Composite Power System Reliability (TR99)

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TECHNICAL REPORT

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Composite Power System Reliability

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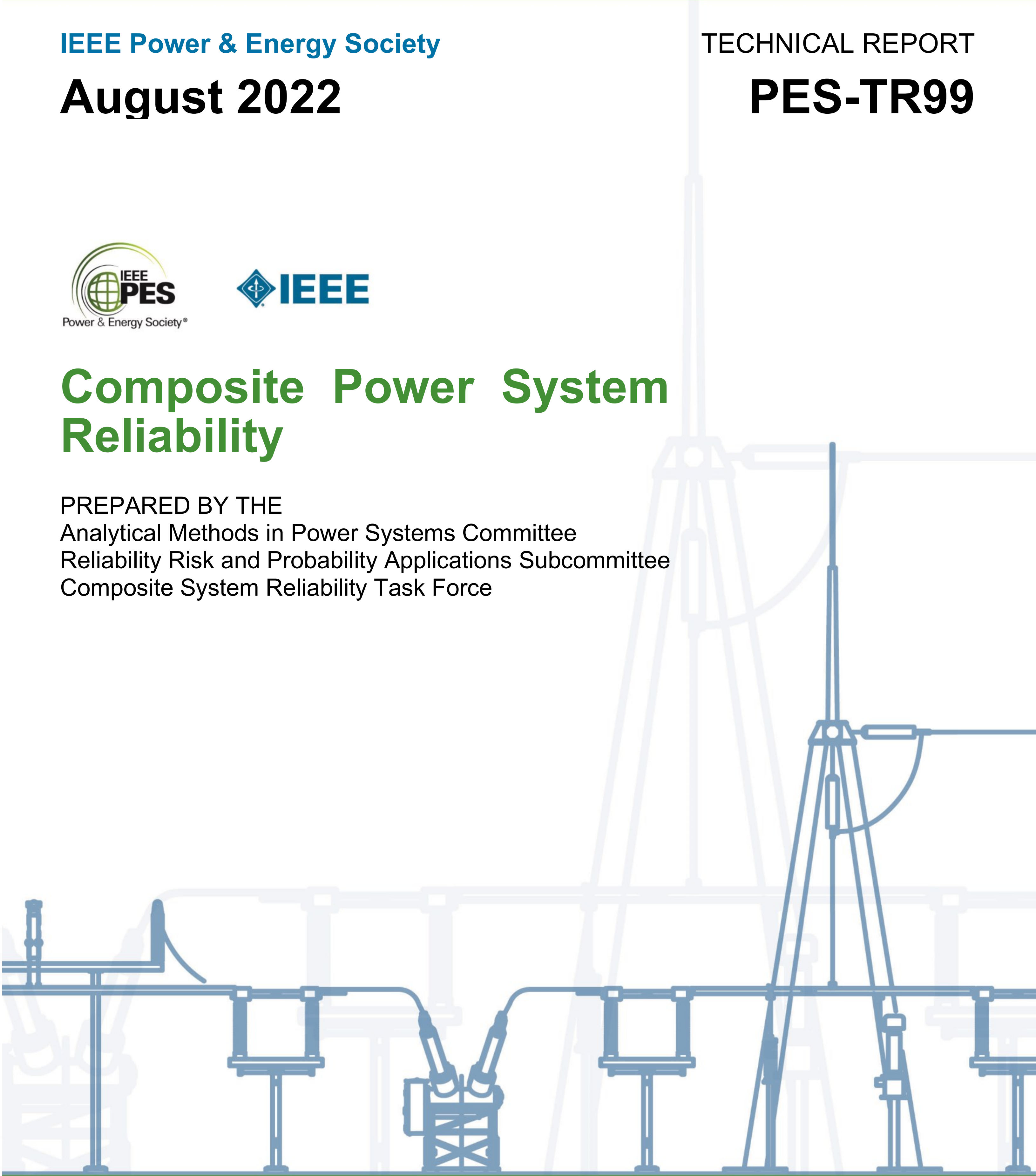
Reliability Risk and Probability Applications Subcommittee
Composite System Reliability Task Force



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KEYWORDS

Analytical Methods

Composite System Reliability (CSR)

Computational Tool

Generation Reliability

Monte Carlo Methods

Probabilistic Methods

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Renewables

Transmission Reliability

Uncertainties

CONTENTS

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EXECUTIVE SUMMARY

This technical report reviews the state-of-the-art in composite system reliability (CSR) evaluation. Reliability assessment methods for composite generation and transmission systems have been developed in recent decades. However, maintaining an adequate level of reliability of the modern power grid is particularly challenging today due to many causes such as increasingly frequent extreme events (e.g., failure of multiple physical components, extreme weather events, and other natural disasters), high penetration of variable energy resources (VERs), and the increasing complexity of energy system infrastructure [1]. Despite the numerous reliability analysis methods that exist today, including enumeration (analytical) methods and Monte Carlo methods, the computational burden is still a major obstacle to applying CSR analysis in an actual large-scale composite system, especially in the area of operations. Organizations and utilities in North America (including the North American Electric Reliability Corporation or NERC), Europe, Asia, and other places in the world have been searching for appropriate methodologies and computing tools.

Based on extensive discussions and experience sharing among task force members from research organizations, utility companies, software developers, and regulatory bodies, the Composite System Reliability Task Force (CSR TF) has focused on some of the most commonly seen concerns and issues related to the adequacy and operational reliability of a composite system. The TF has attempted to address these concerns by gathering best practices from published literature and users of probabilistic tools in the electric power industry. The primary concerns for both planners and operators are to develop and operate a system as reliable as economically feasible, at a meeting, at a minimum, predefined design and operational criteria and standards. Their common objective is to maintain adequacy, operational reliability, and integrity of the system at satisfactory levels, and avoid widespread blackouts.

However, many of the concerns of planners and operators are different. Planners think about long-term goals and how to ensure, at the very least, that the plans for future systems are sufficiently adequate. Operators' goals depend on the time horizon of the study. In the shortest time frame (up to few hours), typical questions are how to provide adequate spinning reserve to keep the risk of system failure below predetermined levels, how to maintain the ability to withstand sudden frequency and voltage changes, and how to employ corrective actions if they are needed [2].

Traditional probabilistic methods for evaluating aspects of adequacy and operational reliability need to be revised due to integration of variable energy resources (VERs) into present and future power systems, retirement of fossil-fired and nuclear central stations, government policies, and regulatory requirements. Due to such system changes, it has become evident that defining secure operating conditions in a power system based on deterministic methods is no longer the most efficient approach, as many of the assumptions used to develop them are no longer effective with the transforming resource mix. There is an evident need to develop a new generation of probabilistic methods, tools, and business practices to replace (or complement) the existing deterministic approaches.

Power industry participants need to know the reliability level of the power system and its components. This information can be obtained by performing a detailed quantitative reliability evaluation of their systems. However, using a probabilistic approach that quantifies reliability at the system and load point levels is a complicated task. A critical challenge in the planning and operation of power systems is the tradeoff between reliability and the cost of investment; and this can be addressed only by probabilistic reliability evaluation.

For reliable and economic operation of composite power systems, the electric power industry maintains sufficient generation and transmission capacity to ensure continuity of electric service to their customers under normal and various abnormal conditions. Deterministic criteria and techniques have been developed and employed by the utility industry and regulators in power system planning and operation for many decades; and these will continue to be benchmark criteria [3].

The objective of this report is to provide guidelines and suggestions for power industry professionals who are considering applying probabilistic methods in CSR analysis. This report, therefore, also investigates other factors that affect the use of probabilistic techniques by electric utilities.

To provide a practical perspective on CSR analysis, this report showcases the progress made by electric utilities across the globe in practical applications of probabilistic methodologies. It includes some of the best practices and case studies to compare different projects and analyze the reliability of a composite system. Those case studies include work at Manitoba Hydro, ERCOT, BC Hydro, and Idaho Power.

Through these case studies, power industry practitioners have demonstrated the benefits of performing probabilistic planning and operation reliability studies both separately and jointly with existing deterministic methods. Further, suggestions are provided about enhancing existing tools for power system software vendors.

Finally, the report provides useful references for the development of NERC guidelines and standards relevant to CSR adoption in the industry.

An appropriate framework for CSR analysis must consider all potential events and scenarios that may have a significant impact on the reliable supply of power to customers. The range of these events and scenarios is very broad, with many of them difficult to predict or control in terms of magnitude and intensity. An effective probabilistic framework should strive to minimize the risk (likelihood versus impacts) to the system from potential events and scenarios, and provide guidance for efficiently mitigating the impact of those events.

Twenty-one CSR tools have been reviewed and analyzed in this work. Although different models and probabilistic methods are employed in these tools, all of them can quantify risks via reliability indices, expressing risks in terms of the probability, frequency, and/or amount of lost load. These indices can provide useful information for planning and/or operations. Among the twenty-one tools, nine have been embedded in planning and/or operation decision systems, while others are not fully integrated in such systems. Such an integration can make it easier for planners and operators to consider risks in their decision making. This would facilitate widespread applications of CSR tools.

The existing CSR tools still exhibit deficiencies, as also outlined in other papers and reports (e.g., [4]). As summarized in this report, further work is needed in 1) data preparation, 2) modelling issues, 3) reliability indices, 4) computational methods, 5) computation tools, and 6) general issues and reliability analysis framework.

A recent CSR TF survey found continuing dissatisfaction with the available tools. Seven of the top 11 impediments to probabilistic analysis concern software tools and their application. These are:

- Obtaining additional data
- Interpreting results
- It's too complicated or takes too much work
- Computation run time
- Analysis is difficult to explain to management and/or regulators
- Lack of confidence in method
- Analysis does not address important issues [5].

When aiming to overcome the deficiencies of CSR tools and expand their practical applications, a tradeoff between computational burden and accuracy is critical. Overall, the gap between analysts' desires and the capabilities of available tools has persisted in spite of continuing algorithmic developments and orders-of-magnitude improvements in processor speed, because expectations for CSR analysis have continued to outpace technological developments as the issues faced by the industry have become more complex.

Traditional reliability and production cost models are inadequate for investment, operational reliability, and resilience planning, including transmission enhancements for timely implementation of greenhouse gas mandates in the energy transition. A probabilistic multi-value transmission benefit assessment model is needed for composite reliability, resilience planning, and operations planning that that quantifies the benefits of an added transmission facility, including production cost benefits, emission reduction benefits, generation capital cost benefits, risk mitigation benefits, resource adequacy benefits and resilience benefits.

This report identifies several research directions for further development and enhancement in CSR analysis, including:

- Reducing the computational time and enhancing the capability of reliability assessment tools for handling large bulk power systems
- Developing more efficient algorithms for evaluating CSR and solving large-scale optimization problems
- Integrating aging and end-of-life failure models into CSR analysis
- Integrating common and dependent mode (CDM) failure models into CSR analysis
- Incorporating operating strategies into CSR analysis
- Applying CSR assessments to developing optimal schedules for building new facilities
- Integrating multiple corrective actions into CSR analysis
- Incorporating the effects of various uncertainties into CSR analysis
- Considering storage and VERs in CSR analysis
- Considering customer and demand side flexibility in CSR analysis
- Incorporating FACTS devices such as phase shifter transformers (PSTs), thyristor controlled series compensators (TCSCs), and static var compensators (SVCs) into CSR analysis
- Integrating demand side management (DSM) into CSR analysis
- Considering weather conditions and seasonal changes in CSR analysis
- Integrating operational reliability criteria violations (cascading and transient stability) into CSR analysis.

This report is organized as follows:

Section 1 summarizes the scope and objectives:

- Review relevant technical literature
- Summarize the results of survey conducted by the CSR TF
- Compare existing deterministic vs. probabilistic approaches and criteria for CSR evaluation
- Review and summarize existing reliability assessment approaches for composite generation and transmission systems
- Review and summarize existing tools for reliability assessment of composite generation and transmission systems
- Review industry standards and practical guides for CSR assessment
- Review industry practices in composite system reliability
- Review enhanced high-efficiency computation methods and tools for reliability analysis of composite power systems
- Summarize needs and identify directions for future work.

Section 2 summarizes important background information, including the significance of reliability and the fundamental concepts of composite power system reliability:

- Importance of reliability
- Functional zones and hierarchical levels
- Basic concepts – adequacy and operational reliability

- Objectives of CSR studies
- Uncertainties
- System failure criteria and remedial actions
- Deterministic vs. probabilistic studies
- Typical probabilistic assessment process
- Industry needs for CSR evaluation.

Section 3 presents an overview of existing and new CSR methods, including component data and effect analysis:

- Modeling of typical system components
- Component reliability parameters
- Effect and impact analysis
- CSR methods
- Other considerations.

Section 4 presents a review of existing tools for CSR assessment and includes:

- Data preparation
- Overview of existing tools
- Description of existing tools
- Classification of existing tools.

Section 5 focuses on utility industry practices:

- Findings of past utility industry surveys
- Findings of a CSR TF survey
- Review of published work
- CSR practice by utilities in North America
- Regulatory policy and compliance assessment

Section 6 discusses the gaps, new challenges, and directions for future work in the area of CSR assessment.

Section 7 provides an extensive list of references in CSR analysis. Section 8 provides a list of acronyms used in the report.

1. SCOPE AND OBJECTIVES

The Composite System Reliability Task Force (CSR TF) was established within the Reliability, Risk, and Probabilistic Applications Subcommittee (RRPA SC) of the Analytical Methods for Power Systems Committee of the IEEE Power & Energy Society in early 2019 to take on this task. It held its first meeting in April that year. The TF has over seventy members from around the world. The scope of the task force includes the following:

- Review and summarize existing reliability assessment approaches and tools for composite generation and transmission systems.

- Develop appropriate high-efficiency computation methods and review tools for industry applications of composite system reliability (CSR) analysis. Provide recommendations for implementation procedures.

- Perform research on the potential applications of cutting-edge technologies to significantly increase computational speed and accuracy at acceptable expense.

- Suggest enhancements of the industrial standards and practical guides for composite system reliability assessment.

This technical report reviews the state-of-the-art in composite power system reliability (CSR) evaluation. Reliability assessment methods for composite generation and transmission systems have been developed in recent decades, particularly with the ever-increasing penetration of renewable energy. However, the computational complexity of CSR analysis is considerable. Despite the numerous methods proposed, including enumeration (analytical) and Monte Carlo methods, the computational burden is still a major obstacle to applying CSR analysis in an actual large-scale composite system, especially for online, real-time applications. Organizations and utilities in North America (including North American Electric Reliability Corporation or NERC), Europe, Asia, and other places in the world have been looking for appropriate computing tools for years. In order to achieve high-efficiency computation of CSR assessments and promote their applications in large-scale systems, further developments are necessary.

The report objectives include:

- Review the relevant technical literature
- Summarize the results of a survey conducted by the CSR TF
- Compare existing deterministic vs. probabilistic approaches and criteria for CSR evaluation
- Review and summarize existing reliability assessment approaches for composite generation and transmission systems
- Review and summarize existing:

    - Reliability assessment approaches for composite generation and transmission systems
    - Tools for reliability assessment of composite generation and transmission systems
    - Industry standards and practical guides for CSR assessment
    - Industry practices in CSR assessment
    - Enhanced high-efficiency computation methods and tools for reliability analysis of composite power systems

- Summarize needs and identify directions for future work.

The report is organized as follows. Section 2 discusses the significance of reliability and the fundamental concepts of composite power system reliability. Section 3 presents an overview of existing and new methods for assessing the reliability of composite power systems. Section 4 presents a review of existing tools for CSR assessment. Section 5 focuses on utility industry practices. Section 6 discusses the gaps and future work. Section 7 provides an extensive list of references in CSR analysis.

2. BACKGROUND

2.1 Introduction

“Composite power system reliability evaluation is concerned with the ability of the combined generation and transmission system to supply adequate and suitable electrical energy to major system load points” [3]. CSR analysis evaluates the reliability of the power system, taking into account the constraints imposed by outages in a steady state environment of generation, transmission, and/or substations [3]. A considerable amount of published work over the past several decades has been devoted to various aspects of reliability calculations for composite power systems [4]–[45]. A set of appropriate reliability indices is computed by quantifying the severity of operating criteria violations and/or the corrective actions needed to alleviate violations following an outage [9]–[13].

The fact that power system operation is subject to an enormous number of random events makes reliability analysis a rather complex issue. A complete analytical approach to what is only a generally defined problem is a practical impossibility. Increased penetration of VER generation such as wind and solar photovoltaic (PV) creates uncertainties an order of magnitude greater than those in legacy power systems and has increased the variability in power flow patterns, volatility of system stress, reserve capacity requirements, cycling of thermal units, and ramping capacity requirements. New approaches are emerging for dealing with these problems from the operational point of view, including demand response (DR) programs, tapping on customer and distributed resource flexibility, construction of transmission, and new control approaches. The key question to be addressed is how the new operational paradigms affect composite system reliability. Methods that quantify these effects are becoming very important for power system planning.

Planning approaches based on using a combination of deterministic and simplified probabilistic approaches do not provide an adequate probabilistic risk assessment for the new realities. Comprehensive probabilistic methods should be capable of taking into account: (a) volatility of VER generators, (b) flexibility enabled by storage, customer-owned generating resources, load management, etc. (c) uncertainty in primary fuel prices, and (d) scenarios with increased weather uncertainty and environmental constraints. The desired outputs of comprehensive probabilistic methods include: (1) expected cost of unreliability, (2) system reliability quantification (via indices), (3) operational limitations (overloads, under-over voltages, ramping violations, etc.), and (4) environmental impacts.

Historically, adequacy and operational reliability calculations have been, and remain today, of paramount importance to the reliable and economic operation of power systems. Electric utilities maintain sufficient generation, transmission and distribution capacity to ensure continuity of electric service to their customers under normal and various abnormal conditions, including uncertainties associated with load variations and variability of renewable energy sources. Power system adequacy and operational reliability have received even more attention in the past decade due to widespread implementation of electricity markets, power industry restructuring, massive integration of renewable energy sources, and major blackouts across the globe.

Today, more and more utilities, to stay competitive in liberalized power markets, operate their systems with heavier flows on transmission lines and lower operational reliability margins. This trend is likely to persist, and has prompted development of new methods and tools, and improvement of existing ones, to ensure reliable operation, prevent widespread disturbances, and further increase the use of the system. Maintaining adequacy and operational reliability becomes more challenging than ever before, especially as the frequency of extreme environmental conditions increases, together with their impacts on VERs, which count on the environment for the energy they need to operate. Increasing interest has been seen in evaluating the reliability impact from high penetration of renewables such as photovoltaics and wind, retirement of fossil-fired and nuclear plants, regulatory requirements, and other policies on a composite system basis—that is, including both generation and transmission. An effort to develop methods and tools to adequately analyze and improve electric grid reliability in planning and operations continues.

2.2 Importance of Reliability

As the economies of countries across the globe are becoming more electrified, the changing resource mix, decarbonization of the grid, and increasing frequency and severity of extreme weather and natural disaster events greater challenges on developing and operating a reliable bulk power system (BPS).

Maintaining an adequate level of reliability of the modern power grid is a particularly challenging problem due to many causes such as frequent extreme events (e.g., failure of multiple physical components, extreme weather events, and other natural disasters), high penetration of VERs, the risk of cyber-attacks, topology changes as a result of forced and planned outages, and the increasing complexity of energy system infrastructure. As environmental factors impact resource availability, scenario planning, coupled with CSR, provides a vantage point to study the extremes and the benefits of infrastructure investments.

Utilities need to know the reliability level of the power system and its components, which can be obtained by performing a detailed reliability evaluation of their systems. However, a probabilistic approach that 'quantifies' reliability and comes up with system and load point indices is a complicated task. Therefore, a critical challenge in the planning and operation of power systems is the trade-off between investment and reliability. Utilities can benefit by using value-based reliability analysis to calculate the value of increased reliability and use that information to make informed decisions.

As noted above, deterministic criteria and techniques have been developed and employed by the utility industry and regulators in power system planning and operation for many years; and they will continue to be benchmark criteria [3]. That said, understanding the forced outage rates of equipment and resources, and how they change based on the environmental conditions they face, is important when projecting the future performance of system components subject to climate change-driven weather patterns.

CSR analysis, introduced by Roy Billinton in 1969 [6], uses probability methods to determine quantitative reliability indices of the composite generation and transmission system, also called the bulk power system, at the delivery point and system levels, accounting for both generation and transmission contingencies, and considering operating procedures and emergency actions. Since then, a significant amount of research has been done and many papers in CSR evaluation have been published [2], [4] – [36].

Many of these publications will be referenced in other sections of the report. Extensive bibliographies on applications of probability methods in power system reliability evaluation are provided in [37]-[45], each of which includes a section on CSR analysis. References [43] and [45] are bibliographies devoted entirely to CSR analysis.

2.3 Functional Zones and Hierarchical Levels

The large size of the power system precludes reliability analysis of the entire system. Instead, the problem is partitioned into sub-problems along the electrical seams of the system. The power system is broadly divided into three functional zones: generation, transmission, and distribution. Electric utilities are either divided into such functional zones for the purposes of organization, planning, operation, and studies, or are solely responsible for one or two of these functions. The functional zones can be combined to form hierarchical levels for which reliability analysis can be applied. Reliability studies are categorized under three hierarchical levels, shown in Fig. 1. Hierarchical level one (HLI) considers the generation system only. Hierarchical level two (HLII) encompasses both the generation and transmission systems. Hierarchical level three (HLIII) includes all three functional zones for conducting reliability assessments [6]-[12].

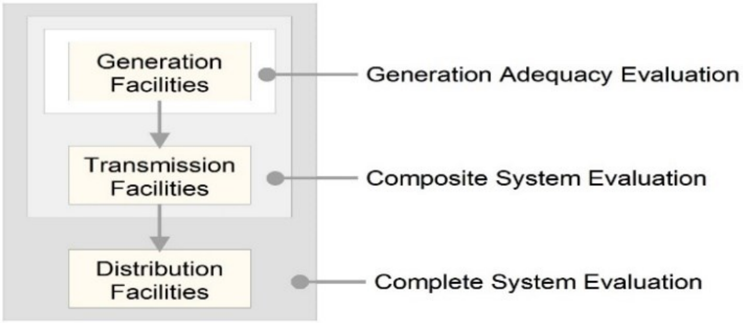


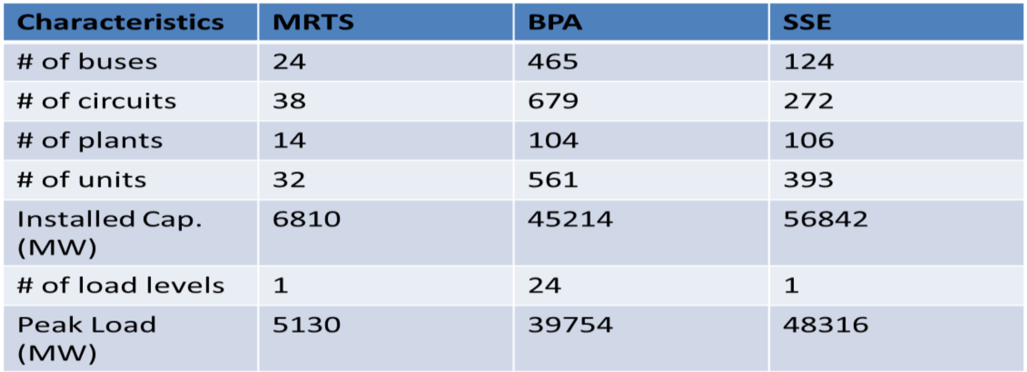
Fig. 1. Definition of Reliability Analysis Problems

HLI studies focus on assessing generation system adequacy to satisfy the total system demand, and to identify corrective and preventive maintenance on the generating units that have the most impact on generation adequacy. In HLI, the transmission network and distribution facilities are not modeled, and a relatively simple generation-load model is used for adequacy assessment [9]-[11].

In HLII studies, the scope widens with respect to HLI, as it involves evaluation of two functional zones: generation and transmission. At HLII, transmission limitations and their effect on energy deliverability are incorporated with generation adequacy assessment. Hence, for HLII studies, a transmission model is added to the generation-load model used in HLI studies and adequacy analysis at this level is called composite generation and transmission system (in short, composite system) reliability (or CSR) evaluation [9]-[11]. Traditionally, HLII studies are conducted to assess the reliability of an existing or a proposed system. The effects of load growth, configuration changes, environmental and social scenarios (e.g. elimination of all nuclear, or fossil-fired plants, long-term cloud cover or high wind speeds, etc.), and reinforcement alternatives in both the generation and transmission functional zones can be analyzed to evaluate their impact on reliability indices for the overall system as well as for the individual buses. CSR analysis is the reliability analysis of the combined generation and transmission systems. It is important that generation and transmission be modeled simultaneously as there is substantial interaction between the two systems. Section 3 will be discussing in more detail both established and emerging methods for CSR assessment. Reference [25] presents CSR study results based on the CREAM program (a software tool developed by PSR of Brazil, in collaboration with EPRI) and quantified this interaction for a specific system, as shown in Fig. 2. Note that 55% of the unreliability is due to a combination of events in the generation and transmission system.

To illustrate the contribution of generation (G), transmission (T), and composite (C) events on CSR indices the following three systems are studied: Modified IEEE Reliability Test System (MRTS), a system derived from Bonneville Power Administration (BPA), and a reduced version of the Brazilian Southern-Southeastern System (SSE) [25]. The basic characteristics of these systems are shown in Table 1 [25].

TABLE 1. Basic Characteristics of studied Systems MRTS, BPA and SSE



Characteristics	MRTS	BPA	SSE
# of buses	24	465	124
# of circuits	38	679	272
# of plants	14	104	106
# of units	32	561	393
Installed Cap. (MW)	6810	45214	56842
# of load levels	1	24	1
Peak Load (MW)	5130	39754	48316

Table 2 presents the loss of load probability (LOLP), expected power not supplied (EPNS), and loss of load frequency (LOLF) for these systems. It is evident that composite G and T events have a dominant impact on the reliability index LOLP for all three systems, and EPNS and LOLF for two out of three studied systems [25].

TABLE 2. Percentage Contribution of G, T, and C Events to the System Reliability Indices

Results	MRTS	BPA	SSE
LOLPg	21.5	9.2	21.2
LOLPt	9.8	29.0	15.4
LOLPc	68.7	61.8	63.4
Total	100.0	100.0	100.0
EPNSg	38.7	19.0	69.6
EPNSt	2.4	15.4	7.4
EPNSc	58.9	65.6	23.0
Total	100.0	100.0	100.0
LOLFg	29.3	13.2	17.6
LOLFt	8.3	53.9	37.3
LOLFc	62.4	32.9	45.1
Total	100.0	100.0	100.0

The percentage contribution of G, T and C events to reliability indices LOLP and EPNS for BPA system is shown in Fig. 2. Note that 61.8% of the BPA system unreliability is due to composite events.

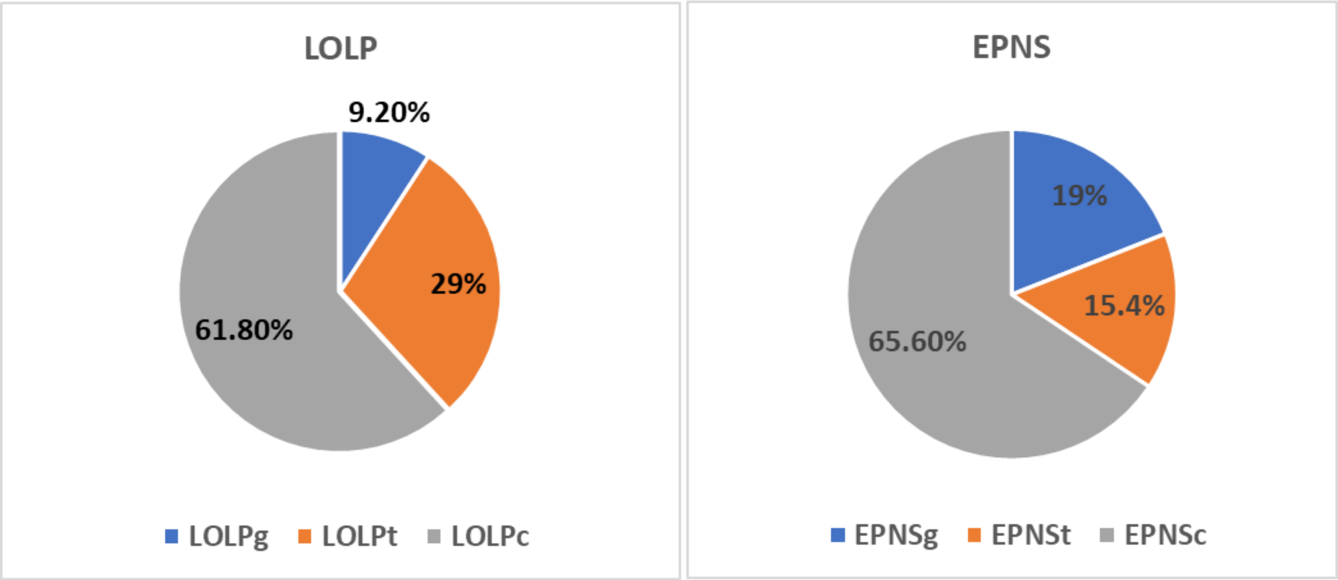


Fig. 2. Composite System of BPA Reliability by Contributing Events [25]

The overall problem of HLIII evaluation (often termed complete system reliability evaluation) involves all three functional zones and requires detailed modeling of the generation, transmission, and distribution systems. The objective of HLIII analysis is to perform reliability assessments at the consumer load point. However, it is not usually conducted for a practical system due to the modeling and computational complexity, and the enormity of the problem. Therefore, the distribution functional zone is typically analyzed as a separate entity [9]-[12]. The introduction of VER generation, mainly wind and PV, has further complicated reliability analysis, as substantial VER generation is appearing on the distribution system as well as the bulk power system.

2.4 Basic Concepts – Adequacy and Operational Reliability

Bulk power system reliability comprises two basic attributes: adequacy and operational reliability (formerly called security). Adequacy is the ability of the electric system to supply the aggregate electrical demand and energy requirements of end-use customers at all times, taking into account scheduled and reasonably expected unscheduled outages of system elements. Adequacy is associated only with static conditions and does not involve system dynamic or transient disturbances.

Operational reliability is the ability of the electric system to withstand sudden disturbances such as electric short circuits or unanticipated loss of system components [3]. Operational reliability relates to the capability of a power system to continuously satisfy total firm power demands when unexpected dynamic or transient disturbances occur. These disturbances can include the abrupt loss of major generation or/and transmission facilities. Another aspect of operational reliability is system integrity, the ability to maintain interconnected operations. Integrity is violated if uncontrolled separation, cascading, or islanding occurs upon the occurrence of severe disturbances [3], [9].

2.5 The Objectives of CSR Studies

The purpose of assessing the reliability of the power system at HLII is to estimate the ability of the system to perform its function of moving the energy provided by the generation system to the delivery points [3]. According to an IEEE definition, the reliability of a bulk system is a measure of the ability to deliver electricity to all points of use within accepted standards and in the amount desired. [15]

The main concerns for both planners and operators are to develop as reliable a system as economically feasible. Their common objective is to maintain the adequacy and operational reliability of the system at satisfactory levels, and avoid widespread outages. In general, reliability indices can be calculated both at the delivery or load points and for the system as a whole, and can be used for planning and operation studies. The expected load to be curtailed to maintain power flows and voltages within applicable limits is used as a measure of unreliability.

Many concerns are different for planners and operators. Planners think about long-term goals and want to ensure, at the very least, that plans are sufficiently adequate to support reliable operations. Operators' goals depend on the time horizon of the study. In the shortest time frame (up to few hours), typical questions are how to provide adequate spinning reserve to keep the risk of system failure below predetermined levels, how to maintain the ability to withstand sudden changes, and how to employ corrective actions if they are needed [3].

CIGRE WG 03 of SC 38 [26] listed the following objectives for utilities when planning, designing, and operating a bulk power system:

- To preserve system adequacy, i.e. to supply the aggregate electric power and energy requirements within acceptable technical quality and service continuity
- To preserve system security (operational reliability) such that recovery from more probable contingencies can be achieved without load curtailment or interruption and avoiding excessive stress on the system and its components
- To preserve system integrity, such that more severe, less probable contingencies, including sequences of contingencies, will not result in uncontrolled separation of major portions of the system
- To limit the extent of failure and minimize the risk of widespread shutdown
- To promote rapid restoration following shutdown.

2.6 Uncertainties

Classification and basic aspects of uncertainties are presented in [46]. In general, they can be grouped as (a) uncertainty in basic variables, (b) model uncertainty, and (c) parameter uncertainty. Reference [47] observes, "In the electric utility industry, we can guarantee only one thing with absolute certainty: we live and work with many unknowns." Probabilistic techniques can quantify the uncertainties and support decision makers in planning and operation environments.

Reference [48] presents a multicriteria model that combines the reliability models of components with fuzzy models to incorporate the uncertainty of load for performing transmission expansion planning. Reference [49] presents a tabulating technique of normal distribution sampling and a correlation sampling technique that are utilized to simulate bus load uncertainty and correlation in CSR assessment. Reference [50] presents the probabilistic collocation method (PCM) based on Gaussian quadrature concepts to select appropriate points from the set of uncertain parameters, in order to approximate the mapping between parameters and an output of the simulation. Such information provides the mechanism for assessing whether system behavior is robust to uncertainty in parameters. Reference [25] notes that "uncertainties in power system reliability predictions may arise at any stage of a reliability investigation." Four main stages associated with some types of uncertainties are: (1) observation of past system behavior in order to obtain outage models and corresponding outage data including that of VERs, (2) creation or selection of a reliability calculation method and its implementation in a computer program, (3) calculation of reliability indices using a program, and (4) installations dates of future generation and transmission additions.

In today's power grid, due to a large number of uncertainties related to generation, transmission, load, etc., it is a significant challenge for planners and operators to supply power to customers reliably and with low cost. The existing probabilistic approaches for reliability evaluation of a power grid are no longer applicable for accurately assessing these uncertainties and evident complexities. The reason for underlying deficiencies of existing approaches for power grid reliability evaluation in planning and operation is that they do not model the new uncertainties and complexities resulting from transformation of the resource mix and higher frequency of extreme weather driven by climate change events. Resulting practical decisions based on results obtained from those approaches may have tremendous economic and reliability implications. Section 3 of this report focuses on existing and new methodologies for reliability evaluation of a composite power system. Also, power grid operators and planners require new computational tools capable of handling these uncertainties and complexities. Section 3 of this report focuses on reviewing the capabilities and possible gaps of CSR tools.

The power grid today is becoming a much more complex infrastructure system with the integration of new generation sources (wind, solar, etc.), new loads (e.g., plug-in-hybrid electric vehicles), and advanced information, communication and control (ICT) technologies. Old rules of thumb are helpful, but not sufficient as they make assumptions that are no longer applicable to the evolving bulk power system. It also is exposed to a larger number of uncertainties that threaten the reliable and secure supply of electricity. These uncertainties relate to contingencies (physical and cyber), VER generators, changing customer load patterns, customer resources, etc. The effects of contingencies on the reliability of power system supply can sometimes be widespread, cause voltage or stability collapse, and lead to blackouts affecting millions of people. Due to the importance of reliable electricity supply and the fundamental changes in the power grid, probabilistic methods for the reliability evaluation of the power grid need to be adapted.

2.7 System Failure Criteria and Remedial Actions

Failure Criteria

Reliability indices for a composite power system are defined in terms of system failure events. The following system failure events are commonly taken into account for computing the reliability indices: [15]-[16]

- Insufficient generation to meet the load demand
- Transmission system component overloaded
- Bus voltages outside tolerances
- Frequency excursions beyond limits
- Real-power deficiencies
- Reactive-power or voltage-support deficiencies
- Customer interruptions (loss of load)
- Ill-conditioned network violations (non-convergence)
- Interruption of continuity of power supply to a delivery point
- Separation
- Instability
- Cascading risks
- Voltage collapse.

Remedial Actions

Some of the failure conditions can be alleviated by corrective remedial actions—automatic or manual. For example, it may be possible to adjust generation or phase shifters to relieve overloads and to adjust generator voltages or transformer taps to bring bus voltages back within range. Acceptable ranges or limits on remedial actions must be chosen consistent with normal and emergency state operating practices and with allowable times for recovery to within long term ratings. It is thus of interest to determine whether it is possible to eliminate a system problem by such permissible remedial actions. A failure occurs when remedial actions are insufficient to eliminate the system problems. After all corrective actions are applied, only the two most severe outcomes remain: loss of load and system collapse. The severity of such system problems may be assessed by computing the amount and location of load curtailment necessary to resolve the problem. In this way, it is possible to compute area or delivery point reliability indices that measure the frequency, duration and amount of expected load curtailment. Generally, in CSR, linear and dynamic programming methods are used to determine generation shifts and loads shed to alleviate overload and voltage violations.

Typical remedial actions include: [30], [51]

- Real power generation adjustment
- Reactive power generation adjustment
- Area interchange adjustment
- Generation bus voltage adjustment
- Transformer phase shifter adjustment
- Switchable capacitor/reactor adjustment
- Transformer tap adjustment
- Generator tripping
- Circuits switching
- Interruptible load shedding
- Firm load curtailment
- Critical load curtailment.

From the above list, generation redispatch is the most often used remedial action in practice. Sometimes switching a line or lines out of service may alleviate violations as result of contingencies; but it is rarely used in practice. Reference [52] studied the removal of lines as a remedial action to relieve capacity limit violations and to enhance service reliability.

2.8 Deterministic vs. probabilistic methods

2.8.1 Deterministic methods

The planning and operation of power systems have been traditionally driven by deterministic reliability standards and criteria (e.g., NERC standards, WECC reliability criteria). NERC has developed mandatory and enforceable reliability standards for planning (TPL-001-5), FAC-002-4) and operation (TOP-002-4, IRO-008-3, IRO-017-1) [2]. NERC's critical infrastructure protection (CIP) standards (CIP-002-5), dealing with cyber security of power systems, are also mandatory and enforceable [3].

Considerable published work over the past several decades has been devoted to the various aspects of adequacy, operational reliability, and risk calculations for planning and operations. Generally, research in these areas moves along three different directions:

1. Evaluation of planning projects and calculation of operational reliability margins based on deterministic criteria [53]-[55]
2. Adequacy and operational reliability assessment based on hybrid deterministic-probabilistic approaches, often called risk-based approaches [56]-[63]
3. Adequacy and operational reliability assessment based on probabilistic approaches [21]-[25].

Deterministic approaches analyze, on a case-by-case basis, a number of reference scenarios by simulating them and evaluating reliability and operational reliability margins. The traditional way to operate a power system involves the deterministic though risk-based N–1 criterion. Operating criteria are designed such that the power system is operated at all times so that instability, uncontrolled separation, cascading outages, or voltage collapse, will not occur as a result of any single contingency (the N–1 criterion) or credible multiple contingencies [3].

Deterministic approaches are conceptually simple to implement, are easy to understand, and enable straightforward assessment and judgment by planners and operators. However, deterministic methods have several shortcomings, which are discussed in references [56]-[63]. Deterministic planning and operation criteria consider the consequences of outages; but probabilities of outages are overlooked. System planning alternatives based only on deterministic analysis may not be the best. Multiple component failures are often excluded from consideration. Another weakness of deterministic assessment is that, though risk-based, it cannot account for the stochastic nature of the system including the random outages of components and system operating states. Many major outage events across the world have indicated that the N–1 criterion may be insufficient for a reasonable level of system reliability.

Finally, the main challenge for N–1 contingency monitoring is difficulty in dealing with model complexity and the uncertainties associated with renewable energy sources, including environmental conditions that are not random, but driven by climate change, as well as other causes. Such scenarios that need to be modelled, and which can result the loss of significant amounts of resources (not random-based equipment failures) include too much or too little wind, smoke, clouds, smog, or snow, and excessively high or low temperatures, and their impact on interdependent critical infrastructures, etc. Thus, deterministic planning may recommend expensive system upgrades to protect against high impact outage events that may never occur. However, because of many years of successful use and the relative simplicity of deterministic approaches, planners are not eager to apply other approaches. The expectation is that hybrid approaches may resolve the deficiencies of deterministic criteria and add the value of risk-based approaches [56]-[63]. Although deterministic criteria have served the electric utility industry well over many years, in order to provide customers with the optimum service reliability at the right cost, the movement towards reliability-based planning and operation criteria and models is inevitable.

2.8.2 Probabilistic methods

Probabilistic criteria and methods are classified into two main techniques: (a) selective contingency enumeration and (b) Monte Carlo simulations. Both methods have their advantages and drawbacks. It is important to know how and when to use each technique so they can complement each other. Contingency enumeration usually uses an enumeration procedure to capture all the contingencies with substantial effects on system unreliability and a fast evaluation process. The depth of contingencies, that is, the maximum number of coincident multiple independent outages and/or common mode outages) varies depending on the objectives of the study. As the depth increases the number of possible combinations of contingencies, and therefore the computational requirements, increases exponentially.

Monte Carlo simulation uses a pseudo-random process to select a sample of contingency cases for evaluation. It is easy to implement; inclusion of multiple independent and common mode outages is straightforward; but for statistically meaningful results the number of contingency simulations must be huge, leading to computational challenges. Probabilistic criteria and methods are discussed in multiple references of this report including [6]-[12], [21]-[25].

Recent years have seen a significant increase in renewable generation in the overall generation mix. This is expected to increase even more in coming years. These renewable sources are non-dispatchable and variable in nature, thus increasing overall uncertainty in the power system planning process. It is difficult to account for these uncertainties using a deterministic planning approach. There are also various other power system variables that are uncertain, for example load forecast, generation pattern, and weather conditions and their duration. In traditional deterministic planning, such uncertainties are accounted for only in a small number of scenarios. Therefore, the planning decisions obtained are of lower fidelity [11], [57].

Risk-based methods add one more dimension to enhance transmission planning and operation processes. They consider both the impact and likelihood of occurrences of outage events and, hence, can identify and rank contingencies that may be problematic for system operation. When combined with the severity of specific events, risk can be quantified. The advantages of probabilistic approaches are noticeable; but they are not widely used in practice. Currently, only adequacy performance is addressed in commercial probabilistic reliability programs and considered in practical studies.

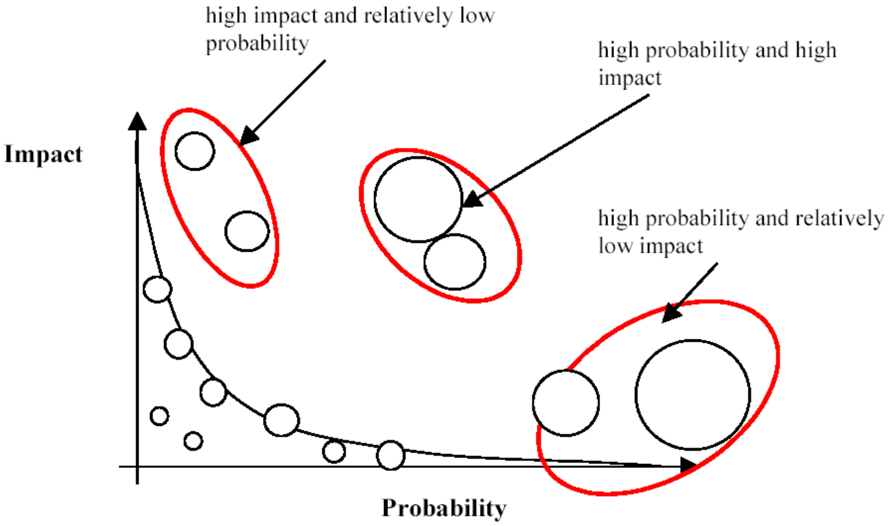


Fig. 3. Risk visualization based on event/scenario probability and its impact

The relationship between an event probability, degree of its impact, and risk is shown in Fig. 3. If the risk of an event/scenario is defined as the product of its probability and impact, the events that lie on the same hyperbolic “risk” curve (as shown in Fig. 3) have equal risk. High impact and relatively low probability events and high probability and relatively low impact events have equal or similar risk as they lie on the same or close hyperbolic risk curve(s) (not shown). Finally, high probability and high impact events lie on different, higher risk curves and have the greatest risk.

2.8.3 Comparison

Generally, both deterministic and probabilistic approaches are available for power system reliability assessment. Both approaches require a year-by-year, system-based analysis considering multiple scenarios with variations in system topologies, system load, import/export conditions, generation dispatch, and seasonal loading conditions. The risks/issues associated with a given system depend on the interactions of all components in the system.

A comparison of basic capabilities for deterministic and probabilistic methods follows.

Deterministic Methods

- A limited set of contingencies is analyzed to account for system problems (overload, voltage, etc.).
- "Worst-case conditions" are analyzed to make sure that deterministic criteria are met.
- The deterministic criteria presently used in planning and operations are not flexible enough to accommodate system changes and uncertainties.
- The same probability of occurrence is implicitly assigned to all contingencies

Therefore, no quantitative reliability index calculated.

Probabilistic Methods

- Probabilistic methods account for system problems with their corresponding probabilities and provide a common measure for the likelihood of various future conditions.
- Probabilistic methods provide a consistent base to better communicate system performance and risks among various parties, including planners, operators, regulators, and customers. However, this language is still not widely understood.
- While the probabilistic approach requires sophisticated analysis, the probability and impact of failures can be calculated and the concept of calculation and trade off of customer interruption costs with cost of construction of new facilities can be clearly interpreted.
- Data required to gather and understand forced outage rates, and project rates for future and new technologies require judgment and can impact the results.

2.9 Typical Probabilistic Assessment Process

The basic steps of probabilistic reliability evaluation of a power system are shown in Fig. 4.

1. Development of base case(s)/scenario(s)
2. Selection of system states/contingency states
3. Evaluation of selected states/contingencies
4. Computation of reliability indices and other statistics
5. Performing economic/value-based reliability analysis.

Step 1. Development of base case(s)/scenario(s). Multiple scenarios are developed based on several conditions representing different seasons, major maintenance periods, periods with different transfer conditions, environmental conditions, and different load levels. Basic operational parameters (e.g., topology and operating limits) and uncertainty information (e.g., probabilistic distributions of renewables and forced outage rates) are also input in Step 1. The number of evaluation scenarios depends on the problem. Typically, scenarios are selected by considering system topologies (system intact or prior outage), system load (peak or shoulder), operating conditions (import/export, high/low generation), environmental conditions, or seasonal loading conditions (summer or winter). The main reason for considering multiple scenarios is to span the inherent risks/issues. Consideration of multiple scenarios in power system analysis is, therefore, very important. However, a deterministic approach focuses more on the worst case scenarios from a prescribed list of contingencies, while probabilistic evaluation tries to model and evaluate all possible scenarios in the state space under consideration. The probability of each scenario can be determined from historical information or engineering judgment, or in some cases can be estimated using mathematical models. For a given scenario, the system can reside in a vast number of different system states. Each state could have different consequences with particular probabilities. The risk inherent in a given scenario is the weighted average of the consequences of all states associated with that scenario. The expected system risk for a given year is the weighted average of risks of all scenarios evaluated [11], [64].

Step 2. Selection of system states/contingency states. System states are selected and characterized by the operating state of each individual component. For BPS assessment, outages of both generating units and transmission circuits are considered. Two techniques—state enumeration and Monte Carlo methods [8], [65]-[66]—are most commonly used for state selection, and will be discussed in more detail in Section 3.

Step 3. Evaluation of selected states/contingencies. Each selected state/ contingency is then evaluated in order to identify system problems [66]-[68]. For BPS reliability assessment, states may be evaluated by power flow, optimal power flow and/or remedial action procedures to eliminate violations, such as overloads and under/over voltages. A power flow model can determine whether a system state results in power flows and voltages that are within component ratings and meet the system criteria. It is essential to use reasonably accurate analytical models, which are in general nonlinear, requiring iterative techniques (power flow, OPF, remedial actions). The computational burden for a large number of system states could be considerable. Consequently, linear models may be introduced for their efficiency and robustness, sacrificing accuracy, or visibility into voltage violations. The optimal power flow calculation minimizes economic loss when load shedding is required to guarantee system operational reliability. A difficult tradeoff between computational time and accuracy is one common issue in both power flow and optimal power flow calculations. This has been a key bottleneck that inhibits practical applications of CSR analysis. To overcome this issue, researchers have performed studies on sampling efficiency improvement, parallel computing, and deep learning methods. Various approaches are presented in Section 3.

Step 4. Computation of reliability indices and other statistics. Reliability indices are computed based on the results of system problems, e.g., states with load curtailment [65]-[68]. The most commonly calculated indices are probability of interruption (P), frequency of interruption (F), duration of interruption (D) and EENS. The four steps are repeated until a stopping criterion is satisfied, which depends on the state selection method being used—enumeration or Monte Carlo. The indices presented here address the following four aspects of system risk—adequacy indices, reliability worth indices, operational reliability indices, and weak link indices.

Step 5. Performing economic/value-based reliability analysis. An economic analysis that includes the cost of unreliability is performed.

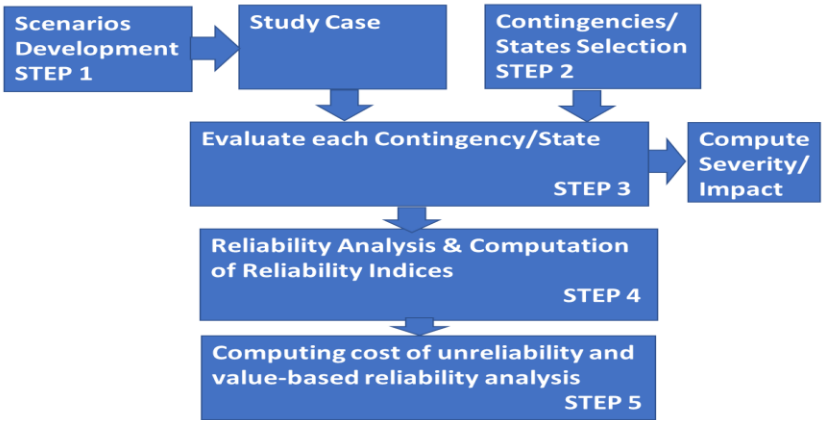


Fig. 4. Basic steps of CSR analysis

Economic assessment of system plans is needed for assessing the economic viability of projects that resulted from either reliability assessment or market analysis. Typically, economic evaluation considers capital cost, operation and maintenance cost, and unreliability cost. Capital cost includes several investment cost components such as direct infrastructure development cost, corporate overhead cost, and financial cost. Operation cost has components such as maintenance cost, taxes, cost associated with network losses, and sometimes a risk component due to uncertainty. Lastly, the unreliability cost is the cost associated with the loss of power supply and is calculated to assess the value of system reliability benefits from the project [11], [70]-[76].

Probabilistic economic approaches are widely adopted in the probabilistic power system planning. Using these criteria, planners compare different alternatives to justify or reject an investment. One approach for probabilistic cost criteria selects the alternative yielding the minimum total expected cost, where the total cost includes components such as capital cost, operation cost, and unreliability cost. Planners usually have good estimates of capital and operation costs. Unreliability cost is calculated as the product of expected energy not served (EENS), in MWh/year) times unit interruption cost (UIC, in $/MWh). The reliability index EENS is calculated using probabilistic reliability assessment methods. Alternately, some utilities use a benefit-cost ratio to rank alternatives in which the capital investment for a planning alternative is the cost and the reduction in operation and unreliability costs due to the alternative is the benefit. The alternatives with higher benefit-cost ratios are usually recommended for investment [7].

2.10 Industry needs for CSR evaluation

Significant research has been conducted on various aspects of composite reliability calculations in the past several decades. Practical applications of probabilistic methods by utilities have been lagging those efforts. More details about practical probabilistic studies by utilities in North America are provided in [26]-[33] and in Section 5 of this report. Reference [26] states "utilities and their customers must strive for a balance of cost and reliability. The occurrence of system outages must therefore be accepted and the reliability criteria respond, in fact, to the level of acceptability," The results of a survey conducted by EPRI with utilities from North America are presented in [27]-[29]. Respondents to the survey identified one or more of the following applications for CSR evaluation in planning:

- Justify addition of facilities (investment decision)
- Evaluate transmission adequacy at delivery points
- Evaluate the effect of transfer capability on system reliability
- Compare expansion alternatives
- Use to modify/defend deterministic criteria
- Use to communicate reliability issues to the management and the regulatory agencies
- Quantify reliability trends
- Evaluate benefits and costs of reliability improvement for use in decision making
- Consider internal transmission limitations in generating capacity reliability evaluation
- Optimize relative investments in generation and transmission systems

- Evaluate trends in resource sharing (economy transfers) and strategic planning
- Evaluate the impact of generation and transmission on BPS reliability
- Assess the contribution to the reliability of dispersed generation (VER generators, battery storage, cogeneration) and load management
- Determine transfer capability for internal transmission and interconnection additions
- Determine sites for large central generators
- Determine sites for dispersed generation/storage devices
- Determine tradeoff between generation and internal transmission
- Reliability assessment of large bulk power systems
- Reliability studies of area supply systems
- Economic studies.

Respondents to the survey identified the following applications for CSR evaluation in operations [27]-[29]:

- Evaluating operating risks (Is the risk acceptable?)
- Balancing economy and reliability
- Minimizing the effects of component failures
- Minimizing the effects of catastrophic failures (system collapse).

Reference [30] describes some typical studies in area of bulk power system reliability evaluation:

- Determination of reliability trends
- Comparison of alternative system plans
- Development of reliability criteria and design
- System performance assessment against reliability criteria
- Selection of appropriate station bus schemes
- Identification of system weaknesses.

Reference [31] presents methods, data requirements and indices for measuring the actual bulk system reliability of individual utilities. It indicates that bulk system reliability performance can be measured in terms of the amount of unreliability created by events on the bulk power system (BPS), where unreliability of the BPS is defined as the inability to provide the required electricity to all load points.

Reference [32] emphases the importance of the results obtained from CSR evaluation, as they can be used to:

- Track the chronological changes in system behavior
- Predict and monitor the result of changing system operational strategies, and
- Compare the performance of different systems and different areas within a system.

Reference [33] presents an overview of trends in the areas of short- and long-term planning. Reference [33] presents the state of the art of CSR assessment including comparison of existing programs for composite system adequacy evaluation. Reference [5] presents the results of a survey conducted by IEEE Composite System Reliability Task Force. It indicates that the high penetration of renewables in power systems such as photovoltaics and wind, retirement of coal plants, government policies, and regulatory requirements have significantly increased uncertainty in power systems. Therefore, existing deterministic approaches are no longer adequate to address these challenges. There is an evident need to develop a new generation of probabilistic methods, tools, and business practices to replace (or complement) the existing ones.

3. METHODS FOR CSR ANALYSIS

3.1 Introduction

Reliability evaluation of composite power systems means that generation and transmission are modeled and analyzed simultaneously. The reason is that there is substantial interaction between these two subsystems that affects overall reliability. Planning studies are normally based on scenarios developed by regional entities (WECC, NPCC, etc.). Scenarios are commonly developed for seasonal, medium-term, or long-term planning studies and usually represent:

- Transmission and generation facilities
- Variable generation facilities
- Interconnections
- Demand.

For proper inclusion of the effects of all relevant factors in probabilistic planning studies, it is necessary to develop reliability models of (a) transmission circuits, (b) legacy generation, (c) variable generation, (d) interconnections, and (e) demand. Because of considerable correlation between variable generation models and system demand, and the fact that they are exogenous to the power system, it is important to use reliability models that combine these two.

3.2 Modelling of Typical Elements in Composite Power System

A composite power system includes functional zones of generation and transmission that may include other systems, such as integrated energy systems and secondary, protection, or cyber-physical systems. This subsection will review the models of typical components needed to perform probabilistic reliability evaluation of the composite power systems. Outages of these components are the root causes affecting reliability in a conventional power system and they are commonly divided into independent and dependent outages. For both independent and dependent outage modes, outage rates are commonly described in terms of a Markov model—average failure rate and average repair rate. Note that the average failure rate and average repair rate can be calculated based on historical data. Dependent outages arise from substation-originated outages or protection system failures. Generally, four types of outages exist on components of a bulk power system—independent; dependent, common cause, or common mode; shared substation; and station-originated outages. Models of typical components in bulk power systems are provided in the next sub-sections.

3.2.1 Generating unit models

The basic reliability model for generating units is provided in several books [7]-[8], and [12]. There are two approaches for modeling the availability or unavailability of conventional generating units:

- State probabilities
- State transition rates.

A state probability is the probability that a generating unit is in at particular state [77]. A two-state model is the simplest model of a generator, having only two possible states: up and down, Fig. 5.

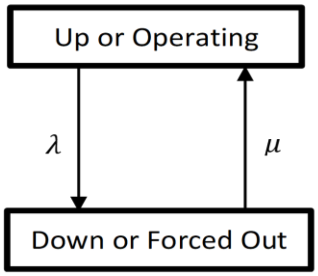


Fig. 5. The Basic Two-state Model [2], [78]

The following relationships hold:

$m = 1/\lambda$

$r = 1/\mu.$

$U = \lambda /\lambda+\mu = MTTR/MTTF+MTTR = f * MTTR/8760$

$FOR= \lambda/(\lambda+\mu)= r/(m+r)$

where:

λ is the failure rate
μ is the repair rate
m is the mean time to failure (MTTF)
r is the mean time to repair (MTTR)
U is forced unavailability

f is the average failure frequency in failures/year
FOR is the forced outage rate.

FOR expresses the probability that the unit is down. Then, $1–FOR$ is the probability that the unit is up.

Note that the state transition approach has two parameters, λ and μ, in comparison with the state probability approach, which has only one, FOR. Which approach may be used depends on the reliability indices to be calculated? The state probability approach may be used if indices like LOLP, LOLE, and EENS (defined in this section) are all that is needed. But if expected frequency and duration are desired, then the additional information in the state transition approach is required.

Another consideration is that a unit may be derated—up, but not capable of generating at its maximum capacity. The amount by which the capability is reduced depends on the reason for the derating, which may be that a particular component has failed, or that the operator wants to reduce the stress on a component in order to postpone failure or taking it out of service for maintenance. The model of the unit may include one or more derated states, with associated probabilities, in addition to fully up and down. Alternatively, an equivalent forced outage rate (EFOR) may be used as the probability of the down state in a two-state model, where the difference between EFOR and FOR represents the expected value of the derating [78].

A multi-state model is needed to capture deratings in the state transition rate approach. This is described in [78].

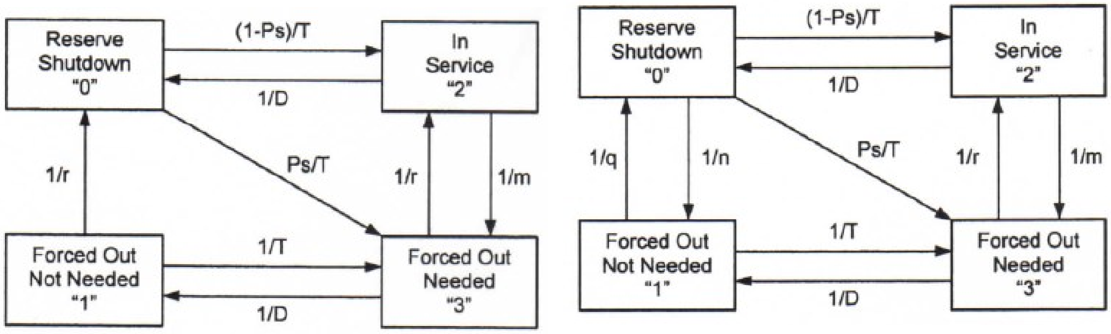
IEEE Standard 762 provides formulas for estimating the parameters for both approaches from historical outage data [79]. For example,

$$FOR = \frac{FOH}{FOH+SH} \tag{6}$$

where FOH is the recorded forced outage hours, and SH service hours. But using these estimates requires a judgment that the operating conditions of the historical period reasonably represent those in the future period for which the analysis is being done.

The expression given in (6) is good for estimating the FOR of a base loaded unit. But it is not appropriate for a peaking unit, or any unit that cycles on and off depending on the need for its capacity. For that reason, a four-state model that includes whether the unit is needed was developed in [80]. Models with even more states have been developed to address shortcomings in the basic four-state model and to capture considerations such as the postponability of maintenance outages [81]. The basic four-state model and one variation are shown in Fig. 6. Billinton and Ge found significant differences in the outage rates calculated from historical data for the different models [82]. Patton et al. analyzed the impact of the different models on production simulation results [83].

Endrenyi presents in detail how to use multi-state models for generating units that experience partial outages (derated) states [2].



(a) Basic four-state model.

(b) Extended four-state model.

Fig. 6. Example four-state models [80]

Another parameter applicable to some generating units is energy limitations, which are common for hydro units but may also be implied by emission constraints. These may be accounted for as outlined in [84].

3.2.2 Transmission circuits models

A transmission circuit (line and transformer) may fail due to hardware breakdowns, or it may develop ground faults due to arcing by flash-overs of insulators or other abnormalities. In either case the line or transformer will be removed from service immediately by the protection system [7]. Hardware failures are commonly called permanent outages since the failed component must be repaired or replaced before the circuit can be returned to service. Removing a circuit as the result of protection system operation usually lasts only a short time from fraction of a second to several seconds, and is commonly called a transient outage. Circuit protection is usually designed to reclose once or twice, after which the circuit will be locked out. A few minutes after a lock-out an attempt can be made by a system operator to return the circuit to service by closing the circuit breakers manually. In this case, if manual reclosure is successful, the circuit outage is called a temporary outage. These types of outages can be described by Markov equations—failure and repair rates shown by the same two-state model shown in Fig. 5. Transmission circuits on common structures and common right-of-way may experience common-mode outages, as described in detail in section 3.4

A planned outage of a circuit can be represented using a similar two-state model, in which all the parameters (transition rates or mean times) correspond to the planned outage. [10].

In the operation time horizon most operational models of components can be described by Markov model failure and repair rates. However, failure and repair rates of operational components are dependent on operational conditions and should be determined considering the time scale and operating conditions, especially weather.

3.2.3 Load Models

Load modeling has significant impact on power system studies, The demand side generally consists of several types of loads, including traditional loads, such as, residential, commercial, and industrial loads; electric vehicles (EVs); and energy storage. Load models can be classified into two broad categories: static and dynamic models, while there are two types of approaches: measurement-based and component-based [85]-[87]. Modeling loads accurately has received more attention recently because of increased integration of modern loads with emerging smart grid technologies such as distributed generators, EVs, and demand side management (DSM). To describe these loads, the following three models are generally considered: load uncertainty model, load curve models, and load correlation model.

Uncertainty model
An uncertainty model, represented by a probability distribution, can be used to describe probabilistic characteristics based on statistical historical data. A probability distribution can be calculated based on several efficient methods, such as parametric density estimation and the stochastic response surface method. Frequently, the probability distribution model of traditional loads is represented by a normal distribution [10].

Curve models
A load curve represents the variation in load level over time. Depending on the purpose or features of the technique, either the chronological load shape or the load duration curve is used in a CSR assessment. Load curves may be clustered in one of two ways. The first one is to cluster load values in one or more load curves into several load-level groups. The second one is to cluster different load curves into several curve groups, in each of which the load curves have a similar shape or time-varying load pattern [10].

Correlation model
Correlation indicates a relationship between stochastic variables. Loads in a power system are generally correlated due to some common factor, such as temperature [10], to a degree that can affect CSR analysis. Correlation can be divided into two categories—linear correlation and nonlinear correlation. The former can be represented by a Pearson correlation matrix, while the latter is generally represented by a copula joint distribution function. Note that both linear correlation and nonlinear correlation are calculated based on historical data. Correlation may also occur between multiple VER generators and between VER generators and load, as discussed further in 3.2.6.

3.2.4 Protection Models

The impact of protection system failures on composite system reliability evaluation can be significant [17], [89]. The protection system mainly consists of relay protection devices, whose operation can affect the topology of a power system, sensors that measure voltages, currents, and phase angles at various locations on the power system, and communications systems linking them. There are two basic types of a protection system malfunction—failure to operate when required and inadvertent operation, also called active failure and passive failure. Active failures are usually ground faults on breakers or buses which cause the appropriate protection breakers to operate and disconnect simultaneously more than one element (line/generator). Inadvertent operation is a result of primary protection breakers failing to trip, and the response from other breakers may cause multiple lines/generators to be disconnected. Historically, about 6% of misoperations in North America are caused by passive failures and the remainder by active failures [90]. More details on these types of failures are provided in [9]. For practical reliability evaluation the stuck-breaker probability can be calculated from data collection that includes the number of times a breaker opened and the number of times the breaker failed to respond. The probability of a breaker responding to a failed component depends on the protection system, its construction and the quality of the components being used [9]. Historical misoperation rates based on NERC data can be found in [90].

3.2.5 Model of an Integrated energy system

A group of multiple energy resources may have coordinated operations to realize efficient energy use. A power system may be the host for one or more such energy systems, called integrated energy systems [91]. The tight coupling among different energy systems results in the need to account for uncertainties in these other systems in CSR analysis of the host power system. Similar to power systems, other energy systems may also include production, transmission and demand functions. In production and transmission, the risk of a component outage can be described by a discrete probability distribution. For the demand side, energy demands may also have the probabilistic characteristics outlined above [92].

3.2.6 VER Generation Models

Modeling variable energy resource (VER) generation, such as wind and solar generation, is more complicated because of the time dependence of the underlying energy resource. Further, although mechanical outages of individual units, such as wind turbines or solar panels, may be independent, the units at the same location will be driven by the same energy resource; therefore, the output of the units will not be independent. In addition, a significant correlation likely exists between the strength of the energy resource at different locations. Thus, there are several aspects that need to be addressed in modeling VER generation in CSR analysis:

1. Seasonal and diurnal profiles
2. Random variation
3. Equipment outages
4. Correlation between VER generation and load
5. Correlation between different VER installations.

This section addresses wind farms primarily, for which the underlying energy resource is wind speed. But most of the concepts can also be applied to solar PV facilities, whose resource is solar insolation. This section will also refer to HLI analysis as well as CSR (HLII) analysis, as some of the more advanced VER modeling approaches have been applied only in HLI analysis in the published literature to date, although they are conceptually applicable to HLII analysis as well. There is no settled methodology for VER modeling in CSR analysis. Therefore, this subsection is not as prescriptive as the one on conventional generation.

VERs are incorporated in a HLI or HLII adequacy model as either a negative load or a generator. Common approaches to modeling VER generation in HLI and HLII analysis include:

1. Observed time series – Historical hourly time series of power output or wind speed for one or more years. In this and other approaches with wind speed explicitly modeled, a power curve representing the relation between wind speed and wind turbine output is applied to calculate power output.
2. Synthetic time series – Time series of power output or wind speed generated by a model based on observed time series.
3. Probability distribution of power output or wind speed.
4. Multi-state generator – Similar to a conventional generator, with output states of 0 and maximum capacity and a finite number of intermediate states, with associated probabilities [66].

Observed or synthetic time series represent the seasonal and diurnal profiles and random variation of a VER and, when used with time-synchronized data for load or other VER installations, can capture correlation. A probability distribution or multi-state generator may be used when correlations are not significant, and is called a "time-collapsed" model [93].

Observed Time Series

Using observed hourly time series for wind speed or solar insolation is, in a way, the default approach for obtaining the hourly data required for sequential Monte Carlo simulation. Hourly wind or solar farm output may then be obtained by applying a wind turbine power curve (described below) or PV production function to the hourly wind or solar series. Time-synchronized hourly weather data including wind speed, insolation, and temperature data, from which electricity demand may be calculated, provide a way to capture the correlation between different VER facilities and between VER generation and loads.

Using observed time series may be thought of a brute force, although effective, approach, in that all 8760 hours of data are used for each year of historical data. Observed time series for wind or solar farm output, rather than meteorological data, is an alternative. However, it assumes that the VER generation fleet remains unchanged through the study period, unless the hourly data are scaled in some way to account for additions or retirements. Yet this latter approach assumes the wind or solar technologies are approximately homogeneous. The number of years of data that can be used is limited, of course, by the number of years of data that are available. If only a few years of data are available, or if only a subset of the years of available data are used, year-to-year variability may be misrepresented and the accuracy of calculated indices therefore impaired. Bothwell and Hobbs examine the use of observed time series in resource adequacy analysis at HLI [93] . Starting with 10 years of data, they show the impacts of using different subsets of years on the optimal mix of VER and conventional generation additions, finding that five years of data are nearly as good as 10, but less than five years risks distorting the results significantly. They strongly advise against using mean observed wind speeds, as they understate variability, even when the means are calculated hourly.

Synthetic Time Series

Synthetic hourly time series may offer one or more of the following advantages in a given situation:

1. A time series may be constructed for a location for which a historical hourly time series is not available, using mean values for that location and hourly data from another location deemed to have similar variability [95].
2. A set of time series may be constructed for a larger number of years than available in the historical series [96].
3. The variability of hourly values within a year may be captured by using fewer than all 8760 hours in a year, yielding computational efficiencies.

Fig. 7 depicts a common synthetic time series approach for VER modeling currently used in HLI and HLII analysis, as applied to wind. An average hourly profile of wind speed is calculated from observed historical hourly wind speed data for multiple years. This average represents the seasonal and diurnal profile. The parameters of a stochastic model are also estimated to capture the random variation. Equipment outages are addressed in a wind turbine availability model. Correlations may be incorporated by including a linkage to the hourly load model or other VER models. Giorsetto and Utsurogi were among the first to outline the synthetic time series approach [96].

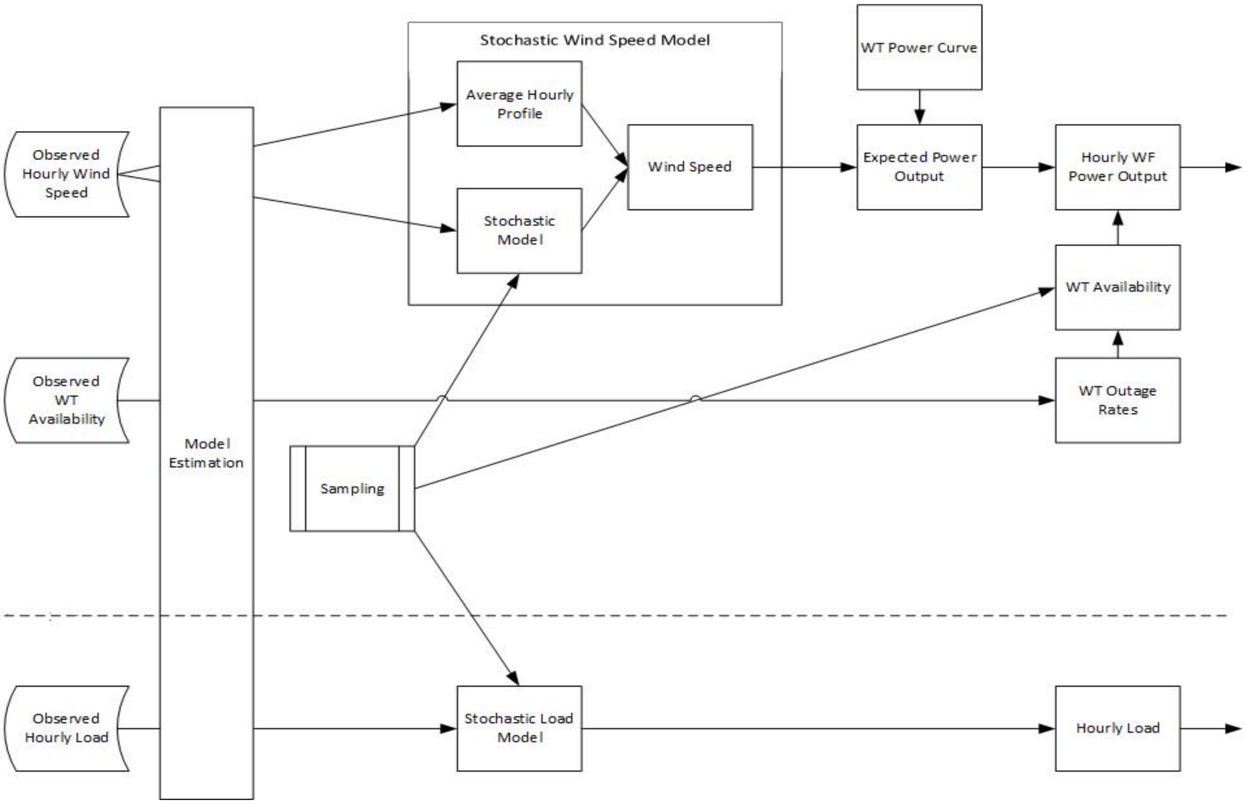


Fig. 7. Synthetic time series approach for VER modeling

Correlation

An important current issue in CSR analysis is modeling the time dependence of VER generation and the correlation among different VER facilities [97] and between VERs and loads.

VER generation and system loads exhibit a degree of correlation. Their deciles (intervals of range divided into 10 equal-probability segments) and vigiciles (20 equal-probability segments) may be strongly correlated [98]. That is, the lowest 5% of wind speeds may tend to occur in the same hours as the upper 5% of hourly loads. The importance of this correlation increases as the penetration of VERs in the generation mix increases.

The most common approach uses synchronously observed hourly time series for wind speed and/or solar insolation [99]. Synchronous historical hourly weather data, including wind speed, insolation, and temperature data, from which electricity demand may be calculated, provide a way to capture the correlation between different VER facilities and between VER generation and loads. For reasonable accuracy, sufficient amount of historical data is needed. Decades of historical meteorological data are available at a medium level of geographical resolution and may be combined with site-specific data for a shorter period using “reanalysis” to obtain longer site-specific series [100]. Use of any historical meteorological data, should consider the need for adjustments for climate change [101].

An alternative approach is to use synthetic time series generated by sampling from a time series model estimated from historical data, as described in [95]. Methods to link the synthetic time series to load models and other VER facilities include a multivariate normal model (also used in analyzing the effects of correlation of bus loads) [49]; copulas [102]-[103], inverse transformation [104], Nataf transformation with Latin hypercube sampling [105], dimension reduction [106], and multi-dimensional clustering [107]-[109]. Chen et al. created models of wind speed for two sites in the Netherlands using various methods: inverse transformation, Nataf transformation, and copula method, with Weibull distributions for the marginal distributions of the wind speeds at the two locations. For these two sites, the Gumbel copula is found to provide the best fit to the means, variances, Weibull distribution parameters, and Kendall correlation coefficient [110].

With high renewable penetration targets in many jurisdictions, it will be important to capture the cross-correlations between VER generators and load. In HLII, wind models at the wind-injection nodes of the network cannot be combined, but should be separate. At the same time, the cross-correlation between them must be captured in the different scenarios selected for assessment. This can be done using models such as autoregressive moving average (ARMA) in sequential MCS. However, in state-sampling and in contingency enumeration, a different approach is needed. One synthetic method using correlated random numbers is described in [111].

Presently, outages of renewable generators are modeled without considering the generation ramping due to the intermittency. Fast ramping can have significant impacts to the power grid, similar to a generator outage [107]. The concept of intermittency induced outages (IIOs) has been proposed to capture the impact of intermittency. Probabilistic outage models for IIOs with loss of generation, under- and over-generation modes due to wind ramping-down and -up events are presented in [113]. The IIO concept was further extended to the modeling of common mode outages (CMOs) for multiple correlated renewable plants [101].

Wind Speed Stochastic Model

A time series model has a stochastic element. Various stochastic elements have been used in wind speed models. Giorsetto and Utsurogi used a simple white noise process for the stochastic model in the Fig. 7 [96]. Billinton, Chen, and Ghajar introduced an ARMA(n,m) model for the stochastic model where integer parameters n and m represent the order of the model and are determined in the estimation process [95]. The autoregressive (AR) process (perhaps the most common) [95]; the birth-and-death Markov chain [113]; a hybrid of Markov and AR processes [112]; and estimating the stochastic model after applying a Logit transform [92].

Wind Turbine Availability Model

The availability of an individual turbine is represented by an up-down-up or up-derated-down-up cycle. A capacity outage probability table may be constructed by sampling state residence times from distributions or transition rates estimated for the turbines, as is done for conventional generators. If the distribution of residence times is assumed to be exponential, the parameters MTTF and MTTR may be used. But other residence time distributions may alternatively be used, including Rayleigh, Weibull, normal, log-normal, and uniform. The capacity outage probability table may alternatively be constructed from the wind turbine FOR or EFOR. These capacity outage probabilities are not related to random equipment failures, but also high wind speeds that cause, for example, wind turbines to feather, or low which causes them to shut down for long periods of time. These scenarios can results in many plants coming offline at the same time.

Ref [114] states that equipment outages in WFs "can be neglected in many practical situations without creating unreasonable errors in the calculated reliability indices," This may be true with low penetration levels of VERs; but at higher penetration levels, the effect can be significant. NERC's 2022 State of Reliability report [115] introduces analysis of wind generation outages in North America, which shows that in 2021, the FOR for wind plants was more than twice that for the conventional generation. Approaches for incorporating WT equipment outages have been developed; failure rates may be dependent on wind speed as, it has been observed that WT outage rates tend to increase with wind speed [112]. These approaches include: individual WT availability; grouped availability; derated availability; state probability table; capacity outage probability and frequency table (COPAFT); and the copula for the relationship between wind speed and failure rate [112]–[113], [116]–[118].

Solar PV

We note two approaches to modeling solar PV: (a) bottom-up model of plant availability [119], and (b) chronological probability model [120]. These are combined with solar equipment availability in similar ways as discussed for wind systems to provide the reliability models of solar farms.

Multi-state generator

When the correlation among VERs and between VERs and loads is negligible, one may use a synthetic multi-state generator, deriving a multi-state generator model from synthetic hourly wind speed time series data [121]–[122]. A five-state model provides a reasonable WF model for CSR analysis [111]. Otherwise more sophisticated approaches must be used [120].

Applications and Results

Synthetic time series models for two locations in Saskatchewan are presented in [121]. The approach is used to estimate a model from three years of actual wind speed data for a particular location, and calculates synthetic wind speed and the total output for a wind farm with 100 turbines for a large number of years [121]. Then the simulated output series are input to a generation reliability analysis (HLI) for a test system with the wind farm added to a fleet of conventional generators. The authors find that about 6000 years of synthetic wind speed data are needed for convergence of calculated LOLE for this case. Reference [124] applies ARMA models, one of which was presented in [121], to represent two WFs. The models are used in a composite system reliability analysis that considers 11 alternatives for interconnecting the wind farms to a modified IEEE reliability test system using a sequential Monte Carlo approach.

Reference [88] quantifies the correlation between wind farms at different locations by a joint probability distribution based on a copula function. Paper [122] models by analytical method the output of large wind farms considering wind variability and turbine forced outages. Paper [123] presents an energy storage system (ESS) sizing model and reliability assessment framework to quantify reliability improvements due to ESS of BPS with high penetration of renewables. Paper [124] presents the results of reliability analysis of BPS with high penetration of renewables.

Several wind speed models are reviewed in [94]. The analysis includes calculating various reliability indices for a test system using both the original data and the wind speed models. The models are compared on the basis of the following criteria: (a) differences between resulting wind speed distributions from the models and the original data, (b) differences between the calculated reliability indices using the models and reliability indices using the original data, and (c) correlation between wind power output and hourly loads. The findings include: (1) The ARMA model provides a more comprehensive representation of wind speeds. It does a good job at matching the observed correlation for all loads and for loads above 80% of peak demand, and (2) the Markov chain model does poorly on the wind-load correlations.

Reference [125] also compares wind speed models and the values of system reliability indices they yield. It finds: (a) An ARMA model is better than other approaches in that it yields reliability indices closest to those obtained from observed wind speeds, (b) Simple sampling from a wind speed probability distribution yields higher frequencies of transitions between healthy, marginal, and at-risk system states and shorter state durations. Therefore, this method is not recommended if frequency and duration indices are desired, and (c) Using mean wind speeds results in relatively optimistic indices. HLI and HLII results using various wind speed models are compared against the results from the original data for various test systems [126]. A key finding is that an ARMA model based on only a few years of data produces reliability indices closer to what would be obtained from using observed hourly wind speeds for a larger number of years.

3.3 Component Reliability Parameters

The quality of reliability analysis depends on the accuracy of the parameters of the component reliability models discussed in the previous section. The parameters are typically derived from historical outage data. Power system components used in reliability calculations are modeled at the unit level, for example, the generating unit (not at the level of the boiler, turbine, etc.), and the transmission unit (not at the level of the conductor, insulator, tower, breaker, etc.). Outage data collected by utilities are used to obtain the reliability indices for system elements at the unit level. Also, outage data can be used for one or both of two reasons: assessment of past performance and prediction of future system performance. CIGRE reference [4] observes that "limitations on data collection and system monitoring, inadequate system performance data (static and dynamic) and inadequate component performance data have been identified as a main cause of limited use of probabilistic methods in the past," Evaluation of past and future reliability of an electric power system strongly depends on data availability.

3.3.1 Predictive Reliability Parameters

Predictive reliability results will be meaningful only if the reliability parameters of system components are calculated from representative outage data. Basic inputs for performing reliability evaluation of a composite power system are reliability indices of system components such as generators, transmission lines, and transformers. The basic indices for components are probability of forced outage, frequency of failure, and average outage duration. Frequency of failure is the expected number of failures per year. Average outage duration is the mean time a component spent in an outage in hours per outage. More details about predictive reliability indices and their calculation are provided in references [7]-[12], [21].

3.3.2 Historical Reliability Parameters

The fundamental concepts of collecting, reporting, and analyzing outage occurrences and outage states of electrical transmission facilities are presented in IEEE Standard 859-2018. These concepts have been used by utilities across the globe in developing collection and reporting systems for various categories of outages. Historical outage data for components of a bulk electric system are the foundation for performing probabilistic CSR assessment. Probabilistic reliability assessment requires good quality system and component performance data. Presently there are several organizations in North America that collect, process, and report reliability and outage data of generation and transmission equipment. Table 3 lists the outage data collection programs from three such organizations. Data needed to perform reliability evaluation of a BPS can be divided into the following four types:

- *Generator data*: (inventory, capacities, outage statistics)
- *Transmission data*: (inventory, outage statistics)
- *Load data*: (historical loads, predicted load levels, load curves)
- *Protection misoperation data*: (failure to trip, unnecessary trip)

TABLE 3. Outage Data Sources

Organization	Name	Data Collection Program
NERC	North American Electric Reliability Corporation [127]	Generating Availability Data System (GADS) GADS – Wind (GADS-W) Transmission Availability Data System (TADS) Misoperation Information Data Analysis System (MIDAS)
CEA	Canadian Electric Association [129]	Consultative Committee on Outage Statistics (CCOS) Equipment Reliability Information System (ERIS)

WECC	Western Electricity Coordinating Council [131]	Reliability Performance Evaluation Work Group (RPEWG) Transmission Reliability Data Task Force (TRDTF)

GADS, which started to collect generation operating data in 1982, is recognized as a valuable source of reliability information and is widely used by industry analysts in a variety of applications. Through GADS, NERC collects information about the performance of electric generating equipment and provides assistance to those researching power plant outages. GADS is a mandatory industry program for conventional generating units that are 20 MW and larger [127].

NERC uses transmission equipment inventory and outage data to analyze outage trends and assist in identifying significant reliability risks to the BPS. Since 2008, transmission inventory and automatic outage data from eight NERC regions have been collected in TADS, one of the data systems supported by NERC. Transmission elements of the BPS reportable in TADS are (1) ac circuits (overhead and underground), (2) transformers (no generator step-up units), (3) dc circuits, and (4) back-to-back ac/dc converters [128].

The CEA ERIS has been collecting data on transmission outages since 1978 [129]-[130]. It includes equipment outage statistics for transmission equipment in Canada with an operating voltage of 60 kV and above.

WECC started to collect transmission outage data in 2006. Results of the analysis performed on the WECC Transmission Reliability Data (TRD) are presented in [131].

Transmission element availability is defined as the probability that the element is in service at a given moment in time; it can also be understood as the expected percent of elements of the given type being in service at a given moment. Unavailability is more informative since it can be tracked by outage type. Fig. 8 provides unavailability of transmission elements calculated from the TADS data [132]. Unavailability is calculated as the total outage duration of all outage types as percentage of time.

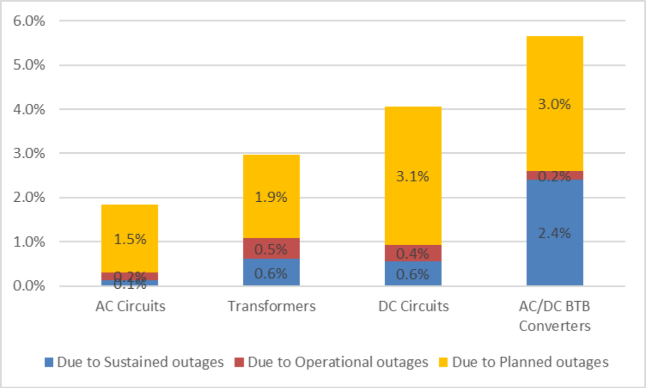


Fig. 8. Component Unavailability by Outage Type (2010-2014)

Besides unavailability, the reliability function of a transmission element is a very useful tool for modeling transmission outages. For a transmission line, the reliability function *R(t)* is defined as the probability that the circuit will continuously operate without a forced outage for at least a time period of duration *t*. Assuming that the time to forced outage for an ac circuit has an exponential distribution,

R(t)=exp(-t/MTTFO)

where MTTFO is the mean time to forced outage. Fig. 9 shows the reliability functions for ac circuits of different voltage classes.

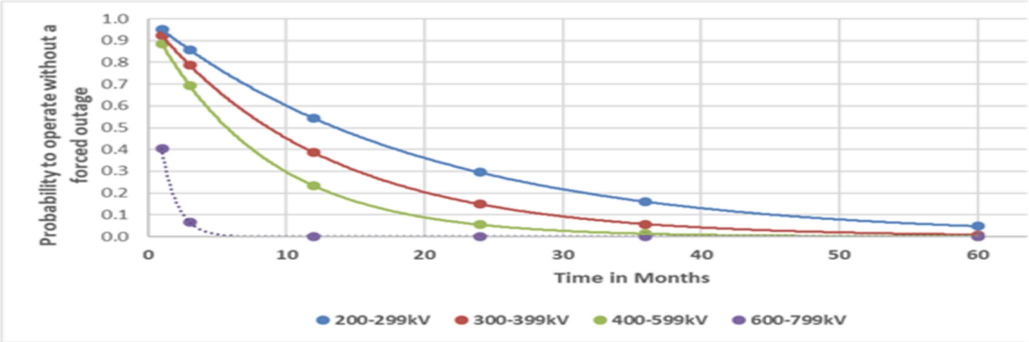


Fig. 9. Reliability Function of AC Circuits by Voltage Class (TADS 2010-2014)

Reliability functions for different types of transmission elements derived from TADS data are provided in [133]-[135].

It is common practice to calculate the parameters of component outage models using a maximum likelihood estimation (MLE), assuming the same frequency and duration for the same types of components across different data sources and a Poisson process to describe outage occurrences. This practice, however, neglects the variability among different utilities, transmission owners, and regions. The factors that may have significant impacts on outage frequency or duration may include environmental conditions and maintenance schedules that differ across utilities. To capture this variability, formal statistical testing was introduced in [136] to determine the "poolability" of outage data for different types of grid components from various NERC regions. For non-poolable outage data from different sources, separate lognormal distributions were developed for the frequency and duration of various component outages [137].

3.4 Operational and Exogenous Factors Affecting Reliability

Today's electric power grid is a complex system and its reliability is dependent upon many interacting uncertain elements. Operational practices that typically optimize the operation of the system of multiple resources with differing characteristics and uncertainties (legacy generation, variable generation, customer DERs, etc.) play a major role in determining the reliability of the system. New technologies (microgrids, storage, electric vehicles, customer flexibility) have been changing the operational characteristics of the power grid and affect reliability. New control capabilities, dynamic ratings, FACTS devices, etc. add another dimension to the operation of the system and affect reliability. Protection and control have become a complex system and affects the response of the system to disturbances and ultimately the reliability of the system. Inherent system characteristics affect stability—both angular and voltage stability—with a major impact on reliability. Exogenous factors such as weather, customer behavior, variable generation and others affect reliability. This section describes the new paradigms generated by the realities of a modern composite power system.

3.4.1 Hurricanes, Cascading, Vegetation, Extreme Weather Events

Hurricanes are among nature's most powerful storms. They produce strong winds, storm surge flooding, and heavy rainfall that usually affect the normal operation of a power system. Reference [138] proposes a methodology that combines a fuzzy clustering technique with a regional weather model to investigate the impact of hurricanes on power system reliability. It models the relationship between transmission line failure rates and hurricane parameters. Reference [139] observes that hurricanes regularly cause widespread and prolonged power outages along the U.S. coastline. These power outages have significant impacts on other infrastructure dependent on electric power and on the population living in the impacted area. It describes a hurricane power outage prediction model applicable along the full U.S. coastline using only publicly available data. Paper [140] identifies hurricanes as the extreme weather events that cause the largest and longest outage events on the North American BPS and studies their impact on system resilience.

Cascading failures present severe threats to power grid reliability and occasionally lead to massive blackouts with multibillion dollar cost to society. Therefore, reducing their likelihood, mitigation, and prevention are of significant importance.

Reference [141] presents a unique methodology developed by Southern Company Services (SCS) to analyze cascading failure scenarios, determine their expected consequences, and rank the scenarios according to their severity and likelihood of occurrence. The paper discusses examples of real-life events. Reference [142] presents a new and efficient operational reliability analysis approach that comprises a cascading failure simulation module (CFSM) for post-contingency analysis and a risk evaluation module (REM) based on a decorrelated neural network ensembles (DNNE) algorithm to address operational reliability threats from cascading outages. Reference [143] emphases the importance of assessing the impact of hidden failures on the vulnerability of the power system. It presents a computer-based intervention approach to identify the relays with high vulnerability indices. Reference [144] defines and quantifies a measure that relates to the vulnerability of the power grid to cascading outages. The approach is to identify and simulate potential cascading modes (PCMs), compute the probability and impact of each stage of the cascade, and display the risk of each potential cascade stage on a two-dimensional chart of likelihood and consequences. Reference [145] summarizes an analytical framework that has been developed, implemented, and used by Southern Company to evaluate system vulnerability to cascading failures using a steady state model.

Vegetation in combination with severe weather conditions is a dominant cause of failures in power systems. Reference [146] presents an approach to assess the impact of vegetation characteristics and weather on outages. Results of the study are important for automated power system monitoring and outage management, since it is possible to predict where and when vegetation may become a risk. Reference [147] discusses the NERC vegetation management reliability standard and provides analysis that shows effectiveness of this standard in reducing the frequency of transmission outages caused by vegetation.

Extreme events are occurrences of unusually severe weather or climate conditions that can cause devastating impacts on communities and power systems. Weather-related extreme events are often short-lived and include heat waves, freezes, heavy downpours, tornadoes, tropical cyclones, and floods. Reference [148] describes how the physical environments in which transmission and distribution systems reside have a major effect on the resulting reliability of the network. Also, the physical stress placed on system components can be much higher in bad weather than that encountered under normal weather conditions. The paper recommends using a three-state weather (normal, adverse, and major adverse) model to incorporate failures occurring in major adverse weather. It observes that results obtained without weather considerations can be quite misleading and optimistic.

Reference [149] presents the integration of accurate forecasts, coming from advanced numerical weather prediction systems and related to the specific hazard of wet snows, with a risk-based security (operational reliability) tool. Simulation results are compared against public information about outages recorded during a recent extreme wet snow event in the North of Italy, confirming the importance of data-driven hazard analyses integrated in operational reliability assessment applications. Reference [150] recommends that transmission expansion planning (TEP) be economically adjusted in order to make the network less vulnerable to extreme events caused by climate change, e.g., floods or ice storms. Numerical results in this paper show that a proposed risk-based TEP model can be used as a flexible decision-making tool, helping decision makers determine an appropriate tradeoff between economy and security (operational reliability). Extreme weather events and their impact on the North American transmission system are analyzed in [140]. This study presents probabilities of weather-related transmission events of different sizes and tracks differences in these probabilities by season.

3.4.2 Climate Change, Emission Considerations, and Aging

Climate change is a long-term shift in global or regional climate patterns. Reference [151] observes that climate change initiatives proposed by governments and industry organizations have the potential for reallocating trillions of dollars, affecting the way energy is used. Differences in the aggressiveness of mandates/targets could lead to different near-term and long-term outcomes, as well as differences in the supply and demand of fuel commodities, technology deployment, and costs. Analysis of scenarios that impact large amounts of resources at the same time is needed to test overall system reliability and identify the need for additional hardening and construction to meet reliability objectives.

Emissions impact system reliability in both planning and operation. As environmental standards are tightened, determinations have to be made as to how plants with higher emissions need to be augmented with cleaner units at the regional level. Operationally, as seasonal or periodic emission caps are imposed on certain units, their coordination with other units affects both system economics and reliability. The modeling of emissions in the CSR framework has two aspects: as part of the constraint set, and as part of the objective function. One or both may be implemented, depending on the circumstance. Emission constraints are used to specify a maximum annual level of emissions for specified pollutants. Reference [152] presents a method for analyzing the reliability of composite power systems under CO_2, SO_2, and NO_2 emissions constraints. Constraints are modeled using the emission of each pollutant from a unit as a function of its heat rate, and limited by the emission cap. This reference also develops relationships for the sensitivities of several reliability indices with respect to emission allowances. Reference [153] shows how the cost of emissions can be reflected in the production cost by adding purchases of allowances and subtracting the sales.

Aging of the power grid is evident in the U.S. and many other countries; and the power grid is already struggling to meet current demand. Reference [154] focuses on aging effects in CSR evaluation. Quantitative reliability indices such as Loss of load expectation (LOLE) are calculated. This paper observes that, "as the components grow older, most power systems may enter a wear out stage indicating an aging trend," Reference [155] presents a probabilistic analysis for decision making on the retirement of aged equipment in transmission systems. The basic approach is to quantify and compare the expected damage cost and capital savings from delaying the retirement of aged equipment.

3.4.3 Voltage Stability

Voltage stability is defined as the ability of a power system to maintain steady acceptable voltages at all buses after being subject to some contingency events as well as under normal operating conditions. It plays an important role in performing reliability studies. Reference [156] presents a methodology for ranking and evaluating contingencies using a voltage collapse performance index that measures the expected loss of energy in a studied area. Reference [157] presents an approach that includes voltage stability considerations in the adequacy assessment of a composite power system. Voltage stability is quantified using an indicator that can be easily included in the framework of an existing composite power system adequacy program. The effect on adequacy indices (load point and system indices) of incorporating voltage stability constraints is illustrated by application to the IEEE Reliability Test System (RTS).

Reference [62] presents a risk based statistical assessment of voltage stability limits in the French Riviera subsystem that was used to construct new operating rules to avoid voltage collapse. The capability of taking into account a large number of network situations and uncertainties enables users to assess accurately and robustly the stability limits of the system. Reference [158] describes an approach to calculate voltage collapse-related bulk reliability indices as well as their impact on the adequacy assessment. In this approach, the adequacy analysis of each selected system state is carried out in two steps. First, the minimum load shedding to restore system solvability is computed, neglecting operational constraints such as bus voltage levels and circuit power flows. Second, the additional minimum load curtailment to alleviate any operating limit violations is determined. The proposed methodology can be used with both enumeration and Monte Carlo methods.

3.4.4 Frequency Stability

As renewable resources displace conventional generation, the frequency regulation capability of the BPS diminishes, because most renewable resources have little or no inertia. This can cause frequency excursions under certain operating conditions to exceed acceptable bounds as specified by regulatory authorities. If such events are considered unacceptable, the reliability impact of reduced inertial generation becomes intuitively apparent. The impact of reduced inertia can be captured based on established load frequency control (LFC) models. Using an LFC model, an expression can be developed for the maximum excursion of the system frequency, and a limit can be imposed on it. The development of this LFC-based frequency operational reliability model, and the impact on reliability, are explained in reference [159]. The limit on the maximum frequency deviation can also be modeled as a general constraint that can be incorporated into any optimal power flow (OPF) formulation, including those used in CSR evaluation, as described in reference [160]. The latter reference also demonstrates that, during periods of high renewable output, an OPF that incorporates the frequency operational reliability constraint will preferentially select higher-inertia generators to maintain frequency stability. This constraint formulation is suitable for both CSR studies and production simulation studies that desire to capture the impacts of reduced inertia.

3.4.5 Substation Related Outages and Maintenance Strategies

Substation-related outages are important in power system reliability evaluation and are usually of the dependent type. Reference [161] presents a probabilistic reliability assessment method for substation configurations and simulation of breaker and switching operations in response to equipment failures. Reliability models of substations, including detailed bus-breaker arrangements, are developed. Failures of substation components, such as incoming and outgoing transmission lines, transformers, bus sections, circuit breakers and disconnect switches, are represented by their respective outage statistics. Reference [162] presents a method for analyzing the effect of substation failures on power system reliability. Reference [163] analyzes the impact of substation configuration on protection system failure propagation and its effect on reliability of a power system. Reference [164] describes and analyzes the dependence of station-originated outages on substation configurations. Station-originated outages resulting in line and/or generating unit outages can be caused by breaker faults, stuck breaker conditions, bus faults, etc. The effect of such outages on composite system reliability indices can be significant. Reference [165] illustrates the importance of considering not just independent outages of generating units, transformers, and transmission lines, but also station-originated outages. IEEE RTS was extended in this paper by including switching configurations at each bus.

Maintenance planning in composite power systems has been studied from various perspectives [166]-[172]. Reference [166] presents a methodology for scheduling preventive maintenance by optimizing the three objectives of maintenance, reliability, and failure costs. Reference [167] proposes a maintenance planning approach to determine the optimal time-based maintenance for circuit breakers considering their locations in the power system. Reference [168] presents a framework for replacement planning of aging power equipment based on identifying the critical components for system reliability. Reference [169] presents an efficient method for long-term generator maintenance scheduling given various constraints. Reference [170] reviews the most frequently used maintenance strategies, distinguishing between strategies in which maintenance consists of replacement by a new component and those with a less costly activity resulting in a limited improvement of the component's condition. Reference [171] presents the results of a survey of various maintenance methods available to utility operators, from the simplest, "follow-the-manual" types to detailed probabilistic approaches. Authors recommend probabilistic models for identifying policies that provide the highest cost savings. Reference [172] evaluates the effects that preventive maintenance of circuit breakers and protection systems inside substations have on the reliability of electricity supply.

3.4.6 Failures of protection and control systems, cyber-attacks, circuits switching, demand response

Failures of protection and control systems such as wide-area monitoring system (WAMS) and wide area monitoring and control (WAMC) may have a significant impact on the reliability of a composite power system. The following references cover a variety of issues associated with such failures. Paper [17] studies terminal effects and protection system failures in CSR evaluation. Paper [88] examines some protection system models and incorporates the results in a practical application of composite system adequacy assessment. Paper [160] examines the impact of substation configurations on protection system failure dependency propagation and its effect on bulk load point reliability indices. Paper [173] develops new models and concepts for incorporating the effect of protection system failures into power system reliability evaluation. The two types of protection failures—undesired-tripping mode and fail-to-operate mode—and their impact on reliability modeling are discussed. A task force paper [174] reviews progress over the past 20 years in analyzing the effect of protection systems on BPS reliability evaluation. Paper [175] studies the impact of WAMS-based monitoring and control infrastructure on the reliability of a BPS. Paper [176] evaluates BPS reliability considering the impact of protection system hidden failures. It proposes a systematic methodology based on a breaker-oriented system network model including detailed substation configurations and protection system schemes.

Paper [177] studies the impact of WAMS and extreme contingencies on BPS reliability. Paper [178] presents a practical analysis of utilizing special protection systems (SPSs) to prevent, and minimize the adverse impact of, system-wide cascading outages, therefore maximizing system power transfer capability. Paper [179] explores hidden failures in protection systems, which have been identified as key contributors in the cascading of wide-area disturbances. Paper [180] describes models developed for different fault types related to protection and control and a methodology for incorporating these fault types in reliability assessment. The enhanced methodology enables assessment of the impact of the protection system on reliability. Paper [181] reviews and summarizes major publications in protection system reliability modeling. The difficulties and challenges of incorporating protection systems into CSR reliability assessment are discussed. Paper [182] addresses the impact of situational awareness and controllability on assessment. A methodology is proposed to simulate a situation in which a limitation of either or both monitoring and control functions could spread the consequence of power system events throughout the grid. It is assumed that the monitoring/control infrastructure is based on a WAMS.

A **cyber-attack** is defined as an unauthorized attempt to access a computer system to either seize, modify, or steal data. Cybercriminals can use a variety of attack vectors to launch a cyberattack including malware, phishing, ransomware, and man-in-the-middle attacks. References [183]-[188] present how various types of cyber-attacks impact power system reliability. Paper [183] presents non-sequential Monte Carlo simulation for evaluating BPS reliability by taking into account cyber-induced dependent failures. The proposed method preserves the dependent features of cyber-induced events and improves computational efficiency. Although motivated by cyber-induced failures, the technique can be used for other types of dependent failures as well. Paper [184] presents a systematic method for evaluating power system reliability by considering the effect of cyber-malfunctions in substations. The quantitative relationship between switching time and system-wide energy unavailability is studied. The results indicate the impact of protection system failures on system-wide reliability indices and highlight the importance of accelerating the line switching process.

Paper [185] presents an approach for incorporating cyber-attacks against supervisory control and data acquisition (SCADA) system and energy management system (EMS) in a wind farm. Bayesian attack graph models are adopted to represent the procedures of successful cyber-attacks, and a mean time-to-compromise model considering different attack levels and various vulnerabilities is used. Simulations are conducted based on an IEEE RTS. Paper [186] explores reliability assurance of cyber-physical systems, to stimulate more research in this area. The paper indicates that addition of more sensing, communication, VER generators, and storage under the renewable energy thrust and smart grid initiative will add even higher orders of dimensionality and complexity to the power grid. Paper [187] proposes a novel approach to analyzing the impacts of cyber layer failures (i.e., protection and monitoring failures) on the reliability evaluation of composite power systems. The reliability and availability of the cyber layer and its protection and monitoring functions with various topologies are derived based on a reliability block diagram method. The objective of [188] is to define the three-layer model and report a generalized framework for combined reliability modeling. It also provides an understanding of the operation of a cyber network and its reliability, and how to integrate the interdependency of cyber and power systems into power system planning and operations. In a three-layer approach, the cyber and power layers are interconnected by the information layer.

Switching circuits in power systems is often used as a mitigation measure to alleviate problems and enhance the reliability. Examples are the switching of shunt capacitor banks or shunt reactors, and de-energization of overhead lines or transformers. References [52], [189]-[192] address issues associated with circuit switching. Paper [52] studies the reliability impacts of manual removal of transmission lines. The existing model is extended to consider optimal transmission switching (OTS) as a remedial action. The proposed model minimizes the total damage cost imposed by load curtailments. Simulation results on the modified reliability test system (MRTS) demonstrate great enhancements in service reliability when OTS is realized. Paper [189] proposes a method for studying the reliability implications of line switching and introduces variance into the analysis. The paper provides a categorization of line switching operations, and classifies transmission lines based on their reliability performance. The categories provide reliability implications of line switching operations and can be used for guidance in actual operations.

Paper [190] presents an analysis of the behavior of the switched system and mitigation of failures through switching, with analysis of load capacity and reliability. Analysis is based on OTS with optimal ac power flow (OPF-AC) to reduce disturbances when faults occur and minimize equipment load and disconnections. Paper [191] emphases that simulation of substation-originated outages for practical substation configurations is difficult, due to the complex switching actions with disconnect switches and circuit breakers that can take place. The paper describes a simulation algorithm, which deduces the contingencies before and after switching actions, with their corresponding reliability indices. The paper reports on results obtained from analyzing six different busbar schemes with redundant components. Paper [192] suggests a probabilistic measure to foresee the likelihood of experiencing an undesirable operating state following execution of an optimal hour-ahead switching plan. The approach can be helpful in selecting the most practical switching action when the optimization engine can provide multiple optimal switching scenarios. The paper also indicates the importance of monitoring the impact on the power system operating state following the switching implementation to make sure the system operational reliability performance in the new, migrated operating state is not jeopardized. The proposed tool is tested on a modified IEEE 118-bus test system to demonstrate its applicability and effectiveness.

Demand response (DR) programs are offered by many utilities for energy consumers to reduce their energy demand, at the utility's request, during peak periods of demand and under-supply. References [193]-[197] cover DRP and emergency demand response program (EDRP). Paper [193] presents a probabilistic modeling approach that uses a two-objective optimization function to minimize aging of a network’s overhead lines (OHLs) and maximize its reliability by use of the available DR in emergencies. The proposed optimization provides the operator with the flexibility to trade off between aging and reliability costs against DR costs. Results of the proposed framework indicate that DR can have a significant impact on reducing aging and maintenance costs at critical lines. Paper [194] aims at developing a general framework to evaluate the contribution of DR and electrical energy storage (EES) to adequacy of supply by specifically modelling and analyzing their operational flexibility parameters and constraints. A study is run using sequential Monte Carlo simulation that allows capturing the relevant inter-temporal constraints. The results suggest that, given a prevailing generation portfolio, DR and EES could reduce the frequency and cumulative duration of interruptions, although these might become more severe. The models and findings of this work are critical to quantitatively inform energy policy debates about the potential of DR and EES to provide system capacity and participate in relevant markets.

Paper [195] presents an approach to assessing the effect of an EDRP on the CSR of a deregulated power system using an economic load model, an AC power-flow-based load curtailment cost function, and reliability evaluation techniques. In calculating reliability indices, the EDRP cost is considered and, in each contingency state, the EDRP cost is compared with the customer load curtailment cost, and the load appropriate value is selected for load shedding or participating in EDRP. This paper indicates that use of EDRP is important for solving problems related to congestion, performance, and power markets. Paper [196] presents an integrated framework for evaluating impacts of demand side management (DSM) on composite generation and transmission system reliability. A set of load management models for peak clipping/shifting and valley filling, strategic conservation and strategic load growth are presented. It uses a CSR evaluation procedure incorporating DSM resources in a Monte Carlo simulation approach. The IEEE RTS is used to illustrate the proposed approach and compare reliability indices with and without DSM activity. Paper [197] presents a review of various initiatives, techniques, impacts and recent developments in DSM and its potential benefits. An extensive literature survey on the impacts of DSM on reliability is provided. Research gaps within the broad field of DSM are also identified to provide directions for future work. The paper indicates that DSM programs offer promising solutions and can considerably improve the reliability and financial performances of electrical power systems.

3.4.7 Load and Renewable Forecast Uncertainty

Load and renewable forecast uncertainty should be taken into account when assessing the reliability of a composite power system. References [49], [198]-[203] consider a variety of issues associated with load and renewable forecast uncertainties. Paper [49] illustrates the effects of bus load uncertainty and correlation in composite system adequacy assessment. A tabulating technique for normal distribution sampling and a correlation sampling technique are used to simulate bus load uncertainty and correlation. These techniques have been incorporated into the MECORE computer program for CSR evaluation. Case studies presented in this paper indicate that recognition of bus load uncertainty results in increased inadequacy indices, and this effect increases considerably as the standard deviation of load increases. The paper shows that the effects of bus load uncertainty and correlation on inadequacy indices are not the same for composite systems which have different sensitivities to load level variation. Paper [198] examines the effects of load forecast uncertainty in bulk system reliability assessment incorporating changes in system composition, topology, load curtailment policies, and bus load correlation levels. It also indicates that load forecast uncertainty is an important factor in long-range system planning and has been shown to have a significant impact on calculated reliability indices.

Paper [199] focuses on the management of historical data related to stochastic renewable and load snapshots and forecasts in order to solve some critical issues in raw data and derive a dependable model of the multivariate distributions of renewables and loads conditioned to the specific forecast state of the grid, with the ultimate aim of generating the “uncertainty region” of states around the forecast state. The paper addresses various needs and objectives, including the definition of a platform architecture, a dynamic data structure, and dynamic model validation. Paper [200] presents a weather sensitive model that can be applied to both short- and long-term forecasting on the utility’s system. The model features a stationary load-weather function and separation of the base load and weather-sensitive load components. This allows trending and independent forecasting of the two components and computation of severity statistics represented by the values of the weather function. Paper [201] presents a methodology for analyzing the risk of short-term power system operational planning in the presence of load forecast uncertainty. The methodology uses a Bayesian load forecaster to estimate load forecast variance. The risk due to load forecast uncertainty is based on the forecast variance, and is found by determining the expected value of perfect information. The paper illustrates the risk evaluation method using a case study with utility-derived system data and temperature forecast data from the National Weather Service.

Paper [202] presents an approach for wind power forecasting in power system operations to address variability and uncertainty. It indicates that accurate wind power forecasting is important for reducing the occurrence and duration of curtailment, enhancing market efficiency, and improving the operational reliability of the BPS. The value of improved wind power forecasting was found to be strongly tied to the conventional generation mix, existence of energy storage devices, and the penetration level of wind energy. To measure economic value, a commercially available production cost modeling tool was used to simulate the multi-time-scale unit commitment (UC) and economic dispatch processes for calculating cost savings and curtailment reductions. Paper [203] proposes an approach to evaluating the uncertainties in balancing capacity, ramping capability, and ramp duration requirements. The approach includes three steps: forecast data acquisition, statistical analysis of retrospective information, and prediction of grid balancing requirements for a specified time horizon and a given confidence level. An assessment of the capacity and ramping requirements is performed using a specially developed probabilistic algorithm based on histogram analysis, capable of incorporating multiple sources of uncertainty—both continuous (wind and load forecast errors) and discrete (forced generator outages and startup failures).

3.4.8 Energy Storage, Microgrid, Smart Grid, Plug-in Electric Vehicles

An **energy storage system** (ESS) is defined by the quantity of energy it is capable of storing (MWh), energy retention time, and rate at which it can be charged and discharged (power, MW), and is used to improve the reliability and/or operational economy of a power system. References [204]-[209] describe a variety of applications related to reliability. Paper [204] presents a stochastic computation framework to assess the benefits of battery energy storage systems (BESSs) from reliability enhancement by performing outage mitigation and frequency regulation, also the commitment failure risks due to service stacking. The paper notes that BESSs are a promising solution for mitigating power system component outages. By installing BESSs to mitigate outages and defer network upgrades, asset owners can also obtain additional services, such as frequency regulation, to accelerate the payback of BESS investments. The computation framework is demonstrated on the IEEE RTS-96 case. Paper [205] proposes a comprehensive evaluation of stacked revenue generated from grid-connected ESSs in a market. The stacked revenue from an ESS cannot be calculated by merely aggregating the benefits from various applications (e.g., energy arbitrage, frequency regulation, and outage mitigation), as the ESS may not be able to perform all types of applications simultaneously. In this paper, different applications are identified, and a model incorporating component reliability, power system operating constraints, and storage system operating constraints is developed to evaluate the composite revenue from these applications. Sequential MC simulation (MCS) is used for evaluating the reliability improvement and a quadratically constrained linear programing model is built for estimating the maximum revenue from arbitrage and regulation markets.

Paper [206] deals with the impact on CSR of integrating energy storage and wind energy considering optimal placement. The paper observes that the benefits of storage include electric energy time shift, frequency regulation, and transmission congestion relief. But if energy storage is installed at non-optimal locations, it will lead to increases in cost, system losses, and capacity requirements, hence the opposite effect of that desired. MCS is used to simulate the chronological history of each component, that is, the up and down cycles of generators and transmission equipment, and load fluctuations. The main contribution of this paper is the proposed MCS framework for accurately quantifying the reliability impact from optimal placement of wind generation and energy storage. Paper [207] presents a recovery-risk analysis-based analytical framework for operating risk assessment of a wind-integrated bulk power system following a major contingency disturbance. Two new indices quantifying the recovery-risk profile of the BPS and its load delivery points following major disturbances are introduced. The indices quantify the impact of increasing wind penetration on operating risk and the reliability benefits using fast-responding ESSs such as flywheel energy storage systems. The proposed methodology is illustrated through several test system case studies.

Paper [208] presents a novel probabilistic method for determining the size of on-site energy storage and the transmission upgrades needed for integrating wind generation into a power system. The paper observes that intermittency of wind generation and the potential need for transmission reinforcements are the major concerns in wind generation integration. One solution is to build on-site energy storage at a wind farm. Practical applications are illustrated using the IEEE RTS. Paper [209] reviews the state of ESS technology, presents installations of several ESS technologies, and analyzes their various characteristics. The analyses include their storage properties, current state in the industry, and feasibility for future installation. The paper also identifies the characteristics of ESS technologies suitable for renewable energy systems.

A **microgrid** is a self-sufficient energy system that serves a discrete geographic footprint, such as a college campus, hospital complex, business center, or neighborhood. References [210]-[211] assess the impact of microgrids on composite system reliability. Paper [210] presents a comprehensive review of current control technology with a discussion of the challenges of microgrid control. It also presents basic simulation results supporting the findings. The paper indicates that interest in microgrids has increased significantly, triggered by increasing demand for reliable, secure, efficient, clean, and sustainable electricity. In addition, the paper provides research needs and a roadmap for microgrid control. Paper [211] focuses on assessing the benefits of microgrids on CSR. Realization of these benefits calls for optimal coordination among the three energy sources within microgrids, namely renewable energy conversion, energy storage and micro-turbine generation. The paper indicates that with the advent of microgrids and their integration in power systems, analysis of their impacts on power system planning, operation, and control becomes an important issue. This coordination is modeled by applying sequential MCS to assess the risk of cascading failure due to relay overtripping, short-circuits induced by overgrown vegetation, voltage sags, line and transformer overloading, transient instability, voltage collapse, and other factors. Comparison of reliability index values shows that microgrids significantly improve the reliability of the system.

The **smart grid** is a technology providing two-way flow of data and electricity. It enables the electricity industry to better manage energy delivery, and empowering consumers to have more control over energy decisions. References [212]-[216] deal with a variety of smart grid technology issues. Paper [212] discusses the models and methods of reliability analysis that are used today, how these models and analysis are being complicated by the growing cyber layer resulting from the move towards a smart grid, and some of the directions of research to surmount the difficulties of analyzing this cyber-physical system. It indicates that calculating the reliability of the power grid is difficult because it is made up of thousands of components, and even though the failure mode of each component may be known, they are not independent of each other. Also, the models required to conduct reliability analysis are difficult to develop and are often complex enough to make the techniques for analysis very cumbersome.

Paper [213] addresses the following topics: emerging trends in energy investment, a holistic smart grid approach, challenges addressed by smart grids, and experiences with deploying smart grid projects. The paper observes that reliable and efficient grid operation is critical to society, and oil dependency and environmental concerns drive the power industry to implement sustainable energy portfolios. A new sense of urgency has been brought to all energy issues, including the power grid. Paper [214] discusses a variety of issues associated with smart grid. It notes that reliability has been the central issue for power system planning and operation in the past several decades. Reliability is maintained by the system operator at the same level for the entire system, and is treated as a public good. But this reliability concept was developed for a centralized system with a manageable level of uncertainty. The paper shows that smart grid technologies could dramatically alter the architecture of the power grid. One prominent feature addressed the smart grid is the unprecedented level of uncertainty brought by variable resources such as wind and solar.

Paper [215] categorizes four types of interdependencies between cyber and power networks in smart grids. The proposed classification permits the assessment of adverse effects of cyber network failures on the power network's operation. The paper notes that a cyber-power system contains two interconnected infrastructures: a power network and a cyber network. The cyber network monitors, protects, and controls the power network. Without the cyber network, the power network cannot operate efficiently or reliably. Two applications of cyber-power systems—automated substations and micro grids—are discussed in this paper, and certain cyber-power interdependencies are listed as examples. Paper [216] presents a new method for probabilistic reliability evaluation with multi-objective meta-heuristics (MOMH) in smart grids. It indicates that probabilistic reliability evaluation has been broadly used for power system operation and planning due to its capability to consider various system uncertainties. It is evident that smart grids increase the degree of uncertainties due to renewable energy. The effectiveness of the proposed method is demonstrated using the IEEE-RTS-79

Plug-in electric vehicles (PEVs) are new type of load that uses electricity from the grid to charge large battery packs. References [217]-[218] present the impact of PEVs on CSR. Paper [217] presents a probabilistic model for integrating full electric vehicles (FEVs) and plug-in hybrid electric vehicles (PHEVs) with characteristics such as battery capacity, charge depleting distance, and charging rates. The paper indicates that widespread integration of FEVs and PHEVs will substantially increase the load on the power system, which will eventually affect the reliability of existing power systems. Furthermore, different charging strategies, i.e., opportunistic charging and controlled charging with and without a vehicle-to-grid (V2G) scheme, have been considered to evaluate the impact of FEVs and PHEVs on the composite power system. The IEEE-RTS-79 system is used to examine the proposed probabilistic technique considering different FEV and PHEV penetration levels as well as charging strategies. Paper [218] proposes an approach to construct a load profile for EVs in CSR analysis considering drivers' behavior in terms of charging time and location. As EVs are movable loads, the amount of load demand at system buses dynamically changes based on drivers' behavior. In this work, the constructed load profile of EVs is combined with the system load profile to evaluate system reliability indices. The well-known CSR indices are evaluated by Monte Carlo simulation method. The proposed method is demonstrated on the IEEE-RTS through several case studies.

3.4.9 Dynamic thermal rating, flexible ac transmission system

Dynamic thermal rating (DTR) systems are used to increase transmission line capacity without exceeding the conductor maximum operating temperature. References [219]-[220] describe issues associated with DTR. Paper [219] presents a probabilistic method to assess thermal capacity based on risk. The authors note that thermal ratings of overhead transmission lines, when computed deterministically, are typically conservative, resulting in under-use of conductors. The paper addresses the potential impacts of thermal overload, a stochastic model of conductor temperature, and the quantitative risk which indicates the average "danger" of an overload. The continuous, short-term, and long-term thermal ratings are calculated using the risk of thermal overload. This method can provide technical justification for increased thermal capacity of a transmission line and an evaluation of risk for given operating conditions. Paper [220] presents a transmission line failure model that is enhanced with the DTR system. The proposed model is compared with the traditional normal distribution model that considers only the end-of-life failure of a transmission line. This paper also investigates the uncertainty effects of line-failure model parameters, effects of the DTR system reliability, and the effects of weather data correlation on the reliability performance of the power system. The proposed methodology and case studies were performed on the IEEE-RTS.

Paper [221] presents a framework that can be applied to different DTR system designs. The methodology's objective is to produce designs that are highly reliable and as such do not impose a significant risk on the transmission system. The paper projects that future grids will be operated much closer to their operational reliability limits due to ever increasing power demand and difficulty in building new transmission corridors. DTR systems can be used to increase transmission line capacity without the conductor maximum operating temperature being exceeded. Hence, DTR systems are of significant interest to transmission system operators. Paper [222] presents a Markov model for reliability analysis of transmission lines equipped with a DTR system. In addition, a fuzzy logic procedure is proposed to determine an annual equivalent fuzzy DTR capacity to represent hourly variations of the line DTR. This method is chosen to address the fuzzy constraints associated with lines equipped with a DTR system. Numerical results are presented using the 24-bus IEEE RTS, and demonstrate the validity of the proposed approaches.

A **flexible ac transmission system** (FACTS) includes the following four types of devices: static synchronous series compensator (SSSC), thyristor controlled series capacitor (TCSC), thyristor controlled series reactor (TCSR), and thyristor switched series capacitor (TSSC). Paper [223] presents reliability modeling and analysis of an HVDC transmission system incorporating a voltage-sourced converter (VSC) tapping station. The paper develops a comprehensive detailed reliability model and then converts it to a manageable and computationally efficient model. Using this equivalent reliability model, various reliability indices are calculated at the load points of the system, and the impacts of the VSC tapping station on these indices are illustrated. Sensitivity analyses are conducted to investigate the reliability impacts of the load level and the location of the tapping station. The conducted studies are numerically applied on a typical HVDC system, and thorough discussions are presented.

Paper [224] examines the impact of an interline power-flow controller (IPFC) on composite system delivery point and overall system reliability indices. The paper analyzes a IPFC with dc transmission lines employed in a system for coordinated control of line impedances of two, distance away, transmission lines with the objective of managing power flows on the two lines. The IFPC is also used to balance the real power being transferred between the compensated lines. For this purpose, the reliability model associated with a converter station has been developed and incorporated in an IPFC reliability model. A number of reliability indices are calculated at both the load point and system levels to illustrate the impact of employing IPFC and examine the effects of different failure modes on the system performance. The technique is applied to the IEEE RTS and the results are presented. The results demonstrate that an IPFC improves system reliability.

Paper [225] presents a comprehensive reliability model for distributed static series compensators (DSSCs). To illustrate the worth of DSSC use, the increment in the expected interruption cost is computed using CSR assessment. Numerical analysis on the IEEE RTS is conducted to examine the effect of a DSSC on composite reliability indices. The results reveal the effectiveness of proposed models and illustrate that DSSCs enhance the system reliability. Paper [226] examines the impact of a TCSC on power system reliability. In this application, the TCSC is employed to adjust the natural power sharing of two parallel transmission lines and, therefore, enable the maximum transmission capacity to be used. The improvement is measured using two reliability risk indices—Loss of load expectation (LOLE) and Loss of energy expectation (LOEE).

3.4.10 Flexibility practices, common mode and dependent (CMD) outage events, and renewable energy sources

Flexibility in power system operation is the ability of a power system to respond to changes in demand and supply. In general, four key categories of assets provide system flexibility: power plants (both conventional and VER, electricity networks, energy storage, and DERs. Paper [227] indicates that penetration of intermittent renewable generation, power market effects, and dynamic conditions are driving the power system to require higher flexibility. The paper presents the DTR concept as a solution to enhance transmission system flexibility. It proposes to include dynamic conductor thermal modeling in CSR assessment using a sequential Monte Carlo Simulation (MCS). An hourly capacity series for each transmission line is generated regarding the type of conductors, voltage levels, weather conditions, and maximum conductor temperature. The IEEE-RTS 79 is utilized to illustrate the proposed methodology. Paper [229] presents ways existing transmission system flexibility can be used. New electronic controller applications, based on thyristor technology, have helped enhance the inherent flexibility in existing transmission systems. The paper provides examples of how system operation and reliability can be enhanced, with conventional equipment by taking advantage of existing transmission system flexibility. CSR Task Force's recent paper [228] addresses composite power system reliability with renewables and customer flexibility

Common mode and dependent (CMD) outage events may result from a number factors, such as failure of equipment, malfunctioning of protective devices, weather conditions, natural disasters, loading conditions, power transfers, maintenance, and human error. Effects of CMD events on composite power system reliability are discussed in [230]-[239]. Paper [230] presents a risked-based integrated expansion planning model that considers the interdependency of natural gas and electricity infrastructures. In this paper, a bi-level model is proposed for investment planning decisions with a renewable energy tax credit and investment risk caused by uncertainties regarding regulatory policies. An eight-bus power system combined with a six-node natural gas system is employed to demonstrate the essential features of the model. Paper [231] examines the effect of the system load level and selected dependent outages on the reliability performance of a system using operational reliability-constrained adequacy assessment. Dependent outages included in the analysis are common mode and station-originated events. The studies are extended to examine the effect on system performance of selected switching station configurations. Station topologies considered are the ring bus, breaker-and-a-half, and single bus configurations. The study results provide power engineers with useful and important information on the impact on system well-being of system dependencies caused by common mode failures and station configurations.

Paper [232] reviews fundamental concepts and practical applications in the area of CMD outage events in power systems. The paper is a result of ongoing activity by the Probability Applications for Common and dependent Mode Events (PACME) Working Group (WG). The paper also presents the state of the art in research, modeling, and applications of CMD outage events in power system planning and operation. Issues considered include data monitoring and collection, and probabilistic modeling and evaluation in the planning and operation of power generation and transmission systems. Additionally, some results obtained from outage data statistics corresponding to CMD outage events in systems such as GADS, TADS, and the Canadian Electrical Association ERIS are presented. The primary objectives of paper [233] are to (1) review and discuss the basic definitions of CMD and cascading outage events, (2) identify the major causes of CMD and cascading outages, (3) recognize the effects of protection system failures and misoperations on the BPS, and (4) assess the impact of weather related outages and extreme events on the performance of the BPS.

Paper [234] describes practical outage data collection efforts in North America and parts of Europe, with particular emphasis on outage data statistics corresponding to CMD outages. The goal is to eventually be able to obtain standard, representative reliability indices for typical transmission elements such as lines and transformers from the available outage data. Paper [235] presents a brief summary of the basic common mode failure models and the relevant equations for their inclusion in power system reliability studies. Differences in the models are illustrated by numerical examples. Models for incorporating transmission outages associated with enhanced failure rates due to adverse weather are also illustrated. These models are combined with common mode events in a numerical analysis to illustrate the relative effects of common mode failures and failure bunching due to adverse weather. Concepts associated with dependent outages are discussed with particular emphasis on station related transmission outages.

Paper [130] describes the Canadian Electricity Association (CEA) outage data and statistics presently available and the information that may be utilized for the analysis of common mode events in electric power systems. The detail of outage event data captured in the CEA outage database is demonstrated through a sample analysis that illustrates the various perspectives that this database can provide. Paper [131] discusses the Western Electricity Coordinating Council's (WECC) experience in the collection of transmission outage data with an emphasis on CMD outage events. The outage data statistics of WECC 230-, 345-, and 500-kV transmission lines constructed on the same tower as well as those constructed in the same-right-of-way have been analyzed in detail. Paper [236] summarizes the causes of dependent mode outages of BPS elements; gives guidance for the estimation and confidence interval for their conditional probability; and indicates how they can be included in a Markov model of multiple outages. It also proposes a conceptual extension of such outages to include power system condition dependent outages due to cascading and instability.

The objective of paper [237] is to provide a valid source of information and references about dealing with common-mode outages in power systems reliability analysis. Also, the paper reviews published literature and presents state-of-the-art research and practical applications in the area of common-mode outages. Evaluation of available outage statistics shows a definite need for collective effort from academia and industry to not only recommend procedures for data collection and monitoring but also to provide appropriate mathematical models to assess such events. Paper [238] presents the results of analysis of the first comprehensive study of the North American inventory of AC circuits on common structures and their outage data statistics collected from 2013 through 2016 in the NERC Transmission Availability Data System (TADS) and the Canadian Electricity Association (CEA) Equipment Reliability Information System (ERIS). The paper discusses the leading causes of common-structure outages and compare calculated frequency and duration indices. Paper [239] presents study of the 2015-2020 CDM outages of ac circuits and transformers collected by the NERC TADS.

Renewable energy sources are virtually inexhaustible in duration but limited in the amount of energy that is available per unit of time. The major types of renewable energy sources studied as part of composite power system reliability are wind and PV. References [240]-[244] deal with assessing the impact of integration of renewables on CSR. Paper [240] discusses the perspective of renewable energy (wind, solar, wave and biomass) in the making of strategies for a sustainable development. It indicates that such strategies typically involve three major technological changes: energy savings on the demand side, efficiency improvements in the energy production, and replacement of fossil fuels by various sources of renewable energy. The conclusion of the paper is that such development will be possible. Paper [241] indicates that constant increases in oil prices and the concern over the reduction of greenhouse gas emissions favor the creation of policies to encourage the production of energy through renewable sources. Thus, non-conventional energy sources, namely wind power, mini-hydro, solar, and cogeneration (e.g., biomass), start having a significant contribution in the energy production matrix.

However, if the volatility of the available capacity from such sources is not properly considered, decisions taken in power systems expansion and/or operation planning can severely endanger the reliability of the power supply. Paper [242] studies the reliability of integrated transportation and electrical power system (ITES). A bidirectional EV charging control strategy is first demonstrated to model the interaction between the two systems. The paper indicates that with the increasing use of EVs, transportation systems and electrical power systems are becoming increasingly coupled. However, the interaction between these two kinds of systems is not well captured, especially from the perspective of transportation systems. The paper proposes a simplified transportation system model whose high efficiency makes the reliability assessment of the ITES realizable with an acceptable accuracy. Novel transportation system reliability indices are then defined from the viewpoint of EV drivers. Based on the charging control model and the transportation simulation method, a daily periodic quasi-sequential reliability assessment method is proposed.

Paper [243] reviews the state of the art of three different kinds of energy storage technologies—pumped hydroelectric storage, batteries, and fuel cells—suitable for the integration and management of intermittency in renewable energy (RE). Within the context of the review, advantages and disadvantages of the various technologies are also presented. Additionally, it also pinpoints the different areas of applications of ESSs for RE integration and offers a review summary on factors to be considered for selecting appropriate ESS technology for either commercial or domestic applications. Finally, the paper concluded that ESS selection is based on performance characteristics and fuel source used, and that no single ESS technology can meet all the possible requirements to be called a supreme ESS. Paper [244] summarizes recent trends of energy usage from renewable sources. It discusses physical modeling of renewable energy systems, several methods and criteria for optimization of the hybrid renewable energy system (HRES). The paper also presents a comprehensive review of the current state of optimization techniques specifically suited for small and isolated power systems. The recent trend in optimization for HRESs shows that artificial intelligence may provide good optimization of systems without extensive long term weather data.

3.5 CSR Methods

CSR assessment is one of the most important concepts in power system planning, operation and maintenance. The problem of assessing the adequacy of the generation and transmission systems in regard to providing a dependable and suitable supply at the delivery points can be designated as CSR evaluation [10]. Failure of a composite power system facility (including the protection and control systems) may result in multiple outages of power system components such as generators, transformers and lines. Failure of a composite system component may also isolate a load or a group of loads. In addition, station-originated (or terminal-related) failures can have significant impact on the reliability performance of composite power systems.

The introduction of probability-related ideas and techniques has significantly enhanced the reliability assessment of composite power systems. The basic steps in probabilistic reliability evaluation of a BPS are presented in Fig. 4, in Section 2.8. This section presents a review of the existing probabilistic approaches used in the reliability assessment of composite power systems, focusing primarily on mainstream evaluation methods including those new techniques developed to capture the reliability impacts of 3D (decarbonization, decentralization and digitalization) on power systems and to use the various advanced statistical approaches to facilitating the probabilistic assessment of large power systems.

The objectives of reliability calculations are to determine for a given design whether sufficient continuity of electric service to their customers is ensured under normal and certain abnormal conditions, including uncertainties associated with load variations, variable renewable energy sources, etc.

3.5.1 Basic Procedure for CSR evaluation:

A basic procedure for CSR analysis is based on “events and effects analysis” approach. It is shown by the flow-chart in Fig. 10 [8]. The entire process involves data preparation, system state selection, consequence assessment, remedial actions and reliability indices calculations. These main steps are briefly described as follow:

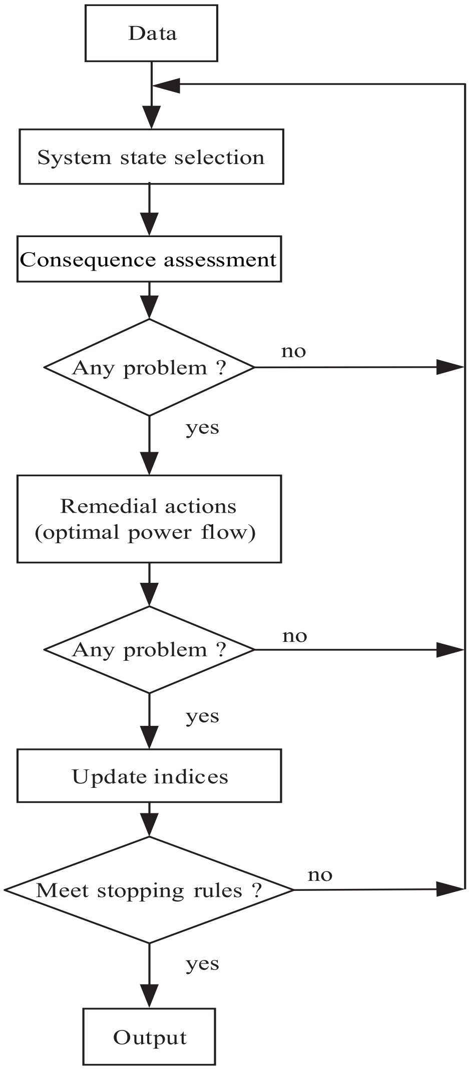


Fig. 10. General Procedure for Composite System Reliability Assessment

Data Preparation

A large amount of input data is needed for the reliability assessment of composite power systems using a probabilistic approach, which can be categorized as follow:

1. Power flow data contains detailed information on the system topology, equipment ratings and various potential loading conditions; for example, summer/winter, peak/light load, drought or export/import scenarios.

2. Boundary data contains the required information for the identification of the composite power system of interest and surrounding areas for state selection. It can be assumed that component failures outside of the defined boundary have negligible impact on the reliability performance of the system of interest. A practical power system simulation model normally contains system topology and data for a number of interconnected systems spread over wide geographical areas consisting of thousands of components. It is practically impossible to perform probabilistic assessment for such a system. Also, if two or more failed components are not in close electrical proximity, the impact on overall system reliability may not be considerably different from that due to their individual failures. Identification of the composite power system of interest can significantly reduce the computational burden.

3. Load data includes load duration curve (LDC) or chronological load variation curves and load forecast uncertainty (LFU) if necessary. These are the standard inputs to probabilistic assessment of power systems and these inputs can be incorporated in the evaluation.

4. Component outage parameters typically include the failure rate, maintenance rate and average outage duration for all components associated with the system of interest including transmission lines, transformers, bus-sections and generating units. In some cases, CMD failures at composite system reliability levels are significant and may also need to be modeled. These CMD failures need to be specified through an input file and the impact of these outages captured in the evaluation using the individual or composite modeling method proposed in [8], [10]. Other failures, such as aging failures [9] and weather related failures [8]-[9] can be easily incorporated in the evaluation, provided that enough information is available to model these failures.

5. Variable generation, with the bulk component of it coming from wind and PV, presents a level of uncertainty an order of magnitude above the usual uncertainties from legacy power systems. For proper inclusion of the effects of variable generation in CSR analysis, it is necessary to develop reliability models of variable generation. Because of the considerable correlation between variable generation output (hot day with high demand, high solar, low wind) and system demand, it is important to use reliability models that capture this correlation. Since most of the time variable generation (wind, PV) is operating at maximum power tracking, lumping variable generation and demand results in a “composite load” (or net load) model. The composite load model must be served by the dispatchable units. This approach provides the basis for including and assess the impact of variable generation on CSR. The process of computing composite load models and their

reliability is illustrated in Fig. 11. References [87], [104], [111], [118] consider the effect of correlation between wind farms on CSR results.

6. Reliability assessment of the system requires consideration of not just models of all components but also the operational practices implemented in the studied power system, as illustrated in Fig. 12. This figure provides the reliability analysis of present day power systems.

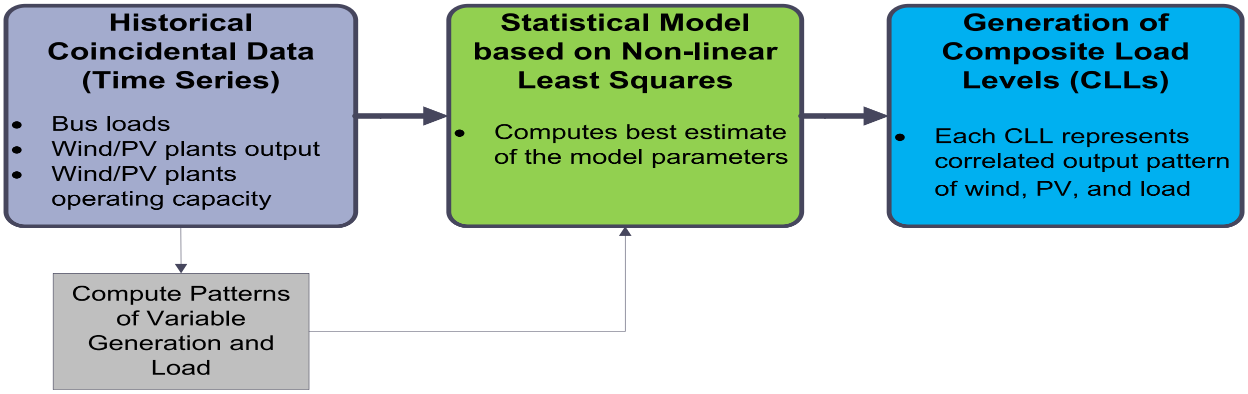


Fig. 11. Construction of Composite Load Model

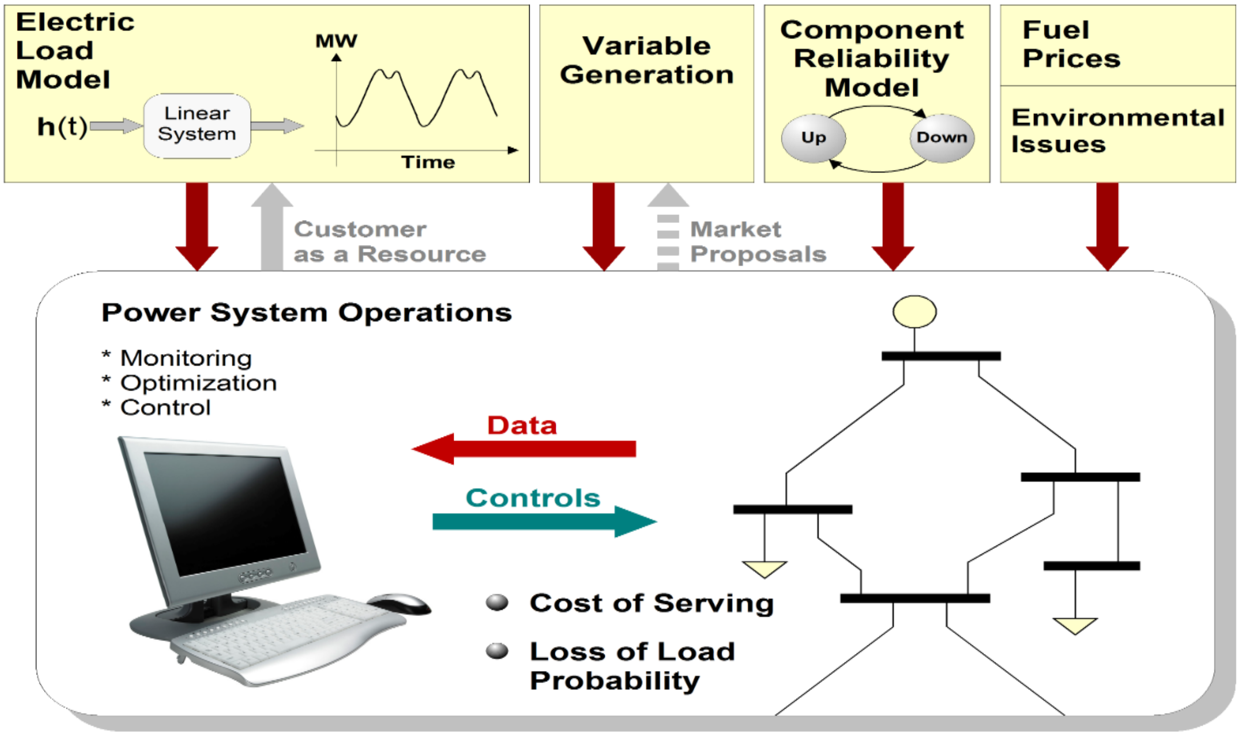


Fig. 12. Illustration of Interaction of Renewables, Power System Component Reliability and Operational Practices on Reliability Assessment

Selection of System States

The state of the system is determined by the states of all elements of the system. A weakened state of the system is considered to be a state in which at least one of the elements of the system has been forcibly taken out from work or its working capacity has decreased. The normal switching state of the system is the state in which all the elements in the random state are completely available. Deficient states are those states of the system in which the supply of energy to consumers is limited, even to only a single delivery point. There are non-deficient states of the system in which there are no restrictions on energy supply to consumers. A key task in identifying deficient and non-deficient system states is based on ac or dc load flow calculations. The power industry uses various power flow models for planning, operating and reliability studies. These power flow models are maintained, updated and used by the industry for various purposes. These models are detailed, accurate and reliable. It is, therefore, recommended to use these power flow models for probabilistic CSR assessment. Typically, each station in a composite power system is represented by a single bus in these industry models.

If station-oriented failures are considered, power flow models with detailed representation of stations may be required. Therefore, the buses representing the stations of interest in the power flow models can be replaced with more detailed node-breaker representation. A node-breaker representation of the composite power system is normally used to replace the single bus model [245]-[246]. Elements of the power system are characterized in the reliability calculations by possible operating conditions, their probability and expected duration. Two commonly used methods - analytical and Monte Carlo - use different approaches to select system states [2], [7]-[12], [65]–[68]. Analytical/enumeration method applied to complex BPS usually doesn't enumerate all possible states in the state space. Instead, it only enumerates up to second or third order overlapping failures. Once the network states are enumerated and the probabilities are calculated, an appropriate criterion as described in the following section is used to identify whether each of the states is a failure or not. The Monte Carlo approach is based on computer generated pseudo-random sequences of system states. The reliability of the system is evaluated after accumulating a sufficient number of realizations.

Consequence Assessment

Once all the system states are selected by either of two methods, the next step is to assess the consequences of these states. As noted previously, there are two basic approaches for the consequence/impact assessment in the power system reliability evaluation. The system analysis in assessing consequences of selected outage states is the same for both analytical and Monte Carlo methods. For practical power system analysis connectivity check is typically performed to identify if there is an isolation of a bus in a composite system due to component outages. Under certain system conditions, interruptions can occur at the designated load point due to component overload or bus voltage violation. In this situation, power flow analysis is performed to determine load point failures [65]–[68]. Typically, ac or dc power flow is performed for contingency analysis for problem recognition and ac or dc optimal power flow for remedial actions.

Evaluation of System States

After selecting the system states to be analyzed, the consequences of each selected state are assessed. There are two basic methods for determining a successful or failed system state. The continuity-based method evaluates continuity or connectivity between source and load points to determine a successful or failed system state. The ac or dc power flow-based method evaluates the consequences of system states expressed as thermal overloads, voltage violations or power flow divergence. This approach should be used if, under certain system conditions, interruptions can occur at the designated load point, due to component overload and/or bus over/under voltage events, which is typically the case.

In general, the electric power system comprises repairable components that are subject to random failures. For this reason, reliability methods are typically based on component reliability models. Reliability evaluation is then the mathematical procedure by which reliability indices are computed from known reliability models of the individual components that make up the system and the success or failure in each state as determined by one of the two previously mentioned methods. As an example, consider the illustration of Fig. 13.

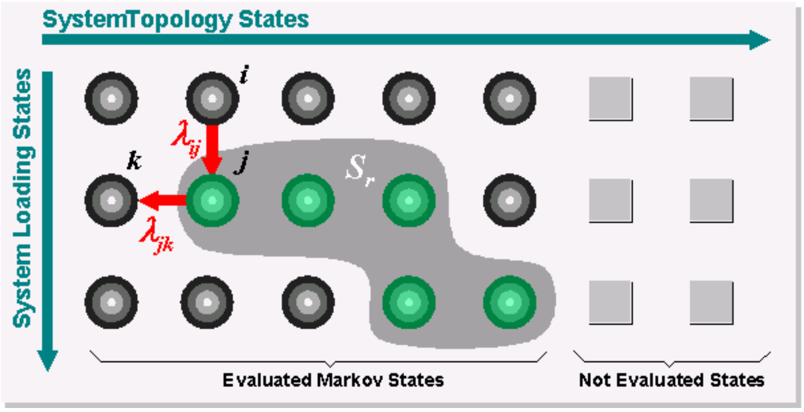


Fig. 13. State-Space Diagram.

An event S_r is indicated that consists of the union of several system conditions or states. Each state may represent a contingency at which the system has failed by a specific reliability criterion. Each state is characterized with a certain probability p_i and transition rates to and from other system states, such as λ_{jk} and λ_{ij}. The three classes of reliability indices—(a) probability, (b) frequency, and (c) duration—are computed as follows:

Probability index: The probability of S_r is obtained by adding all the state probabilities in the set S_r:

$$P_r[S_r] = \sum_{j \in S_r} p_j$$

***Frequency index*:** The frequency of event S_r is the total of the transition frequency of a state j inside S_r to a state i outside S_r, therefore

$$f_{S_r} = \sum\nolimits_{i \notin S_r} \sum\nolimits_{j \in S_r} f_{ji} = \sum\nolimits_{i \notin S_r} \sum\nolimits_{j \in S_r} p_j \lambda_{ji} = \sum\nolimits_{j \in S_r} (p_j \sum\nolimits_{i \notin S_r} \lambda_{ji})$$

where:

λ_{ji} is the transition rate from state j to state i

f_{ji} is the frequency of transfer from state j to state i, which is defined as the expected number of direct transfers from j to i per unit time.

The relation between $f_{ji}$and λ_{ji}can be written as

$$f_{ji} = \lambda_{ji} p_j$$

***Duration index*:** The duration index of event $S_r$is calculated using the probability index and frequency index:

$$T_{S_r} = \frac{P_r[S_r]}{f_{S_r}}$$

The application of this straightforward procedure to power systems becomes very complex and computational demanding because of the size of the power system and the complex operational practices. In CSR studies, two evaluation methods are predominantly used, one based on MCS and the other based on the state enumeration method (SEM). Both approaches will be discussed in detail as follow.

3.5.2 Monte Carlo Methods

In order to estimate reliability metrics for a given power system model, one must analyze the possible states of the system, considering their probability of occurrence and the states' impact on the power supply to end users. As the complexity of a system model increases, enumerating all relevant states becomes cumbersome and error-prone at first, and eventually impossible due to the combinatorial explosion of possibilities. In such cases, MCS is often the tool of choice: power system states are selected at random according to the probabilistic system model and analyzed according to the success/failure criterion. By repeating this process across many randomly selected states and averaging the results, the average performance of the system can be estimated. Despite the procedure being stochastic, strong probabilistic bounds can be derived for the accuracy of the results thus obtained. The simulation process stops either after a fixed number of simulations or on the basis of statistical stopping rules [8].

Almost without exception, metrics of interest in CSR studies are expectation values $r = E[H(X)]$ of random variables $H(X)$ that represent the 'impact' associated with random (outage) states X of the system. For example, the *EENS* is the expectation of the energy not supplied across states. Using MC integration, the value of this reliability metric is approximated by the sample average approximation:

$$\hat{r} = \frac{1}{n}\sum_{i=1}^{n} H(x^i),$$

where,

$\hat{r}$ is the estimate of the system risk $r = E[H(X)]$,
n is the sample size/number of simulations,
x^i is the system state, randomly drawn from the system's probability distribution $P(x)$,
$H(x^i)$ is the impact of the (outage) state x^i.

The simulation of selected system states in Monte Carlo approaches is done with the use of load flows that consider typical planning scenarios including elements such as generation profile, remedial action schemes, selected operating policies etc. Simulation results are distributions of the variables of interest (i.e., circuit flows, voltage levels, energy curtailment, etc.). These results are utilized in the computation of appropriate reliability indices [7]. Although the average impact $r = E[H(X)]$ is often of most interest, some studies additionally report the probability distribution of the outcome $H(X)$ [247]. Those can also be expressed in terms of expectations of (cumulative) distributions [248]. Therefore, the same general approach can be used. Risk-averse conditional variance (CVaR) constraints in system planning can similarly be expressed in the form of expectations [249].

At a high level, we can distinguish two types of Monte Carlo simulation methods for reliability evaluation of transmission systems: sequential simulation (also called time-sequential) and non-sequential simulation (also known as state sampling) [8], [12], [247]-[256]. Whereas non-sequential simulation generates random snapshots of the system at a particular point in time, sequential simulation generates 'extended states' that trace the system's behavior through time, e.g. using state duration sampling (an event driven method) [8]. The choice of whether to use sequential or non-sequential simulation is determined by the specific needs of the study. If it is necessary to consider dependent events and temporal relationships (e.g., when dispatching energy-limited storage), then sequential simulation is necessary; if these dependencies do not exist or can be considered negligible, then non-sequential simulation is often preferred because it generally converges faster than sequential methods.

A typical workflow for performing the reliability analysis using the basic sequential method is presented in Fig. 14.

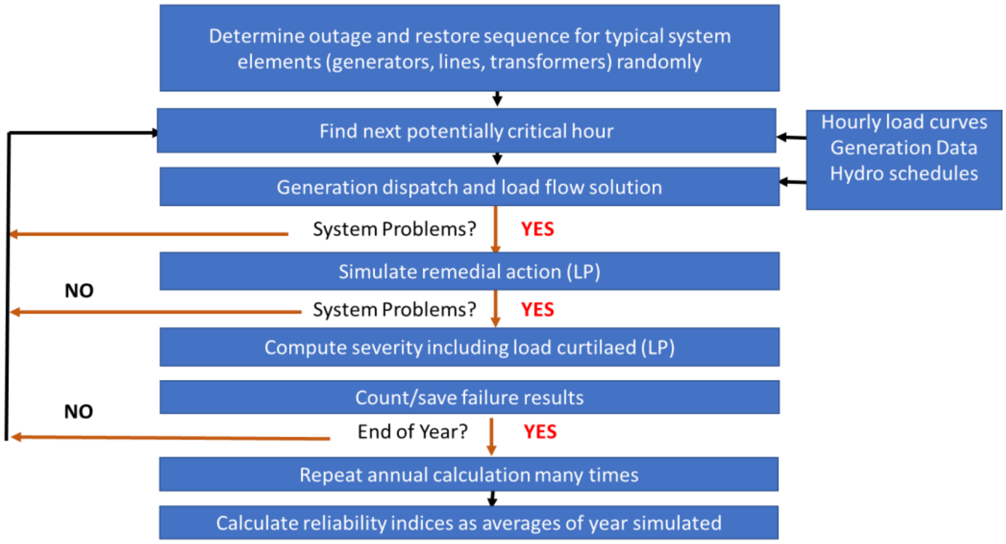


Fig. 14. Basic Diagram of Sequential Monte Carlo Reliability Analysis

By comparison, a typical workflow for a non-sequential (state sampling) MC CSR assessment is [7]:

1. Input system data (component state capacities and probabilities, dependencies, interconnection information, maintenance schedules and load states). Define convergence criteria for indices.
2. Based on the maintenance schedules, divide the study period into intervals.
3. For every maintenance interval, arrange the load levels in ascending order and construct a discrete probability distribution function over the load levels.
4. For every system component, construct a discrete probability distribution over the capacity states that the component can assume.
5. Initialize sample index $i = 1$ and sample size $N = 1$.
6. For the sample index i, draw a system state x^i which represents the combination of component capacities and load levels sampled in steps.
7. Determine if the system experiences loss of load in state x^i. If so, update estimates of indices and test for convergence. Annualized indices are calculated first by using only a single load level and expressed on a one-year basis. All the load level steps are considered successively and the resulting indices for each load level are weighted by their probability to obtain annual indices.

MC simulation is a powerful general-purpose technique, as it can easily incorporate complex decision-making, including interactions with forecasts, and it can be used to estimate complex risk metrics. However, the random selection of states introduces a sampling error in the estimate $\hat{r}$ of the reliability metric. This sampling error has zero mean (i.e., the method is *unbiased*), and for large numbers of samples n, the error is approximately normally distributed with standard deviation:

$$\hat{s}(\hat{r}) = \sqrt{\frac{var(H(\hat{X}))}{n}}$$

where $var(H(\hat{X}))$ is the estimated variance of the sampled values. This equation can be used to quantify the accuracy of the result for a simulation with a given number of samples, or the (relative) accuracy can be used as a stopping criterion [5]. Note that despite its conceptual and algorithmic simplicity, the computational cost associated with a Monte Carlo simulation can be staggeringly high. In general, the method requires many samples to get a good approximation, which may incur an impractically large total runtime. Similar states with large probabilities of occurrence are likely to be analyzed several times, whereas high-impact low probability events may be overlooked, unless very long run times are used.

The expression for the *standard error* above also illustrates the two essential methods to reduce the error incurred: by increasing the sample count n, or by reducing the variance $var(H(X))$. Increasing the sample count can be done by running the program for longer, coding it efficiently, or by the use of advanced computational resources such as Graphic Processing Units (GPUs) [257] or parallel computing [258]. Extracting rare failure events in composite system reliability evaluation via subset simulation is presented in [259]. Multilevel Monte Carlo method can be applied to speed up computation of system adequacy without compromises on model complexity and accuracy of the results [260]. The alternative, reducing the effective variance of the sampled values, is achieved by the various methods discussed below.

Recent Advances in MCS

In many cases, Monte Carlo methodology is similar for composite and simpler network models, but the need for acceleration of simulations is greater in composite system models due to their greater model complexity. Several new efficient techniques for MCS based reliability evaluation of a composite power system have been developed and published in the recent past. These new techniques can be broadly categorized into four groups: state space pruning, intelligent search techniques, variance reduction techniques, and population-based techniques. A brief summary of these techniques is provided below. It should be noted that many of the methods listed below can be combined for further efficiency gains.

State Space Pruning

State space pruning is a methodology applied in Monte Carlo simulations to reduce the number of states and computation time and to improve the convergence. Singh et al. in their book [7] have presented the state space pruning methodology in detail. The basic concept is to prune success states away from the main state space in order to create a higher density of failure states. This higher density of failure states allows the MCS to sample more failure states and make the MCS converge more quickly. After the MCS has converged, the reliability indices can be calculated more efficiently. In addition to [7], references [173], [261]-[263] deal with a variety of aspects of the pruning methodology. Reference [173] presents a pruning method for computing the reliability indices of a composite power system that applies Monte Carlo simulation selectively on those regions of the state space where loss of load states is more likely to occur. The results of this method show a significant reduction in the number of sampled states, thereby reducing the computational effort required to compute system and bus indices. The proposed method may be used in conjunction with the variance reduction techniques to further improve its efficiency.

Reference [261] examines the role of artificial intelligence to improve a search procedure for efficiently identifying states to be examined. References [262]-[263] present the state-space portioning method that combines the advantages of the SEM and MCS. SEM is effective at handling low-order contingencies that constitute a significant portion of the total state space but is computationally inefficient for higher order contingencies. MCS is very effective at sampling larger state spaces. The system state space is partitioned into two regions according to whether SEM or MCS is advantageous. The results of the evaluation of IEEE RTS demonstrate the computational efficiency of the proposed method.

Intelligent Search Techniques

Traditional MCS techniques search the system state space randomly. New intelligent search techniques based on neural networks, genetic algorithms, self-organizing map, intelligent systems and particle swarm optimization use non-random or intelligent searches [12]. Search techniques based on neural networks are described in [264]-[266], genetic algorithms in [267] and particle swarm optimization in [268]. Reference [264] presents a new methodology for reliability evaluation of composite power systems, based on nonsequential MCS and artificial neural network (ANN) concepts. ANN techniques are used to classify the operating states during Monte Carlo sampling and provide significant reductions in the computational cost. The presented approach can be used to assess not only the overall system but also for areas and buses. Reference [265] proposes a fast method using a fuzzy self-organizing map (SOM) neural network as a system state filter to evaluate the reliability of a composite power system. The proposed method of a fuzzy SOM neural network combined with sequential MCS results in a significant reduction in the computational effort required to calculate reliability indices.

Reference [266] proposes use of intelligent systems techniques such as SOMs and linear vector quantization to tackle the computational time required for convergence. Reference [267] introduces a genetic algorithm (GA) based approach for the assessment of composite system reliability. The proposed approach recognizes multi-state components such as generation units with derated states and common mode failure for transmission lines. The superiority of the proposed approach over other conventional methods comes from the ability of GA to trace failure states in an intelligent, controlled, and prespecified manner through the selection of a suitable fitness function.

Reference [268] presents a new method based on the particle swarm optimization (PSO) for CSR analysis. The proposed method is based on applying swarm intelligence to search the state space for failure states. Population-based approaches belong to this category. They maintain and improve multiple candidate solutions, often using population characteristics to guide the search by using population-based metaheuristics that include evolutionary computation, genetic algorithms, and particle swarm optimization. Population-based methods, in general, move through a solution space and search for solution of the data mining task.

References [269]–[270] cover some aspects of population-based approaches. Reference [269] presents a heuristic approach to local load shedding scheme to improve the calculation efficiency of CSR assessment. The basic ideas of the proposed method are to search the node sets to conduct load curtailment which can alleviate system problems effectually according to local load shedding principle and through power flow tracing in the vicinity of the failed system components. Reference [270] describes some of the present problems that exist in the operation of power systems, and how an expert system may be utilized to enhance the performance of the system by implementing load shedding as one of alternatives in the restoration of a large scale power system. The proposed method is a part of an integrated package for power system restoration which will help a system operator recognize bottlenecks in the operation of the system and develop strategies for providing a reliable service to customers. The governing rules for load shedding are introduced and the proposed approach is tested on the IEEE 30-bus system.

Variance Reduction Methods

Monte Carlo (MC) simulation tends to be a computationally-intensive (i.e., time-consuming) method, especially for reliable systems. This is because one needs to draw a larger number of samples (in non-sequential MC methods) or simulate a larger number of events (in sequential MC methods) to encounter a sufficient number of failure events so that the index estimates can stabilize, i.e., the simulations converge. It is therefore advantageous to use variance-reduction methods where possible. This may be understood as follows. As described in section 5.5(a), the simulation is said to converge when the variance of an estimated index drops to within an acceptable tolerance. Therefore, if by some device the variance of an estimate can be reduced, the simulation can converge faster, i.e., with less effort. Alternatively, with the same effort, i.e., length of simulation, the index can be estimated with higher accuracy.

Variance reduction techniques include stratified sampling, control variates, importance sampling (often in combination with the cross-entropy method) and Latin Hypercube sampling [12], [251], [253]–[254], [271]–[276]. Reference [251] proposes a three-stage algorithm based on importance sampling (IS) for evaluating a composite power system. The key idea is to search out the bottle-neck components which have the largest impact on CSR index calculation at the first stage (the screening stage).

The remaining stages are performed by combining cross-entropy (CE) optimization and IS. Numerical tests show that the proposed method has good estimation accuracy performance and substantial variance reduction. Reference [253] proposes that variance reduction techniques be used together with the sequential simulation process to enhance the efficiency of the simulation. The paper specifically discusses two commonly used techniques—control variates and antithetic variates. References [254], [271]–[276] propose a new approach that combines a CE-based optimization process and nonsequential MCS to evaluate loss of load indices in composite power systems.

Reference [272] presents an efficient control variable based dagger sampling technique for reducing the computational effort in Monte Carlo reliability evaluation for composite systems. The proposed variance reduction method is unique in combining offline calculations with online computation. Reference [273] proposes improvements in the sequential MCS-based approaches for CSR evaluation by introducing two sampling techniques—random sampling (RS) and Latin Hypercube sampling (LHS). The performance of the proposed approach and traditional MCS are compared using the IEEE RTS. Results demonstrate that the proposed approach considerably reduces computational requirements during state evaluation, and that the application of LHS can further decrease the simulation time and required sample size to reach convergence.

Reference [274] undertakes a review of the variance-reduction techniques used in MCS such as stratification, importance sampling, use of a control variate, and the method based on antithetic variables. In addition, some refinements are described which promise to significantly increase the power of the simulation approach by combining applications of the various techniques. Reference [275] proposes a new methodology to calculate reliability indices considering time-dependent power sources and loads. Reference [276] presents an efficient control variable based dagger sampling technique for reducing the computational effort in Monte Carlo reliability evaluation for composite systems.

The control variate approach to importance sampling can be considered a means to approximate the sample output with a low-complexity surrogate model. This is used in [255] (by another name) and [252] to reduce the variance of the sampled output. The surrogate construction approach has been generalized using the multilevel MC framework in [248] and combined with machine learning for further speedups in [260].

3.5.3 Selective Enumeration Methods

The contingency enumeration method is the most frequently used approach to perform reliability evaluation of a large composite power system. It is straightforward and very easy to implement into computation tools. States selection and its state evaluation are two important steps in reliability evaluation of a composite power system as shown in Fig. 4 and Fig. 10. The examination of contingencies/states starts with N-1 contingencies (states in which only one component is failed), then N–2, N–3, and so on. The process of selecting contingencies will continue until (at least theoretically) the state space is exhausted. In large bulk power systems it is impossible to evaluate all the states in the space, so the procedure must be terminated before the computing effort becomes unreasonably large [8]. In practical studies it means selecting single contingencies of all system elements, double contingencies of lines and up to N–4 outages of generators. The contingency enumeration approach is, in general, based on systematic selection of contingencies, classification and analysis of contingencies and compilation and calculation of specified reliability indices [30]. The total number of contingencies selected in the first step can be reduced by ranking them according to specified criteria, using either predetermined contingency levels or a probability or frequency cut-off criterion. The basic structure of the enumeration approach is presented in Fig. 15.

Selection of system states

Selection of system states by the contingency enumeration approach is based on monitoring the operating state of each individual component of generation and transmission zones in a composite power system. A variety of methods for selecting contingencies have been developed [51], [277]–[278].

One class of screening methods perform contingency ranking based on approximate network solutions, such as fast decoupled power flow solutions [51], [278]. The method can take care of the nonlinearities to some extent and therefore it is better able to produce more accurate results than that of the PI method. However, contingency selection by screening methods is very inefficient because it requires the approximate solution of post-contingency states. Therefore, the method is accurate but not efficient.

The hybrid contingency selection and ranking method is developed to achieve both efficient and accurate contingency selection and ranking. The hybrid scheme combines the PI and screening methods. In hybrid methods, efficiency is achieved by employing the PI method first to quickly identify the contingencies that may have an adverse effect on system reliability. Screening methods are then applied to the above defined subset of contingencies [277]–[278]. The combination of these two methods can take advantage of the best properties of both methods to achieve efficient and accurate contingency selection. The contingency ranking methods are typically used in a contingency selection algorithm that identifies the contingencies that affect system reliability. The wind-chime enumeration scheme [261], as shown in Fig. 15, illustrates the contingency enumeration procedure using the ranking order obtained by the hybrid ranking method.

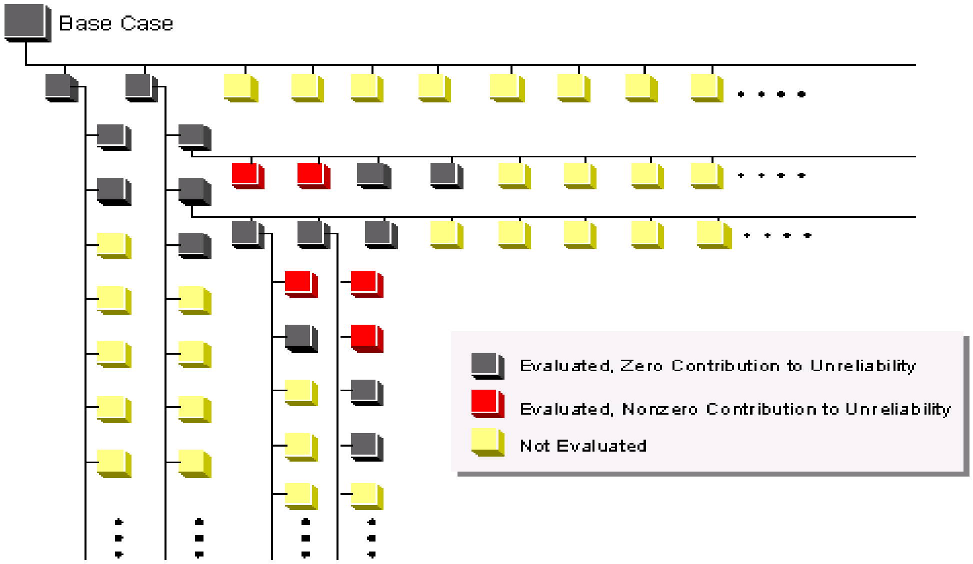


Fig. 15. Wind-Chime Enumeration Scheme.

The procedure starts from a base case. All the first level contingencies are enumerated and ranked in the decreasing severity order. The second outage level contingencies are obtained from each contingency in the first outage level by having one more component. The new outage component should be selected according to a certain rule to make sure the obtained contingencies are distinct. This procedure continues until it reaches the predefined depth level or probability criteria of contingencies. In each outage level, contingencies are evaluated in decreasing severity ranking order. The most severe contingencies are evaluated first. If there are several successive contingencies that are evaluated but have zero contribution to system unreliability, then it is reasonable that the rest of the contingencies at this level which have lower severity indices need not to be investigated. Fig. 15 shows these three types of contingencies, they are (1) contingencies that are evaluated and have nonzero contribution to unreliability, (2) contingencies that are evaluated but have zero contribution to unreliability, (3) contingencies that are not evaluated. The wind-chime enumeration scheme is very effective in minimizing the number of states that need to be evaluated. Subsequently, we present an analytical approach for evaluating states.

Evaluation of system states

The evaluation process should predominantly account for contingencies that result in violations, increased variability in generation resources (wind, PV), increased flexibility on the customer side as well as additional fast responding storage such as pumped hydro, BESS, customer storage (electric vehicles, thermally controlled loads and other), and demand response programs, increased concerns of more frequent bad weather, and increased volatility in prices and environmental issues. A framework for a probabilistic contingency enumeration methodology to power system reliability analysis is shown in Fig. 16. The framework is based on a stochastic dynamic programming approach that integrates computational reliability analysis procedures. Each node in the figure represents a system “state” at a specific time interval (“stage”). The system state reflects specific planning decisions. There is a transition from each state to any other state on the next time interval (stage). The number of stages define the planning horizon, for example twenty stages, one year each, will make a 20-year planning problem. Transitions can be feasible or infeasible. For example, if a transition requires the dismantling of a healthy facility, it is infeasible; if it requires the addition of a facility that cannot be constructed/completed by this time interval, this too is infeasible.

The computational complexity resides in the probabilistic evaluation of each state at a stage. This evaluation uses a selective enumeration of contingencies algorithm [65]–[67], [277]–[278] as shown in the upper right corner of the figure and probabilistic computational algorithms [279]–[284], which are integrated to provide a number of probabilistic performance measures (metrics) for the state at that stage. The metrics are numerous. The results of above analysis are used in stochastic dynamic programming framework to determine the optimal expansion plan, where optimal is defined in the sense of a linear combination of metrics and, parametrically, in terms of existing flexibility in the system. Obviously, changing the coefficients of the linear combination of the metrics (relative importance) may change the optimal expansion plan. Stochastic dynamic programming enables the evaluation of the expansion plans with different combinations of metrics and results in a number of "best" expansion plans. The dynamic programming optimization is symbolically illustrated in the figure. The subscripts *i, k* of state *X* (highlighted in the figure) represent the state *i* of the bulk transmission system at stage *k* (time interval *k*). Note that at each stage a number of candidate bulk power system states are generated in terms of possible expansion decisions. The generation of the states uses a combination of sensitivity methods, and identification of congested paths and available transmission paths. The computational problem can be defined as determining the optimal sequence of decisions as the plan moves from stage 0 (present time) to the final stage of the horizon period.

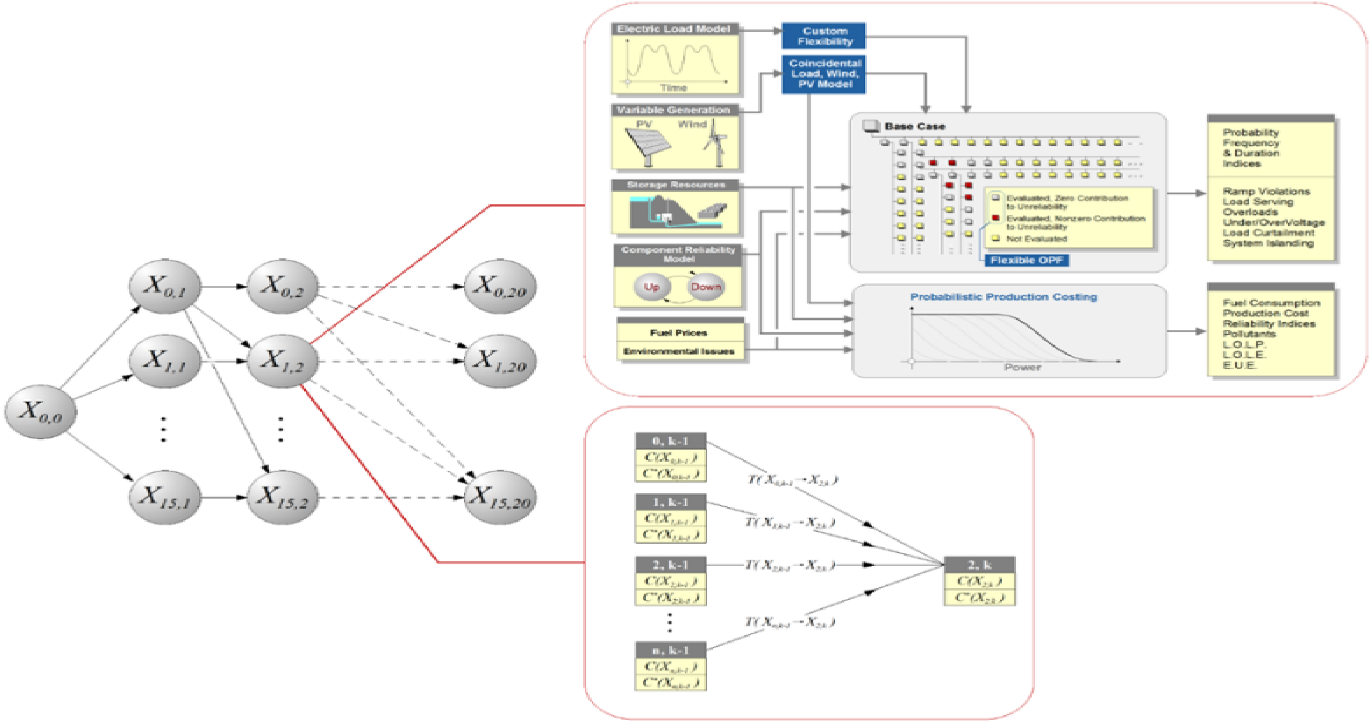


Fig. 16. Framework for composite reliability analysis and planning

The optimization algorithm computes the optimal cost of reaching a designated state in a stage by computing the minimum cost transition from any state in stage $k-1$ to a state i in stage k, $X_{i,k}$, symbolically shown in Fig. 16. The proper formulation of the dynamic programming algorithm guarantees that the optimal trajectories are characterized by transitions between two successive stages, resulting in an efficient algorithm. On the other hand, the number of states (decisions) in a stage may be very large resulting in a very large decision space (the curse of dimensionality). This issue is addressed by using a successive dynamic programming algorithm that limits the number of states (decisions) to only a small number around the current optimal trajectory. The end result is an efficient method to solve a challenging computational problem. An important feature of the method is the identification of the first n best expansion plans, where "best" is defined in terms of the selected linear combination of a number of metrics, allowing planners to perform trade-off analysis. This feature is very important for planners as it is important to have several options for expansion of the system and to know the cost and reliability implications of each one of these plans.

Calculation of System Reliability Indices

A number of indices can be evaluated for each load point in a particular composite power system. The most commonly used indices are the probability of load curtailment and the expected energy not supplied, but additional indices can be calculated. The individual load point indices can also be aggregated to produce system indices.

Probability of Load Curtailment (PLC)

This index can be expressed as:

$$PLC_k = \sum_{i=1}^{N_k} P_{ik}$$

where:

P_{ik} is the probability of the ith network failure state associated with load bus k
N_k is the number of the failure states in which the load at the load bus k has to be curtailed

Expected Energy Not Served (EENS)

$$EENS_k = \sum_{i=1}^{N_k} P_{ik} L_k T$$

where:

L_k is the average load in MW at the load bus k during the period of T.

It should be noted that the above calculation assumes the average load at a load point for a given time period. If a load duration curve is considered, the total index is the sum of the products of the indices for each load level and its probability. A load duration curve in an analytical evaluation is normally represented by a multiple step model. Load forecast uncertainty can also be incorporated in the evaluation, typically modeled as a discrete distribution in analytical assessment of composite power system reliability. If load forecast uncertainty is considered, the final indices should be the weighted average considering the probabilities of each discrete load in the forecast uncertainty.

3.5.4 Comparing Monte Carlo with Contingency Enumeration Methods

The Monte Carlo method differs from the contingency enumeration method in the way power system states including load, dispatch, and component outages are selected. The actual network solution and corrective action models may be the same or similar for both methods. The major advantage of the Monte Carlo method is the ease with which comprehensive statistics of power system states may be included. If the sequential approach is used, a simulation through time is performed, making it possible to account for interdependencies over time including those required to deal with the scheduling of limited energy resources. The contingency enumeration method is capable of going into great depth in identifying and testing severe transmission contingencies. However, with this method, one cannot at present afford to look in detail at the variations in system preconditions. Table 4 presents comparison of contingency enumeration vs. Monte Carlo capabilities. Neither of the two approaches discussed, contingency enumeration or simulation, is superior to the other, both have applications where they are better. A paper by Salvaderi and Billinton [68] illustrates some of the fundamental differences between these two techniques that have been applied to the IEEE RTS.

TABLE 4: Comparison of Enumeration Method versus Monte Carlo Simulation

Modeling Aspects	Contingency Enumeration	Monte Carlo Simulation
System conditions	Selected snap shots	Hourly basis
Time dependent relationships	Limited capability	OK
Ease of modeling probabilistic relationship	Difficult beyond the basics	Much easier
Impact of infrequent transmission events	Reliable	Unreliable
Numeric results	Reproducible	Random component
Application aspect	Suitable more for 3-5 year planning	Suitable for operational studies

Shaded is best

State enumeration is best applied when comparatively rare but high-impact component failures are of prime importance. Monte Carlo simulation is more suited to evaluating systems with a large number of less reliable components where the effects of higher-level multiple failures may not be negligible, as in the case of thermal generating units.

3.5.5 Risk-based Methods

Risk based transmission planning affords transmission planners significant benefits over deterministic transmission planning. Deterministic transmission planning relies on selecting a number of operating conditions (e.g., peak, off peak, maximum renewable etc.) and then evaluating whether the transmission system can reliably supply the load under different planning contingency conditions. In a risk-based approach, a transmission planner accounts for the probability of occurrence of both the operating condition as well as the contingencies being studied. Using the probability of the scenarios and the contingencies along with the severity of each event allows a transmission planner to evaluate the risk that the system is exposed to. The risk can be mathematically computed as:

$$\begin{aligned} &\mathit{Risk} \\ &= \mathit{Probability\ of\ an\ operating\ condition} \\ &\times \mathit{Probability\ of\ an\ event} \times \mathit{Severeity\ of\ an\ event} \end{aligned} \tag{16}$$

Once the transmission planner is able to quantify the risk, reinforcement options can be identified that can mitigate the risks posed to the system. The details of the various steps are illustrated in the following subsections.

Probability of an operating scenario

One of the first steps towards risk quantification is identifying the probability of the operating condition being analyzed. It is also important to ensure that the scenarios being selected for the transmission planning study covers the most vulnerable conditions that the grid might be exposed to in the future year.

Typically, transmission planners develop a variety of load shapes using normalized load shapes representing prior weather years and scaling them based on the load forecast. An assessment of such load shapes helps a transmission planner capture the hourly variability of load that has been observed over years driven by weather.

In addition to analyzing load variability, it is also important to consider the variability in solar and wind-based generation. Historical data on wind and solar output along with projections can be used to create projected data on solar and wind output levels for the target planning year. The coincident levels of load and variable generation can then be used to create a joint probability distribution either by plotting these points together or using statistical techniques like copula functions [285], [103]. Once such a probability distribution is created, a transmission planner can select operating conditions for assessment and compute the probability of each operating scenario.

Computing the probability of a contingency event

The probability of contingencies can be calculated based on historic outage data for transmission and generation assets. In North America, NERC collects and processes such data, aggregated statistics of which are publicly available from the TADS [128] and GADS [127]. Outage data from these databases can then be used for computing the probabilities of simple N−1 and N−2 contingency definitions and for custom contingencies that are defined by the NERCs TPL-001-4 standard, which includes N−1−1 contingencies as well. A two-state Markov model has been proposed to demonstrate the computation of probabilities of NERC TPL-001-4 contingencies as shown in Fig. 17. Details on different ways of computing probabilities of contingencies can be found in [76], [78], [286]. It is worthwhile to mention that using the same probability of contingencies throughout the year may not be good assumption for certain utilities, since most of the outages (especially for transmission lines) might be clustered in one season. In such cases weather variation might need to be accounted for when estimating the probabilities of contingencies. Reference [76] provides further details on this.

Computing risk metrics

Once the probabilities of contingencies and operating conditions are computed, a contingency analysis along with an optimal power flow-based corrective actions routine is performed. The results of the contingency analysis can be used to compute thermal and voltage violation risk in the system.

The thermal probability risk index *(Thermal PRI)* can be calculated using:

$$Thermal\ PRI = \sum_{All\ Contingencies} Probability * Thermal\ Impact \tag{17}$$

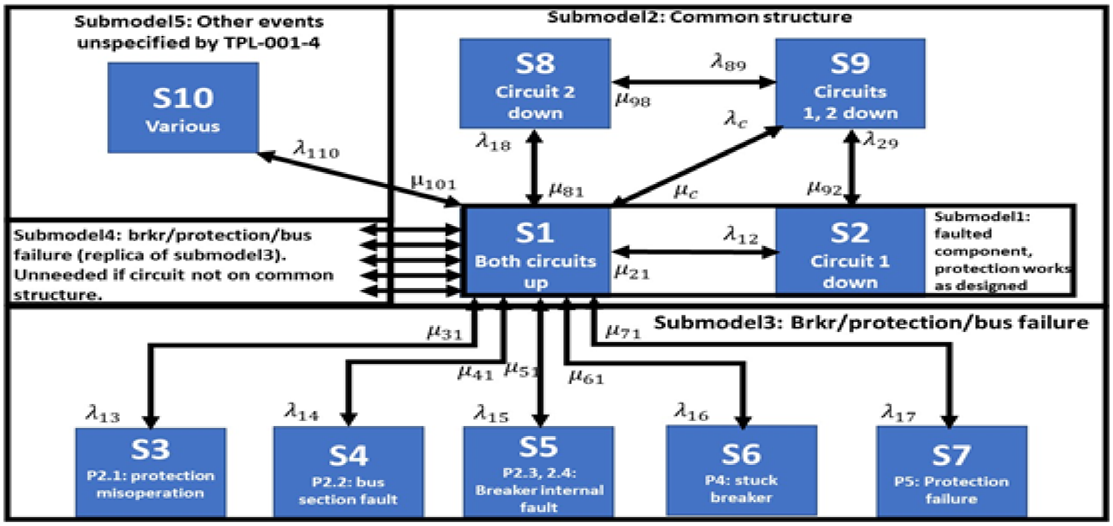


Fig. 17. Two state Markov model for computing probabilities of custom contingency definitions [8].

where, the *Thermal Impact* is the sum of overload above the thermal limit. The thermal impact is measured in terms of MVA as follows:

$$Thermal\ Impact = Contingency\ MVA\ flow\ - Rate\ A$$

As given by (17), an increase in the *Thermal PRI* indicates that the system has more thermal violation risk and vice-versa. The voltage probabilistic risk index *(Voltage PRI)* is given by

$$Voltage\ PRI = \sum_{All\ Contingencies} Probability * Voltage\ Impact$$

where the *Voltage Impact* is the sum of voltage deviations from the upper and lower limits. The voltage impact is measured in terms of kV as follows:

$$Voltage\ Impact = |(Voltage\ Limit\ - Contingency\ P.U\ Bus\ Voltage) * Bus\ kV\ Level| \tag{20}$$

As given by (20), an increase in the *Voltage PRI* indicates that the system has more voltage violation risk and vice-versa. More details on these metrics can be found in

[51]. The thermal and voltage violation risk indices computed using (17) and (20) provide an indication of the risk each contingency poses to the system. The OPF-based corrective actions provide a list of changes in terms of switching voltage control devices and generation redispatch as well as load shedding that might be needed to remedy the voltage and thermal violations in the system. When a corrective action requires load shedding the MW amount of load shed can then be used to compute the expected unserved energy (EUE) [162], which is given by

$$EUE(MWHr/Yr) = MW\ load\ shed\ * \\ Probability\ of\ a\ contingency\ * 8760 \tag{21}$$

where, the probability of a contingency is given as the number of hours of outage per 8760 hours. The financial implications of the outage can be computed by using metrics like value of load loss (VOLL) or unit interruption cost (UIC) [162]. Once these metrics are computed for the base case, the metrics are re-evaluated for the different transmission reinforcement options that are being considered. These metrics can then be compared across different projects to evaluate the benefits of each of the reinforcement options in terms of reducing the system risk due to contingencies. Metrics like incremental reliability index (IRI) provide a suitable ranking metric for the different reinforcement options. Examples of risk-based comparison of transmission projects can be found in [11], [57], [61], [63], [142]. It is worthwhile to note that current planning practices and regulations may require utilities to invest in reinforcement options that mitigate violations due to certain categories of contingencies irrespective of their probability. In such cases, the risk-based ranking can be used to prioritize projects that can provide maximum benefit in reducing the risk in the system.

3.6 Other considerations

The ultimate utilization of composite power system reliability evaluation is planning methods. Considering the multiplicity of uncertainty sources and new complex operational models for modern power systems, probabilistic planning methods are becoming a necessity and rely more and more on reliability methods. This section discusses these needs and industry activities in this area.

3.6.1 Probabilistic planning

The present NERC Standard TPL-001-4 for system planning performance requirements require utilities in North America to perform comprehensive studies of all contingency events called P1–P7 and some of the extreme contingencies in their power transmission systems [3]. Electric utilities goals are to maintain sufficient generation and transmission capacities in their systems and ensure reliability and continuity of supply under normal and particular abnormal conditions including uncertainties associated with load variations, intermittency of renewable energy sources, topology changes, etc. Results of deterministic-based contingency analysis can take into account impact (transient stability, thermal overload, voltage violations, and voltage stability); but the likelihood of evaluated contingencies is neglected. Successful transmission planning should employ risk-based approaches by taking into account the likelihood of contingencies and uncertainties associated with:

- Size and location of new power plants.
- Decommissioning of existing power plants.
- Growth of customer demand.
- Growth of embedded generation.
- Evolution of transit flows.
- Trend of import/export level.
- Equipment availability data.
- Weather.

The probabilistic measure of likelihood of contingencies can be calculated from NERC TADS and GADS and/or outage data sources at a regional or utility level. Transmission system owners are faced with the task of identifying system upgrades to meet reliability requirements, to connect new generation facilities, and to provide economic benefit. The demand on capital requires that transmission upgrades be prioritized so that the projects that provide the greatest benefit are undertaken first. Utilities are seeking to reduce the cost of energy to consumers by finding ways to mitigate congestion.

Many utilities perform coordinated expansion planning that encompasses both generation and transmission systems. Also, the expected growth of energy storage, distributed generation, and demand side management has led to the adoption of various integrated planning approaches that focus on generation and transmission coordination [287]. Consequently, power system planners analyze the reliability of multiple associated functional zones during the system planning process [15], [48]. For system planning (investment, reinforcement planning), alternative system configurations must be screened for multiple generation and load patterns and a large number of contingencies in order that investments can be well targeted and quantified for risk. References [252], [287]–[294] present different aspects of probabilistic and risk-based planning.

Any transmission plan proposed for adoption on the basis of reliability criteria must ultimately be justifiable when economic, financial, strategic, and environmental considerations are accounted for as well.

- The system shall be designed to operate within normal operating ranges for credible load and generation patterns for base case operation.
- The system shall be designed to withstand the more probable contingencies without widespread system failure and instability, maintaining power quality within specified voltage and frequency fluctuation ranges and maintaining voltage and thermal loadings within operating limits.

- The more probable contingencies are comprised of single contingency (N−1), overlapping single contingency and generator outage (N–G–1) and trip-maintenance (N–1–1) disturbances.
- In the immediate aftermath of a disturbance, the system should reach a steady state that is within emergency limits. Then, by use of remedial actions specified in the criteria, the system should be capable of being returned to normal limits.
- The system should be able to meet anticipated load with a margin that allows it to withstand credible treats and avoid cascading outages [10].

Probabilistic planning is superior to traditional deterministic planning for the following reasons:

1. It yields more efficient use of resources.
2. It directs capital to be utilized where most needed.
3. We live in a probabilistic world.
4. None of the key drivers of power systems is deterministic.
5. Random events control the critical conditions [10].

There are various probabilistic planning criteria. The ones to be used for planning studies should be selected on the basis of current planning issues and the utility's business objectives. References [287]–[294] discuss various probabilistic planning criteria.

3.6.2 Impact of operational practices

For operation planning (maintenance scheduling, design of operating strategies, protection settings, etc.) operational reliability assessment is needed to make better use of available resources and reduce system operating costs without compromising operational reliability of supply and system integrity. In the operating horizon (up to one year) the reliability of a system is maintained on any given day by maintaining operating reserves appropriate to existing conditions. References [295]–[303] present various aspects of CSR assessment in operations. A basic process for calculating probabilistic reliability indices (PRIs) using probabilistic reliability assessment (PRA) is shown in Fig. 18. A PRI is calculated as:

$$PRI = \sum_{i \in \{Critical\_Situations\}} p_i \cdot I_i \tag{22}$$

where p_i is the probability of the ith critical situation, I_i describes the impact that quantifies the severity of the ith critical situation.

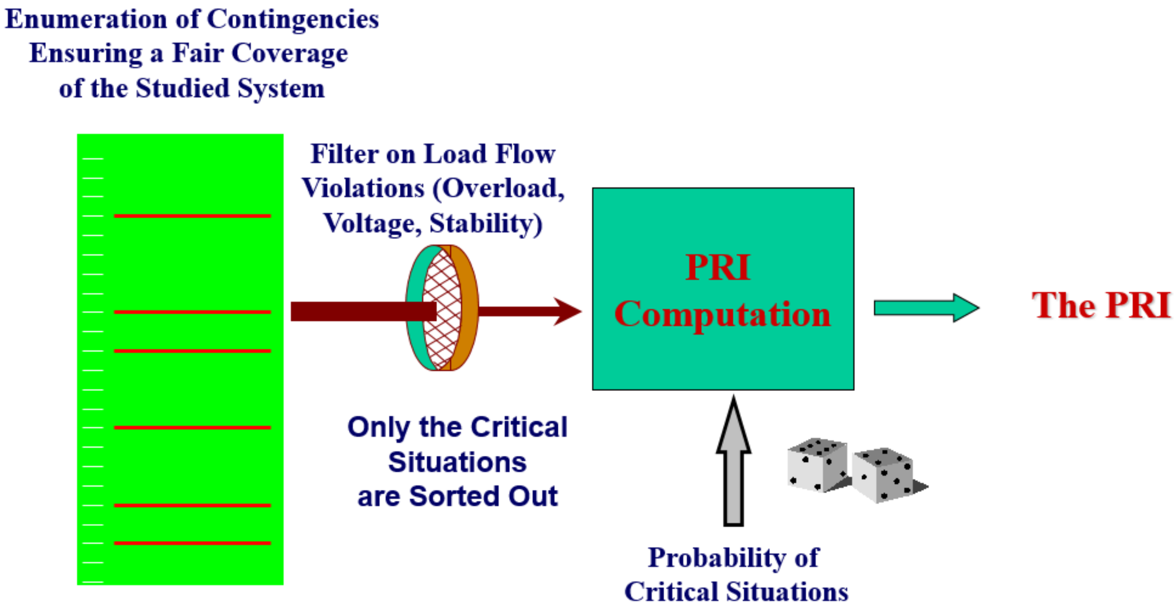


Fig. 18. Basic diagram of calculating PRI

In addition, PRA includes the following items:

- **Interaction Analysis** unveils cause and effect relationships among user-defined zones.
- **Situation Analysis** ranks the situations according to their contribution to an overall reliability index. It helps users identify the scenarios that have high probability or high impact or both.
- **Root Cause Analysis** indicates the components (lines, transformers, generators) whose outages cause critical situations**.**
- **Weak Point Analysis** identifies the buses and branches that are most violated.

3.6.3 Probabilistic cost analysis

The general objective of value-based reliability analysis is to determine the degree of reliability that can be justified based on a cost/benefit analysis [6]–[8], [69]–[75], [154], [304]–[305]. The optimization objective is to reinforce the system such that the total cost is minimized. This is equivalent to finding the point at which the marginal value including the value of increased reliability equals the incremental cost of the reinforcement. There are two basic cost components in probabilistic economic analysis. They are:

1. Utility cost (investment, operation)
2. Customer interruption cost.

Investment cost is calculated using traditional engineering economic analysis in a transmission planning process. Operation cost includes operation, maintenance, and incremental administrative expenditures, network losses, financial charges, and other ongoing costs. Customer interruption cost is obtained using the reliability index

EENS in MWh/year multiplied by the unit interruption cost (*UIC*) in \$/kWh. The *UIC* calculation is usually based on the customer's damage functions (an example from [72] are shown in Fig. 19. The basic concept of the probabilistic value-based criteria can be illustrated using the cost-reliability curves in Fig. 20. The unreliability cost due to interruptions decreases as system reliability improves while the investment and operation cost increases. The total cost is the sum of the utility and customer costs. The total cost exhibits a minimum point at which an optimum or target level of reliability is achieved.

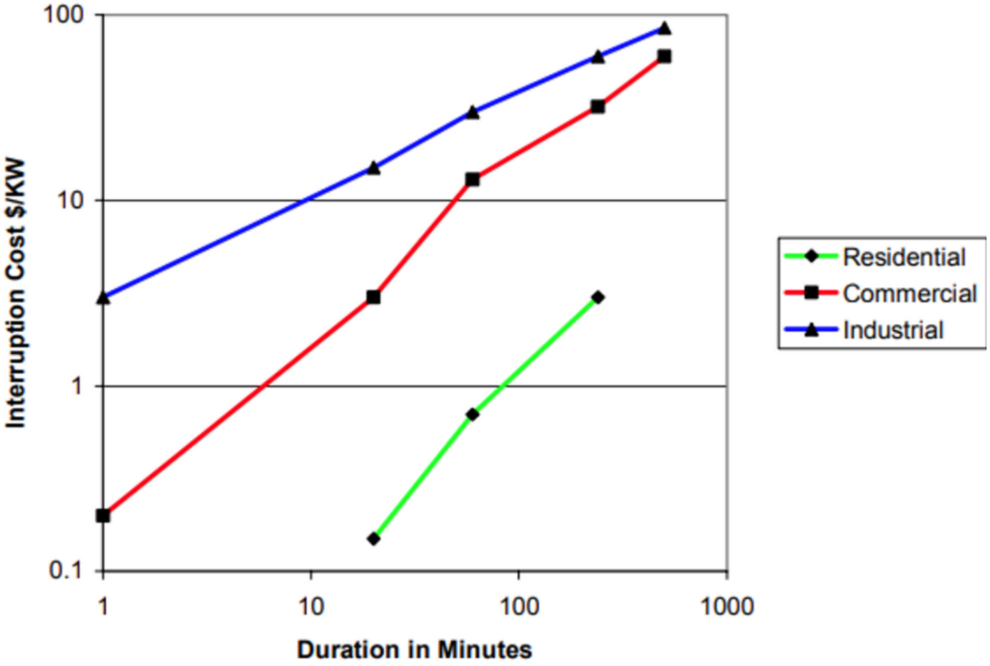


Fig. 19. Consumer Damage Functions

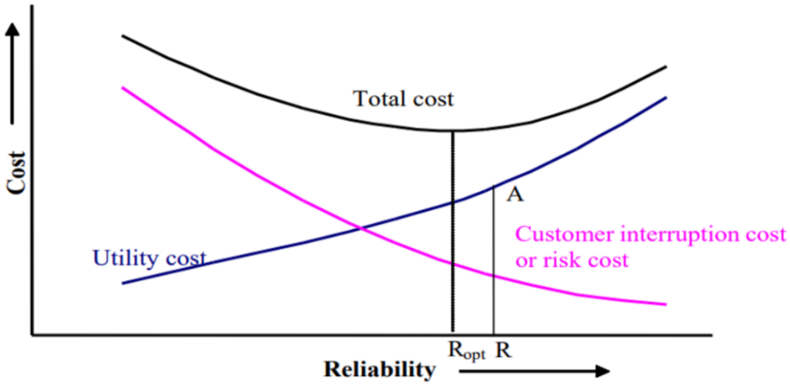


Fig. 20. Graph for Obtaining Optimal Reliability (R_{opt}) Based on Total Cost

The present NERC Standard TPL-001-5 for System Planning Performance Requirements requires utilities in North America to perform comprehensive studies of all P1-

P7 contingencies and some of the extreme contingencies in their power transmission systems [3].

3.6.4 Power System Health (PSH) Evaluation

Paper [306] presents an approach to evaluating the health of a composite generation and transmission system. The functionality of the system is identified as being healthy, marginal, or at risk. The outage contingencies leading the system to each of the three operating states can be identified and calculated using an operational reliability-constrained adequacy evaluation procedure. The probabilities associated with outage events in the classified domains can be utilized to calculate system operating limits and risk indices. The identified system outage events can provide power engineers with additional information that can be used in evaluating reinforcements or additions.

Paper [307] proposes a probabilistic power system health index (PSHI). The paper describes several kinds of power system health indices based on the two categories of adequacy and operational reliability. Calculated health indices in adequacy are based on frequency, voltage, operating reserve margin, and overloading of lines and transformers. All indices are mapped with three domains—healthy, marginal and at-risk— defined on the basis of expert judgment.

4. TOOLS FOR CSR ANALYSIS

4.1 Data Preparation

Data preparation is the first step in using CSR analysis tools. Generally, data preparation can be different for different tools and user needs. This section briefly introduces data preparation for two CSR tools: (1) the Operational Scheduling Decision Support Platform based on Reliability Assessment (OSDSP-RA) by Chongqing University, and the EPRI composite power system programs Transmission Reliability Evaluation of Large-Scale Systems (TRELSS) and Composite Reliability Assessment by Monte Carlo (CREAM).

4.1.1 OSDSP-RA

Fig. 21 depicts data flows in the Operational Scheduling Decision Support Platform based on Reliability Assessment, by Chongqing University, in China [309]. The state estimation database, OMS database, PMS database, meteorological database, general reliability parameter database, and user setting database are called “original” databases. The equipment average reliability parameter database, equipment operation reliability parameter database, and system reliability index database are called “result” databases. The power flow database and reliability assessment input database are “intermediate” databases, and are available for users to browse and query.

Calculation Functions

As shown in Fig. 21, the operational reliability calculation includes three calculation functions: 1) the power flow calculation considering the equivalence of external networks, 2) the equipment reliability parameter calculation, and 3) the operational reliability assessments. We introduce data flows based on the three calculation functions above.

Calculation function 1: power flow calculation considering external network equivalence

Based on state estimation data, and borders nodes and tie lines (obtained from the configuration data for power flow calculation) specified by users, an equivalent network of external networks (i.e., physically connected networks outside the focused network) is constructed, yielding power flow data of the focused network considering the external network equivalence.

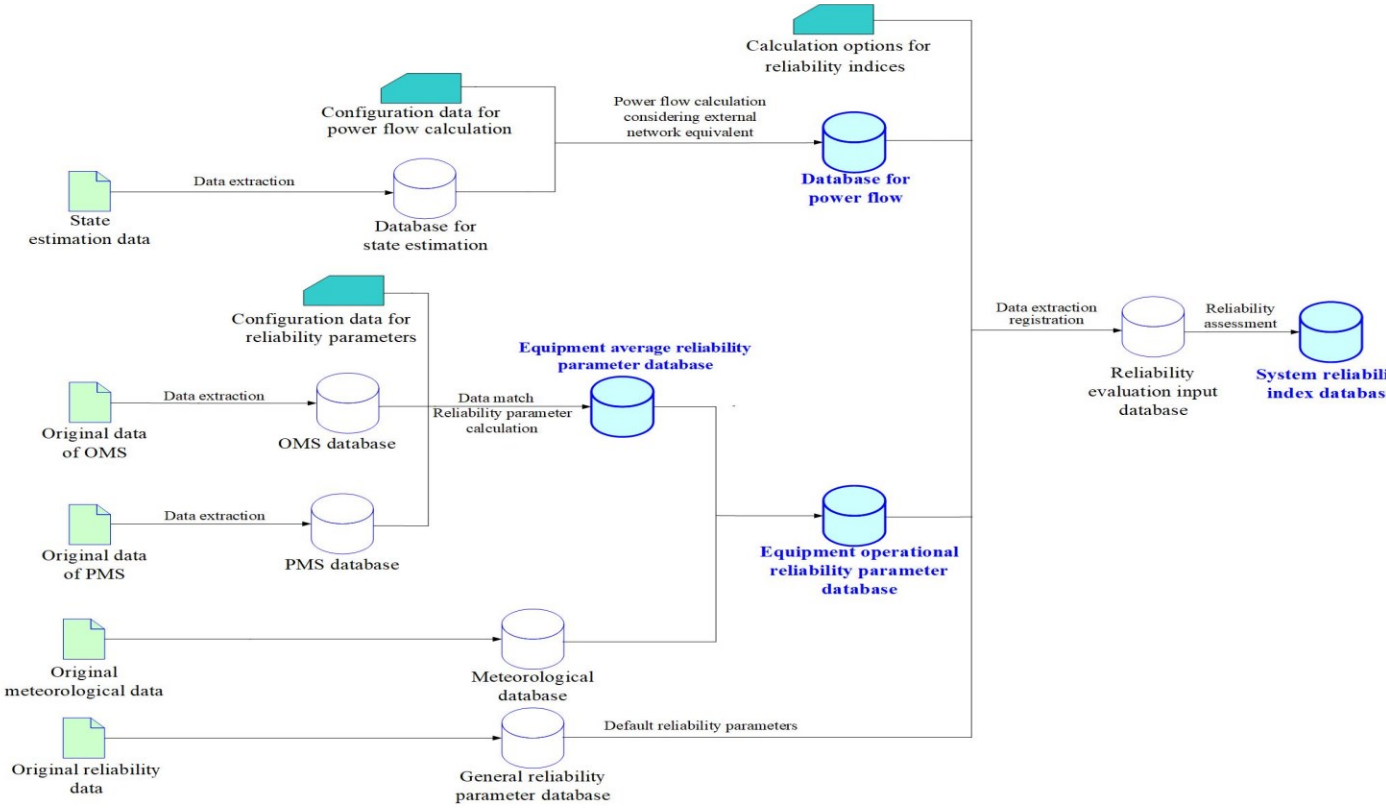


Fig. 21. Schematic diagram on data flows in system operational reliability assessments [309]

Calculation function 2: Equipment reliability parameter calculation

Based on OMS and PMS data, the average reliability parameters of each component—generation and transmission—are calculated for the statistical period set by the user. The operational reliability parameters are then calculated from the average reliability parameters, adjusted for weather impacts calculated from differences between the historical meteorological data and current weather information.

Calculation function 3: Operational reliability assessments

Based on power flow data for the focused network and the reliability parameters of equipment, the reliability of the focused network is quantified by the reliability indices for nodes, lines, and transformers.

Original Databases

The data contained in each original database is introduced.

State estimation database

The state estimation database primarily includes the state sampling time, reference values, substations, buses, ac lines, generators, transformers, loads, parallel compensators, series compensators, dc controllers, dc lines, electrical islands, topologies, circuit breakers, and switches.

OMS database

The OMS database provides basic data for the power grid equipment, including generators and ac lines whose voltages are 220 kV or higher, cables, transformers, capacitors, and reactors.

PMS database

The PMS database records power grid fault data, including historical faults of transmission lines and substations whose voltages are 220 kV or higher.

Meteorological database

The meteorological database includes historical meteorological data and meteorological correlations among different stations.

General reliability parameters database

The general reliability parameters include the typical reliability parameters of transmission lines, transformers, generators, etc. The data are issued by authoritative organizations such as the China Reliability Management Center and the Canadian Power Grid Reliability Management Agency.

User setting database

The user setting data include options for 1) power flow calculation, 2) reliability parameters, and 3) reliability index calculation. The power flow calculation options include the border nodes of the focused network, tie-lines, and control zones. The reliability parameters primarily include the same-tower double-circuit line settings and statistical period settings. The reliability index calculation options primarily include the assignment of areas to be evaluated, default data from China/Canada/North America, etc. sources, current limits, weather impacts, correlated failures, generator outages, and failure modes (e.g., N–1 and N–2 criterion).

4.1.2 TRELSS and CREAM

The following five categories of input data are used to perform reliability evaluation of a composite power system using the EPRI TRELSS program:

- Network data/ load-flow cases

- Outage data
- Remedial actions
- Load bus data
- Load curve data.

The following are specific input data for the above categories

- A single or multiple load flow cases
- Generator data file
- Circuit outage data file
- Generator outage data file
- Common-mode outage data file
- Must run contingency data file
- Cascading contingency data file
- Network adjustments data file
- Circuit switching data file
- Out-of-service circuits data file
- Switchable shunt data file
- Remedial actions
- Bus characteristics data file
- Hourly load duration curve.

The following input data are used to perform reliability evaluation of a composite power system using the EPRI CREAM program:

- General data (execution parameters, Monte Carlo parameters, etc.)
- Load flow case
- Bus data
- Circuit data
- Plant data
- Demand data
- Maintenance data
- Probabilistic data.

4.2 Overview of existing tools

Two 1988 papers outline requirements for CSR analysis tools. In one, Bhavaraju et al. derived their recommendations from a survey of utility planners [28]. A shortcoming of existing models at the time was that they could not model the “sequence of events in system operation and time available for operator actions.... Because of this limitation, the credibility of the load curtailment indices calculated by the current adequacy methods was questioned by respondents.”

In Table 5, various system planning studies are categorized by five general objectives:

- Generation reserve objectives
- Transfer capability objectives (Interconnection requirements)
- Internal Transmission Reinforcements
- Generator siting
- Generation and Transmission Investment Trade-offs.

Table 5 also identifies the generic model required. Note that a CSR model is required for seven of these studies.

TABLE 5. Role of Composite System Reliability Evaluation in System Planning Studies [28]

Study Objective	Specific Studies	Generic Model Required*
Generation Reserve Objectives	Determine generating capacity reliability	GCR
	Determine economic generation reserve requirements	OGM
Transfer Capability Objectives	Determine transfer capability requirements for reliability	MGCR
	Determine transfer capability requirements for economic transfers or diversity exchange	MPC
Internal Transmission Reinforcements	Determine long range transmission needs	CSR
	Justify specific transmission line additions(investment decision)	CSR
	Compare transmission line addition alternatives	CSR
	Determine transmission needs to meet area reliability	TSR
	Determine transmission needs to improve economic dispatch	TSR
	Determine transmission needs (savings) with dispersed generation/storage devices	CSR/TSR
	Determine effects of load management on transmission system	TSR
Generator Siting	Determine sites for large central generators	CSR
	Determine sites for dispersed generators/storage devices	CSR
Generation and Transmission Investment	Determine trade-off between generation and interconnection	MGCR
*Legend for Generic Models: GCR — Generating Capacity Reliability OGM— Optimum Generation Mix MGCR— Two or Multi-area Generating Capacity Reliability MPC — Two or Multi-area Production Cost CSR — Composite System Reliability		

TSR — Transmission System Reliability

A desirable CSR analysis tool would include the following features:

- "Static assessment capability for generation and transmission.
- "System problem and capability options with provision for remedial action, generation and phase shift or dc line flow control and load curtailment.
- "Linearized network models, dc load flow solution, or in the ultimate, ac network models.
- "Line limits defined as flow limits, but determined by consideration of both thermal and angle related (voltage and SIL) limits.
- "Transformer limits defined by long term and contingency load carrying ability,
- "Security (operational reliability) constrained dispatch capability for system problem type evaluations.
- "System load models capable of representing seasonal or discrete load level, bus. loads determined by specification of load distribution factors.
- "Load and resource models capable of meeting requirements for hydro and energy limited generation.
- "Weather and station dependent effects for line and transformer outages,
- "Generating unit capability and outage models with provision for multiple capacity state representation.
- "Generating unit maintenance schedules." [28]

In the second 1988 paper, Endrenyi et al. also examine the features needed for different types of CSR analyses [30]. They observe that, "For a program to be useful, it should meet the following objectives:

- "The program must accommodate the size of the system under study.
- "The system and load models must be accurate enough for the purposes of the study.
- "The computational process must be accurate enough to keep the error in the output quantities within acceptable bounds.
- "The computations must be fast enough to keep the computer time acceptably low."

As these objectives are conflicting, design of a CSR tool entails finding a balance between these requirements. This report addresses applications of CSR analysis in operations, as well as in planning. In operations, "Since frequent re-evaluations are required, an ideal program would produce them 'on line.'" The paper also discusses various modeling and computational difficulties. It notes, "In general, the degree of sophistication in reliability modeling must match the computational accuracy.... One must also remember that many of the reliability indices need not be calculated to several decimals; often the correct order of magnitude is all that is required." [30]

There is a wide range of tools that are used for various aspects of probabilistic planning analysis. Table 6 provides a list of tools gleaned from the CSR industry practices survey [5], an SPP probabilistic planning study [289], and a review by CIGRE [4]. This list also shows the applications for which the tools are used, and their transmission modeling and probabilistic analysis approaches.

TABLE 6. Probabilistic planning tools

Product	Developer/ Vendor	Application†	Transmission Modeling Approach	Probabilistic Analysis Approach	Status/ User Base‡
ANTARES	RTE (France)	RA	Multi-area	Monte Carlo	Open source‡
ASSESS	RTE, France and NGT, UK	RA	DC	Monte Carlo	Commercial
AURORA	EPIS (USA)	PF, AV	Multi-area	Monte Carlo	Commercial/Large
BESRE-TH	Tisinghua Univ. (China)	CSR	AC/DC	---	Research-Grade
COMREL	U. Saskatchewan (Canada)	CSR	AC/DC	Enumeration	Research-Grade, Superseded by CRUSE
CONFTRA	CEPEL (Brazil)	CSR	AC/DC	Monte Carlo	Unknown
CORAL	PSR (Brazil)	CSR	DC	Monte Carlo	Unknown
CREAM	EPRI (USA)	CSR	AC/DC	Monte Carlo	Research-Grade
CRUSE	PowerTech (Canada)	CSR	AC	Enumeration	Discontinued
EGEAS	EPRI (USA)	RP	Generation	---	Non-commercial
GATOR	Florida Power Corporation (USA)	CSR	Generation	Enumeration	Non-commercial
GENESYS	NWPCC (USA)	RA	Multi-area	Monte Carlo	Non-commercial/Single‡
Grid360 TA	NEXANT (USA)	RP	AC	---	Commercial
GridView	ABB	RA, TP	DC	Monte Carlo	Commercial‡
JHSMINE	Johns Hopkins	Other (1)	Multi-area, DC	Scenario	Non-commercial
LARA	Power Technology Inc. (USA)	Local Area	AC	Monte Carlo	Discontinued
MAPS	GE	RA, TP	---	---	Commercial
MAREL	Power Technology Inc. (USA)	CSR	Multi-area	Monte Carlo	Discontinued
MARS	GE (USA)	CSR	Transportation	Monte Carlo	Commercial‡
MECORE	BC Hydro (Canada)	CSR	AC/DC	Enumeration & Monte Carlo	Non-commercial‡
METRIS	EDF (France)	CSR	AC/DC	Monte Carlo	---
NETREL	ABB (USA)	CSR	---	---	Commercial
NARP	Associated Power Analysts (USA)	CSR	DC	Monte Carlo	Commercial

Product	Developer/ Vendor	Application†	Transmission Modeling Approach	Probabilistic Analysis Approach	Status/ User Base‡
NH2	CEPEL (Brazil)	CSR	AC/DC	Enumeration & Monte Carlo	Non-commercial
OPTGEN	PSR (Brazil)	CSR	---	---	Commercial
OSCAR	Kinectrics (Canada)	CSR	AC/DC	Analytical/Monte Carlo	Non-commercial
PLEXOS	Plexos Group	PS, RP, RA	DC	Monte Carlo	Commercial/Large‡
PRA	EPRI (USA)	CSR	AC	Enumeration	Non-commercial
POM	V&R (USA)	CSR	AC	Contingency Enumeration	Commercial
PowerFactory	DIgSILENT, Germany	CSR	AC	Analytical	Commercial‡
PROCOSE	Ontario Hydro (Canada)	CSR	DC	Enumeration	Non-Commercial
PROMOD IV	ABB	PS, RA	DC	Monte Carlo	Commercial/Large‡
PROSYM	ICF (USA)	PF, AV	---	---	Commercial
PS-MORA	Federal University of Itajubá, (Brazil) & INESC TEC (Portugal)	CSR	AC	Monte Carlo	Research-Grade
PSS/E Tool – TPLAN MACC Reliability Module	PTI (USA)	TP, CSR	AC/DC	Enumeration	Commercial/Large‡
RECS	Georgia Institute of Technology (USA)	CSR	AC	Enumeration	Research-Grade
REMARK	ESRE (former CESI), Italy	Generation, CSR	DC	Monte Carlo	Commercial
RELNET	UMIST (UK)	CSR	AC/DC	Enumeration	Non-commercial
SERVM	Astrape	PS, RA	Transportation	Monte Carlo	Commercial‡
SICRET	ENEL (Italy)	CSR	AC/DC	Monte Carlo	Commercial
SRRM	Manitoba Hydro (Canada)	CSR	AC	Analytical	Non-commercial
SYREL	EPRI/PTI (USA)	CSR	AC	Enumeration	Superceded by TRELSS, then TransCARE
TransCARE	EPRI (USA)	CSR	AC/DC	Enumeration	Non-Commercial
TRANSREL	General Reliability (USA)	CSR	AC	Interfacing with tools (Power World, Ge PSLF, PTI and POM)	Commercial‡
TRELSS	EPRI	CSR	AC	Contingency Enumeration	Superceded by TransCARE
UPLAN	LCG	PS, AV	DC	Monte Carlo	Commercial

Product	Developer/ Vendor	Application†	Transmission Modeling Approach	Probabilistic Analysis Approach	Status/ User Base‡
PRISM	PJM (USA)	RA	Generation	Monte Carlo	Non-commercial

† Legend for applications:

AV: Asset valuation
CSR: Composite system reliability
OP: Operational planning
PF: Price forecasting
PS: Production simulation
RA: Resource adequacy
RP: Resource planning
TP: Transmission planning
Other: (1) Policy analysis, (2) Storage modeling.

‡ Mentioned as used in a CSR industry practices survey Error! Reference source not found..

Note: The following tools mentioned in [4], [5] are not included in the above table because they are not used for probabilistic analysis or could not be found: EMTP, ETAP, GRARE, KERMIT, MiniTab, NEPLAN, PowerWorld Simulator.

The current status and user base of the tools are also shown where known.

The remainder of this section describes tools with the following characteristics that have been used for CSR analysis in published research, whether currently in use or discontinued, commercial or non-commercial:

- AC or DC power flow
- Consideration of both generation and transmission contingencies
- Calculation of probabilistic reliability indices

4.3 Descriptions of existing tools

The first papers on CSR analysis demonstrated the concepts using simple examples that could be calculated by hand. One of the first published papers for CSR analysis appeared in 1969 [6]. Vignettes of 21 CSR models follow, in approximate chronological order.

Composite Reliability Using State Enumeration **(CRUSE)** was developed by Power Tech, Canada, as an enhanced version of the ***Composite Reliability*** **(COMREL)** program [310] that was developed by the University of Saskatchewan [24]. The CRUSE program was used by the University of Queensland, Australia, to compare the reliability of different network configurations [311].

Reliability Evaluation via Contingency Simulation **(RECS)**. RECS was developed at Georgia Tech in collaboration with Georgia Power, U.S. [281]. It uses contingency enumeration and includes stochastic power flow and modeling of remedial actions prior to load curtailment. It also analyzes the cost penalty of deviations from economic dispatch owing to transmission constraints.

Probabilistic Composite System Evaluation Program **(PROCOSE)** was designed by Hydro One, Canada. PROCOSE calculates reliability indices, system production costs, and various reliability indices for the system and for individual buses [312]–[313]. PROCOSE can simulate system operation in a specific time interval (hourly/weekly/monthly) based on the Monte Carlo method and a DC power flow model.

SICRET was developed by ENEL, Italy [254]. It performs a Monte Carlo simulation with two versions: (1) “fast,” to evaluate only system adequacy, and (2) “detailed,” to perform a detailed cost analysis. The fast version organizes the computational flow around a pure “safety” operation policy, with a heuristic for generation redispatch and load shedding minimization. The detailed version includes relatively complex operation policies and optimization.

Composite Reliability Assessment by Monte Carlo **(CREAM)** was developed by EPRI, U.S. [25], [285]. CREAM utilizes a Monte Carlo method and a DC power flow model for reliability assessment. For both the whole system and individual buses, CREAM can calculate common reliability indices (e.g., LOLP and EPNS). Also, CREAM can provide a sensitivity analysis of the impacts of generator or circuit capacities on reliability indices. A description of the input data requirements appears in section 4.1.2.

MECORE was first developed by the University of Saskatchewan and then upgraded by BC Hydro, Canada [256], [314]. MECORE calculates an unreliability cost that reflects reliability worth. A combination of Monte Carlo simulation and state enumeration is used with an AC/DC power flow model. The Monte Carlo method is used to select component states and calculate annualized indices at peak loads. A hybrid enumeration approach with aggregate load states can calculate annual indices from an annual load curve. A strength of the MECORE model is its ability to calculate certain reliability indices associated with individual load points. It has been used in analyzing the effect of load uncertainty [49], , the integration of large-scale wind generation [111], and the reliability of a composite system that includes HVDC links [256].

Transmission Reliability Evaluation of Large-Scale Systems **(TRELSS)** and ***Transmission Contingency Analysis and Reliability Evaluation*** **(TransCARE)** were both developed by EPRI, U.S. They are designed to aid system planners in considering the reliability of composite systems and transmission systems using state enumeration with an AC or DC power flow model. Various aspects of the contingency enumeration methodology that is implemented in program TRELSS is presented in [51], [277]–[280], [288]. TRELSS classifies each contingency according to a failure criterion and then calculates cumulative reliability indices. TransCARE is an upgraded version of TRELSS TransCARE takes additional probabilistic variables such as renewables into account. TRELSS and TransCARE have been used in a wide variety of studies [315]–

[316]. Note that although TransCARE is presently available, it does not have a large user base. A description of the input data requirements appears in section 4.1.2.

NH2 was designed by CEPEL, Brazil [320]–[321]. NH2 measures system risks under different planning alternatives and operational situations [66]–[67]. It provides traditional frequency and duration reliability indices at three levels: system, area, and individual bus. The reliability assessment process can be performed based on a contingency enumeration or Monte Carlo simulation. Also, NH2 can provide statistical information including probability density functions of state variables and failure mode indices.

Reliability and Market **(REMARK)** was designed by ERSE, Italy [322]–[323]. REMARK is used to conduct analyses of adequacy in complex electric systems, which are operated in a deregulated market context. REMARK provides a quantitative assessment of reliability and economic benefits including indices that are widely used to assess the reliability of electric systems and economic indices for the electricity market. A DC power flow model is employed for the network representation and optimal power flow calculation. The probabilistic power system simulation of one year is based on the non-sequential Monte Carlo method.

Operational Scheduling Decision Support Platform based on Reliability Assessment **(OSDSP-RA)**, developed by Chongqing University, can assist operators in considering operational reliability in making scheduling decisions [309]. The connected external system can be considered in OSDSP-RA by equivalence technologies. Also, the impact of operational environments on component reliability is accounted for in this platform. The platform uses Monte Carlo sampling and analyzes each sample using an AC power flow model. On this basis, ***Coordinated Planning for Multi-Energy Power Systems*** **(CPMEPS)** was further developed in collaboration with China Electric Power Research Institute for CSR analysis in integrated energy systems [324]. Various objective functions can be established in this tool to match different operational scenarios. Once inputs and the focused objective function are given, numerous reliability indices (e.g., LOLP and EENS) are calculated. A description of the input data requirements for OSDSP-RA appears in section 4.1.1.

PowerFactory is a product of DIGSILENT, Germany. PowerFactory can be used for generation adequacy and CSR assessment [325]. Based on an AC power flow model and state enumeration, PowerFactory can handle risk issues, load transfer, and load shedding within a fast topological analysis for fault clearance, fault isolation, and power restoration. The sensitivities of reliability indices to the parameters of different components can be analyzed as well. PowerFactory has been used to evaluate the integration of wind generation [326] and microgrid architecture in power systems [327].

Bulk Electricity System Reliability Evaluation-Tsinghua **(BESRE-TH)** was developed by Tsinghua University, China. BESRE-TH can provide a decision support system for both planners and operators. Its major functions include CSR assessment, reliability sensitivity analysis, generation system reliability assessment, and the coordination of dispatch between reliability and economy. This tool can be used in large-scale high- and medium-voltage power systems [328].

System Reliability Risk Model **(SRRM)** is a set of in-house tools developed by Manitoba Hydro, Canada. SRRM simulates the performance of the composite power system with and without the proposed enhancements including modules for analyzing the reliability impacts of AC projects (SRRM-AC), DC projects (SRRM-DC), substation projects (SRRM-ST), and incorporating the impacts of aging infrastructure (SRRM-AI). The SRRM-AC and SRRM-ST modules employ a commercial power flow program. The methodologies in SRRM are documented in [329], and the suite is described further in sections 5.2 and 5.3.

CORAL and ***NetPlan*** are products of PSR Inc, Brazil. CORAL can evaluate composite generation and transmission reliability in large-scale power systems [330]. CORAL considers generation and transmission outages, the effect of hydrological uncertainty, load variation, and production uncertainty from renewable generation. CORAL can estimate system and bus reliability indices, including LOLP and EENS. Concurrently, this software can disaggregate the contributions to reliability indices from generation, transmission, and combined generation and transmission outages. Also, some bus and area indices (e.g., the expected bus-level marginal impacts of generation and transmission reinforcements) can be estimated. A combination of Monte Carlo simulation, stratification, and enumeration is applied to sample system states. A DC power flow model is used to identify constraint violations, then remedial actions are calculated. NetPlan is derived from CORAL [330].

TRANSREL was developed by GR, U.S. It uses a contingency enumeration approach to evaluate power system reliability [331]. TRANSREL can identify the worst contingencies and evaluate their impacts. The process includes identifying contingencies and performing AC power flow analyses to find system problems. Then, TRANSREL determines the effective remedial actions when the worst contingencies occur. TRANSREL can be utilized in three applications: computing reliability indices for a transmission network, comparing alternative transmission configurations, and providing a basis for risk/benefit analysis of investment alternatives. Selecting and evaluating contingencies is done by any commercially available software (GE_PSLF, Power World, etc.)

Outage Scheduling and Reliability Analysis of Electric Power System **(OSCAR)** is a product of Kinectrics, Canada. OSCAR employs both state enumeration and Monte Carlo simulation approaches [4]. Then, based an AC or DC power flow, each selected state is analyzed.

Enhanced Probabilistic Contingency Analysis **(ePCA)** is an open-source research grade tool developed by Brookhaven National Lab [332]. ePCA features "population variability" modeling of outage rates [333] , impact assessment of renewable generation intermittency on contingency analysis, and exact quantification of probabilistic reliability indices [137].

Power Systems Model for Operational Reserve Adequacy (PS-MORA) is a research-grade tool developed by Federal University of Itajubá, (Brazil) & INESC TEC (Institute for Systems and Computer Engineering, Technology and Science, (Portugal). PS-MORA employs Monte Carlo simulation approach and was originally used by Redes Energéticas Nacionais (REN), Portuguese TSO and Red Eléctrica de España (REE), Spanish TSO) only for operating reserve assessment, considering high penetration of renewable sources. The updated PS-MORA version is a full CSR computational algorithm to quantify the long-term adequacy of static and operational reserves, considering the short and long-term uncertainties arising from load, wind and solar generation forecast, as well as the unplanned outages of the generating units committed for operation. PS-MORA considers energy-limited representations for hydro capacity usage, models for the transmission network and interconnection circuits and policies for energy and operational reserve exchange between different bidding zones/control areas [335]–[336].

In addition to the individual use of each tool mentioned above, use of a combination of tools has also been reported [333]–[334]. Utilities and other organizations have assembled systems for CSR analysis that include one or more commercial tools coupled with one or more in-house tools. The in-house tools may perform such tasks as data preparation, scenario construction, contingency enumeration, probabilistic calculations, and reporting, and may include a database. An advantage of this approach is that the powerful capabilities of the commercial tools can be exploited and augmented with the in-house components. Bagen and Huang [334] describe such a system developed at Manitoba Hydro built around PSS/E [338], which is used for load flow analysis. Another case study involving a combination of tools, with TransCARE performing the probabilistic analysis, is described in [337]. CSR Task Force's recent paper [339] addresses a variety of issues associated with research grade and commercially available tools for composite power system reliability evaluation.

4.4 Classification of existing tools

This section provides a systematic review of the CSR tools profiled above. They are compared and categorized by design purposes, probabilistic methodologies, and CSR indices.

4.4.1 Purpose-based classification

CSR assessment measures the power system reliability, reflects power system operational reliability (that is, power outages will not occur in a reliable power system, with respect to the relevant constraints) and the risk of economic loss to customers who suffer power outages. Tools with a primary focus on CSR assessment are listed in Table 7.

TABLE 7. CSR tools focusing on reliability assessment

Software	Descriptions in documents
PROCOSE	"PROCOSE is developed primarily for reliability and production costing assessment of bulk power systems." [4]
MECORE	"MECORE program can be used to provide a wide range of reliability indices at the individual load points and for the overall composite generation and transmission system. [4]
OSCAR	"The Outage Scheduling and Reliability Analysis of Electric Power System (OSCAR) model is a computer program for analyzing the generation and transmission reliability of large power systems." [4]
NH2	"The NH2 software is designed for probabilistic reliability assessment of composite generation and transmission systems." [4]
TRANSREL	"TRANSREL is a computer program to calculate reliability indices for bulk power systems, transmission systems, and /or station switchyard."[4]
CORAL	"Coral evaluates the composite generation and transmission supply reliability of large-scale power systems…" [4]
CREAM	"The program calculates the most commonly used reliability indices such as Loss-Of-Load Probability (LOLP) and Expected Power Not Supplied (EPNS) at both system and individual bus levels." [4]
CRUSE	"…using bulk reliability indices obtained with the Composite Reliability Using State Enumeration Software." [310]
RECS	"It is a modular and expandible program for assessing the reliability of the combined (generation/ transmission) power system." [281]
PowerFactory	"The DIGSILENT PowerFactory Reliability Analysis tool incorporates standard reliability assessment features together with sophisticated modeling techniques that enable both generation adequacy and composite generation and transmission reliability assessment to be carried out." [325]
SRRM	"Currently the SRRM includes four different modules for different purposes of applications. These are: 1) SRRM-AC for evaluating reliability impact of AC projects, 2) SRRM-ST for evaluating reliability impact of substation related projects, 3) SRRM-DC for evaluating reliability impact of DC projects, and 4) SRRM-AI for evaluating reliability of aging infrastructures." [329]

CSR assessment of power systems reliability can inform power systems operation and planning decisions in the face of uncertainties. Tools that incorporate CSR assessment into power systems operation and planning are shown in Tables 8 and 9.

TABLE 8. CSR tools for power systems planning

Tools	Descriptions in documents

SICRET	“When planning composite generation/transmission systems, for quantitative evaluation of system adequacy and of fuel costs, ENEL uses the SICRET program…” [254]
TRELSS	“TRELSS is designed to aid planning engineers in representing systems in as much detail as possible and studying as many contingencies as possible, while using accurate power flow algorithms.” [315]
TransCARE	“TransCARE provides a comprehensive probabilistic planning framework that can be used to properly value and prioritize investments in a transmission infrastructure.” [316]
CPMEPS	“Risk-based planning for multi-energy power systems can be implemented” [309]
BESRE-TH	“BESRE-TH, developed by Tsinghua University, can provide a decision support for both planners and operators on the reliability and economy assessment in large-scale high- and medium-voltage power systems.” [328]
ePCA	“Facilitation of the Decision-making Process in Transmission Planning Using Probabilistic Reliability Metrics” [332]
PSS®E	“Each CLL can be analyzed in a deterministic planning software like Siemens PTI PSS®E…” [338]

TABLE 9. CSR tools for power systems operation

Tools	Descriptions in documents
REMARK	“The purpose of this tool is to conduct analyses of static reliability (or adequacy) of complex electric systems that operate in a liberalized market context and are divided into areas.” [4]
OSDSP-RA	“Operational Scheduling Decision Support Platform based on Reliability Assessment (OSDSP-RA), assists operators in managing data related to operational reliability.” [309]
BESRE-TH	“BESRE-TH, developed by Tsinghua University, can provide a decision support for both planners and operators on the reliability and economy assessment in large-scale high- and medium-voltage power systems.” [328]
PS-MORA	“Long-term operational reserves evaluation of multi-area systems,” [335]

4.4.2 Solution-based classification

CSR assessment includes three major steps: select a system state, analyze the selected system state, and calculate risk indices. Based on different methods of selecting a system state, CSR can be categorized into two types: one is the analytical method, and the other one is the simulation method.

The analytical method works through the exhausted combinations of component contingencies to construct system states, while the simulation method works through sampling. Although the enumeration in the analytical method leads to heavy computational burden in utility systems, the clear physical meaning of the analytical method still draws attention of users. Consequently, a few tools still use the analytical method with the limited enumeration. On the other hand, the simulation method needs a large amount of samples to guarantee the accuracy of CSR assessment results, leading to heavy computational burden. However, some tools still employ the simulation method because the simulation method has the potential to implement the accurate CSR assessment in utility systems by some advanced technologies (e.g., the acceleration of sampling). To get a tradeoff between the analytical method and the simulation method, hybrid analytical and Monte Carlo method are developed in some tools.

The solution methodologies in different tools are summarized in Table 10 as follows:

TABLE 10. Solution methodologies in different tools

Method	Tools	Descriptions in documents
Analytical method	PowerFactory	"The basic calculation method used is analytical state enumeration." [325]
	RECS	"Since the reliability model is based on selective contingency analysis…" [281]
	CRUSE	"…Composite Reliability Using State Enumeration Software…" [310]
	TRELSS	"The enumerative procedure, on the other hand, describes the life process of the system by a mathematical model and the computation of reliability indices involves the solution of this model." [315]
	TransCARE	"Transmission Reliability Evaluation of Large-Scale Systems (TRELSS) is a five program software package that uses enumeration of generation and transmission contingencies to evaluate power system reliability. " [316]
	SRRM	"…SRRM-AC employs a subsystem based analytical technique," "…SRRM-ST uses a new enhanced analytical approach…," "SRRM-DC uses the analytical method…" [329]
	BESRE-TH	"Its major functions rely on listing possible failures based on probability." [328]
	TRANSREL	"TRANSREL uses contingency enumeration approach to evaluate power system reliability." [331]
Simulation method	REMARK	"REMARK applies the Optimal Power Flow (OPF) algorithm, and analyses the system by probabilistic simulation of one year of

Method	Tools	Descriptions in documents
		operation of the power system using a non-sequential Monte Carlo method.” [322]
	CREAM	“The Composite Reliability Assessment by Monte Carlo (CREAM) software is based on Monte Carlo sampling…” [285]
	PROCOSE	“The program uses a DC power flow model to simulate the operation of the power system during a specific period of time (hour, week, month, etc.)…” [4]
	SICRET	“…, ENEL has been using for many years a Monte Carlo-based program (SICRET).” [254]
	OSDSP-RA	“The Operational Scheduling Decision Support Platform based on the Reliability Assessment program uses simulation methods to deal with the reliability assessment problems.” [309]
	CPMEPS	“…, simulated demand levels and renewable levels.” [309]
Hybrid analytical and simulation	CORAL	“A combined Monte Carlo, stratification and enumeration scheme is used… [4]
	OSCAR	“OSCAR use both analytical and Monte Carlo simulation approaches.” [4]
	ePCA	“… a generic scheme for improving the PCA capability of current contingency analysis tools was developed …” “The scheme uses a Monte Carlo simulation to calculate probabilistic indices based on a deterministic CA ...” [137]
	MECORE	“MECORE is based on a combination of Monte Carlo simulation (state sampling technique) and enumeration techniques.” [256]
	NH2	“The software enables both deterministic and probabilistic reliability assessment, providing two methods for this evaluation: contingency enumeration based on a user-defined contingency list and a non-sequential Monte Carlo simulation.” [320]
	PSS®E	“The PSS®E reliability functions allow for deterministic reliability to evaluate certainty of service, and for probabilistic analysis to evaluate consequences that can be expressed in terms of cost.” [338]

4.4.3 Index-based classification

Generally, risks can be measured from three perspectives: probability of occurrence, frequency of occurrence and amount of either power loss or economic loss. The probability is related to the likelihood that "unreliable situations" will occur. The frequency is related to how many times "unreliable situations" will occur. The amount indicates the power or economic loss caused by "unreliable situations." Therefore, CSR indices in different tools are similar. Some major indices in different tools are listed in Table 11.

TABLE 11 Reliability indices in different tools

Probability	Frequency	Amount
Probability of Load Curtailments (PLC)	*Expected Frequency of Load Curtailments* (EFLC)	*Expected Duration of Load Curtailments* (EDLC)
Probability of Healthy State (PHS)	Frequency of overload	*Expected Load Curtailments* (ELC)
Probability of Marginal State (PMS)	*Loss of Load Frequency* (LOLF)	*Expected Demand Not Supplied* (EDNS)
Probability of Risk State (PRS)	*Frequency of Loss of Stability* (PLOS)	*Expected Energy Not Supplied* (EENS)
Probability of Flow operational reliability (PFOR)	*Customer Average Interruption Frequency* (CAID)	*Expected Interruption Cost* (EIC)
Probability of Voltage operational reliability (PVOR)	*System Average Interruption Frequency* (SAIF)	*Bulk Power-Supply Average MW Curtailment Index* (BPACI)
Loss of Load Probability (LOLP)	*Dynamic Loss of Load Frequency* (DLOLF)	*Bulk Power/Energy Curtailment Index* (BPECI)
Probability of Overload (PO)		*Service Availability* (SA)
Probability of Voltage Violation (PVV)		*Severity Index* (SI)
Probability of Line Overload (PLO)		*Expectation of Overload* (EO)

5. INDUSTRY PRACTICE

5.1 Findings from Prior Utility Industry Surveys

An EPRI project report [27] observes that methodology for CSR evaluation needs to address the complexity associated with single and multiple outages of generation and transmission facilities. A survey conducted in the course of that project provided valuable information about utilities practices in CSR evaluation. Responses to survey questions showed that only a limited number of utilities were using CSR methodologies and tools in their planning studies. Typical studies performed by utilities were area reliability and transfer capability evaluation. One limitation of the tools existing at that time was that they had limited or no capability to model generating unit outages, and deficiency in modeling of contingencies, reactive power representation, and computational efficiency. A second important limitation was that they did not recognize realistic operating practice, and therefore load curtailment indices calculated by these models were not meaningful. In spite of these limitations the majority of respondents agreed that probabilistic reliability assessment has a role in system planning. This report also noted that the model accuracy requirement should be a function of the application and be in balance with other information used in decision making and with the uncertainties involved in system planning [27].

Reference [28] presents further survey results from the same EPRI project and highlights methodologies for gathering data and trend of emerging reliability planning practices to assess value-based reliability planning. For the survey, 27 U.S. utilities and 11 Canadian utilities were selected based upon:

- A general preference for mid- to larger-sized utilities;
- A desire to maintain some geographical diversity; and
- Other considerations such as projected load growth rates, regulatory climate, and whether the utility was known to be an industry leader in some aspects of reliability planning.

Twenty-nine out of the 38 utilities provided fairly complete responses, resulting in a response rate of 76 percent. Over 75 percent of the respondents (22) reported using deterministic criteria for designing their transmission systems. Approximately 21 percent or 6 of the respondents use a combination of deterministic and probabilistic criteria. Of these, one of the companies develops its expansion plan using deterministic criteria. A probabilistic analysis is then performed to check for compliance with their probabilistic criteria. Plans that do not meet the probabilistic criteria are modified. Another utility reported using probabilistic criteria to prioritize projects selected by deterministic methods. At least three utilities reported "examining" or "considering" the use of probabilistic criteria on an experimental basis. Contingencies considered in deterministic analysis and the conditions under which they are tested vary with the utility and are selected to best suit the concern of each. Typically, the specific types of contingencies considered are one or more of the following:

- Loss of one or two circuits;
- Loss of a right of way;
- Loss of a transformer; and
- Loss of one generator and other elements.

However, the first contingency was by far the most often mentioned by respondents and only four of the respondents' utilities indicated use of a composite system reliability program.

Reference [28] summarized more results from the survey conducted by EPRI [27] in the mid-80s with electric utility system planners as the primary users of CSR evaluation programs. Based on survey responses, the status of existing applications of bulk system reliability was divided into four categories:

1. Some utilities were actively using probabilistic tools for bulk transmission system planning (e.g., Florida Power Corporation, Georgia Power Company, Ontario Hydro, Mid-continent Area Power Pool). These utilities made a number of suggestions of improvements needed in these tools. The following applications were identified:

    a. to evaluate transmission adequacy at distribution points
    b. to compare alternate facilities for area transmission planning;
    c. to justify transmission facilities
    d. to evaluate the effect of transfer capability on system reliability,
    e. to evaluate benefits and costs of reliability improvement for use in decision making

2. Some utilities had reviewed the existing tools and concluded that they were not satisfactory. They decided to use alternative approaches. For example, one utility was developing detailed probability distributions of transfer capability for use in making decisions on capacity transactions. Another utility decided to use deterministic studies but consider probabilities of multiple outages in applying the planning criteria. Yet another utility decided not to use probability approaches. A conclusion is that deterministic approaches provide minimum criteria for planning; and the resulting systems have relatively high reliability. Probabilistic approaches may suggest reduction of reliability levels, and a utility would be reluctant to relax the current planning criteria, which were based on many years of experience.
3. Some utilities were actively looking for probabilistic tools and were are following industry developments. For example, these utilities had a strong interest in EPRI Project RP1530-2 "Bulk Transmission System Reliability Evaluation for Large Scale Systems."
4. Some utilities were not using any probabilistic tools other than for generating capacity reliability evaluation and did not indicate strong interest in probability approaches for composite generation and transmission systems.

The survey also highlighted the following difficulties with current methods:

- Difficulty in interpreting the expected load curtailment as calculated by existing models. Respondents felt that the load curtailment index as calculated by the models was not based on realistic operating practice. These respondents felt that the

probability (or frequency) of operating problems (e.g., not being able to meet operational reliability dispatch) would be more meaningful.
- Reliability isnot the primary driver of the need for facilities. The need for system facilities at the time of the survey was to achieve economic operation or to meet new constraints such as wheeling for third parties.
- Various difficulties with then-current computer programs, including not adequate for specific utility needs, too complex or cumbersome to use, not available for the available computer system, lack of awareness about what the programs can do, inadequate support for programs available in public domain, and lack of manpower in utilities to try new methods.
- Lack of transmission outage data.

In conclusion, reference [28] presented the following modeling needs for CSR :

- Static assessment capability for generation and transmission
- System problem and capability options with provision for remedial action, generation and phase shift or dc line flow control and load curtailment
- Linearized network models, dc load flow solution, or in the ultimate, ac network models
- Line limits defined as flow limits, but determined by consideration of both thermal and angle-related (voltage and surge impedance loading (SIL)) limits
- Transformer limits defined by long term and contingency load carrying ability
- Security-constrained (operational reliability) dispatch capability for system problem evaluations
- System load models capable of representing seasonal or discrete load level; bus loads determined by specification of load distribution factors
- Load and resource models capable of meeting requirements for hydro and energy-limited generation
- Weather- and station-dependent effects for line and transformer outages
- Generating unit capability and outage models with provision for multiple capacity state representation
- Generating unit maintenance schedules.

Additionally, reference [28] provided the following observations:

- There had been considerable activity in the area of CSR evaluation as seen in the available technical publications. However, only a small number of utilities were using the reported methods in their planning studies.
- Utilities (except those who had developed their own programs to suit their specific needs) were generally dissatisfied with the methods available in the industry for CSR evaluation.
- It appeared that the available computer programs for CSR evaluation were being used primarily for area transmission reliability and transfer capability evaluations because of unsatisfactory or computationally inefficient modeling of generation in these programs.

- It appeared there was a strong need to dialogue with industry on potential use and applications of CSR methods for practical problems while the methods are being developed in research projects or by consultants. This would assure a better match between the industry problems and the methods.
- Combined generating unit and transmission line outage events could contribute significantly to the unreliability of the composite system; and this is the primary motivation for composite (combined) generation and transmission system reliability evaluation.
- Composite system reliability evaluation should consider events leading to alert, emergency, controlled load curtailment, and forced off-economic operation states and isolation of one or more buses.
- Operational reliability constraints must be included in the CSR evaluation scope. However, it is impractical to include system dynamic performance evaluation to identify the potential extreme emergency state.

5.2 Findings of a CSR Task Force Survey

The CSR TF conducted a survey to assess the state of industry practice in probabilistic assessment in general and CSR analysis in particular [56]. The survey questions addressed the types of analyses being done, the contexts and purposes of these analyses, the software tools in use, the importance of various features of the software tools, and whether the implementation of these features is adequate or lacking. The survey also sought to identify impediments that may be constraining more widespread implementation of probabilistic and CSR analysis.

The survey was administered in two ways: as a PDF form and as an online survey implemented by the Strategic Research staff of IEEE headquarters. The form and a link to the online survey were both distributed to members of the RRPA SC; the Probabilistic Assessment Working Group of NERC, a not-for-profit international regulatory authority that enforces reliability regulations in the continental United States, Canada, and a portion of Baja California, Mexico; the Reliability Assessment Committee of the Western Electricity Coordinating Council, a regional entity with enforcement authority for the Western Interconnection of North America delegated to it by NERC; and a list of potentially interested IEEE members developed by the Strategic Research staff, in addition to the CSR TF.

This section summarizes the responses received, organized as follows: uses of probabilistic analysis, tools for probabilistic analysis, probabilistic reliability criteria, impediments to probabilistic analysis, general comments by respondents, and summary and conclusion.

The power industry is facing many challenges and these challenges have made the traditional deterministic approaches more difficult than in the past for planning and operation of power systems. The use of probabilistic planning is a beneficial supplement to the existing system planning and operation process. The industry has recognized this fact for a long while and is trying to do some probabilistic work. However, currently there are a lot of challenges and obstacles and particularly a lot of misconceptions regarding probabilistic concepts and methodologies.

A total of 182 responses were received from North America, Europe and Asia. Of these, 91, or 50%, indicated that that their organizations have done probabilistic analyses within the past five years. The purposes for which probabilistic analysis is used are shown in Fig. 22. The largest number are using probabilistic analysis in the context of generation planning or integrated resource planning. Transmission planning is a close second. The graph in Fig. 23 summarizes the responses on the size of the studied system and the graph in Fig. 24 shows how the transmission system was represented [5].

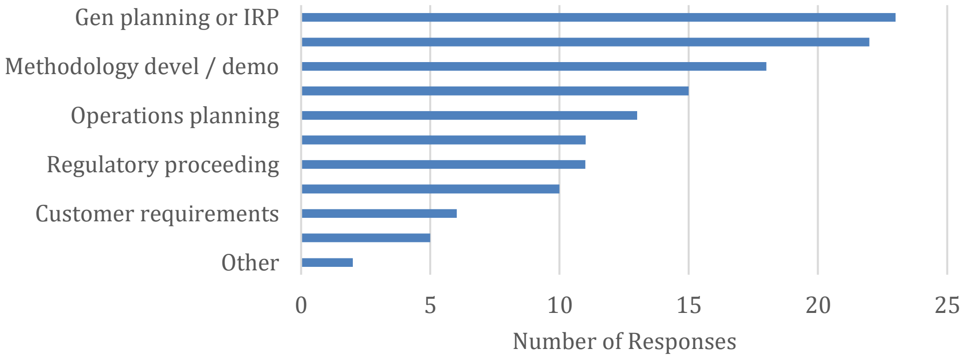


Fig. 22. Primary goals of probabilistic analysis

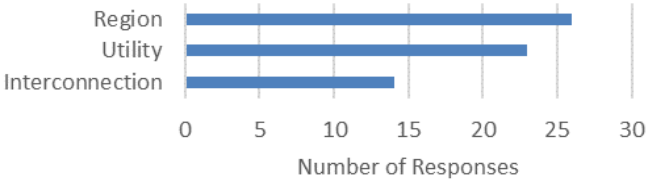


Fig. 23. Geographical study area

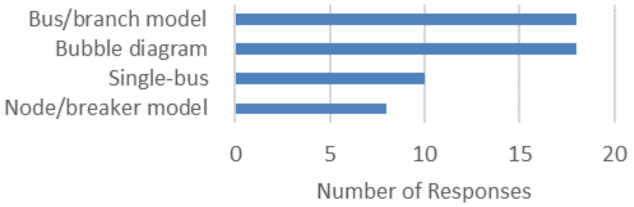


Fig. 24. Representation of transmission system

The survey invited respondents to describe their activities in greater detail. Several entities provided comprehensive responses, which are presented below, lightly edited, and organized geographically and alphabetically

5.2.1 Europe

Elia

Elia Transmission Belgium, the operator of the Belgian high-voltage grid, responded that its analysis includes generation outage modeling, transmission outage modeling, hourly modeling of variable energy resources, long-duration storage modeling (for example, hydropower), short-duration storage modeling (for example, batteries and pumped storage), contingency enumeration, Monte Carlo simulation, other common-mode or dependent outages, modeling of market impacts (for example, merit order, interaction with neighboring markets), and transmission congestion management.

The company noted that for:

- Transmission outage modeling: It is considered only for HVDC links and is taken into account in the "flow based" electricity exchange domains for DE, FR, BE, NL, AT.
- Weather-dependent outage modeling: Outages are not dependent on weather conditions in the model.
- Other common-mode or dependent outages: Pump-storage outages are considered.
- Modeling of market impacts: This is very important for generation adequacy assessments.
- Reliability metrics: Belgian legal criteria for the operational reliability of supply are:
    - LOLE < 3h
    - LOLE95 < 20h, where LOLE95 is the 95th percentile of the distribution of LOLE. That is, the probability that load curtailments will exceed 20 hours must not exceed 5%.

Spain

A generation company in Spain, which has assets in Portugal, Spain, and France, indicated that the company has conducted probabilistic analysis in examining the future needs of the power system in the medium- and long-term horizons. PLEXOS was used, along with in-house developed tools, for resource adequacy studies with 3-hour/year hourly LOLE criterion. The company noted the effective contributions of demand side management (DSM) and distributed generation (DG) as important issues. The company also indicated several obstacles in implementing probabilistic assessment: 1) defining relevant uncertainties and contingencies, 2) computational run time, and 3) analysis that is difficult to explain to management and/or regulators.

TenneT
TenneT, the national electricity transmission system operator of the Netherlands, stated that it performed exploratory studies to extend existing deterministic contingency analysis to probabilistic reliability analysis. The primary purpose was to develop a methodology that considers contingency probabilities, asset health (via object-specific failure rates), all operational reliability constraints (not just the worst one), and generation re-dispatch as a remedial action in order to define a total Cost of Risk reliability metric. The tools used by TenneT are the PowerFactory Reliability Analysis Tool, together with Python scripts. The company also indicated several obstacles in implementing probabilistic assessment: 1) computation run time and 2) analysis not required by regulatory commission.

5.2.2 North America

BC Hydro
BC Hydro responded that its Transmission Planning activities encompass generation outage modeling, transmission outage modeling, Monte Carlo simulation, other common-mode or dependent outages, dc optimal power flow (OPF), emergency operating procedures.

BC Hydro noted that the vendors of system planning software tools have not put serious effort into providing effective, efficient, and integrated solutions to address CSR. BC Hydro also noted that in-house development is useful, but expensive, and does not work in the long-term. This is the main gap that the industry needs to address to make CSR an integral part of system planning. Section 5.4 describes BC Hydro's activities in further detail.

ERCOT
ERCOT has conducted probabilistic analysis primarily for resource adequacy, generation and transmission planning. For the resource adequacy study, ERCOT considered various scenarios and sensitivities to address uncertainties such as wind, solar and demand forecasts corresponding to different weather patterns. The tool used for the resource adequacy study is SERVM and one of the key metrics considered is LOLE (hours/year).

ERCOT also explored a probabilistic approach to consider various system uncertainties and compare reliability benefits of each transmission project alternative by using risk metrics. ERCOT noted several obstacles in implementing probabilistic assessment: 1) defining relevant uncertainties and contingencies, 2) obtaining additional data (e.g., outage rates for lines, units, and station components), 3) interpreting results, 4) computation run time, 5) lack of confidence in method, 6) analysis not required by regulatory commission and (7) analysis unfamiliar to management and/or regulators. More details of the probabilistic approach can be found in Section 5.4.

Idaho Power

Idaho Power responded that it used TRELSS, CREAM, TRANSREL, RTS3, and internally developed tools to perform CSR studies. For integrated resource planning, Idaho Power used various scenarios to consider the uncertainties of system conditions along with historical profiles of renewable resources. The main two objectives of the studies were: 1) to evaluate reliability of Idaho Power delivery points (customer focus) and 2) to monitor the reliability of entire system by evaluating both generation and transmission. The company indicated several obstacles in implementing probabilistic assessment: 1) interpreting results, 2) lack of confidence in method, and 3) analysis not required by regulatory commission. The company also stated that an adequate methodology should be incorporated into tool to perform full composite system reliability evaluation, since presently there is not available any such methodology/tool. It also emphasized the importance of addressing the impact of variable energy sources on the system reliability. Section 5.4 describes Idaho Power's activities in further detail.

IID

The Imperial Irrigation District (IID) energy service territory covers 6,471 square miles in southern California. Probabilistic analysis performed for its service territory includes, but is not limited to, transmission planning, generation planning or integrated resource planning and operations planning. IID responded that it conducts LOLP analysis that is modeled through load and forced outage variations. The company indicated that features used are hourly modeling of variable energy resources, long-duration storage modeling (for example, hydropower), short-duration storage modeling (for example, batteries and pumped storage), Monte Carlo simulation, weather-dependent outages, other common-mode or dependent outages, load or generation isolation or system separation, and modeling of market impacts (for example, merit order, interaction with neighboring markets). IID identified some improvements are needed for hourly VER modeling, long-duration storage modeling and short-duration storage modeling.

ISO-NE

ISO New England (ISO-NE) responded that it uses GridView and MARS for generation outage modeling, hourly modeling of variable energy resources, long-duration storage modeling (for example, hydropower), Monte Carlo simulation, emergency operating procedures.

ISO-NE stated that probabilistic analyses have served reasonably well to provide metrics related to resource adequacy, providing a computational basis to determine the appropriate general load-resource balance. Some analysis models incorporate transportation limits ("pipe and bubble"), which are coarse representations of deterministic transportation limits. While coarse, these models try to capture both probabilistically calculated base conditions and the inherent deterministic potential contingencies upon which the transportation/transmission limits are based.

However, ISO-NE indicated that it is their observation that some composite tools completely and unfortunately abandon the deterministic representation of (pre-contingency) transmission constraints and attempt to address the contingencies (upon which the transportation limits would have been based) on a solely probabilistic basis. ISO-NE believes that such approaches can provide metrics, but they are not really metrics of comprehensive system reliability, even in the same manner as models that use transportation limits.

Manitoba Hydro

Manitoba Hydro uses a suite of in-house tools collectively referred to as the System Reliability Risk Model (SRRM). SRRM simulates the performance of the transmission system with and without proposed investments and compares the impact on reliability by considering potential single and simultaneous failures on the related system network. The model factors in the system topology, load data (peak, duration curves, and load forecast uncertainty), equipment reliability data, and network specific conditions (e.g., tapped lines, special protection schemes, common-mode outages), to calculate expected probabilistic indices expressed in terms of MWh/year such as the change in expected unserved energy (EUE), the change in expected bottled energy (EBE) and the change in expected curtailed export (ECE). Currently SRRM includes five different modules for different purpose of applications. These are:

- SRRM-AC for evaluating reliability impact of ac projects
- SRRM-DC for evaluating reliability impact of dc projects
- SRRM-SB for evaluating reliability impact of substation related projects
- SRRM-AI for evaluating reliability impact of aging infrastructures
- SRRM-RI for evaluating reliability impact of projects in remote isolated locations

Regarding CSR, Manitoba Hydro experience in CSR assessment is based on a sub-system or area, so that the contingency analysis is manageable; but interconnection impacts have been considered in the model. They take advantage of the calculation accuracy of commercial programs for consequence analysis by using PSS/E for power flow analysis whenever possible instead of creating their own power flow program. The complexity of the models should be based on data availability. It is not meaningful to develop a sophisticated model without any data to support it. Relative values are used instead of absolute values because the deficiencies in some common assumptions may canceled each other out. With more experience, this could be overcome and absolute values may be used and even be able to develop a criterion.

More detailed descriptions of the SRRM modules can be found in [243], [326], [331]. Section 5.4 describes Manitoba Hydro’s activities in further detail.

NYSRC

New York State Reliability Council (NYSRC) responded that NYSRC has conducted probabilistic analysis for integrated resource planning, determination of equivalent capacity value, and resource adequacy studies for the New York Control area. NYSRC modeled various system parameters stochastically (e.g., generation and transmission outages), while fixed values were used for maintenance schedule modeling. NYSRC adopted the “bubble and transportation” model to represent existing transmission constraints, and used the GridView, MARS, and PSS/E tools to conduct a Loss-of-load expectation (LOLE) study.

5.2.3 South America

PSR

PSR, in Brazil, has been a global provider of technological solutions and consulting services in the areas of electricity and natural gas (E&G) since 1987. PSR conducts analysis to support generation planning or integrated resource planning, operations planning, and investment decisions. The company indicated that features used are generation outage modeling, hourly modeling of VERs, long-duration storage modeling (for example, hydropower), short-duration storage modeling (for example, batteries and pumped storage), Monte Carlo simulation, and dc optimal power flow (OPF). PSR noted:

- Hourly VER modeling: With the fast penetration of renewable sources worldwide, hourly modeling representation (or even smaller time steps) is even more important.
- Long-duration storage modeling: Brazil has a predominantly hydroelectric energy matrix. Therefore, it is important to have not just adequate generation outage modeling, but also an adequate representation for the available capacity that depends on reservoir levels and inflow scenarios.
- Short-duration storage modeling: Similarly, to renewable sources, storage devices are increasing in number around the world. This motivates their representation in reliability adequacy studies. Using a pseudo-sequential method for representing batteries and pumped storage in simulations reduces the computational effort if compared to a chronological simulation.
- Contingency enumeration: The importance of contingency enumeration in reliability analysis depends on the horizon under analysis. For instance, in long term operation planning contingency enumeration plays a secondary role. However, in "real-time" analysis performed by system operators, contingency enumeration should be a primary consideration for the sake of operating the electrical system in " reliability regions."
- Flowgate violations, load separation, operational reliability, and cascading outages: Their importance varies according to the study/simulation that is being performed and whether it is a study for long, medium, or short-term analysis and evaluations.

5.3 Review of published work

CSR includes generation and transmission facilities, substations, protection and control systems and delivery points. Fully reliable power systems do not exist if any of these segments are negatively impacted by factors, such as random failures of system components, variable energy sources, and load uncertainties. Reliability—encompassing the two attributes of adequacy and operational reliability—is considered to be the most important criterion in the planning and operation of a power system.

Maintaining an adequate level of reliability is a challenging problem today due to frequent extreme events (e.g., failure of multiple physical components, natural disasters, and cyber-attacks) and the increasing complexity of energy system infrastructure.

An effort to develop methodologies and tools to adequately analyze and improve electric grid reliability in planning and operations continues. Enhancing reliability needs to be coordinated across all segments (generation, transmission, distribution, and customers), and solutions are required for both physical and cyber contingencies. We next review published works on applying probabilistic reliability methodologies to solve practical problems in generation, transmission, distribution, substations, and the cyber side of the power system.

In the planning horizon, various models have been used by the utility industry across globe.

Braga and Saraiva [48] describe a multicriteria model based on combining probabilistic models of power system components with fuzzy models to incorporate demand uncertainty. The model was used to select an optimal six-year expansion plan for the Portuguese national transmission system.

Kwon et al. [287] present the results of reliability evaluation of the Korea power system for future years 2007-2012 using the probabilistic reliability assessment (PRA) framework developed by EPRI and the POM software suite developed by VR Energy Research. In addition, study results include information on possible weak points in the system and root causes of likely reliability problems.

Xu and Edmonds [340] discuss several analytical probabilistic methods and tools such as contingency enumeration, multi-area reliability assessment, and Monte Carlo simulation that can be used for transmission planning, generation expansion, and system reliability. The authors applied these tools to several real system transmission and generation examples in provinces of Jiangsu, Zhejiang, and Anhui, and the Municipal Area of Shanghai, China.

Choi et al. [341] present the results of a reliability evaluation of the interconnected power systems of six countries in northeast Asia, using the tie line constrained equivalent generator model (TEAG). The study results show tie line transfer capability for three interconnection scenarios.

Xu et al. [342] present a reliability assessment method considering electrical load, generation, and transmission constraints on the performance of a power system. The methodology is based on three typical reliability indices—LOLE, EENS, and the cost of load curtailments. The method has been applied to study the Bolivian National Interconnected System (BNIS).

Tran et al. [318] present sensitivity analysis of a probabilistic reliability evaluation of transmission congestion on the KEPCO system. This paper focuses on analyzing the impact of line and transformer capacity constraints on bulk system probabilistic reliability indices. To perform the analysis, the authors used the EPRI TRELSS program.

Elmakis and Benhaim [343] propose a methodology to define a coherent criterion to support decision making. The methodology was applied to the Israel electric system.

Maruejouls et al. [344] describe a practical method of probabilistic reliability assessment for large interconnected power systems. The method was demonstrated on the US Eastern Interconnection and has been applied by several EPRI member utilities.

Li and Choudhury [345] discuss the basic concepts, criteria, procedures and methods in probabilistic transmission planning. Two key steps are probabilistic reliability evaluation and economic analysis. An actual example at British Columbia Transmission Company provides more insights, and indicates that probabilistic transmission planning is a powerful means and can help save capital investment in planning while keeping an acceptable system reliability level.

Li and Turner [346] document BC Hydro's development of a probabilistic transmission planning methodology using the metropolitan North Vancouver system as an example, using the MECORE program to conduct reliability and reliability worth studies.

Li et al. [347] present a probabilistic reliability planning method for transmission systems. The procedure includes comparison among reinforcement alternatives, an impact study of component retirements, a contingency plan for possible delay of the reinforcement project, and probabilistic economic analysis of the in-service year. The procedure is demonstrated on an actual reinforcement project for the BCTC Vancouver Island supply system.

Li and Korczynski [300] present a reliability-based method for transmission maintenance planning. A time shift based Monte Carlo simulation technique and a linear programming optimization model are used to perform reliability evaluation of the transmission system with planned outages. Analysis of the planned replacement of a 230-kV cable in the BC Hydro North Metro system is given to demonstrate practical application of the method.

Agarwal and Torre [348] present an approach for evaluating overall transmission system performance. The approach provides a consistent and quantifiable method to rank transmission projects and helps to provide a measure of impact on reliability for each project addition. Actual cases from SDG&E have been evaluated and benchmarked.

Bull [349] describes the background and resource planning environment in the U.S. Pacific Northwest, the analytical tools used to pursue power system planning objectives, and the direction in which policy decisions are headed, using Bonneville's 1987 resource strategy process as the example.

Hamoud et al. [350] describe a probabilistic approach for determining the portion of non-utility generation (NUG) capacity that can be relied on as a firm resource when assessing the adequacy of the Ontario Hydro customer delivery system. The proposed analysis could be a useful tool for consideration of NUGs in planning customer delivery systems.

Dalton et al. [69] present a value-based reliability planning (VBRP) process proposed for planning Duke Power Company's (DPC) regional transmission system. The process balances the costs of improving service reliability against the benefits that these improvements bring to customers. The objective is to provide DPC's customers the required level of reliability while minimizing the total cost of their electric service.

Udo et al. [75] document a system improvement study conducted by Atlantic Electric (AE) Company using EPRI's now discontinued analytical tool TRELSS. They present a dollar value quantification of the level of reliability from a given system improvement option. Based on this quantification, the improvement option that best balances the improvement cost and the incremental reliability is selected.

Varadan et al. [351] present a practical application of the inclusion of risk, based on the widely accepted Australia-New Zealand (AU-NZ) Risk Model into the transmission planning process at Bonneville Power Administration (BPA). The authors show that identification of risk factors at each stage of the transmission planning process, and their likelihood and associated consequences, are critical and necessary in gaining the maximum benefits.

Chowdhury et al. [352] present a value-based Monte Carlo simulation model to compute popular customer-oriented reliability indices for a local area supplied by the main Alberta Power Limited (APL) grid. The calculated outage costs can be merged with operating costs, including transmission losses, to determine the optimal reinforcement alternative.

Chowdhury and Koval [353] present the concepts and practical application at MidAmerican Energy Company of a value-based reliability cost-benefit evaluation model to select capital projects that improve supply reliability of a practical transmission system. Also, they show how a reliability cost-benefit methodology helps quantify transmission network reliability in dollars.

Chowdhury et al. [354]–[355] present results of a survey that was conducted with customers of MidAmerican Energy Company with a primary focus on outage costs. Customer damage functions derived from survey results are being used routinely for power delivery project justification in the annual delivery system budgeting process.

Hsu et al. [178] present the methodology and results of reactive power planning involving proper coordination between the distribution and transmission business units. The yearly plan at Alabama Power Company (APC) includes capacitor additions, autobank tap changes, and installation of LTC transformers, or the addition of regulators in substations where regulation is not present. The authors have utilized two tools, OPF and the EPRI TRELSS program to identify the most cost-effective var plan.

Harris and Strongman [356] present the enhancement of the existing N-1 criterion using a program called @Risk. The authors' method can be used to compare transmission development options intended to relieve congestion between areas, or to rank transmission projects intended to improve reliability.

Nagle et al. [357] present preliminary investigations and experience with a probabilistic framework and present a case study to rank transmission projects for the Entergy transmission system.

Yu and Singh [358] describe a probabilistic method to calculate total transfer capability (TTC). The authors incorporate operational reliability constraints, and Monte Carlo simulation is used to calculate TTC. The WSCC 9-bus system is used to demonstrate the methodology.

Chang et al. [298] present study results for steady-state operational strategies of a unified power flow controller (UPFC) in the Korean system. The study contributes to transmission operational studies with FACTS applications.

Anders et al.[359] present the results of a Canadian Electrical Association project where several probabilistic methods and computer programs for reliability evaluation of station bus configurations were compared by applying them to a number of such configurations. The methods studied included the state enumeration method and Monte Carlo simulation.

Bruce [360] presents a method for evaluating the reliability of a SCADA system. A case study of an actual system implemented by Trans Power was used for demonstration.

Paska [361] presents the methods and programs used in Poland to perform HLI and HLII reliability studies. For these studies, two programs are used—the Generation Reliability Assessment (GRA) developed in Poland and the EPRI TRELSS program.

Drayton et al. [362] describe the Western Interconnection's evolving transmission expansion planning process and the role OPF modeling plays in aiding decision-making. The paper identifies opportunities for improvement in modeling, highlights two state-of-the-art models with capabilities that go beyond those of other models used for long-term transmission planning, and makes a case for why we need to invest in better modeling and databases. Two models—PLEXOS, developed by Drayton Analytics (now Energy Exemplar), and SDDP, developed by a Brazilian company—are selected for practical cases because they can model complex, cascaded hydro networks, an essential feature in the Pacific Northwest.

Dearman [363] stresses the goal of Southern Company Services (SCS) to provide a high level of reliability to customers. The foundation of SCS reliability is long-term and real-time planning, with a commitment to build assets when needed and to continue developing better systems.

Abi-Samra et al. [364] assess Polish transmission system reliability using TRELSS. Results are presented for an actual Polish system that was represented in two ways: (1) a detailed model of the 400-kV and 220-kV networks with an equivalent of the 110-kV network, and (2) a detailed model of all high voltage networks—110 kV, 220 kV and 400 kV. The comparison of results for network configurations in 1998 and 2010 are provided.

Rei et al. [66]–[67] - depict some important practical aspects regarding the application of contingency enumeration and nonsequential Monte Carlo simulation methods, emphasizing how they can be used in a complementary way. The Brazilian interconnected electrical system is used to illustrate the risk assessment of an actual large-scale power system, utilizing both techniques.

Valente et al. [365] address the impact on the transmission grid of a large amount of wind generation, which, being a notoriously variable, non-dispatchable resource, creates power flows that risk saturating the available transmission corridors. A probabilistic Monte Carlo approach has been successfully applied to the Italian power system, and results include the traditional reliability indices LOLP, LOLE, and EENS.

Application of probabilistic methods to solve a variety of reliability issues in utilities across North America is presented in the following references. Sanghvi et al. [292] present the results of an EPRI research project covering current and emerging reliability planning practices in the North American utility industry, especially regarding interest in value-based reliability planning. Another important goal of the project was to develop and test methodologies for gathering data on how utility customers value service reliability, as measured by either the cost of outages or the willingness to pay for reliability. Neudorf et al. [74] present a cost-benefit approach that quantifies the reliability benefits of alternatives in terms of the reduction in unserved energy costs. It enables the evaluation of generation and transmission capacity additions on a consistent, economic basis. The proposed approach has been applied to two utility case studies at Pacific Gas and Electric Company and Duke Power Company. Vojdani et al. [366] present experience with application of reliability and value of service for five electric utilities in North America.

Billinton et al. [293] describe the considerable change occurring in the structure and operation of electric power systems throughout the world. They also describe the forces driving those changes and the possible reliability issues associated with them. Papic and Canderan [367] address past and predictive reliability indices and provide their comparison at the delivery point level. The comparison is illustrated using a model of the Idaho Power Company (IPC) system that includes 46-kV and above transmission facilities. Papic [319] presents a probabilistic reliability planning (PRP) approach at Idaho Power Company for selecting 75-year transmission buildout strategies for the Treasure Valley. The PRP approach is based on an analytical enumeration technique; and the TRELSS program has been used for evaluating composite system reliability. Burns and Gross [305] present a value of service (VOS) reliability evaluation approach that explicitly incorporates into the planning process customer choices regarding reliability "worth" and service costs. The proposed approach was applied at PG&E, and results are presented.

Papic et al. [245] present an approach to automatically generate a large number of contingencies from a node breaker model (NB) that can be used in performing system reliability studies and complying with the NERC Transmission System Planning Performance Requirements (TPL) standards. The approach is illustrated using a portion of the actual IPC system that includes all 230-kV and higher voltage substations.

Xi'an Jiaotong University (XJTU) began to explore the theory, method, and industry practice of probabilistic CSR assessment decades ago. Its relevant research directions include, but are not limited to, the reliability-based planning and operation of composite/renewable energy/multi-energy systems, weather-dependent reliability, operational reliability assessment, and machine learning-based assessment algorithms. The specific techniques used by XJTU include: 1) probabilistic modelling of components and systems; 2) system state assessment based on the Monte Carlo simulation, machine learning, or analytical methods; and 3) probabilistic reliability indices, including LOLP, EENS. XJTU developed its in-house tool "Planning Decision Support Platform for Electrical Power Systems with High-Proportion Renewable Energy" based on probabilistic reliability assessment techniques, and applied it in Northwest branch of state grid and Hainan power grid. XJTU noted several obstacles in implementing probabilistic assessment: 1) defining relevant uncertainties and contingencies, 2) obtaining additional data (e.g. outage rates for lines, units, and station components), 3) computation run time, and 4) analysis not required by regulatory commission [368]

The Coordinated Planning for Multi-Energy Power Systems (CPMEPS) was developed to implement CSR analysis by China Electric Power Research Institute in China. Inputs of this tool primarily include 1) reliability parameters (e.g., unavailability of lines and forced outage rates of units), 2) operational parameters (e.g., capacities and inter-temporal capabilities of various plants and energy storages), and 3) simulated demand levels and renewable levels. Also, various objective functions can be established in this tool to match different operational scenarios. Once inputs and the focused objective function are given, numerous reliability indices (e.g., LOLP and EENS) are calculated based on existing reliability assessment methods [309].

5.4 CSR practices of utilities in North America

5.4.1 BC Hydro

BC Hydro is one of the leading utilities in using probabilistic approaches extensively in power system planning and operation. Over the years BC Hydro has developed a portfolio of concepts, models, and methodologies applying probabilistic approaches in generation source evaluation, transmission system enhancement, composite generation and transmission planning, substation and radial distribution system planning, reliability centered maintenance, asset management, and power system spare planning. Systematic descriptions of various aspects of probabilistic planning based on BC Hydro's experiences can be found in books [11]–[12] and papers [49], [65], [155], [290]–[291], [300], [345]–[347] listed as references to this report. Great efforts have also been devoted to composite system reliability assessment, for example, development of the MECORE program described in Section 4.3. BC Hydro's composite system reliability modeling also includes addressing new challenges facing power systems such as the application of risk evaluation to composite power systems with renewable sources [300], [345]–[347] and assessment of the impacts of aging infrastructure [155], [371]–[373]. The modeling and evaluation of renewable energy sources and aging-related equipment unavailability are important aspects in power system reliability assessment. According to Google Scholar, the textbooks, papers, and industry reports that present BC Hydro's approaches have been cited extensively. BC Hydro's contributions are widely used in the industry.

5.4.2 ERCOT

ERCOT's grid has about 86,000+ MW of available generation capacity as of summer 2021. Wind resources on the ERCOT grid have increased significantly over the past 15 years. Texas has the most installed wind capacity of any state in the United States at over 27.4 GW, a record hourly wind penetration in April 2022 of 69.15%, and a historical peak record of more than 26 GW. In addition to wind, approximately 6.1 GW of utility-scale solar capacity has been installed as of September 2021. As more and more renewable resources are installed, the traditional resource mix continues to change. In fact, more than 4,000 MW of coal-fired units were retired in early 2018. Fig. 25. shows the trends of the energy fuel mix in the ERCOT grid from 2007 to 2020. ERCOT hit a historical peak demand of 74,820 MW in August 2019. The demand is expected to grow at an average annual growth rate (AAGR) of approximately 1.2% from 2022-2027[1].

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[1] https://www.ercot.com/files/docs/2022/02/24/2022_LTLF_Report.pdf

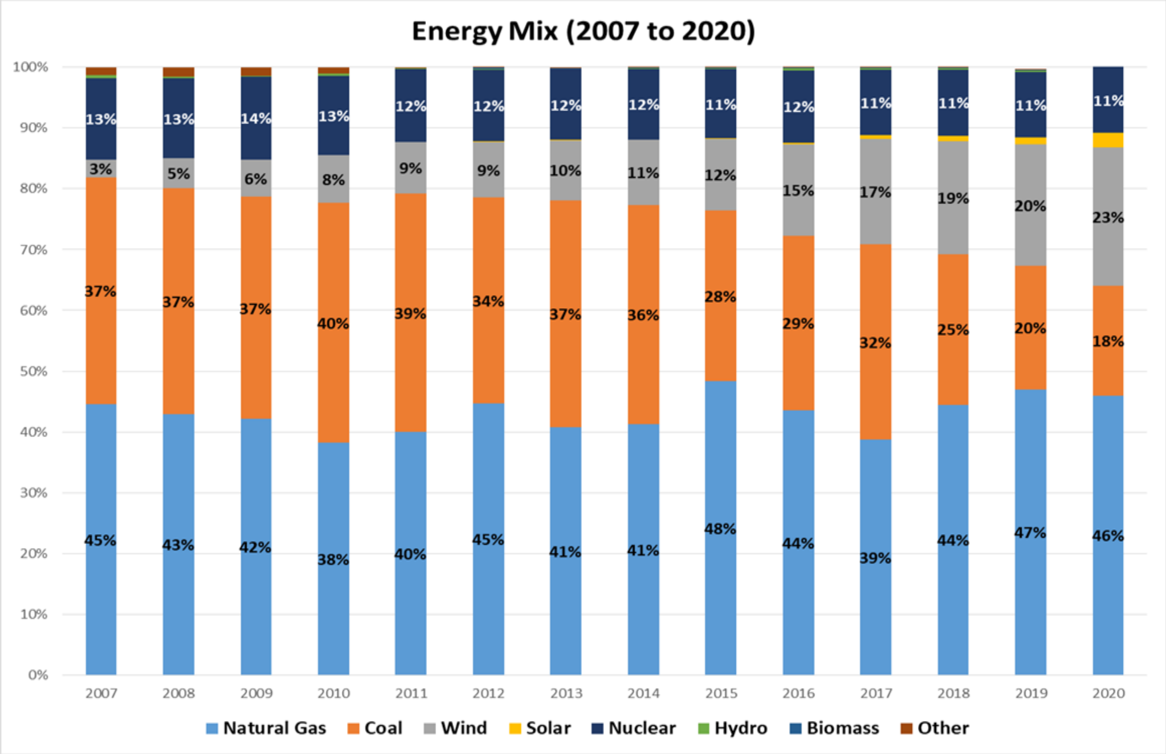

Fig. 25. Historical energy fuel mix

Every year ERCOT performs a planning assessment of the transmission system. This assessment is primarily based on three sets of studies:

- The Regional Transmission Plan (RTP) addresses region-wide reliability and economic transmission needs and includes recommendation of specific planned improvements to meet those needs for the upcoming six years.
- The Long-Term System Assessment (LTSA) uses scenario-analysis techniques to assess the potential needs of the ERCOT system up to 15 years into the future. The role of the LTSA is to provide a roadmap for future transmission system expansion and identify long-term trends that should be taken into consideration in near-term planning.
- Stability studies are performed to assess the angular stability, voltage stability, and frequency response of the ERCOT system.

The transmission planning studies are typically done using summer peak and off-peak conditions based on engineering judgement and past experience. In addition to seasonal variations, the studies also include various sensitivities to address uncertainties such as wind, solar, and demand forecasts corresponding to different weather patterns. The growing complexity in generation, transmission, demand, and weather conditions continues to add more challenges to transmission planning, and precipitates the need to consider them in a more rigorous manner than the approach traditionally done via engineering judgment and sensitivity analysis. Rigorously choosing which scenarios to study in light of increasing uncertainty surrounding system conditions and determining which events to study for the most severe system impacts when there is an intractably large number of combinations of elements, is a difficult task using deterministic planning methods alone. The level of uncertainty in electric power systems will continue to be challenging. Traditional deterministic planning process and standards may need to be upgraded by adopting probabilistic approach in order to help make better decisions on transmission investment.

ERCOT continues to make efforts to improve the transmission planning process and to address these challenges in system planning. As part of these efforts, ERCOT explored a probabilistic composite system planning approach [369]. The approach considers a wide range of operation conditions with various system uncertainties (e.g., wind, solar and weather). As demonstrated using a large-scale power system, transmission planners can utilize the approach to perform probabilistic reliability analysis to quantify all system issues into single risk metrics such as Expected unserved energy (EUE) and Incremental reliability index (IRI). The approach can be used in various applications such as project evaluation, weak area detection, critical contingency identification, and development of system hardening options for extreme events. Transmission network models and all the costs of operating a fleet of generators were explicitly modeled. Using general Monte Carlo technique improved with K-means clustering, the approach produced a reasonable and manageable number of scenarios representing a wide spectrum of operating conditions in addition to the probability of occurrence of each scenario. ERCOT used multiple tools including UPLAN, PowerWorld, POM/OPM, and Matlab to implement the probabilistic approach. Some of the key challenges and obstacles identified by ERCOT include:

- streamlining the steps in the process or using one single tool to avoid loss of data during data transfer between tools,
- unavailability of a better tool for estimating system impact in terms of the load curtailment that is necessary to eliminate not just thermal or voltage issues but also voltage collapse issue due to significant system disturbances or critical contingencies, and
- lack of probabilistic transmission planning criteria.

5.4.3 Idaho Power

Considerable effort has been devoted by Idaho Power Company in implementing reliability tools and developing data sources for quantitative reliability evaluation of the Idaho system. Several reliability tools such as EPRI programs TRELSS and CREAM and substation reliability tool SUBREL are used to evaluate the reliability impacts of a variety of projects in Idaho. Illustration of interaction among different data sources, system models, and reliability tools are presented in Fig. 26. The abbreviations in Fig. 26 are defined in Section 8.

Outage data for transmission and generation facilities in the Dispatching Outage Reporting System (DORS) are used to calculate reliability indices of generating units and transmission circuits (lines and transformers). The plant information (PI) system is used to obtain the profile of system load and load points as well as the generation profile of hydro generating plants. WECC provides load flow cases for different seasons. Basic input data to perform a study using the TRELSS program are outlined in section 4.1. TRELSS output files include failure by contingency with frequency and duration, load curtailment by contingency with frequency and duration, system failure by type with frequency and duration, system indices (probability of load loss, frequency of load loss, duration of load loss, expected un-served energy and expected un-served demand). The studies performed can be grouped as follow:

1. Reliability evaluation of proposed upgrades to the system
2. Reliability evaluation of long term transmission planning strategies [319]
3. Comparing the reliability of different zones and delivery points in system. [367]
4. Comparing expansion/design alternatives
5. Monitoring reliability trends at the system level
6. Determination of reliability “weak” spots in the system
7. Identification and ranking of system violations
8. Evaluating the reliability of station alternatives [370].

Reference [319] presents the results of probabilistic reliability assessment of long-term planning strategies at Idaho Power. Study results have demonstrated that the implemented approach is a comprehensive and conceptually sound method to evaluate future transmission planning strategies. The results of a study helped to identify the most reliable 75-year build-out supply strategy for Treasure Valley (TV) area customers. Consideration of several calculated reliability indices was found to be necessary for the selection of the preferred strategy. A network topology called LOOP shows better reliability performance, and is used at the 230-kV level to supply the TV 138-kV and below network. A system with a radial topology called ISLD is less reliable but has lower cost, and is used primarily to supply customers at distribution level. A combination of LOOP and ISLD strategies is called the HYBRD strategy. The graph on Fig. 27 shows EUE contributions resulting from islanding and remedial actions. Reliability performance of both the ISLD and HYBR strategies can be improved by actions that would reduce the islanding component of EUE. The most effective way to increase the reliability of the LOOP strategy is to utilize actions that would reduce the EUE component resulting from remedial actions. Presenting the results in this way helps to identify the most effective ways to increase the reliability of studied strategies.

Reference [367] focusses on evaluating past and predictive reliability indices and comparing them at the delivery point level. The comparison is illustrated using a model of the Idaho system including transmission facilities 46 kV and above that deliver power from the bulk transmission system to the distribution system, large municipalities, and large industrial customers. This effort resulted in an approach for continuously monitoring past reliability performance of selected delivery points.

Reference [370] presents a probabilistic process for selecting substation design by balancing cost and reliability. Four station designs were evaluated using reliability indices and economic analysis to come up with the most cost effective and reliable design overall. For each design option economic analysis was performed using the net present value (NPV) of total costs (capital, O&M, and outage). The results were then used to rank the options. A number of sensitivity studies on the NPV of total cost were conducted to examine the effect of varying major parameters on the ranked options. The process was applied to a real case study performed of an Idaho Power substation using the SUBREL program.

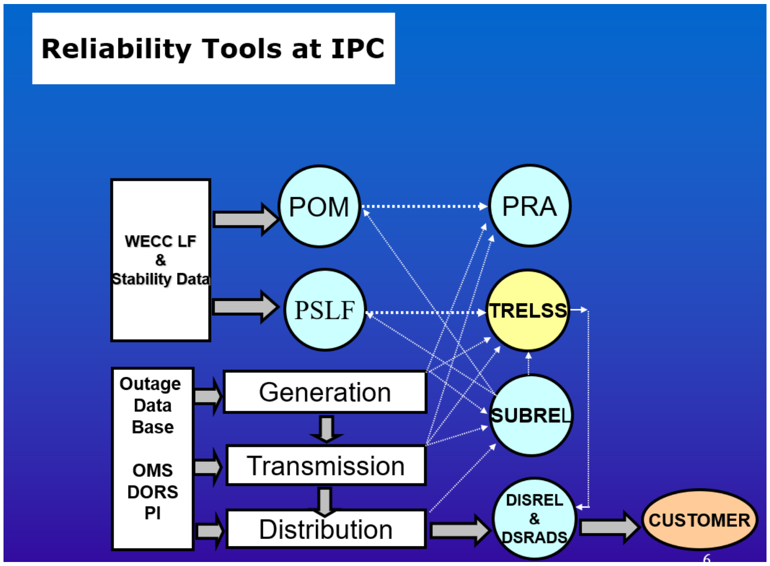

Fig. 26. Illustration of interaction among different data sources, load flow models and reliability tools at Idaho Power

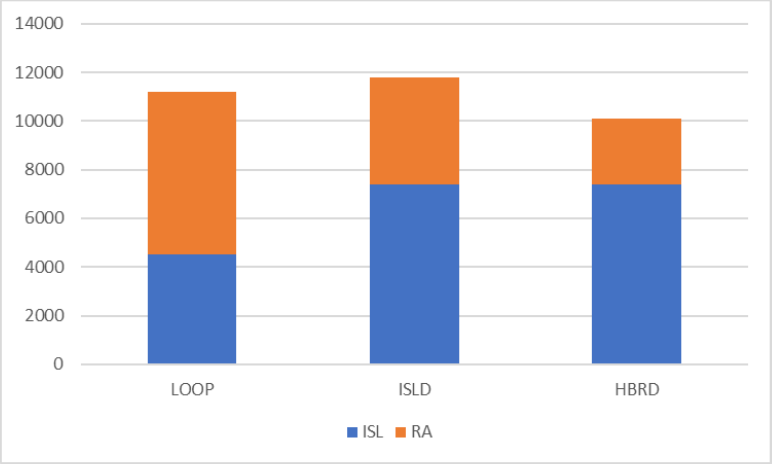

Fig. 27. EUE (MWh/y) Index at system level for TV transmission strategies

5.4.4 Manitoba Hydro

Manitoba Hydro uses probabilistic or risk-based methodologies inCSR analysis primarily to evaluate the reliability benefits of system enhancement alternatives and prioritize investments. Manitoba Hydro employs an analytical approach to simulate the performance of the composite power system. The approach employs a scenario-based technique and takes advantage of the calculation accuracy of a widely used commercial program for power flow analysis [329], [334], [374]. The approach also uses efficient computing techniques such as the breadth-first search algorithm and the recursive invocation method to facilitate probabilistic simulation of large systems [329], [334].

An in-house suite of simulation tools collectively called the System Reliability/Risk Model (SRRM) and described in sections 4.3 and 5.2 has been developed by the Manitoba Hydro Grid Infrastructure Planning (formerly System Planning) Department to perform CSR. Probabilistic reliability indices and other measures are input to a corporate wide project assessment and management system referred to as the Corporate Value Framework (CVF) evaluation process for scoring projects based on an assessment of the risks to be mitigated and the benefits to be realized by doing a project or a group of projects. Examples of applications are provided below.

Example 1: Comparison of Investment Alternatives

Fig. 28 illustrates use of SRRM to evaluate alternative solutions to a reliability problem. Project A represents a proposed capital investment to solve insufficient transformer capacity and low voltage issues in southwestern Manitoba. Five viable alternatives were identified. All of the options could be in place by 2025 and would last until approximately 2033. The cost of each option was estimated by the project management experts, while power system planning experts used SRRM to assess each option's impact on CSR performance. Four of the five options had a staged implementation that would result in partial reliability improvements occurring by 2022 to 2024, while Option 5 would not result in any reliability improvement until 2025.

Looking at implementation cost alone, Option 3 would seem to be the most attractive because it would cost the least. However, by converting the system reliability/risk result (ΔEUE in this case) into an avoided cost per year using a societal cost rate, it is possible to compare the present value of system reliability/risk mitigation with the present value of the spend profile (i.e., cost flow) of implementation costs, to see the net value of each option. Doing so reveals that Option 3's negative cost points are greater than its system reliability/risk points, yielding a negative net value. In other words, Option 3 would cost more than the value it would bring to improving system reliability. On the other hand, although Option 5 is the highest cost option it also had the highest value in terms of system reliability risk mitigation, yielding a positive net value of 30,000 points.

This demonstrates how risk-based analysis not only improves the decision-making process but also provides better clarity on how reliability-related decisions are reached.

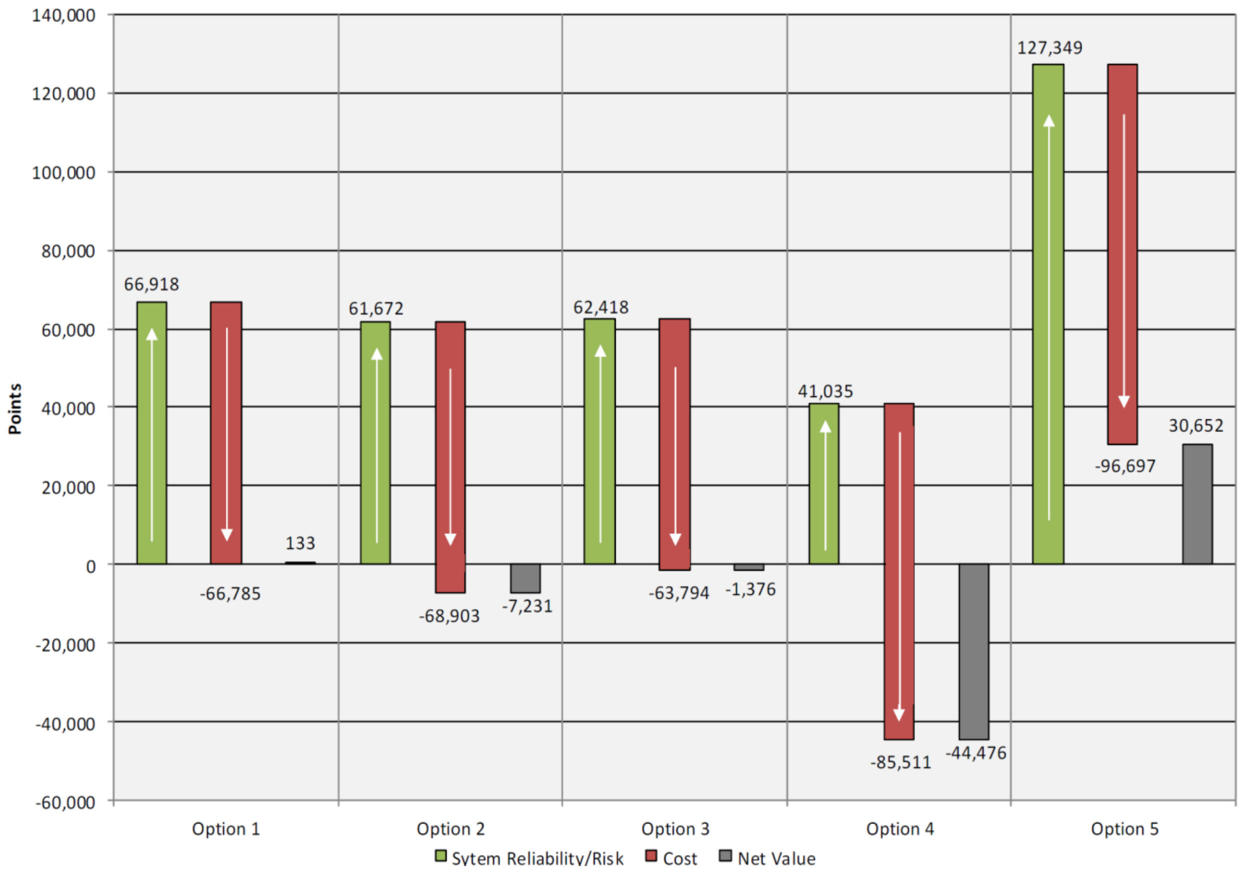

Fig. 28. Alternative Comparison (Project A)

Example 2: Prioritization of Investments

When capital funding or labor resources are limited, SRRM provides a means of prioritizing reliability-based projects to fit within those limits. Conversion of the system reliability/risk results (ΔEUE/(ΔEBE/ΔECE) into an avoided cost per year (using the societal cost rate) allows for a comparison of reliability risk mitigation vs. cost across a portfolio of projects, as demonstrated in Fig. 29. All eight projects shown were necessary and would eventually be completed; but funding or resources were limited at the time of the analysis, so not all of them could be completed in the planned timeframe.

Consider a simplified scenario of having funds equivalent to approximately 100,000 cost points, but only enough labor resources to do one project. To maximize use of the available funds, we might look at the project with a cost score closest to that limit, Project A. However, the cost score for Project D is also close, and it has a substantially higher score for system reliability/risk mitigation of 946,781 points compared to 127,349 points for Project A, such that its net value is more than 27 times greater than Project A, making Project D the clear choice for the given scenario.

As another situation, consider that there is not a resource limitation and the funding available is still the equivalent of 100,000 cost points. In that case, completing just Project D will mean the available labor resources will be under-utilized. However, the combination of Projects B plus Projects E to H has about the same cost points total (91,560) as Project D alone (95,702), and has about the same score for system reliability risk mitigation (922,297) as Project D alone (946,781). Completing the combination of projects will maximize the use of both the funding and labor resource availability, and achieve nearly the same net value as Project D alone, making it the clear choice for the given scenario.

Once again, risk-based analysis allows for more informed decision-making and provides a framework for communicating the rationale behind such decisions.

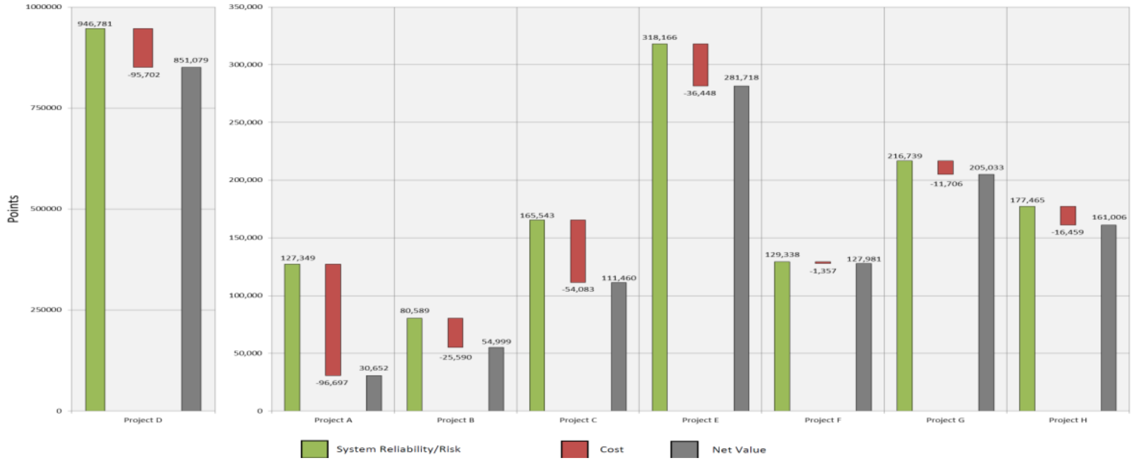

Fig. 29. Project Prioritization

5.5 Regulatory Policy and Compliance Assessment of NERC Reliability Standards

In the U.S., the Federal Energy Regulatory Commission (FERC) plays an important role in stimulating investment in the grid and has a broad range of regulatory and oversight roles. FERC is not the sole federal authority with an interest in the grid. Other federal agencies and departments with transmission responsibilities are the Department of Energy, Department of Homeland Security, and Nuclear Regulatory Commission.

The industry is advocating a number of regulatory policies, including that FERC work closely with state policy makers to:

- allow full recovery of all prudently incurred costs to design, study, pre-certify, and permit transmission facilities and allow full recovery of prudently incurred costs of transmission projects that are later abandoned
- ensure that the appropriate regulatory mechanisms are in place to allow for full cost recovery and avoidance of unrecoverable or trapped costs, which arise when federal and state regulatory polices diverge.

FERC is responsible for protecting the reliability of the bulk power system in the United States through setting, approving, and enforcing mandatory reliability standards—for example, through civil penalties—and has contractually delegated that responsibility to NERC. Thus NERC, whose members comprise all segments of the electric industry, is the entity that takes responsibility for ensuring that the bulk electric system in North America is reliable, adequate, and secure. NERC comprises eight regional reliability councils, which cover the continental United States, Canada, and parts of Mexico, and to which NERC has delegated authority to monitor and enforce compliance with reliability standards. For example, the Western Electricity Coordinating Council (WECC) is the regional council that enforces NERC standards for the Western region of the U.S.

The councils oversee compliance with NERC reliability standards such as TPL-001-5 (planning), TOP-001-5 (transmission operation), TOP-002-4 (operation planning), CIP-014-2 (physical security) etc. [3]. Utilities in North America must meet these standards to ensure that the grid is planned reliably and operated securely. The NERC reliability standards are continually evolving to keep pace with technological and regulatory changes. Existing standards are assessed and revised, and new standards are developed when necessary. Each of the reliability standards set by NERC is developed to support at least one of the reliability principles that form the foundation of North American power system operations. Together, the NERC standards help deliver an adequate level of reliability, as defined by specific power system characteristics, such as operating within acceptable limits, limiting the scope of cascading outages, and restoring service promptly following an outage.

The main purpose of NERC compliance studies by utilities in planning (Standard TPL_001-4) is to verify whether their systems are planned to operate reliably over a broad spectrum of system conditions and following a wide range of probable contingencies. The TPL-001-5 standard is developed to:

- ensure an annual planning assessment is performed on the BES
- identify planning events that cause an inability of the BES to meet the performance requirements
- develop corrective action plans to achieve required system performance for the listed system deficiencies
- simulate the actions of the protection system, automatic controls, and remedial action scheme (RAS) in contingency analyses
- identify the planning events and extreme events which are expected to produce more severe system impacts, and evaluate their consequences including cascading
- conduct a cascading evaluation to develop possible actions to reduce the cascading likelihood or “mitigate the consequences and adverse impacts” [3].

Contingencies in the TPL-001-5 standard are grouped into two categories:

1. planning events: seven categories of planning events designated P1-P7, with minimum performance criteria for each one
2. extreme events including loss of multiple facilities (generator, lines, etc.) simultaneously, which may result in a wide area disturbance such as voltage collapse, widespread interruptions, and cascading.

Extreme contingency events are triggered by many types of initial events, such as forced outages of system elements (lines, transformers, buses, circuit breakers, etc.), protection system failures or misoperation, natural incidents, reduced or lack of system awareness, cyber-attacks, failures of information communication technology systems used in protection and control, human errors, terrorist threats, and unpredictable fluctuating characteristics of renewable energy sources [296]. Identification and analysis of extreme contingencies are two challenges that system planners and operators face today due to the complexity of the power system infrastructures and complicated physical processes. The identification and mitigation of system risks and vulnerabilities, as results of extreme contingencies, are critical to ensuring the reliable operation of the BES.

To meet the compliance requirements the transmission planning method should be able to, at a minimum]–[:

- identify critical contingencies among studied planning events and extreme events
- develop and apply adequate mitigation measures to achieve required system performance
- rank critical contingencies by severity [375]–[379].

NERC planning and operation standards are based on deterministic planning and operating criteria and therefore identification and ranking of critical contingencies can be done by severity/impact. The likelihood of these contingencies is not taken into account. Deterministic system planning criteria have served the power industry well for many years. However, the weaknesses of deterministic planning criteria have also been unveiled. Many uncertain factors in power systems cannot be handled by traditional methods and deterministic criteria. Reference [63] presents a systematic and comprehensive approach for computing the probabilities of contingencies P1–P7 specified by the NERC standard TPL-001-4. These probabilities are useful for performing risk-based and probabilistic planning studies and can be computed from NERC data collection systems GADS, GADS-Wind, TADS, and MIDAS.

The necessity of probabilistic system planning has been gradually recognized and often discussed by researchers and utility engineers, with many challenges. To tackle these challenges, new tools that properly capture the probabilistic nature of bulk power system conditions and uncertainty of the rapidly changing power grid are needed (see section 2.8).

6. CONCLUSIONS AND FUTURE WORK

6.1 Conclusions

This report presents the state of the art in the area of composite system reliability (CSR) evaluation. Reliability assessment methods for composite generation and transmission systems have been developed in recent decades. However, maintaining an adequate level of reliability of the modern power grid is a challenging problem that utilities face today due to many causes such as frequent extreme events (e.g., failure of multiple physical components, extreme weather events, and other natural disasters), high penetration of intermittent renewables sources, and the increasing complexity of energy system infrastructure.

The main concerns for both planners and operators are to develop a system as reliable as economically feasible. Their common objective is to maintain adequacy, operational reliability, and integrity of the system at satisfactory levels, and avoid widespread outages. Furthermore, many of the concerns addressed by planners and operators are different. Planners think about long-term goals and want to ensure, at the very least, that plans for future systems are sufficiently adequate. Operators' goals depend on the time horizon of the study. In the shortest time frame (up to few hours), typical questions are how to provide adequate resources to keep the risk of system failure below predetermined levels, how to maintain the ability to withstand sudden changes, and how to employ corrective actions if they are needed.

The objective of this report is to provide guidelines and suggestions for power industry professionals who are considering applying probabilistic methods in composite system reliability. This report also investigates other factors that affect the use of probabilistic technics by electric utilities.

Through various case studies and results referenced in this report, power industry practitioners have demonstrated the benefits of performing probabilistic planning and operation reliability studies both separately and jointly with existing deterministic methodologies. Utilities can benefit by using value-based reliability analysis. Further, suggestions are provided about enhancing existing tools for power system software vendors.

In summary, probabilistic transmission planning is essential to develop the system as economically as possible and maintain an acceptable reliability level.

Based on extensive discussions and experience sharing among task force participants, including researchers, grid operators, utility companies, and software vendors, the task force has identified the most commonly seen concerns and challenges. The task force attempts to address these concerns through best practices learned from published literature, a task force survey, and users in the industry.

A survey, conducted by the IEEE Composite System Reliability Task Force indicates the key challenges and obstacles that companies experience in implementing probabilistic assessment. It also indicates that the high penetration of renewables in power systems such as photovoltaics and wind, retirement of coal plants, government policies, and regulatory requirements have significantly increased uncertainty in power systems. Therefore, existing deterministic approaches are no longer adequate to address these challenges. There is an evident need to develop a new generation of probabilistic methods, tools, and business practices to replace (or complement) the existing ones.

6.2 Future Work

As result of system changes and the increasing complexity, this report finds that further work is needed in areas of 1) data preparation, 2) modelling issues, 3) reliability indices, 4) computational methods, 5) computation tools, and 6) general issues and reliability framework.

6.2.1 Data preparation

A large amount of input data is needed for the reliability assessment of composite power systems using a probabilistic approach, which can be categorized as follow:

- Selection of scenarios, power flow data, system topology, equipment ratings and various loading conditions
- Load data represented as load duration curve (LDC) or chronological load variation curves and load forecast uncertainty (LFU), if necessary
- Component outage parameters

- VER reliability models including correlation between variable generation output and system demand
- Operational practices.

In future work electric utilities need to identify the type of data to be collected, what data are presently available, and what are the gaps for future planning and operating studies.

6.2.2 Modelling issues

This report's section 3.2 discusses various modeling and computational difficulties related to a power system and its components. For example, some improvements are needed for VER and storage modeling, modeling of contingencies, common-mode and dependent outages, market impacts, reactive power representation, operational practice and remedial actions. In general, the degree of sophistication in reliability modeling must match the computational accuracy.

6.2.3 Reliability indices

Further work is needed to establish which reliability indices need to be calculated to benchmark performance of the system and to guide planning and operating decisions. In addition, to better support decision-makers, approaches should be developed to present the sensitivity of these metrics to uncertainty in input parameters, as well as methods to support their calculation.

6.2.4 Computational methods

Reliability studies play an important role in ensuring the continuity and quality of power supply to customers. Developing more robust and efficient power system reliability assessment techniques plays a key role in improving reliability studies. Furthermore, traditional methods developed for CSR evaluation are not adequate to capture system complexity, increased integration of renewable energy sources, and data uncertainty, and therefore need to be revised. Developing new enhanced methods that consider these effects are needed. Organizations and utilities in North America (including NERC), Europe, Asia, and other places in the world have been looking for appropriate methodologies and computing tools. The deterministic criteria are based on the "worst case" study. Generally, system peak load is used as one of the worst conditions. But problems may not happen at peak load and the system can be exposed to risk under various other conditions. A hybrid approach, as a combination of deterministic and probabilistic approaches, might be one of the intermediate solutions for utilities to move forward in probabilistic transmission planning studies. Section 3.5 of this report notes that a variety of solution techniques may be needed to adequately address issues related to the CSR evaluation. Although algorithmic advances have been plentiful, many of these have been illustrated on relatively simple test systems. Care should be taken that such systems are representative of the algorithmic complexity faced by analysts. Finally, the Task Force also sees a substantial opportunity to leverage recent advances in machine learning, although concerns about the blackbox nature of some algorithms may need to be addressed before deployment as standard operating procedure.

Traditional reliability and production cost models are inadequate in reliability, operational reliability, and resilience planning, including transmission enhancements for timely implementing greenhouse gas mandates in the energy transition. A probabilistic multi-value transmission benefit assessment model is needed in composite reliability and resilience planning and operation that would enable quantification of benefits of an added transmission facility, including production cost benefits, emission reduction benefits, generation capital cost benefits, risk mitigation benefits, resource adequacy benefits, and resilience benefits.

6.2.5 Computational tools

Utilities and research organizations need to determine the requirements for composite system reliability tools to be developed by vendors. The existing CSR tools exhibit various deficiencies, as outlined in the Section 4 of the report. When aiming to overcome deficiencies of CSR tools and expand their practical applications, an appropriate tradeoff between computational burden and accuracy is critical. Overall, the gap between analysts' desires and the capabilities of available tools has persisted in spite of continuing algorithmic developments and improvements in processor speed. To advance this area further, it is essential to develop user-friendly probabilistic tools to be acceptable by utilities and regulatory organizations. There are several research directions for further development and enhancements in the area of CSR analysis that can be summarized below:

- Reducing the computational time and enhancing the capability of reliability assessment tools for handling large bulk power systems
- Developing more efficient algorithms for evaluating CSR and solving large-scale optimization problems
- Integrating aging and end-of-life failure models into CSR analysis
- Integrating common and dependent mode (CDM) failure models into CSR analysis
- Incorporating operating strategies into CSR analysis
- Applying CSR assessments for developing optimal schedules for building new facilities.
- Integrating multiple corrective actions into CSR analysis
- Incorporating the effects of various uncertainties into CSR analysis
- Considering storage and VERs in CSR analysis
- Considering customer and demand side flexibility in CSR analysis
- Incorporating FACTS devices such as phase shifter transformers (PSTs), thyristor controlled series compensators (TCSCs), and static var compensators (SVCs) into CSR analysis
- Integrating demand side management (DSM) into CSR analysis
- Considering weather conditions and seasonal changes in CSR analysis

- Integrating operational reliability criteria violations (cascading and transient stability) into CSR analysis.

6.2.6 Reliability framework

Utilities, together with NERC or the corresponding organization in their country or region, need to develop required standards for probabilistic BES planning and operation. This report provides useful references for the development of such guidelines and standards relevant to CSR adoption in the industry. Case studies from the literature demonstrate that probabilistic CSR assessment has advantages to deterministic assessment such as quantification of system and delivery point reliability and helps provide customers with optimal service reliability at the right cost. The movement towards reliability-based planning and operation criteria and models is inevitable. The advantages of probabilistic approaches are noticeable; but they are not widely used in practice. The necessity of probabilistic system planning has been gradually recognized and often discussed by researchers and utility engineers, with many challenges. To tackle these challenges, new tools that properly capture the probabilistic nature of a bulk power system and uncertainty of the rapidly changing power grid are needed.

Quantifying reliability would be critical if regulators insist on value-based benefit/cost analysis for projects exceeding a specific capital cost threshold.

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8. LIST OF ACRONYMS

Acronym	**Definition**
BES	Bulk Electric System
ALR	Adequate Level of Reliability
CIP	Critical Infrastructure Protection (NERC)
CPPS	Cyber-Physical Power System
CSR	Composite System Reliability
CI	Customer Interruptions
CIGRE	International Council on Large Electric Systems
DER	Distributed Energy Resources
DG	Distributed Generation
DOE	US Department of Energy
DORS	Dispatching Outage Reporting System
EENS	Expected Energy Not Serviced
ERCOT	Electric Reliability Council of Texas
EUE	Expected Unserved Energy
FERC	US Federal Energy Regulatory Commission
GADS	Generator Availability Data System
HILP	High Impact Low Probability (event)
HPLI	High Probability Low Impact (event)
IEEE	Institute of Electrical and Electronics Engineers
LOLE	Loss of Load Expectation
LOLP	Loss of Load Probability
MG	Microgrid
MISO	Midcontinent Independent System Operator
NARUC	National Association of Regulatory Utility Commissioners

NERC	North American Electric Reliability Corporation
NYSRC	New York State Reliability Council
OMS	Outage Management System
PES	Power Energy Society
PMAPS	Probabilistic Methods Applied to Power Systems
PNNL	Pacific Northwest National Laboratory
POM	Physical Operational Margins
PRA	Probabilistic Reliability Assessment
RES	Renewable Energy Sources
SG	Smart-Grid
SUBREL	Substation Reliability
TADS	Transmission Availability Data System
TRELSS	Transmission Reliability Evaluation of Large Scale Systems
T&D	Transmission and Distribution
VBR	Value Based Reliability
VER	Variable Energy Resources
VOLL	Value of Lost Load