overview:

+ The ***Measure-Correlate-Predict (MCP)*** method is an effective deterministic strategy to fill gaps in location specific load and resource generation data. The method uses correlations (usually linear) of the available observations at the target site and high-quality observations at a nearby location to predict the missing data.
  - The MCP method is commonly used in wind resource assessment, however MCP-like methods can also be used to synthesize load time series. Measurements from two sites are correlated and then estimates are created with a transfer function
+ ***Numerical Weather Prediction (NWP)*** models are the basis for modern-day weather forecasts and the core component in datasets utilized for power system modeling. These models can be deterministic or probabilistic and are also used for ***Global Climate (GCM)*** modeling to understand climate change.
  - Complex models are used which mathematically describe atmospheric processes as a system of regular and partial differential equations which could describe the state of the entire atmospheric system

Inputs and Tools:

+ ***MCP:*** Reference high-quality long-term meteorological record from a nearby site and short-term observations from a target site. Data must coincide in length and time-period for determining correlations. Simple commonly available statistical models (such as linear or moving average) can be utilized.
+ ***NWP:*** Requires extensive highly detailed observations from many weather stations to produce detailed outputs. Physics-based models are utilized, and forecasts are produced by large national forecast centers like NOAA and NCEP in the US. ***Generative Machine Learning (ML)*** models are a new class of method for downscaling of NWP outputs and can be trained to produce multivariate (wind, temperature, etc.) data-sets.

Key Takeaways:

+ ***MCP*** is relatively simple and can be performed using common statistical modeling tools. The method yields reasonable distributions with average errors between target and candidate site but can lead to very large errors in any given hour. MCP methods typically relate 1 or 2 predictions (i.e., wind and/or temperature) and is not effective in predicting a daily profile of wind or solar generation
+ **NWP** modeling is an extremely complex process which can yield much more detailed results such as daily weather correlated wind, solar and load profiles. Power system planners need to have a basic understanding of how the data were produced or engage with a meteorologist with an NWP background.

Source: MCP Method Visualization ; Meteorological Data Fundamentals for Power System Planning

Weather Related Variability

Composite Load Level (CLL)

Method Overview:

- **The CLL methodology takes synchronized, chronological wind and PV generation output and coincidental bus load data and probabilistically represents the inherent correlations in renewable generation and load levels**
  - These generation and load levels are represented as composite snapshots of wind and solar outputs at the plant-level with time-correlated load at the bus-level which can be used as part of a power flow base case
- **CLL uses a mathematical model to express variability and uncertainty in load and coincident wind and PV generation using a small number of independent, random variables**
  - The model aims to fit historical data as closely as possible to the random variables, and the parameters are found using least-square estimation
  - Once the model parameters are found, the model can be used to provide a user specified number of wind/PV output as well as load level scenarios called CLLs

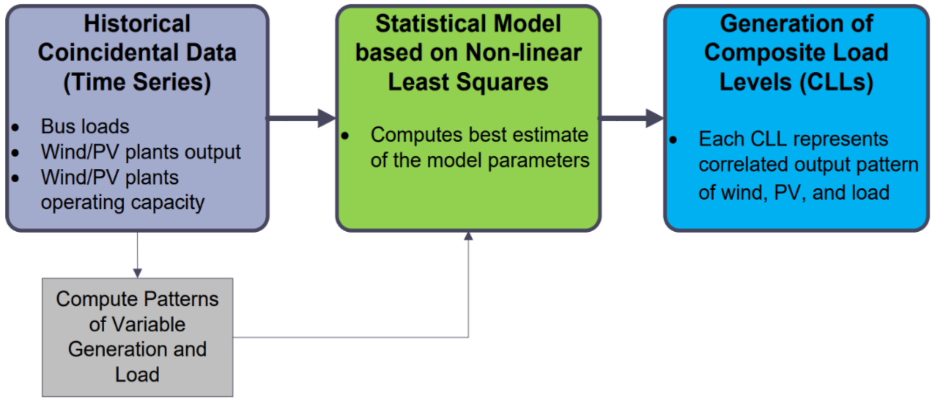
Inputs and Tools:

- Time series data for each wind and PV plant as well as system load
- EPRI developed tool that generates CLLs as power flow cases

Key Takeaways:

- **Data requirements are onerous:** historical time series for each plant is required. Any gaps in datasets must be filled before use
- **Computationally intensive:** calculation involves inverting metrics of large dimensions. In the EPRI SPP case study sparsity techniques were used to reduce the computational time and storage required for large power systems
- **Unit Commitment and SCED required** to solve the power flow for the CLLs for the entire case

CLL Methodology



Statistical model uses historical time-coincident data of loads and renewable generation to produce composite power flow cases for weather variability

Composite power flow cases can be used to evaluate to perform granular analysis of the reliability of existing and proposed resources and transmission networks under different weather conditions

Weather Related Variability

Case Study: EPRI SPP

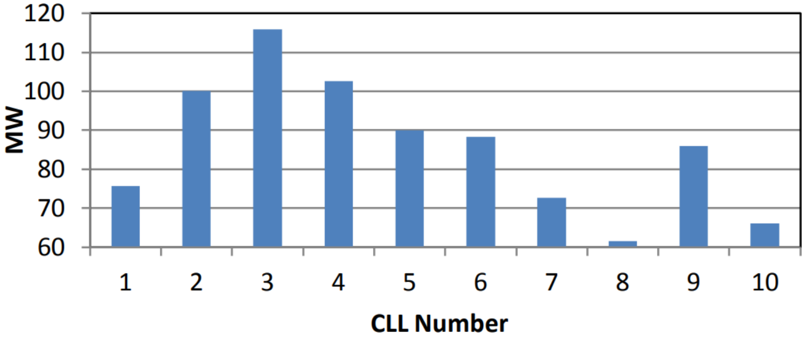
Approach:

- **EPRI demonstrated the applicability of the CLL tool in SPP to assess variability and uncertainty in renewable generation and system load**
  - CLL tool developed 10 reduced generation and load level scenarios (CLLs) for evaluation in TransCARE
- **Power flow case used was developed by EIPC for the 2030 SPP system with 30% of load met by renewable resources**
  - 23 GW of wind and 5GW of solar capacity was modeled and the case was modified to include a new 765kV sub-network to provide new paths for the incremental renewable generation
  - SPP provided historical hourly time series data of the loads and renewable plants and synthesized data from NREL was used for proposed wind and solar plants
- **28GW of incremental generation created a significant imbalance in generation and load**
  - Unit commitment and dispatch was performed on each CLL to redispatch thermal generation to accommodate incremental renewable generation
- **Generated CLLs were 10 snapshots of annual system variation (with redispatch) and were analyzed in TransCARE**
  - Study was very large, so TransCARE's contingency enumeration logic was used to evaluate one generator and one transmission component simultaneously (i.e.,N-2).
  - No remedial actions were applied for thermal overload or voltage violations. Remedial actions were applied for outages and system loads were dropped as a last resort.

Key Outcomes:

- **Results demonstrated the CLL tool could be used to capture variability and uncertainty of renewable generation and load**
  - Planners often use engineering judgement deterministically to consider, so CLLs could be a significant improvement
- **Load loss indices were generated which provided granular reliability numbers for individual load buses which could be used for identifying system weak spots**

CLL Results for a Sample Wind Plant



Variation in Wind Generation Output for 10 CLLs

Thermal and Voltage Violations

Type of System Problem	Frequency (Occurrence /yr.)	Duration (Hrs/ Occurrence)	% Average Overload	% Max. Overload	# of Contingencies
Thermal Overload	0.667	15.15	119	163	163
Low Voltage	0.0325	17.5	0	3.9	13
High Voltage	0.0823	133.8	0	0	11

Thermal overloads were more prominent than voltage violations

Weather Related Variability

Chronological AC Power Flow Automated Generation (C-PAGE)

Method Overview:

+ **The Chronological AC Power Flow Automated Generation (C-PAGE) tool is used to convert system dispatch from a Production Cost model (PCM) into time-sequenced Power Flow model (PFM) runs for a reliability study**
  - The tool allows for the convergence of PCM with power flow cases to improve power flow modeling practices
  - Can reduce runtime for a converged AC PFM from hours (or days) to a minutes for any large, interconnected system. Allows system planners to assess the solutions of thousands of chronological power flow cases
+ **AC Power Flow Convergence Process:**
  1. **Preparing DC power flow cases using production cost modeling results:** System topologies between the PFM and PCM must match so generation and load outputs are disaggregated from the power plant and BA level to the nodal level. Mappings are illustrated in the flow diagram
  2. **DC-to-AC convergence process:** Line losses need to be equal between the DC PCM and the AC PFM. Nodal loads were required to be iteratively reduced until an AC PFM solution was found
  3. **Reactive power planning for voltage improvement:** C-PAGE scanned all bus voltages to identify voltage violations and adjusted or added local reactive power devices to mitigate bus voltage violations.
+ **Chronological power flow cases are selected using an intelligent sampling method**
  - Approach finds a small number of hourly cases representative of the full year to account for seasonal and diurnal variability of renewable generation. Slicing and Latin-hypercube sampling was leveraged for this step.

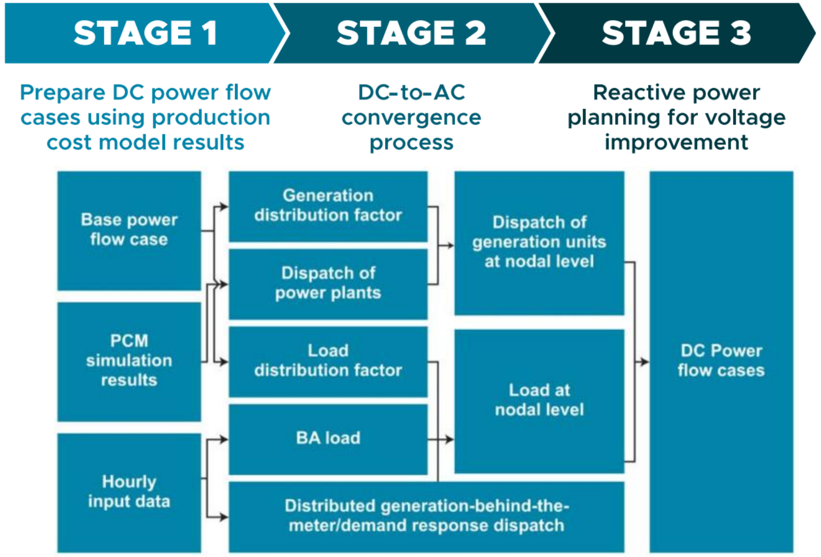
Inputs and Tools:

+ **C-PAGE Tool developed by Pacific Northwest National Laboratory is used to create the linkage between PCM and PFM**

Key Takeaways:

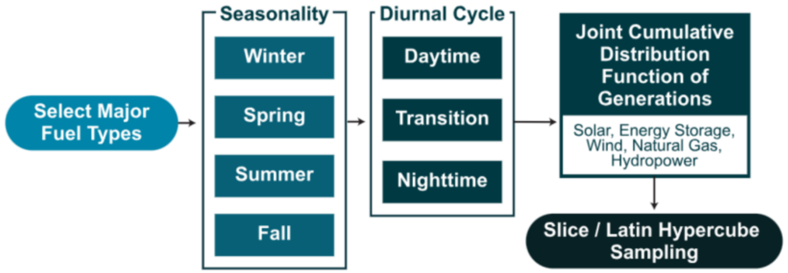
+ **Linkages between PCM and PFM is critical** for evaluating the reliability of future scenarios. Creating linkages between the PCM and the PFM enables planners to investigate reliability scenarios with high penetrations of wind, solar, and storage (i.e., the future decarbonized grid).
+ **Down sampling is necessary** to reduce the problem size. Intelligent sampling was an effective method to account for representative variability in generation and load across an entire year

PNNL C-Page Tool Methodology



Disaggregation process from PCM to PFM

Intelligent Sampling Method



Weather Related Variability

Case Study: Chronological AC Power Flow Automated Generation

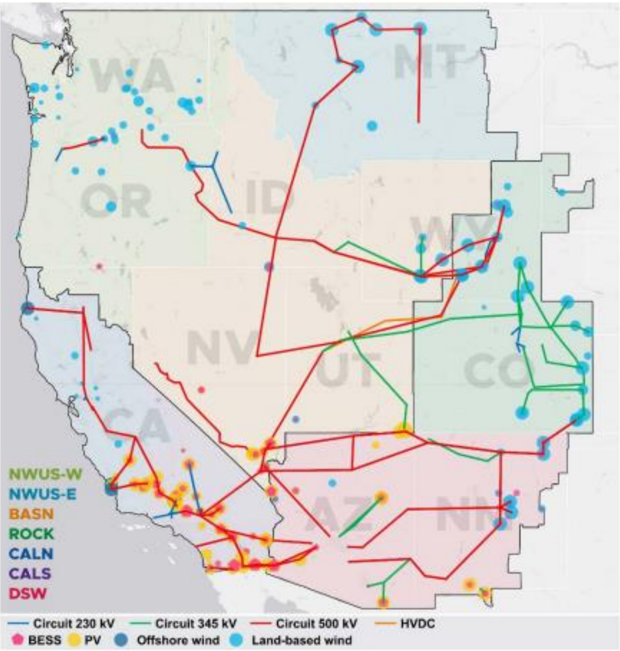
Approach:

+ **C-PAGE tool was used to convert system dispatch time series from Production Cost model (PCM) into time-sequenced Power Flow model (PFM) runs for a reliability study of transmission expansion scenarios**
  - The study used C-PAGE to demonstrate performance on the 2028 WECC System Stability Planning Anchor Dataset (ADS) PCM - 22,509 buses, 4,417 generators, 11,126 load buses, and 1,766 transmission lines
  - Transmission projects that are either under construction or have significantly progressed through permitting were deemed likely to materialize
+ **The study identified additional transmission capacity for 2035 across two scenarios**
  - Both scenarios were characterized by high demand growth (21% relative to 2030 Industry Case) and a 90% decarbonization by 2035 constraint.
  - AC scenario facilitated transmission expansion between planning regions (FERC Order 1000) and the Limited scenario only allowed intra-regional transmission buildouts (including minor exceptions)
  - The zonal models from the capacity expansion results were converted to a detailed nodal PCM
+ **The procedure proposed an approach to maintain voltage within acceptable range across large, interconnected systems.**
  - All procedures were designed to be integrated into an automation tool to minimize manual intervention
  - GridView was used for production cost, and the developed tool was capable of saving power flow cases in PowerWorld, PSS/E and PSLF formats

Key Outcomes:

+ **Approach integrates all model frameworks:** the study method incorporated transmission capacity expansion, production cost and power flow frameworks across multiple models in an integrated approach. Primary application is linkage between PCM and PFM
+ **Linkages between PCM and PFM is critical** for evaluating the reliability of future scenarios. The study developed AC power flow models, including peak load models for different seasons.
  - The models included scenarios that correlated to high solar penetrations, as well as models that show peak wind. Creating linkages between the PCM and the PFM is critical for investigating the reliability scenarios with high penetrations of wind, solar, and storage

AC Scenario Transmission Expansion



500, 230 and 345-kV circuits were added or updated. New HVDC circuits were also added

Sources: *Automated Tool to Create Chronological AC Power Flow Cases for Large Interconnected Systems*
DOE National Transmission Planning Study

Technical Review

Production Cost Modeling

Energy+Environmental Economics

Addressing Uncertainty within Production Cost

Outage and Contingency Risk

		Production Cost		
Source of Uncertainty	**Details**	**PCM and PFM Modeling Linkages**	**Monte Carlo**	**Economic Cost of Uncertainty**
Outage and Contingency				
Outage Events & Failure Rates	**Technique**	**Deterministic**	**Probabilistic**	**Hybrid**
	Overview of Method	Capturing key constraints and topology from power flow model as contingencies and/or monitored elements	Randomly selected draws across a specified set of inputs. Probabilistic production cost modeling can capture the uncertainty many variables including unit availabilities, loads and generation	Using reliability indices and associated unreliability costs to compare the value of transmission projects while ensuring there are linkages to the probability of contingencies
	Workflow	Involves modeling and enforcing contingencies in the unit commitment and economic dispatch stages of the production cost model. “Snapshot” periods may be selected from the resulting PCM runs and further evaluated in the PFM for reliability. May be a manual process for re-running PFM scenarios but room exists for automation using APIs	Involves running many simulations to assign multiple values to an uncertain result to achieve. Estimates the probability function of random variables by simulating the system using a random number generator to produce a sample from the probability function. Process is repeated many times (hundreds of draws or more) and the results are averaged to estimate the expected value	The approach evaluates the tradeoff between incremental investment cost of transmission (for a higher degree of reliability) and the societal cost of interruption. Quantifies the economic costs associated with outages and the(i.e., LOLE & EUE) by calculating the financial impact of unserved energy
	Models Used	Hitachi Gridview, PLEXOS, PROMOD, PNNL C-PAGE, Custom Tools	PLEXOS, UPLAN, PROMOD, many commercial models available	UPLAN, PROMOD, SERVM, MECORE (BC Hydro)
	Data Needs	System topology, understanding of contingency are criticality (i.e., power flow results)	Load & renewable profiles under different weather patterns, historical outage patterns	Load, wind and solar profiles under different weather patterns
	Existing Case Studies or Applications	Many RTOs	Common industry practice to assess expected value of a variable TVA SERVM/TransCare Case Study	ERCOT, BC Hydro

Outage and Contingency

SERVM + TransCARE Linkage Demonstration

Approach:

- A combined generation and transmission adequacy modeling approach was assessed which included full simulations in SERVM and a smaller subset of representative snapshots to be run in a full AC power flow model in TransCARE
  - ***TransCARE*** is a transmission reliability tool that utilizes state-space (Markov) approach in computing bulk power system reliability. The tool uses fast decoupled AC power flow and takes post contingency corrective actions to alleviate system problems
  - ***SERVM*** is a hybrid resource adequacy and production cost model that stochastically simulates unit performance, weather conditions, resource outages and other stochastic variables. SERVM can also evaluate trade-off between reliability and costs of unserved energy
- To create the linkage SERVM was modified to accept files in PSS/E RAW format and tables were created which allowed system topology (generators, regions and transmission component) matching between the PSS/E model and SERVM
  - SERVM was also modified to output information to the RAW file for input into TransCARE, which was specific to the snapshot. This included generation output and economic commitment and dispatch.
- SERVM uses Monte Carlo to calculate likelihood of generator availability, so this logic was extended to transmission components to develop contingency files.
  - The model was used to generate several thousand iterations of generation and transmission components outages which were written to the contingency files
  - Iterations with identical outages were consolidated and the probabilities were calculated. For example, a combination of outages that occurred in 20 out of 5,000 iterations would have a probability of 0.4%

Outcomes:

- The method allowed users to test any number of snapshots based on specified criteria. High load, low load, high renewable output or economic criteria could be used to select the specific snapshots
- The approach was tested on a simple test system while considering a wide range of weather, load, etc. without running billions of full AC power flow models.
- The approach proved that the two tools could be linked to combine assessment techniques
- Results from the test case were not fully scalable to larger systems, but revealed strengths from combining generation adequacy and transmission adequacy modelling

Sources: EISPC Study on Probabilistic Risk Assessment for Transmission
EIPSC Whitepaper on the Incorporation of Risk Analysis into Planning Processes

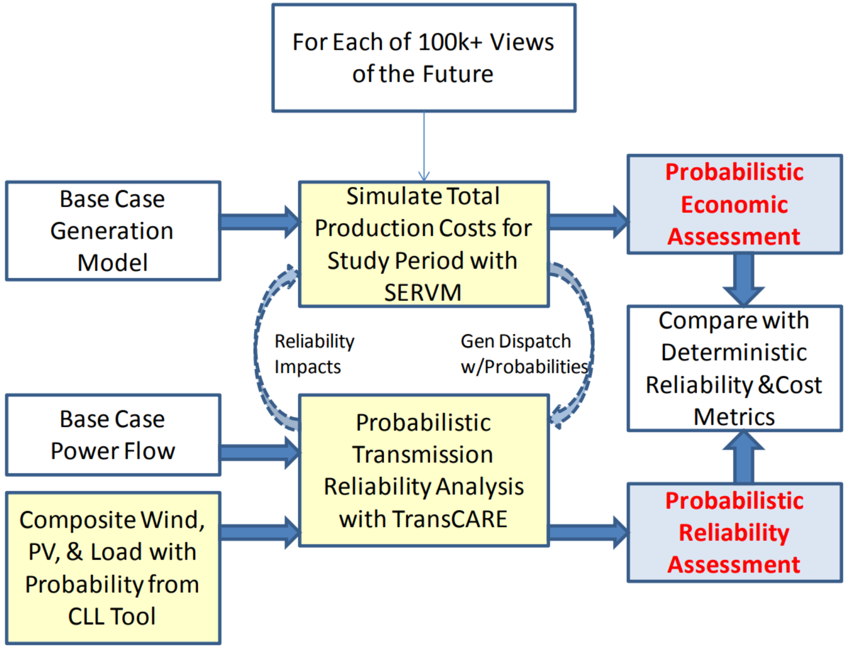
Outage and Contingency

Case Study: TVA SERVM + TransCARE Linkage

Approach:

- A combined generation and transmission adequacy modeling approach was explored which allowed for full simulations in SERVM and subsequently selecting a smaller set of representative snapshots to be run in TransCARE
- To bridge the gaps between model assumptions, 20 snapshots from millions of SERVM hourly scenarios were selected to put through TransCARE.
  - The selection process was manual. SERVM was modified to accept files in PSS/E RAW format, and SERVM commitment & dispatch were transferred into, and run through TransCARE
- Outage data need be supplied for only the components in the study area of interest and included annual failure frequency, outage duration and forced outage rate
- For each snapshot SERVM, using Monte Carlo, developed 3,000 distinct contingencies (limit of 9 generators and Tx components) which were then simulated in TransCARE

SERVM + TransCARE Process



Key Outcomes:

- LOLE results from the linkage run were similar to separate runs (SERVM and TransCARE) and the Tx lines could not be justified on the economic or reliability front
- Across all runs there were 20,000 contingencies that posed system problems, while 2000 of those resulted in loss of load.
- Many of the contingencies could not be solved without manual intervention in the TransCARE environments

Outage and Contingency

Case Study: TVA Economic Model Monte Carlo + SERVM

Tie-line additions between TVA and AECI (+1,000 MW ATC) and another between TVA and PJM (increasing import capacity by 1,000 MW and export capacity by 2,000 MW).

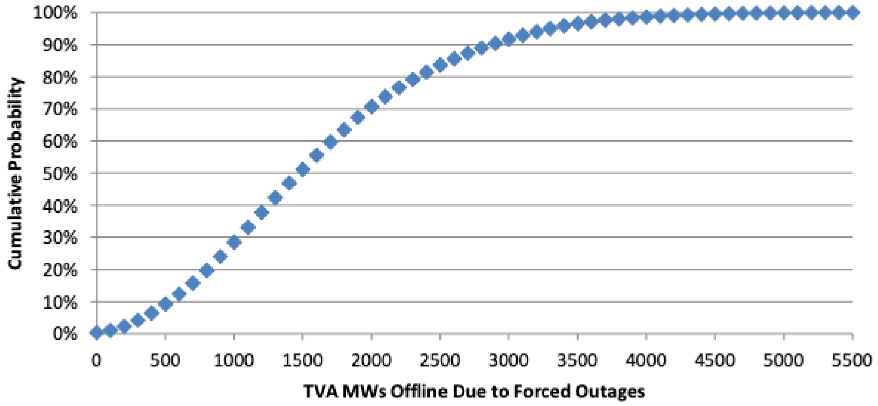
Approach:

- SERVM used multi-state Monte Carlo simulations to model generator outages over 8760 hours/year:
- Full and partial generator outages were modeled based on historical rates (forced outages, maintenance, and startup failures)
- For each year, 10 different outage scenarios were simulated across 2,970 iterations, combining weather, load growth, and fuel price variations
- In each simulation, units failed stochastically. The first chart shows that 90% of the time TVA has less than 2.9GW offline due to forced outage.

Key Outcomes:

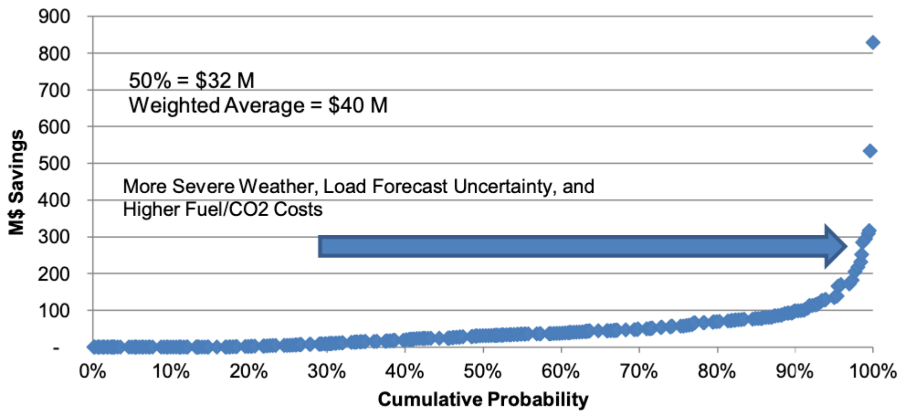
- Economic Benefits: Probability-weighted cost savings varied from median estimates. The most cost savings happen in rare events (including severe outage scenarios)
  - In the second graph, "probability-weighted" ($40M) averages all outcomes by their likelihood, unlike the median ($32M), which shows only the midpoint
- LOLE and EUE did not show significant improvements.
- SEVRM reliability targets did not include transmission outages, and generation was assumed to be delivered within TVA region.

Cumulative Outage Distribution



Cumulative distribution of outages from each of 2,970 iterations

Distribution of Production Cost Savings



Outage and Contingency

Case Study: TVA SERVM + TransCARE Tie-Line Assessment

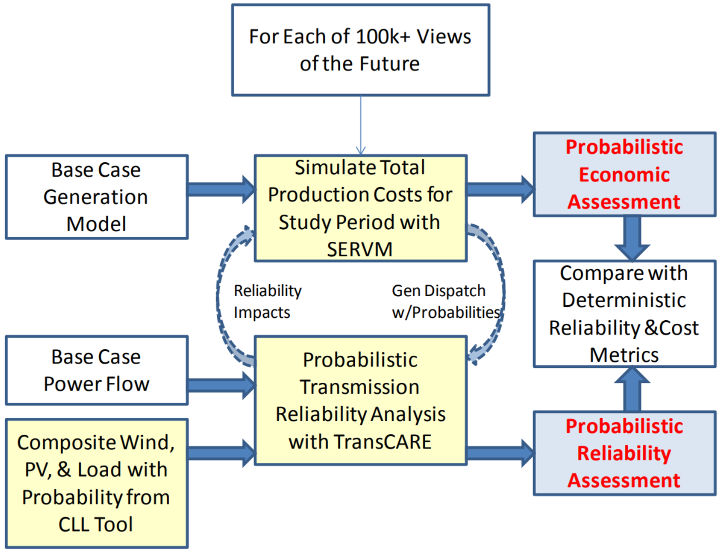
Approach:

+ A combined generation and transmission adequacy modeling approach was explored which allowed for full simulations in ***SERVM*** and subsequently selecting a smaller set of representative snapshots to be run in ***TransCARE***. The reliability used the ***System Problem Approach*** and the ***Capability Approach***
  - **System Problem Approach** – A pessimistic approach that provides frequency, duration and severity indices of system problems but does not consider corrective actions by system response or operator actions
  - **Capability Approach** – Estimates the amount of EUE if problems persist after remedial actions. Provides a single set of load-loss indices as a measure of unreliability. Includes probability, frequency and duration of load loss at each point
+ The analysis involved evaluating the economic and reliability impact of building two tie-lines[1]. Each were considered separately as separate case studies which were structured with three tasks:
  - Transmission reliability assessment using TransCARE
  - Generation adequacy assessment and probabilistic economic analysis using SERVM
  - Combined analysis using both tools to assess contribution to EUE due to transmission constraints
+ Prior to the TransCARE analysis TVA performed deterministic N-1 and N-2 outages and found no significant reliability benefit. TVA planners sought to understand if different conclusion could be reached using probabilistic analysis
+ TransCARE n-2 analysis was performed for circuits and generators across two zones in the TVA control area, chosen for the study area.
  - Outage generation statistics from NERC's GADS and TADS were used for each component
  - The study utilized three 2016 Peak load cases, one for the existing TVA system, one with the 765kV line and one with the 500kV line

Key Outcomes:

+ **System Problem Approach** – Indices from the base case were not improved by the addition of either line, so reliability benefit could not justify the projects
+ **Capability Approach** – Load loss indices aligned with the conclusions from the voltage and thermal violations that the lines would not provide a reliability benefit

SERVM + TransCARE Process



1 – 765kV between TVA and AEP and a 500kV between TVA and AECI

Source: EISPC Incorporation of Risk Analysis into Planning Processes

Economic Cost of Uncertainty

Case Study: ERCOT PRA Framework

The ERCOT case study applied a ***Probabilistic Reliability Assessment (PRA)*** framework to evaluate three fictional transmission investments using both production cost and power flow analysis

Approach:

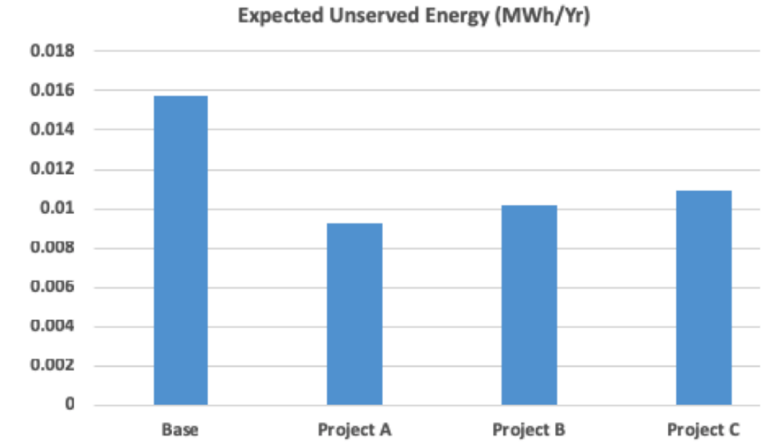
- **Scenario Selection**: Conducted 8760-hour production cost simulations using the UPLAN tool across four historical weather patterns to generate 35,040 scenarios. Applied Monte Carlo sampling with K-means clustering, selecting eight clusters based on the Elbow method[1]. Two samples per cluster were chosen to adequately represent the state space.
- **Reliability Analysis**: Developed eight base cases, performing reliability assessments for 342 extreme events using POM-OPM and Power World software for the power flow analysis. *Outage probabilities were calculated from NERC TADS and GADS data, assuming independent outages.*
- **Risk Metrics**: Based on the reliability analysis, calculated the Expected Unserved Energy (EUE**).**

$$\boldsymbol{Incremental\ Reliability\ Index\ (IRI)} = \frac{\boldsymbol{EUE_{before\ project}} - \boldsymbol{EUE_{after\ project}}}{\boldsymbol{Capital\ cost\ of\ project}\ (\$)}$$

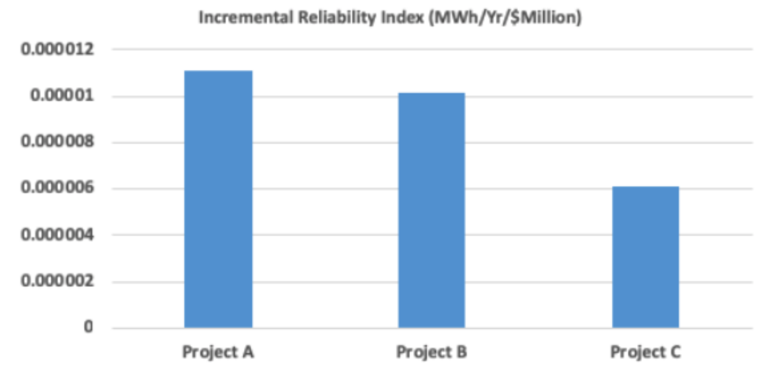
Key Outcomes:

- The EUE metric demonstrated that Project A provided the greatest reliability improvement. The IRI metric indicated that Project A offered the best reliability enhancement per million dollars invested, supporting it as the most effective option among the alternatives

Expected Unserved Energy



Incremental Reliability Index



1 - *The elbow method finds the optimal k by identifying where adding clusters no longer significantly reduces clustering error*

Source: *An Approach for Probabilistic Composite Power System Transmission Planning - ERCOT*

Economic Cost of Uncertainty

Case Study: BC Hydro Vancouver Island Reinforcement

The study objective was to measure the reliability improvement and transmission loss reduction of several transmission alternatives to supply the Central Vancouver Island, along with a cost/benefit analysis for each alternative

Approach:

- Five Central Vancouver Island transmission reinforcement alternatives were considered
- BC Hydro used their internally developed MECORE and PLOSS software
  - Analysis was performed over a 10-year period using full duration curves
  - Annual Expected Energy Not Served (EENS) and peak load transmission losses were computed for each alternative
- Costs were assigned to Reduced EENS and Reduced Losses
  - Interruption Cost = $9,040/MWh ; Transmission Loss Cost = $88/MWh

Key Outcomes:

- A Benefit/Cost ratio was computed for each alternative
- The economic benefits from reduced EENS outweighed the economic benefit from reduced transmission losses
  - All alternatives were economically viable, with cost-benefit ratios from 6 to 14.
  - The most cost-effective option was the 230 kV injection.

Metrics for Evaluating Tx Investment Options

Transmission alternatives costs and benefits	a. 230 kV injection	b. Phase shifters	c. 500 kV conversion	d. Reconductoring	e. Substation Transformation
Estimated project cost, in millions	$82.2	$114.7	$153	$169.5	**$78**
EENS reduction (year 2020/21), in MWh	**9,305**	8,553	8,665	8,599	8,672
Transmission loss reduction, in MWh (year 2020/21)	32,331	13,351	**77,241**	39,783	13,095
Benefit/Cost ratio	**14.53**	8.74	7.42	6.22	13.04

BC Hydro concluded that the selection of the "best" alternative depended on the metric being used:

Project cost, reduced EENS, reduced transmission losses or total benefit/cost ratio

Addressing Uncertainty within Production Cost

Weather Related Variability

Source of Uncertainty	Details	Production Cost: Representative Weather Year	Production Cost: Monte Carlo	Production Cost: Stochastic Load & Renewable Production	Production Cost: Statistical Weather Prediction
Weather Related Variability					
Extreme Weather Events & Renewable Output	Technique	**Deterministic**	**Probabilistic**	**Probabilistic**	**Deterministic or Probabilistic**
	Overview of Method	Evaluating the system's performance over a complete and contiguous weather dataset. A sample weather year with correlated load and generation is selected and evaluated across a full year or set of years.	Randomly selected draws using probability distributions for load and renewable generation based on historical patterns	Seasonal variation in generation (or load) is aggregated into a profile detailing generation as a function of probability of occurrence. Refers to a wide range of methods to quantify the variability of load and resource production in response to weather conditions.	Simple methods such as Measure Correlate-Predict (MCP) are used for filling gaps in location specific load and resource generation data. Extremely complex Numerical Weather Prediction (NWP) and Global Climate (GCM) models are to mathematically describe atmospheric processes
	Workflow	Comprehensive weather impacts to load and generation can be evaluated by selecting or constructing representative weather years.	Yields aggregated power system impacts by assessing weather variability impacts on many constituent parts.	Historical data is used to build probability distributions that can be assessed in many ways to yield a quantification of weather-related variability across a wide set of weather conditions.	Correlations between existing measurements at a renewable resource site and a nearby site with a complete dataset are established through statistical models such as linear or moving average.
	Models Used	PLEXOS, ENELYTX PSO, PROMOD, many commercially available tools	PLEXOS, ENELYTX PSO, PROMOD, many commercially available tools	Out-of-model pre-processing step which relies on statistical methods, typically Monte Carlo.	MCP (common statistical models) NWP (NOAA, NCEP)
	Data Needs	Complete weather year and correlated load/generation	Probability distributions for load and renewable generation	Historical load and renewable generation data	Ranges from site specific to highly detailed observations across many stations
	Existing Case Studies or Applications	Industry standard modeling practice	Common industry practice to assess expected value of a variable	NREL Evaluation of Xcel Energy's 2030 Colorado Preferred Plan	MCP commonly used in wind site assessment. NWP used for weather forecasting and climate change

Weather Related Variability

Stochastic Load and Renewable Production

Method Overview:

- Refers to a wide range of methods to quantify the variability of load and resource production in response to weather conditions
  - Most common (and well established) is Monte Carlo
- Historical data is used to develop a generation or load profile as a function of probability of occurrence
  - It is important to ensure correlated weather year data is used across all weather-dependent technology and load models and any temperature dependent data
  - Can also create probability profiles for generation proxies, such as wind speed data or solar irradiance
- ***Distributions can be used to quantify expected generation during specific events or over a long-term average***

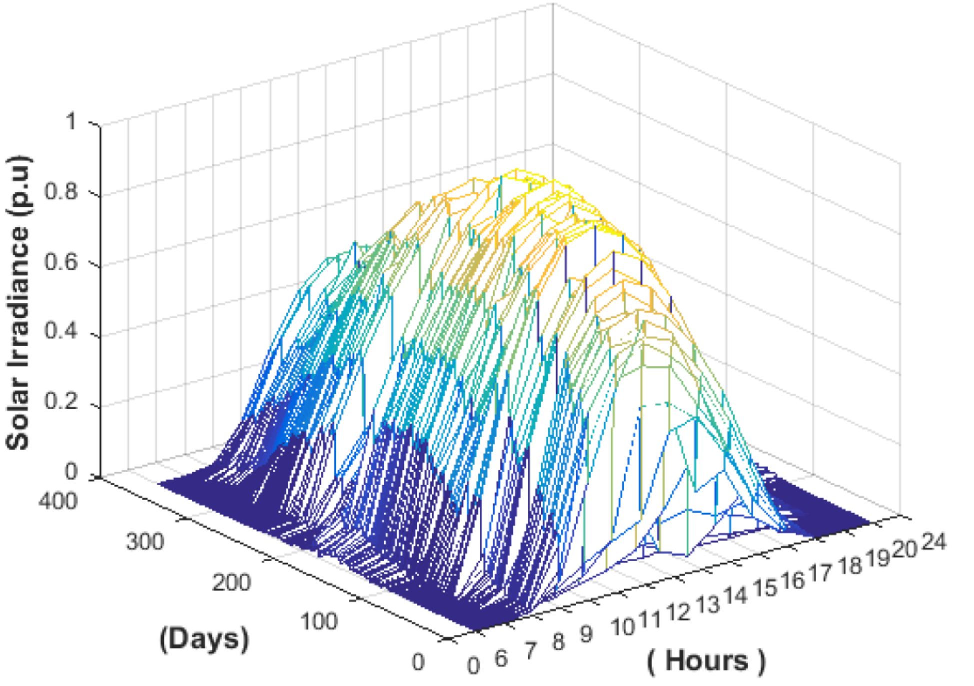
Inputs and Tools:

- Historical time series data of load and renewable generation as a function of weather conditions
- Fundamental statistics-based correlation methods such as regressions and moving averages

Key Takeaways:

- Probability distributions serve as a foundation for probabilistic analysis of weather variability
- Used in other methods such as Monte Carlo simulations, CLLs, and C-PAGE

Solar Irradiance Probability Distribution



Stochastic load and renewable production is a key input in evaluating weather variability in power flow modeling, production cost modeling, and capacity expansion planning

Weather Related Variability

Case Study: NREL Weather Analysis

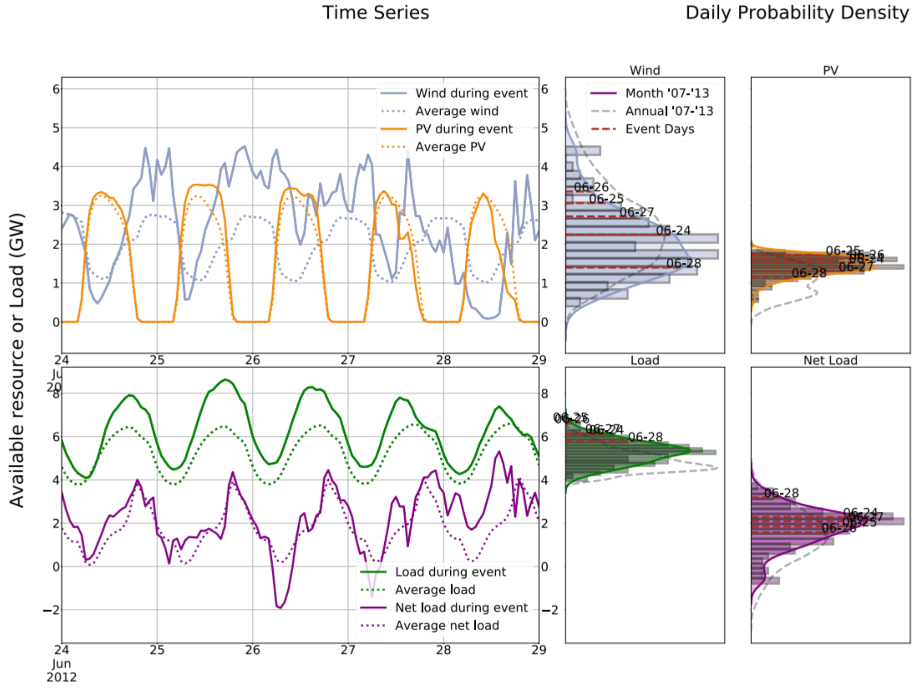
Approach:

- NREL evaluated the resiliency of Xcel Energy's 2030 Colorado Preferred Plan using stochastic and deterministic methods
  - Renewable generation and load are quantified using probability profiles based on historical data
  - Resiliency evaluated by "stress testing" the system with extreme events
  - Production cost modeling used to evaluate dispatch results
- The impact of extreme events on load and generation was evaluated by identifying historical events within probability profiles
  - Performed by "placing" the applicable extreme event on the load/generation profile to identify the deviation from standard output driven by extreme weather conditions
  - The identified extreme event effect is applied to the future resource plan and locations to assess the impact on a future grid
  - Allows for identification of which events are most valuable to evaluate

Key Outcomes:

- ***Findings suggest that peak load periods are not the most concerning period anymore. Near-peak load periods with low wind generation output in the evening lead to very narrow but high net load peaks***
- Demonstrated the ability of stochastic load and resource production to effectively evaluate reliability outcomes

Probability Density of PSCo Highest Load On Record



Wind, solar PV, load, and net load in PSCo during the highest load in the record

Addressing Uncertainty within Production Cost

Future Uncertainty

		Production Cost	
Source of Uncertainty	**Details**	**Scenario Analysis**	**Stochastic Portfolio Risk Evaluation**
Future Uncertainty			
Future Clean Energy Policy & Climate Change	**Technique**	**Deterministic**	**Probabilistic**
	Overview of Method	Industry standard approach used by system planners to evaluate system economics while capturing uncertainty in future loads and resource portfolios. Planners develop of deterministic future scenarios using engineering and stakeholder judgement to capture long-term uncertainties.	Scenarios are optimized deterministically and evaluated post-optimization among a wide variety of alternate futures. Using probabilistic post-model risk analysis, planners can evaluate the likelihood or impact of a selected scenario across a range of scenarios being evaluated.
	Workflow	Involves identifying key inputs to vary across scenarios. Modeling is performed across scenarios to determine the impact of the defined inputs.	This class of methods accounts for uncertainty by considering a range of possible futures and their associated probability of occurring, as opposed to a single Scenario. Primary probabilistic analysis methods are Monte Carlo sampling and probability trees, which are both well understood and documented process. Involves identifying targeted risk metrics, selecting inputs, and developing probability distributions for inputs. Monte Carlo simulations are used to evaluate performance.
	Models Used	Scenarios developed by experienced system planners and informed by stakeholder input. Scenarios are evaluated using many commercially available PCM tools such as PLEXOS, MIDAS, PROMOD, among others.	Out-of-model post-processing step. Leverages probability trees or Monte Carlo sampling.
	Data Needs	Portfolio options, policy, system topology, weather correlated loads and generation, load growth, etc.	Defined set of alternate futures and probabilities of outcome
	Existing Case Studies or Applications	Typical industry practice for evaluating long-term uncertainty. Used to develop MISO Futures	TVA 2019 IRP

Future Uncertainty

Stochastic Portfolio Risk Evaluation

Method Overview:

- Stochastic Portfolio Risk Evaluation accounts for uncertainty by considering a range of possible futures and their associated probability of occurring, as opposed to a single Scenario
  - ***Monte Carlo*** analysis and ***Probability Trees*** are common frameworks for Stochastic Portfolio Analysis
- Portfolio Risk Evaluation is unique because the approach can quantify the distributions of total system costs and environmental outcomes for each future
- This method is commonly used by system planners to evaluate risks under each future portfolio
  - A 2024 EPRI Study evaluated how Idaho Power, CEI South, PacifiCorp, TVA and AES Indiana were implementing this framework

Inputs and Tools:

- Monte Carlo analysis is most commonly used for stochastic risk analysis (included in commercial software such as PLEXOS and Aurora)
- Inputs include portfolio options, key decision variables, and stochastic variables with applicable distributions

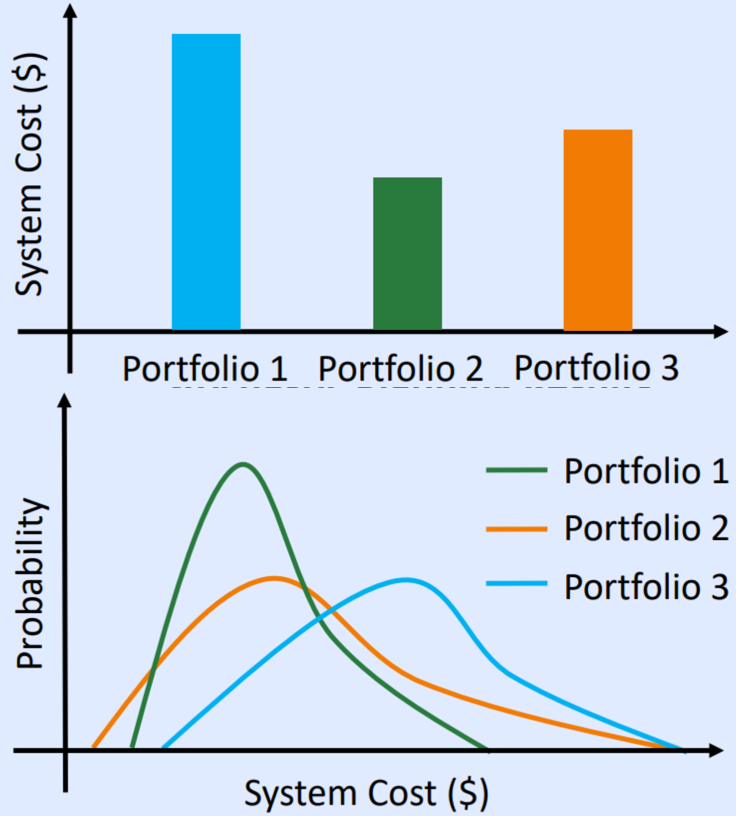
Key Takeaways:

- Stochastic portfolio risk evaluation is a feasible method to improve the performance of scenario analysis in addressing uncertainties

Deterministic and Stochastic Portfolio Analysis

Deterministic planning provides a snapshot for a single assumed future

Stochastic planning quantifies economic and other risks posed by a range of possible futures



Probability distributions of system costs for each future scenario allow system planners to quantify their relative risks

Future Uncertainty

Stochastic Portfolio Risk Evaluation – Probability Trees

Method Overview:

- Probability trees entail the explicit enumeration of a combination of discrete events and their conditional probabilities
  - Allows for the determination of the probability of each combination of outcomes
- Enhances scenario modeling by assigning conditional probabilities to each scenario
  - This allows for more quantitative analysis of scenario modeling results
- Ameren Missouri uses probability trees in their IRP process to assign weighting factors to different combinations of inputs
  - Evaluated 23 different resource plans through a probability tree with 81 total branches to determine the lowest probability-weighted revenue requirement

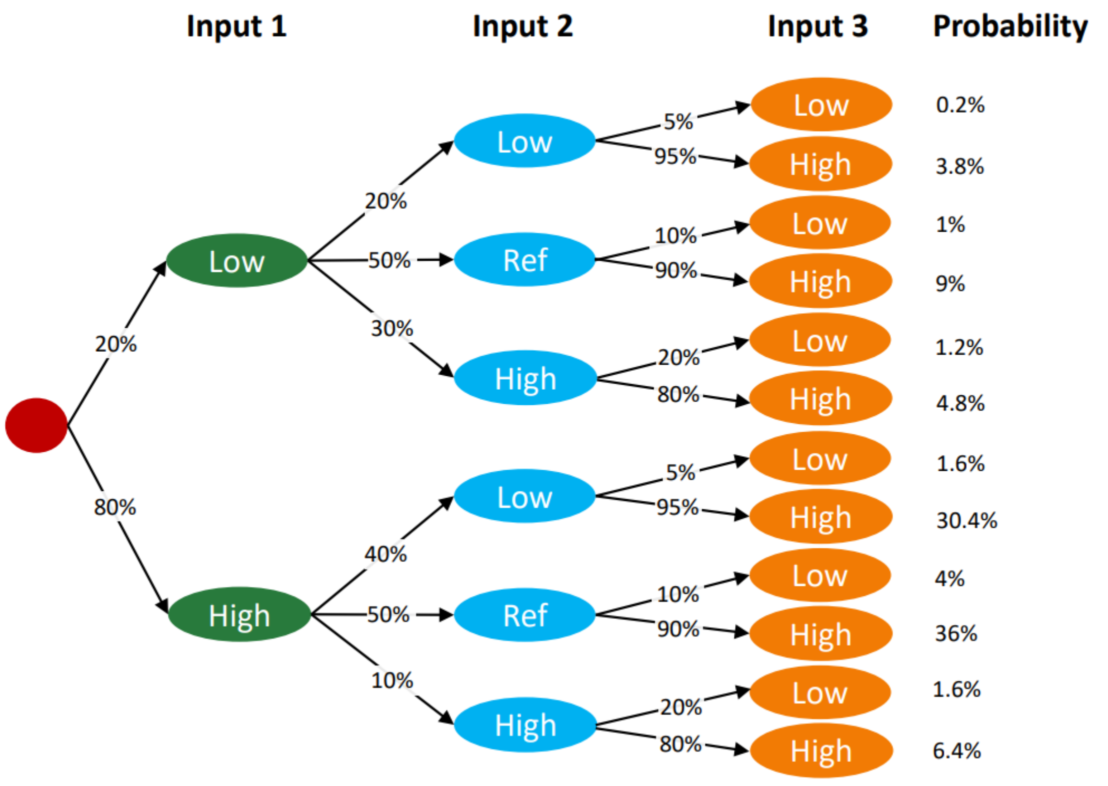
Inputs and Tools:

- Dependent inputs are carbon prices, load growth, and natural gas prices
- Requires assigning probabilities to each input branch

Key Takeaways:

- Used to inform portfolio selection by weighting scenario importance
- Provides a more robust analysis of portfolio performance across futures
- Dependent on judgement-based determinations of input probabilities

Probability Trees



Scenarios with probability-dependent inputs can be enumerated in a probability tree to quantify the expected probability of combination outcomes, useful for enhanced risk analysis of scenario modeling.

Future Uncertainty

Stochastic Portfolio Risk Evaluation – Monte Carlo Analysis

Method Overview:

+ Requires the identification of key risk variables and the development of probability distributions for each variable
    - Key risk variables include load growth, natural gas price, and carbon prices
    - Probability distributions determined by collecting historical data and fitting it with the most applicable distribution
+ Analysis can be enhanced by correlating values between relevant inputs (such as natural gas prices and electricity prices)
+ Repeated random sampling is used to create sets of inputs to the production cost model
+ Visualizations and identified risk metrics (such as risk/benefit ratio or standard deviation of cost) are used to analyze results

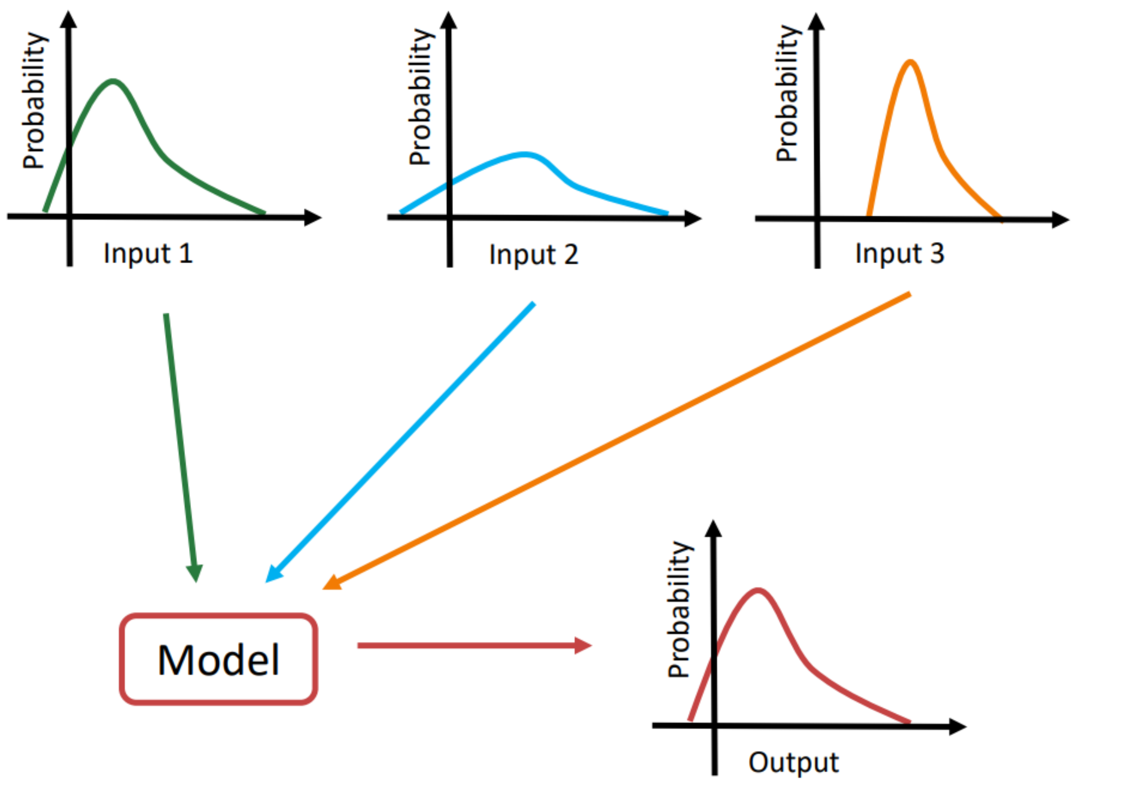
Inputs and Tools:

+ Inputs include historical data for stochastic inputs and portfolio decision options
+ Commercial tools are used to simulate dispatch of portfolios with stochastic inputs such as PLEXOS and EnCompass

Key Takeaways:

+ Results interpretation and visualization is a key step to inform decision-making that is often under-performed
+ Widely accessible approach with limited effort, model, and data requirements to substantially improve the robustness of portfolio planning

Monte Carlo Analysis



Idaho Power performed stochastic analysis as a part of their 2023 Integrated Resource Plan using 4 different risk variables and 60 Monte Carlo samples

Future Uncertainty

Case Study: TVA 2019 IRP

Approach:

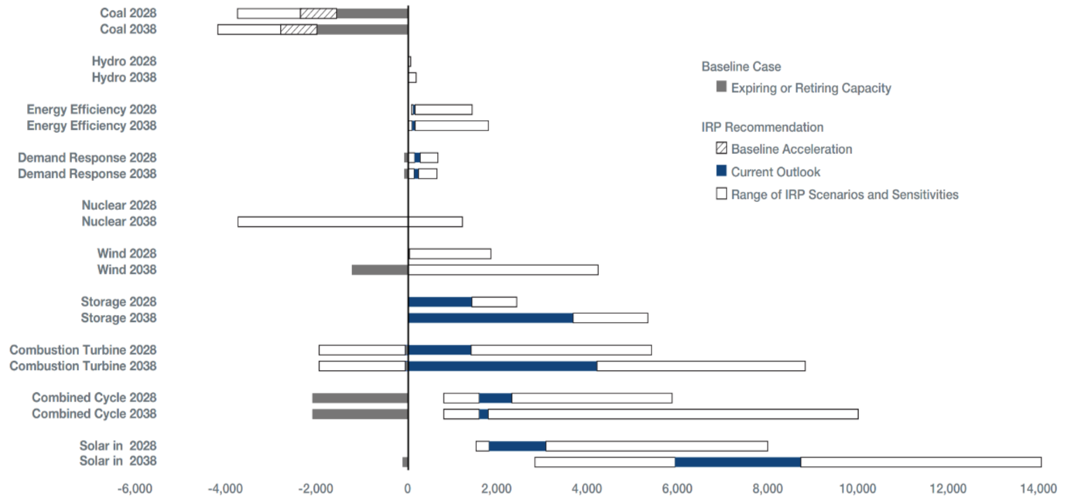
+ TVA's 2019 IRP employed industry leading stochastic portfolio risk evaluations
  - Analyzed 30 different deterministically optimized portfolios – a product of 6 different futures scenarios with 5 different strategies
  - Evaluated 8 different risk metrics as a function of 11 different stochastic inputs
  - NREL's Multi-Timescale Integrated Dynamic and Scheduling (MIDAS) was used to perform hourly dispatch over the 20-year planning horizon for each portfolio
+ Included extensive stakeholder engagement to identify risk metrics, stochastic inputs, and portfolio sensitivities

Key Outcomes:

+ Stochastic evaluations informed an integrated, least cost recommended plan
+ Included signposts guiding decisions in the long-term, such as natural gas prices, electricity demand, and regulatory requirements
+ Demonstrated that stochastic portfolio risk assessment is an excellent opportunity for stakeholder engagement

Stochastic Inputs		Risk Metrics
Natural gas prices	Fuel oil price	Water use
System load	Carbon price	Total CO_2 emissions
Electricity prices	Technology costs	Total resource cost
Forced Outages	Wind & Solar generation	System average cost
Hydroelectric generation	Coal Prices	PVRR
		Risk benefit ratio
		Risk exposure
		CO_2 intensity

TVA 2019 IRP Results



Range of capacity additions and retirements

Technical Review

Capacity Expansion Modeling

Energy+Environmental Economics

Addressing Uncertainty within Capacity Expansion

Future Uncertainty

		Capacity Expansion	
Source of Uncertainty	**Details**	**Scenario Analysis**	**Stochastic Programming (JHSMINE & ACEP)**
Future Uncertainty			
Future Clean Energy Policy & Climate Change	**Technique**	**Deterministic**	**Probabilistic**
	Overview of Method	Industry standard approach used by system planners to evaluate system economics while capturing uncertainty in future loads and resource portfolios. Planners develop of deterministic future scenarios using engineering and stakeholder judgement to capture long-term uncertainties.	Approach which is used to stochastically evaluate transmission planning investments across multiple futures and identify generation and transmission expansions while minimizing the cost of adapting to each future. Method is considered primarily academic with no industry adoption to date.
	Workflow	Involves identifying key inputs to vary across scenarios. Modeling is performed across scenarios to determine the impact of the defined inputs.	JHSMINE uses a decision-tree logic where investment costs are assigned to initial strategies, and decisions are made on decision nodes with assigned probabilities. ACEP is a similar approach, but key differences are a network reduction step to improve computational requirements and a single investment trajectory through time, rather than a branched approach
	Models Used	Scenarios developed by experienced system planners and informed by stakeholder input. Scenarios are evaluated using many commercially available PCM tools such as PLEXOS, MIDAS, PROMOD, among others.	JSHMINE, ACEP
	Data Needs	Portfolio options, policy, system topology, weather correlated loads and generation, load growth, etc.	Portfolio options and system topology, and probabilities
	Existing Case Studies or Applications	Typical industry practice for evaluating long-term uncertainty.	BPA/WECC and MISO Case Studies

Future Uncertainty

Stochastic Programming - JHSMINE

Method Overview:

+ ***Johns Hopkins' Stochastic Multi-Stage Integrated Network Expansion (JHSMINE)*** approach developed by Ben Hobbs which is used to stochastically evaluate transmission planning investments
  - Evaluates transmission investments across a stochastic set of assumptions to identify best-choice investments under a wide range of possible scenarios
  - Two-stage optimization separating optimal investments into near-term and long-term decisions, accounting for the system's ability to adapt to changes
+ Defines up to 25 scenarios based on probabilistic inputs of key uncertain variables such as gas price, load growth, technology prices, policy decisions, and more
  - Scenarios are given composite probabilities based on inputs of the uncertain variables and the applicable standard deviations, means, and correlations of the variable
+ Performs multi-stage linear optimization to minimize the present value of investments and costs over the near and long-term horizon
  - Objective function: $Min(\, Present\ Worth\ of\ Transmission\ \&\ Generation\ Capital + Operating\ Costs)$

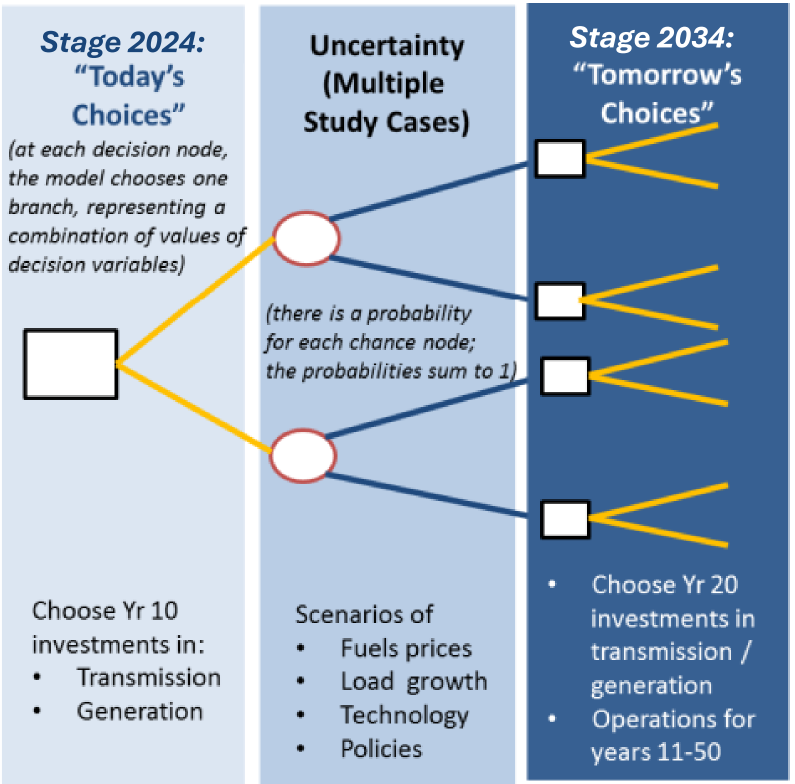
Inputs and Tools:

+ Defined transmission investment candidates in the near-term and long-term, system topology, existing generation information, renewable profiles, generation investment information, stochastic input variables
+ Johns Hopkins Stochastic Multi-stage Integrated Network Expansion (JHSMINE)

Key Takeaways:

+ Stochastic transmission planning yields significantly lower expected costs than deterministic planning
+ Stochastic planning justifies more transmission investment than deterministic
+ Method is considered primarily academic – no industry adoption to date

Two-Stage Optimization Decision Tree



Stochastic programming is an effective method to prioritize the selection and timing of transmission investments when choosing from a defined set of options

Future Uncertainty

Stochastic Programming – ACEP

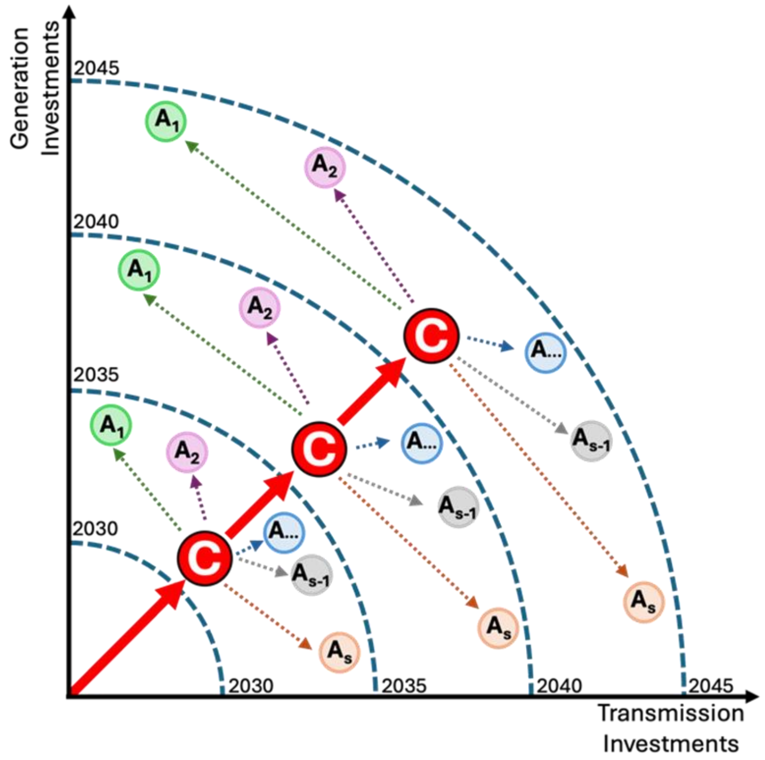
Method Overview:

+ ***Adaptive Co-optimized Expansion Planning (ACEP)*** formulation, developed by James McCalley at Iowa State University is not a traditional stochastic programming model, instead the method provides a single investment trajectory through time, rather than a branched approach.
  - Used a stochastic programming approach like JHSMINE, however the key difference is the additional dimension of model reduction to improve the computational requirements
  - Key similarity with JHSMINE is that the model aims to provide a hedge against uncertainty which is often not captured in deterministic models. ACEP seeks to estimate the costs across multiple futures and identify generation and transmission expansions while minimizing the cost of adapting to each future
+ Method is a ***co-optimized generation and transmission*** expansion planning approach which aims to minimize the cost of the Core (denoted by C) investment trajectory subject to constraints. The model provides a singles investment trajectory through time (red).
  - Objective function: $Min(\, Cost\ of\ Core + Probability\ of\ Future\ x\ Cost\ of\ Adapting\ Core\ to\ Future)$
  - Constraints for each future include: network flow laws, flow limits, generation limits, reserve requirements, environmental targets, investment targets and resource adequacy targets.
+ Model Steps include:
  1. Network reduction steps which can simplify a 90,000-bus system to 1,500 or less busses. This is an important tradeoff to make on high dimensional models when considering computational requirements.
  2. Adaptive Capacity Expansion Plan (CEP) and Resilience CEP are evaluated followed by a folding horizon simulation to check the answers of the optimizers. This is an iterative process to ensure that the capacity expansion plan meets resilience requirements. This is an iterative process between the CEP optimizer and the reserve margin/LOLE calculation.
     – GE-MARS is used for LOLE evaluation, then iterations are made to adjust the planning reserve margin back into the AECP model
  3. Following the optimization stage, the results of the reduced model are translated back to the full (90k) bus system

Key Takeaways:

+ Addresses linkages between planning models while also capturing uncertainty and minimizing investment costs
+ Adaptation investments provide insight into future investments – indicates to planners which investment options are riskier compared to core investments.
+ Provides a flexible investment plan – each core investment portfolio can be adapted to each future scenario via the adaptive investments
+ Method is considered primarily academic – no industry adoption to date

ACEP Investment Trajectory



Method minimizes the Investment Cost (C) + Prob * Cost of Adaptation (A), while providing a single, adaptable investment trajectory through time

Future Uncertainty

Case Study: WECC Expansion Demonstration

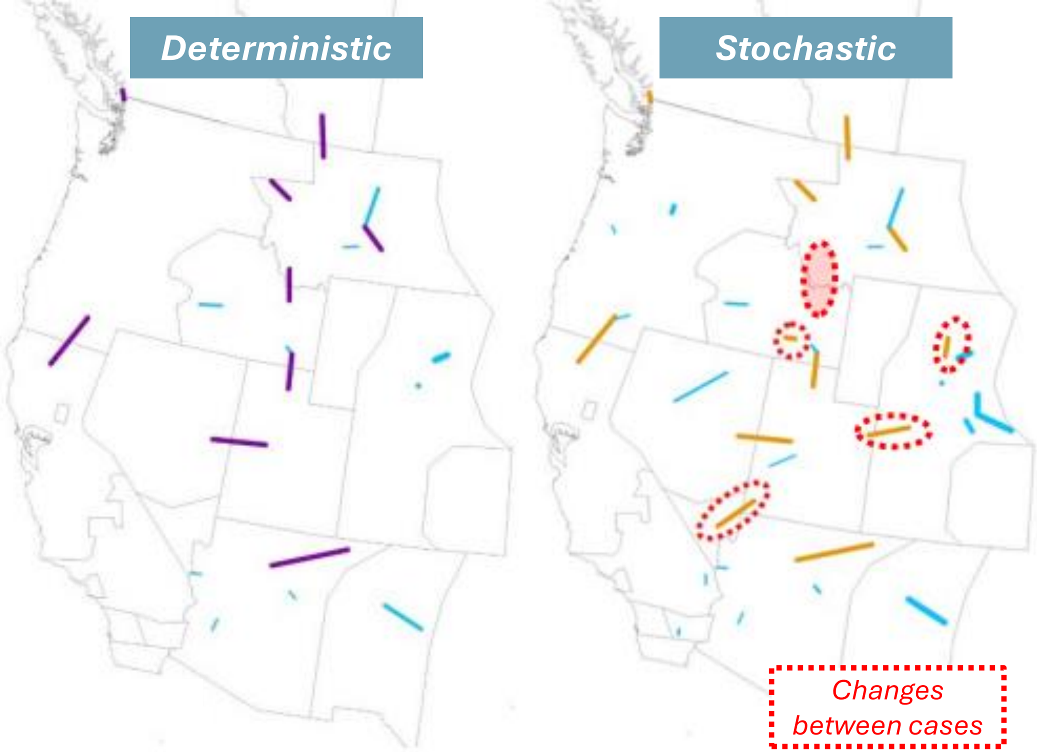
Approach:

+ Demonstrated stochastic programming using JHSMINE on two simplified WECC models
  - Zonal Model: 21 zones, pipes-and-bubbles load flow
  - Nodal Model: 300 buses, enforces basic voltage physics
+ Included 18 different stochastic variables for fuel & carbon prices, capital cost for technologies, and electricity demand
+ Assessed 20 different scenarios representing plausible combinations of the stochastic variables, including 9 scenarios identified by a stakeholder group
+ Incorporated climate change impacts to hydropower production

Key Outcomes:

+ Stochastic programming outcome justifies more investment in transmission
  - Despite more spending on transmission, the stochastic outcome yields $11.66 billion in expected savings over a 50-year time horizon
  - Stochastic outcome performed materially better across different scenario results, demonstrating a more robust solution
+ Realistic additions to the production cost elements of JHSMINE (such as unit commitment constraints) can have a material effect on planning outcomes, depending on scenario carbon prices

Stochastic Programming Results Comparison



Identified transmission investments yield $11.66 billion in expected savings over the 50-year analysis time horizon

Other Modeling Frameworks for Addressing Uncertainty

Energy+Environmental Economics

Addressing Uncertainty within Other Frameworks

Future Uncertainty

Source of Uncertainty	Details	Forecasted Climate Impacts	Robust and Adaptive Planning	Risk-Based Planning with Climate Variability
		Other Modeling Frameworks		
Future Uncertainty				
Future Clean Energy Policy & Climate Change	**Technique**	**Deterministic**	**Hybrid**	**Hybrid**
	Overview of Method	Accounting for the forecasted impact of climate change on electric power system assets.	Uncertainty and risks management methodology employed out-of-model to improve long-term planning. Strategies to adapt decision-making to ensure least regrets investments and manage risks under long-term uncertainty.	Involves assessing climate risk at the asset level and incorporating mitigation measures to reduce the threat of climate change. Can be used to quantify asset-level climate risks for planning purposes
	Workflow	Methods such as downscaled climate model projections, adjusted weather year weighting, and trends in forecasts to account for climate impacts. Climate impacts can be incorporated into model weather years through several methods. Numerical Weather Prediction (NWP) and Global Climate Change (GCM) are the most promising but require forecasts from national forecast centers such as NOAA or NCEP in the US.	Involves a vulnerability assessment to identify uncertainties that pose the highest risk and a monitoring plan to identify new information regarding key uncertainties. Signposts establish thresholds for monitored variables which trigger re-evaluation. A probabilistic extension of this framework uses sequential Monte Carlo analysis to extend the sampling strategies.	Data and effort-intensive process that requires asset-level understanding on climate exposure, risks, and impacts. Steps include: determining the exposure of assets to a climate event, evaluating the probability of damage to assets due to exposure, assessing the consequences of damage to assets and establishing mitigation measures to reduce the consequences.
	Models Used	NWP and GCM Climate Models. ML seeing increased applications	Robust and Adaptive Planning Framework	PNNL & DOE Developed Best Practices
	Data Needs	Historical and Recent Weather Data	Identification of key risk factors	Detailed climate data, extensive understanding of system risks
	Existing Case Studies or Applications	Con Edison Climate Vulnerability Assessment	Con Edison Climate Vulnerability Assessment	Con Edison Climate Vulnerability Assessment

Future Uncertainty

Robust and Adaptive Planning

Method Overview:

+ ***Robustness*** refers to the ability of a selected outcome to perform well across a range of plausible future scenarios
    - Involves identifying performance measures to evaluate the effectiveness of decision options
    - Requires performing a vulnerability assessment to identify uncertainties that pose the highest risk
+ ***Adaptive Planning*** is designed to be continuously updated over long-time horizons in response to new information on uncertainties
    - Requires a monitoring plan to identify new information regarding key uncertainties
    - Uses signposts to establish thresholds for monitored variables that trigger action processes
+ An extension of this framework has been proposed called the ***Robust Adaptive Monte Carlo Planning*** (RAMCP) algorithm
    - Existing work focused on planning over a discrete distribution across models, but extended sampling strategies such as sequential Monte Carlo has been proposed

Inputs and Tools:

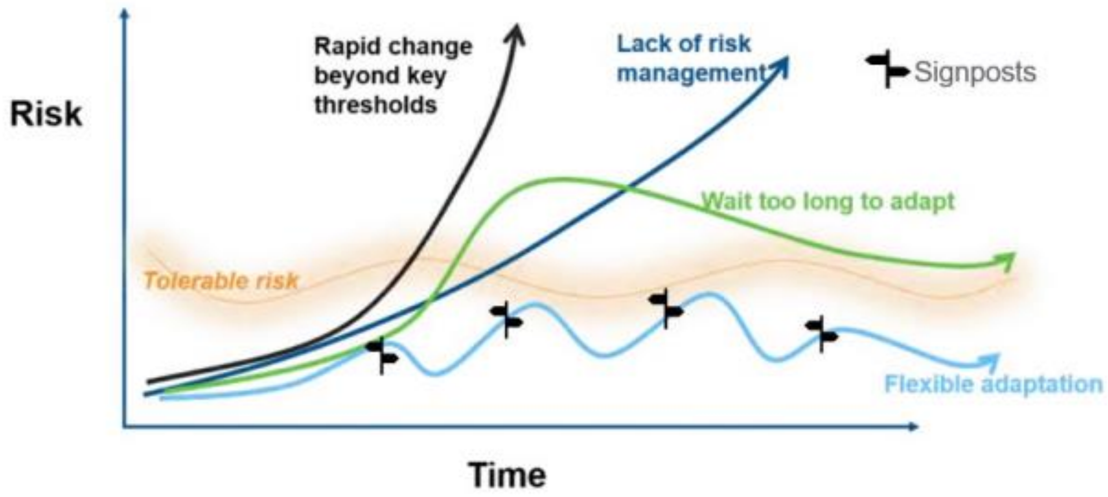
+ Requires identified decision options and key risk variables

Key Takeaways:

+ Adaptive planning approaches are growing in popularity as a no-regrets method to deal with decision making under long-term uncertainty
+ Many different probabilistic and hybrid planning approaches can improve the robustness of planning decisions

Robust and adaptive planning is an uncertainty and risk management methodology employed out of model to improve long-term planning practices and outcomes

Con Edison's Adaptive Signpost Approach



Con Edison established a monitoring plan for key risk variables with signposts to trigger management processes in their 2023 Climate Vulnerability Plan

Future Uncertainty

Case Study: Con Edison Climate Change Assessment

Approach:

+ Case study illustrates the application of both ***Risk-Based Planning*** and ***Robust and Adaptive Planning*** methods
  - Evaluated climate risks including increased temperature and humidity, flooding, wind and ice, and extreme events
+ Used a qualitative vulnerability assessment to determine climate risk to specific assets from climate impacts
+ Incorporated signposts for adaptive decision making in response to changing climate conditions

Key Outcomes:

+ Con Edison's 2019 climate vulnerability assessment combined several methods for dealing with uncertainty to deliver the "gold standard" of climate vulnerability studies
+ Established a structure for continuous risk assessment and identified $5.2 billion in potential improvements

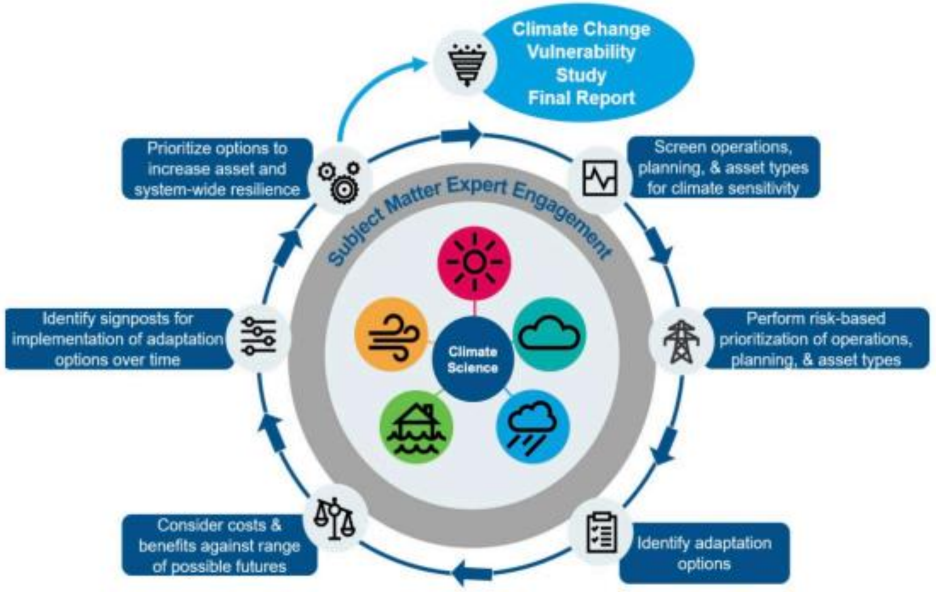
ConEdison Vulnerability Framework

Low	• Asset/system has low vulnerability to the given climate hazard • Minimal or no negative outcomes

Secondary	• Asset/system is moderately vulnerable to the given climate hazard
	  • Exposed to increased degradation over time
	  • Moderately sensitive / limited increase in magnitude

Primary	• Asset/system is highly vulnerable given the climate hazard • High risk of major failure/ increase in magnitude is high

Con Edison's Climate Vulnerability Strategy



Identified up to $5.2 billion in asset investments by 2030 to improve resilience such as undergrounding of lines, installing stronger poles, and expanding monitoring capabilities

Future Uncertainty

Risk-Based Planning with Climate Variability

Method Overview:

+ ***Risk-based planning with climate variability involves assessing climate risk at the asset level and incorporating mitigation measures to reduce the threat of climate change***
+ Required steps:
  1. Determining the ***exposure*** of assets to a climate event
  2. Evaluating the ***probability of damage*** to assets due to exposure
  3. Assessing the ***consequences of damage*** to assets
  4. Establishing ***mitigation measures*** to reduce the consequences
+ Approaches for calculating probability of damage to assets vary in method, depth of analysis, and quantitative complexity

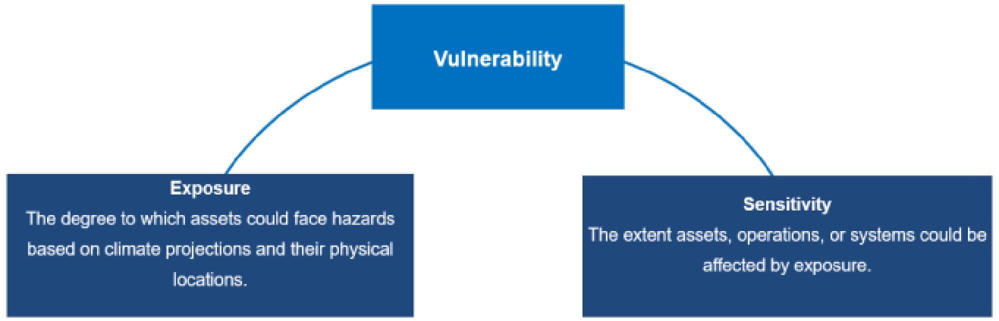
Inputs and Tools:

+ Data and effort-intensive process that requires asset-level understanding on climate exposure, risks, and impacts
+ Utility asset risk assessment frameworks can be adapted to incorporate climate risks

Key Takeaways:

+ Asset level planning is a data and effort-intensive process that yields robust climate risk reductions
+ Required effort can be reduced by implementing simplified versions of asset level planning, such as updating equipment outage rates due to heat exposure for climate impacts

Con Edison's Climate Vulnerability Strategy



Qualitative assessments of exposure, probability, and consequences are often used. For example, Con Edison separated asset vulnerabilities to different climate impacts into three categories: "Primary," "Secondary," and "Low"

Sample Mitigation Measure	Description
Undergrounding and Relocation	Undergrounding and relocating assets (such as out of flood zones or to avoid sea level rise)
Grid hardening and updating equipment	Upgrading or replacing critical equipment to higher design standards such as broader temperature ratings
Vegetation Management	Mitigating wildfire risk through trimming and removal of vegetation around utility infrastructure
Emergency Trainings	Trainings to promote effective response to emergency situations and hazard conditions