



Data Development and Composite Probabilistic Adequacy Evaluation

Final Project Report

S-104G

Power Systems Engineering Research Center
*Empowering Minds to Engineer
the Future Electric Energy System*



Data Development and Composite Probabilistic Adequacy Evaluation

Final Project Report

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PSERC Publication 25-03

December 2025

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Acknowledgements

We wish to thank engineers at the New York Power Authority (NYPA) for their participation as advisors in this project. Shayan Behzadirafi met regularly with us, providing invaluable advice throughout the course of the project. In addition, he arranged for the graduate student supported by this project, Elijah Goossen, to spend the summer of 2024 at NYPA's offices as an intern. During this time, Mr. Goossen was supervised by Dr. Denis Osipov, the Manager of NYPA's Reliability Planning group, to whom we express appreciation, as the experience not only deeply added value to our project but also enhanced Mr. Goossen's knowledge of his research area.

Executive Summary

The reliability of the bulk power system has traditionally been assessed based on whether the time frame is operational, operational planning, or long-term planning, and based on whether the motivating concern is for transmission system performance or an adequate supply of generation to meet the load. Standard TPL-001-5 of the North American Electric Reliability Corporation (NERC), a standard for long-term planning, specifies seven types of contingencies, denoted P1-P7, and minimum performance requirements for each. Because TPL-001-5 generally requires a higher performance level for more likely contingencies, it is philosophically risk-based; however, it is deterministic in its implementation in that performance for a given contingency is either satisfied or it is not. Although TPL-001-5 is a planning standard, its essence is applied in operations as well, where performance following single component (so-called “N-1”) outage must be satisfactory. On the other hand, long-term evaluation of resource adequacy has long been assessed probabilistically, based on the probabilistic metric loss of load expectation (LOLE), with a general performance requirement guideline that LOLE be less than 0.1 day per year. We have also developed an approach called risk-based security assessment (RBSA) which applies a probabilistic measure to transmission system performance.

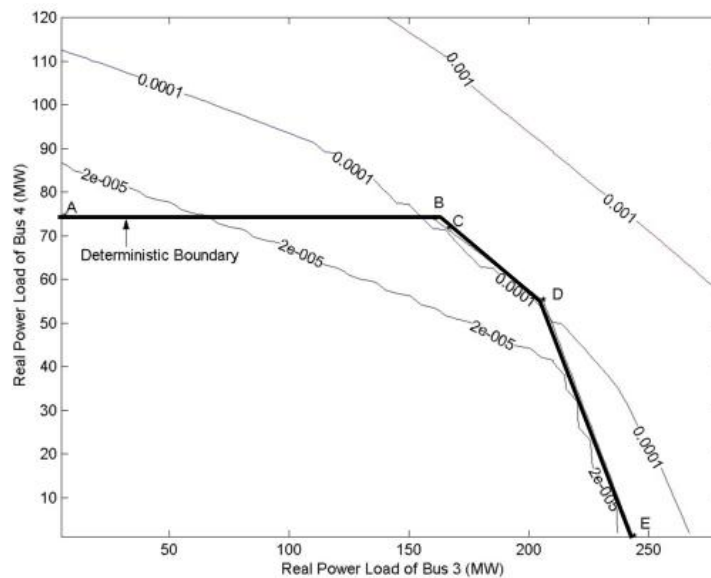
In this study, these three approaches, deterministic transmission assessment, probabilistic resource adequacy evaluation, and RBSA were compared. The deterministic transmission assessment approach and RBSA were illustrated on a utility subsystem; the power flow solver PSS[®]E was used for the deterministic approach, and in-house software was used for RBSA. Resource adequacy evaluation was evaluated on a US subregion using the Monte Carlo approach encoded within GE-Vernova’s application GE-MARS.

There were three main takeaways from this project.

1. ***Contingency probability estimation:*** A key tool necessary for probabilistic evaluation of transmission performance or of resource adequacy is the contingency probability estimation tool (CPET). CPET operates on the NERC databases Generation Availability Data System (GADS) and Transmission Availability Data System (TADS) to compute contingency probabilities for either short-term assessment as performed in real-time operations or in operational planning, or for long-term assessment as performed in long-term planning. These probabilities are essential for resource adequacy evaluation; they are also essential for risk-based transmission contingency evaluation. CPET has the ability to use GADS and TADS data characterizing only the geographical area of interest. In addition, if outage data for the geographical area of interest is sparse, CPET is capable of “borrowing strength” from outage data of other regions by appropriate statistical methods to increase the precision of the resulting estimates.
2. ***Risk-based security assessment:*** RBSA provides a metric to reflect the risk associated with an operating condition stemming from multiple contingencies, their occurrence probability, and the severity of the post-contingency system performance. This metric may be applied when the post-contingency performance problem is overload, undervoltage, voltage instability, or transient instability. We illustrated its use in this report for contingencies resulting in overload and undervoltage. The RBSA was originally intended to be used on-line, and we envision its initial trial to be done side-by-side with a conventional Energy Management System contingency processor. Although the RBSA

evaluation illustrated in this report is specific to an operating condition, it can also be deployed within a production cost simulator to provide cumulative risk and therefore to evaluate the performance of a long-term plan.

3. **Risk-aware decision-making:** The deterministic approach for evaluating system performance for contingencies can result in operational, operational planning, or long-term planning decisions that are risk-inconsistent. This means that some operating conditions identified as acceptable (secure) can actually be of higher risk than other operating conditions identified as unacceptable (insecure). The thick path A-B-C-D-E in the nomogram below represents the boundary between secure and insecure operating conditions based on the deterministic approach, for a particular power system. The thin lines represent contours of constant risk, where it is clear that points A and E have lower risk levels than points B, C, and D.



Our main conclusions in this project are that (i) CPET is a foundational tool for both resource adequacy analysis and for transmission system performance evaluation; (ii) the RBSA approach offers an approach to unify operations and planning transmission performance evaluation; and (iii) RBSA should be deployed side-by-side with an EMS contingency evaluator; it should also be built into a production cost simulator.

Project Publications:

- [1] Elijah Goossen, James McCalley, and Shayan Behzadirafti, “Data development and probabilistic adequacy evaluation,” to appear, Proc. of the North American Power Symposium, Oct. 26-28, 2025.

Student Theses:

- [1] Elijah Goossen, “Data development and probabilistic adequacy evaluation,” Masters of Science Thesis, Iowa State University. Graduated May, 2025.

Table of Contents

1. Introduction.....	1
1.1 Background.....	1
1.2 Literature review	1
1.3 Decision-making horizons.....	2
1.3.1 Operations.....	2
1.3.2 Operational planning	3
1.3.3 Long-term planning	4
1.4 Objective.....	5
1.5 Report Organization	6
2. Contingency probability estimation.....	7
2.1 Overview	7
2.2 Contingency probability estimation tool	7
2.2.1 Datasets.....	7
2.2.2 Internal model.....	7
2.2.3 P3/P6 model.....	9
2.2.4 Transition probabilities.....	10
2.2.5 State probabilities	10
2.3 “Borrowing strength” from larger datasets.....	11
2.3.1 Calculation of weights.....	12
2.3.2 Weighted averages.....	13
2.3.3 Weighted least squares regression.....	14
2.3.4 Illustration of weighted regression	15
2.4 Contingency probabilities.....	16
2.4.1 Branch contingency probabilities	16
2.4.2 Generation contingency probabilities.....	20
2.5 Discussion.....	20
3. Contingency evaluation using traditional deterministic limits	22
3.1 Overview	22
3.1.1 Deterministic contingency analysis.....	22
3.1.2 Deterministic transfer studies	23
3.1.3 PSS®E	23

3.2	Case studies	23
3.2.1	NYPA subsystem load growth	24
3.2.2	Corrective action	25
3.3	Discussion.....	26
4.	Traditional resource adequacy evaluation	28
4.1	Overview	28
4.1.1	Contingency modeling.....	28
4.1.2	Generation modeling	28
4.1.3	Transmission modeling	29
4.1.4	GE MARS	29
4.2	Case studies	30
4.2.1	NYPA subsystem load growth	30
4.2.2	500-bus NYISO reduced model load growth	31
4.3	Discussion.....	37
5.	Risk-based contingency analysis	39
5.1	Overview	39
5.1.1	Probability	39
5.1.2	Severity.....	39
5.1.2.1	Loss of load approach.....	40
5.1.2.2	Quality of service approach.....	41
5.1.3	On-line risk-based security assessment tool.....	41
5.1.3.1	Severity functions	41
5.1.3.2	Uncertainty	43
5.1.3.3	Additional features	43
5.1.4	PSS®E.....	44
5.1.4.1	Reports.....	44
5.1.4.2	Impact.....	45
5.1.5	Probabilistic contingency analysis	46
5.2	Case studies.....	47
5.2.1	NYPA subsystem load growth	47
5.2.2	NYPA subsystem heavy load	48
5.2.2.1	Effect of probability	49
5.2.2.2	Effect of non-violations.....	49

5.2.3	Corrective action	49
5.3	Discussion	50
6.	Conclusion	53
6.1	Summary.....	53
6.1.1	Deterministic contingency analysis	53
6.1.2	Resource adequacy assessment	53
6.1.3	Risk-based contingency analysis.....	55
6.2	Suggestions for future work	55
Appendix A:	Contingency probability estimation tool calculations.....	56
A.1	Line length calculation.....	56
A.2	Theoretical failure rate calculations	56
A.2.1	Submodel 1 – faulted component, protection working as designed	56
A.2.2	Submodel 2 – common structure	56
A.2.3	Submodel 3 – breaker/protection/bus section failure	56
A.2.4	Submodel 4 – various	57
A.3	Theoretical repair rate calculations	57
A.4	Implemented mean transition rates calculations	58
A.5	Markov model.....	59
Appendix B:	Contingency probability estimation tool error calculations	61
Appendix C:	Contingency probability estimation tool regional regression plots.....	62
Appendix D:	Severity functions.....	63
References		65

List of Figures

Figure 1-1: Reliability-Related Decisions: Type and Decision-Horizon [6, Fig. U17.2].....	2
Figure 1-2: A nomogram [12].....	4
Figure 1-3: Process overview.....	5
Figure 2-1: CPET internal Markov model [16, Figure 1].....	8
Figure 2-2: CPET P3/P6 Markov model, adapted from [19].....	9
Figure 2-3: Calculated regression weights by region	13
Figure 2-4: AC Line P1 Probability vs. Line Length.....	15
Figure 3-1: Power system operating state diagram, originally proposed in [23].....	22
Figure 3-2: Simplified subsystem model for NYPA subsystem load growth.....	24
Figure 3-3: Original scenario	26
Figure 3-4: Simulation of preventive action	26
Figure 5-1: OL-RBSA overload severity functions	42
Figure 5-2: PRA overload severity function.....	46
Figure 5-3: Nomogram with deterministic and probabilistic boundaries [12]	51

List of Tables

Table 2-1: Summary of contingency categories in TPL-001-5 [1, Table 1].....	8
Table 2-2: Summary of contingency categories [16, Table 1-3]	9
Table 2-3: Calculated regression weights by region.....	13
Table 2-4: Linear regression statistics	16
Table 2-5: Transmission Line Contingency Probabilities	17
Table 2-6: Transformer Contingency Probabilities	19
Table 2-7: Generation contingency probabilities.....	20
Table 2-8: Wind turbine generation contingency probabilities	20
Table 3-1: Summary of TPL-001-5 Disturbance Performance Table, adapted from [1, Table 1]	22
Table 3-2: Contingency Analysis Subsystem Results	25
Table 4-1: Summary of RA tools across ISO/RTOs from [33, Table 2]	30
Table 4-2: Resource adequacy subsystem results.....	31
Table 4-3: Calculated connected LOLE	32
Table 4-4: Calculated indices.....	32
Table 5-1: Summary of risk indices, adapted from [40]	43
Table 5-2: PSS®E Probabilistic Reliability Assessment Module available reports.....	44
Table 5-3: Risk-Based Contingency Analysis Subsystem PRA Under-Voltage Results	47
Table 5-4: Risk-Based Contingency Analysis Subsystem PRA Overload Results	47
Table 5-5: Risk-Based Contingency Analysis Subsystem OL-RBSA Low Voltage Results.....	48
Table 5-6: Risk-Based Contingency Analysis Subsystem OL-RBSA Overload Results	48
Table 5-7: Branch Overload Impact for 100% and 90% of Branch Loading (NYPA Subsystem 2050)	49
Table 5-8: Risk-impact of corrective action case study.....	50
Table 6-1: Insights into reliability-related questions	54

1. Introduction

1.1 Background

The power industry has historically analyzed the reliability of the bulk power system (BPS) using deterministic performance criteria on an enumerated set of contingencies. These criteria have served the industry well, resulting in an overall reliable system. The North American Electric Reliability Corporation (NERC) continues to use these criteria in standards such as TPL-001-5 [1], but the industry has also adopted some probabilistic methods of assessing reliability, especially in resource adequacy.

Recently, there has been a shift to using probabilistic methods not only in resource adequacy but also in assessment of the system network itself. These probabilistic methods are becoming more desirable for use in operational and planning decisions, especially with the increase in uncertainty from load growth and variable energy resources (VERs). The work presented in this thesis will examine three reliability-related assessments using both deterministic and probabilistic methods and will illustrate each assessment's application to decisions made in three different time horizons.

In this chapter, Section 1.1 provides additional background to the analysis of the reliability of the BPS and also provides definitions of terms used in this thesis. Section 1.2 provides an overview of three decision horizons—operations, operational planning, and long-term planning—and different decisions inherent to each horizon. Section 1.3 describes the objectives of this project and provides an overview of the remaining

1.2 Literature review

According to NERC, a reliable BPS is one that is able to provide the electrical needs of its end-use customers, even during unexpected equipment failures and other events that reduce the amount of available electricity. NERC defines the reliability of the BPS in terms of security (also referred to as operational reliability) and adequacy. Security refers to the capability of the system to withstand sudden disturbances while maintaining certain performance criteria such as the standards set by NERC in TPL-001-5 [1]. Adequacy refers to the ability of the system to continue to supply the aggregate demand of electricity at all times, accounting for scheduled and reasonably expected unscheduled outages [2], [3].

Reliability has historically been analyzed using deterministic assessments that test the performance of the BPS against disturbances selected based on their credibility, severity, and representatively [4]. The BPS was deemed reliable if it performed acceptably under the selected disturbances.

With the increase in uncertainty from VERs and government policies, there has been a recent trend toward using probabilistic assessments that would obtain a more refined view of the system's operating limits [3], [5]. Probabilistic analysis has the potential to provide more accurate system limits than the typically conservative deterministic limits, which would enable the operating of the system in a more economically advantageous state while still maintaining a reliable system.

The importance of a reliable BPS is increasing with electrification and the increasing dependency on electricity [3]. In order to maintain a reliable BPS, Independent System Operators (ISOs) and utilities need to be able to analyze the BPS accurately and properly account for uncertainties present in the system. Various assessments present different perspectives on the reliability of the BPS, giving decision-makers a more complete picture of the system on which to base their decisions.

1.3 Decision-making horizons

Reliability related decisions can be separated into different categories based on the timescale in question, as shown in Fig. 1.1. Operational decisions are those decisions in the shortest timescale, spanning from minutes to days. Operation planning decisions are on the order of days to one or two years, and planning decisions exceed two years. The nature of decisions differs across these different time scales, and so the methods and tools related to these time scales will also differ.

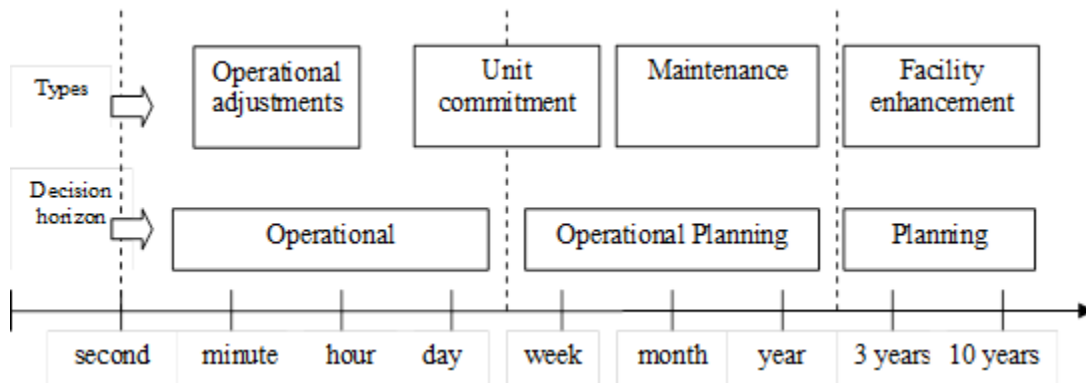


Figure 1-1: Reliability-Related Decisions: Type and Decision-Horizon [6, Fig. U17.2]

1.3.1 Operations

Operational decisions are made in real time to manage the current conditions of the power system and to adjust the operating condition in response to changes in load and generation [7]. To facilitate making these decisions, ISOs use energy management systems (EMSs) to monitor the real-time state of generation and transmission in the system, resulting in a model of the system with a high degree of certainty. Analysis of this known operating condition is important to inform the operators' decisions, making computation time a very important factor in methods used in operations.

Reliability criteria used in operations focus on operating the system in an economically advantageous way and ensuring that the system will perform adequately during any unscheduled event or disturbance [8, p. 11]. Reliability criteria that operators follow is NERC's Transmission System Planning Performance Requirements [1], which states that following any of several disturbances (specified as P1–P7), component loading and voltages within the system should remain within acceptable limits. A common example of this is ensuring N-1 compliance (identified in the NERC criteria as P1), where the loss of any one component in the system will not result in

violations. Operators will also ensure system security for other credible contingencies involving more than one component.

In addition to determining a desirable operating condition that meets performance requirements, operators must also adjust the operating condition in response to changes in load or generation to maintain the security of the system. While some changes in demand and generation are predictable, like the daily profile of electricity use, disturbances involving outages can be unplanned, and the operator must respond quickly to redispatch resources or change the system configuration.

1.3.2 Operational planning

Operational planning decisions are characterized by decisions made about the utilization of existing hardware. NERC requires that balancing authorities and transmission operators have plans outlining the operation of the system for the next day. This includes forecasting the demand and scheduling generation and power interchanges to meet this demand, as well as developing operating rules for operators to follow during normal and contingency events. Additionally, the plans must contain capacity and reserve requirements, and the system must be assessed to ensure it will remain within its operating limits under normal specified contingency conditions [9].

To obtain these required plans, decisions are made to determine the utilization of existing infrastructure over the course of weeks or months. Component maintenance must be scheduled such that components can be out of service without violating NERC's performance requirements. Depending on the region, energy bids and operational reserve bids in the day-ahead market need to be obtained, and unit commitment scheduling decisions must be made to accommodate intertemporal needs such as unit ramp rates, start up times, and shut down times.

Nomograms are a tool used in operational planning to help operators maintain the system in a secure state [10]; they are also used in the modeling of market constraints [11]. Nomograms visually depict the system state with respect to a number of parameters, usually two or three. The nomogram in Fig. 1.2 depicts a region of acceptable performance with respect to the real power loads at two buses, but parameters such as generation or line power flows are also used. The regions within a nomogram identify stress patterns within the system that do not cause insecurity. Fig. 1.2 shows the deterministic limits (this same nomogram together with contours of constant risk are illustrated in Chapter 5).

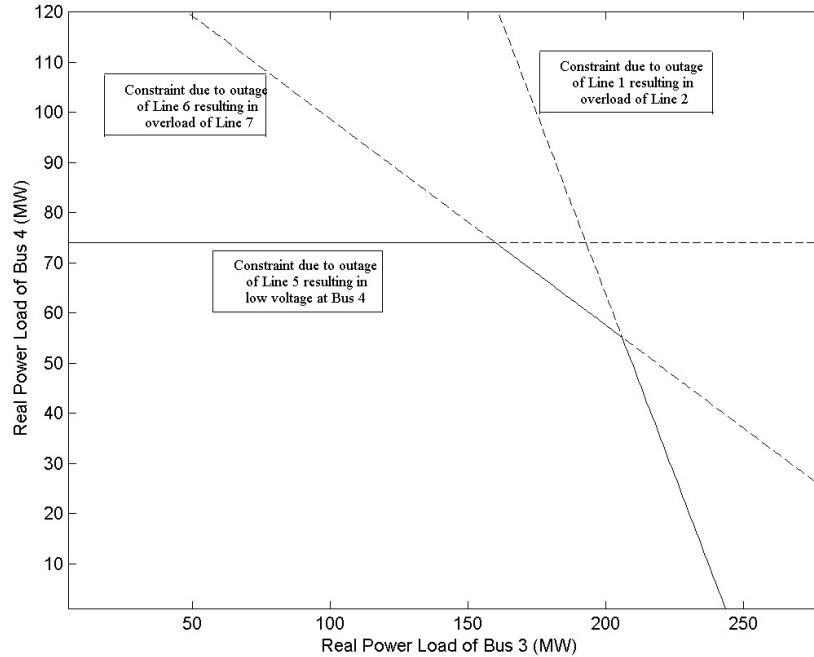


Figure 1-2: A nomogram [12]

Operational planning decisions are not only impacted by reliability concerns but also by other factors such as economics and technical limitations. The day-ahead and capacity markets inform some of these decisions, as generation is dispatched using the marginal pricing, but system configuration decisions can have an effect on these prices due to congestion. These decisions must also account for uncertainty in the operating condition, as decisions about unit commitment are based on demand forecasts which have uncertainties that increase with the forecast horizon.

1.3.3 Long-term planning

Long-term planning decisions are characterized by decisions involving changes to the existing infrastructure, for instance, facility enhancements or the addition or removal of facilities. System planners must also consider policy decisions, such as goals to move toward carbon-free energy. Infrastructure plans need to account for the subsequent retirement of fossil-fuel based resources and incorporating of newer energy resources such as wind and solar. Large load growth is another factor that plays into system planning, for example, the data centers being built in response to the growth of artificial intelligence (AI) and large plants for generating alternative clean fuel, such as hydrogen. Due to the nature of forecasting the system's environment, system planning decisions are associated with a lot of uncertainty which needs to be managed to ensure that the system is robust enough to satisfy future demand while continuing to meet reliability requirements.

System planning can be subdivided into two categories: resource planning and transmission planning. The goal of resource planning is to ensure adequate resources to supply the forecasted load as well as ancillary services such as frequency control and fast response. In addition, long-term planning needs to account for the distinct behaviors of different technologies. Some technologies, such as solar, are only available at certain times and are more difficult to dispatch,

whereas others, like natural gas, have higher availability and ease of dispatch, but are more expensive to operate. These factors all play into determining the ideal mix of resources needed to supply the demand [13].

The other aspect of system planning is transmission planning. Energy must be transferred effectively from the generation to the demand. Unlike thermal generation, the energy source for wind turbine generators and some other renewable resources cannot be relocated, so they must be built where the resource is instead of near load centers. This results in an increased demand for long-distance transmission, as seen by the Midcontinent Independent System Operator's (MISO) transmission planning efforts in Tranches 1 and 2.1 to improve reliability and facilitate renewable development [14] and New York State's Accelerated Renewable Energy Growth and Community Benefit Act, which outlines an extensive transmission plan to support the interconnection of renewables [15]. These efforts illustrate that transmission planning aims to reduce congestion, reduce costs, increase reliability, and provide more capacity for transferring power between generation and load [13].

1.4 Objective

The objective of the work described in this report is to develop and illustrate a functional system to calculate contingency probabilities and outage statistics from collected outage data and to demonstrate the use of this data in traditional contingency analysis, resource adequacy evaluation, and risk-based contingency analysis, illustrating the insight each assessment provides in relation to decisions in operations, operational planning, and long-term planning. Fig. 1.3 provides a visual representation of this process.

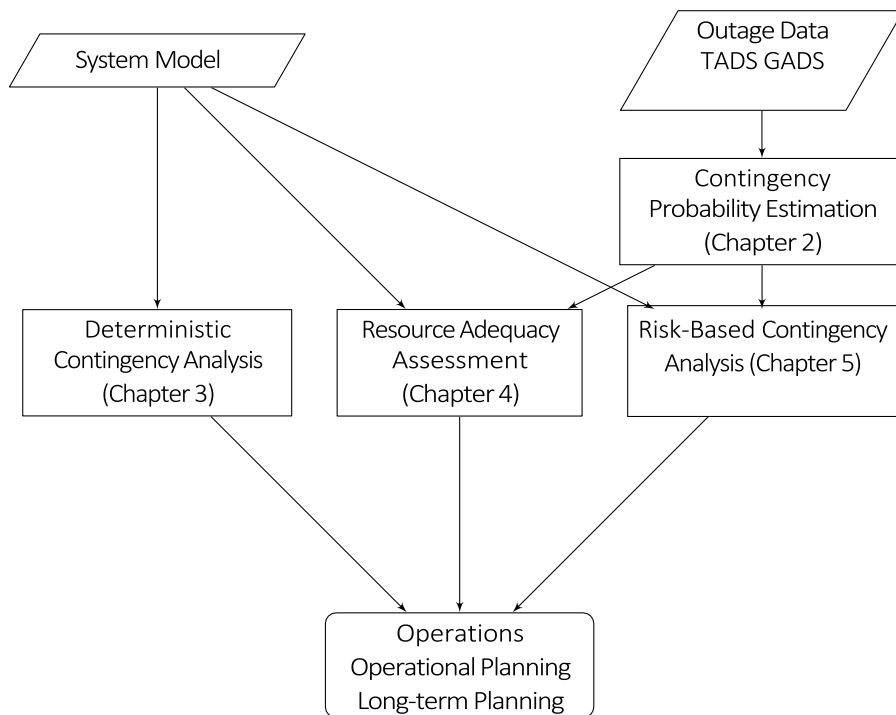


Figure 1-3: Process overview

1.5 Report Organization

This report is organized as follows. Chapter 2 provides an overview of the process of calculating probabilities of contingencies based on outage data collected by utilities. Chapter 3 describes the traditional process of performing contingency analysis with deterministic limits. Chapter 4 demonstrates the traditional probabilistic approach of resource adequacy assessment. Chapter 5 summarizes and illustrates reliability evaluation methods that include transmission, largely focusing on methods that evaluate loss of load and methods that use other metrics. Chapter 6 provides conclusions.

2. Contingency probability estimation

2.1 Overview

The first step in probabilistic reliability evaluation is to obtain contingency probabilities using equipment outage data. This is accomplished with the Contingency Probability Estimation Tool (CPET) [16], a tool developed at Iowa State University that uses data from NERC's outage datasets to estimate the probabilities of NERC's P1 to P7 contingencies. These probabilities are then used as input to the probabilistic reliability tools, discussed in Chapters 4 and 5. Although the development of CPET was not part of this work and is therefore not claimed as a contribution, CPET was used heavily in this thesis using industry data to develop the necessary probabilities and subsequently use those probabilities in probabilistic reliability evaluation.

2.2 Contingency probability estimation tool

2.2.1 Datasets

NERC maintains several datasets containing outage data for the bulk electric system (BES) across the USA. CPET was designed to use the Transmission Availability Data System (TADS) [17] and the Generating Availability Data System (GADS) [18]. TADS contains outage records for BES AC circuits, transmission transformers, and BES DC converters and circuits. GADS contains outage records for generation resources, divided into smaller datasets for conventional generation (GADS-Conventional, hereafter referred to as GADS), wind turbine generation (GADS-Wind), and solar generation, (GADS-Solar). Both of these datasets contain information about the type, time, and duration of each outage, as well as the type, capacity or length, and NERC region of each component associated with an outage. This information allows CPET to pool similar components together and estimate outage and repair rates, as discussed in following sections.

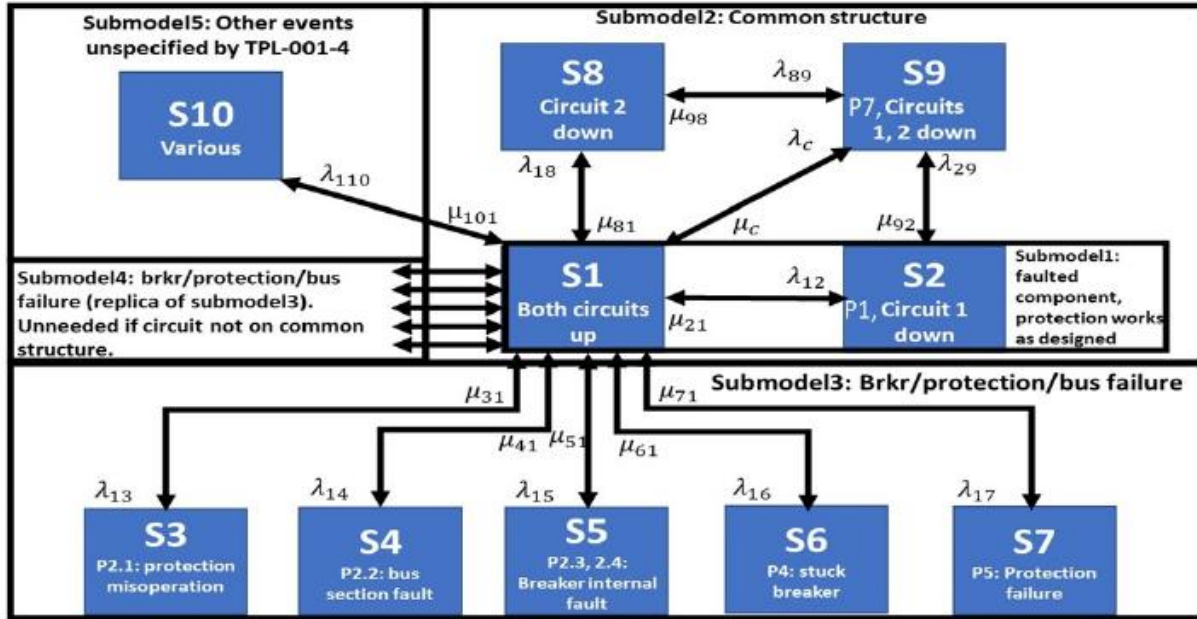
2.2.2 Internal model

CPET estimates the probabilities of NERC's P1 to P7 contingencies shown in Table 3.1 using the ten-state Markov model shown in Fig. 2.1.

Table 2-1: Summary of contingency categories in TPL-001-5 [1, Table 1]

Category	Contingency Type	Description
P0	None	Normal system
P1	Single	Loss of a single component
P2	Single	Loss of a single component due to protection failure
P3	Multiple	Loss of generator unit followed by loss of a single component
P4	Multiple	Loss of multiple elements caused by a stuck breaker
P5	Multiple	Fault plus non-redundant component of a protection system failure to operate
P6	Multiple	Two overlapping single contingencies
P7	Multiple	Common structure failure

Figure 2-1: CPET internal Markov model [16, Figure 1]



Each of the ten Markov states of Fig. 2.1 corresponds to a subcategory within NERC's P1 to P7 contingency definitions, as shown in Table 2.2. The transition probabilities are calculated using outage data, either from the utility's records or from other databases such as NERC's TADS and GADS databases. The outages within these databases are sorted into different categories using the event type number (ETN) and the type of initiation. The failure and repair rates for each component are calculated from the number of outages, outage durations, and total service length of each component [16].

Table 2-2: Summary of contingency categories [16, Table 1-3]

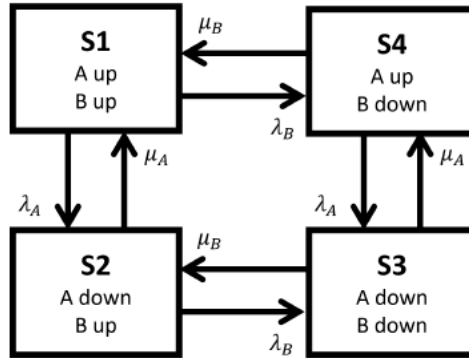
TPL Contingency Type	CPET Markov State	Event Type Numbers
P0	S1	N/A
P1	S2	10, 11, 13, 49, 50, 90, single mode & dependent mode initiating outages
P2.1	S3	62 without fault
P2.2	S4	5
P2.3 & P2.4	S5	6
P3	N/A	N/A
P4	S6	60
P5	S7	61
P6	N/A	N/A
P7	S9	31 & two independent common structure outages

2.2.3 P3/P6 model

The P3 and P6 contingency types are N-1-1 contingencies, meaning that one component outage is followed shortly by an independent outage of a separate component. The long-term probabilities from Fig. 2.1 cannot be used for these types of contingencies since the second component must fail within a short time period of the first, specified at 30 min. A separate Markov model for P3 and P6 contingencies is described in [16], [19] and shown in Fig. 2.2. The four-state model involves two components, A and B, with failure rates λ_A and λ_B , and repair rates μ_A and μ_B , respectively. A P3 or P6 contingency involves component B failing within time t of component A, which corresponds to the probability of entering state S3 from state S2 within time t . As described in [19], the probability of a P3 or P6 contingency occurring is given by

$$P(S3) = P(S2) \cdot \frac{\lambda_B (e^{-\lambda_B t} - e^{-(\mu_A + \mu_B)t})}{\mu_A + \mu_B - \lambda_B} \cdot e^{-\mu_A t} \quad (2.1)$$

where $P(S2)$ is the probability that A will fail and $t = 0.5$ h. The P3 and P6 multi-element contingencies are not specifically analyzed further in this report.

**Figure 2-2: CPET P3/P6 Markov model, adapted from [19]**

2.2.4 Transition probabilities

Two types of probabilities can be calculated from this Markov model. The first type is the transition probabilities, which represent the probability that the component will fail at any given time over the next time period t . This probability is more useful on the short-term timescale, as it answers the question, “Given the current state of the component, what is the probability that it will fail now?” The transition probabilities give the operators a sense of which contingencies are more likely in the near future, e.g., over the next hour.

CPET calculates each transition rate λ in Fig. 2.1 by analyzing component outage data from GADS, TADS, or utility data. For each group of components, CPET divides the number of outages for a specific contingency type (NERC P1–P7) by the total in-service time of the group of components,

$$\lambda = \frac{\sum_i N_i}{\sum_i T^{(I)}_i} . \quad (2.2)$$

Assuming that the probability of a contingency’s occurrence is modeled by a Poisson process, in which the likelihood of occurrence only depends on the present state of the component, the probability of a specific contingency or type of contingency within the next time period can be calculated using

$$P_n(t) = \frac{(\lambda t)^n e^{-\lambda t}}{n!} \quad (2.3)$$

where λ is the transition rate to the Markov state corresponding to the specific contingency type, and n is the number of failures within the time period t . Since repair times typically exceed one hour, only one failure can occur within an hour, so for the short time periods associated with operations, (2.3) simplifies to

$$P(t) = \lambda t e^{-\lambda t} . \quad (2.4)$$

2.2.5 State probabilities

The second type of probability is the state probabilities from the Markov model, referred to as long-term or long-run probabilities; they are also sometimes called “steady-state” probabilities. These probabilities are useful in planning, as they answer the question “Given the data for this component, what percent of time will it exist in a specific outage state?” This probability does take the repair time into account, since the amount of time the component remains offline affects the probability that it will be offline in a given hour during the year.

The state probabilities of the Markov model shown in Fig. 2.1 are given by

$$\dot{\mathbf{p}} = \mathbf{A}\mathbf{p} \quad (2.5)$$

where the state probability vector $\mathbf{p}$ is given by

$$\mathbf{p} = \begin{bmatrix} p_1 \\ p_2 \\ \vdots \\ p_n \end{bmatrix} \quad (2.6)$$

for states s_1 to s_n , and the transition matrix A is given by

$$\lambda_i = - \sum_{\substack{j=1 \\ j \neq i}}^n \lambda_{ij}. \quad (2.8)$$

(See Section A.5 for the derivation of (2.8)) The long term state probabilities can be obtained by setting $dp/dt = 0$ and replacing one equation with $\sum p_i = 1$, since only $n - 1$ equations in (2.5) are linearly independent. Equation (2.5) becomes

$$\begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix} = \begin{bmatrix} 1 & 1 & \cdots & 1 \\ \lambda_{12} & \lambda_2 & \cdots & \lambda_{n2} \\ \vdots & \vdots & \ddots & \vdots \\ \lambda_{1n} & \lambda_{2n} & \cdots & \lambda_n \end{bmatrix} \begin{bmatrix} p_1 \\ p_2 \\ \vdots \\ p_n \end{bmatrix}. \quad (2.9)$$

Using the mean failure rates λ_{ij} and repair rates $\mu_{ij} = \lambda_{ji}$ as the transition probabilities, the long-term state probabilities for Fig. 2.1 can be calculated using (2.9). Appendix A and [16] include more in-depth calculations.

2.3 “Borrowing strength” from larger datasets

CPET was designed to use NERC’s TADS and GADS databases to calculate contingency probabilities and has been adapted to process outage data from individual utilities. However, due to the relatively low failure rate of individual components, the number of observations within an individual utility’s outage data may be very small, making it difficult to obtain statistically significant outage and repair rates. Increasing the size of the dataset by using TADS and GADS increases the statistical significance of the results, but doing so loses the focus on the individual utility’s assets and may result in less accurate estimates for that utility’s failure and repair rates. To address this problem, it is desirable to “borrow strength” from large datasets such as TADS and GADS while remaining focused on the individual utility’s assets.

“Borrowing strength” refers to a type of statistical method that seeks to increase the precision of estimates from small or sparse samples by using information from related samples or populations. An example of this type of method is a Bayesian hierarchical model, which forms a complex predictive model using information on the individual and group levels to inform estimations about the other level. Another example is the James-Stein Estimator, which is useful in increasing the

precision of multiple distributions by “shrinking” estimates toward a central value and thereby increasing the reliability of the estimates. The approach taken in this project uses weighted averaging and weighted least-squares linear regression to obtain this “borrowed strength.” Doing so only requires slight modification of CPET’s code to introduce the necessary weights.

2.3.1 Calculation of weights

The method of calculating weights should ensure that statistics obtained from the larger dataset (the national data in our case) will apply on the utility scale. For instance, the national datasets include data from areas like Texas or California which have warmer climates than New York, so statistics calculated from these data will not be as applicable in New York as statistics calculated using data from Pennsylvania, which has a climate much more similar to New York. Additionally, outage and repair rates may be affected by factors such as terrain or policy decisions, which can vary significantly across the country. The statistics should therefore be biased toward the region surrounding the utility of interest, while still receiving input from the larger dataset to ensure conclusions are based on enough data and are statistically valid.

The data available from NERC anonymizes utility names and precise locations in order to protect the critical energy infrastructure information (CEII) data of the various utilities; however, the TADS and GADS datasets include the NERC reliability council information for each component which can be used to geographically locate each component. By assigning a weight to each reliability council, outage statistics can be biased based on proximity to regions of interest.

The statistical similarity of regions with respect to proximity was assumed to vary by an inverse-square relationship similar to other interactions that obey distance decay. The region weights w_i are calculated as

$$w_i(d_i) = \frac{1}{d_i^2} \quad (2.10)$$

where d_i is the distance from the location of interest. The weights are normalized by dividing by the maximum weight so that the study region has a unity weight. A nonzero distance should be assigned to the area of interest to avoid the vertical asymptote at $d_i = 0$ in (2.10). Keeping the distance of the study area within one or two orders of magnitude of those of the other regions ensures that the weighting does not skew toward the study region so much as to make the effects of other regions negligible.

For this project, outage data was weighted based on its proximity to New York State. Table 2.3 and Fig. 2.3 show the calculated weights for each region.

Table 2-3: Calculated regression weights by region

Region	Distance ^a $\sqrt{(\Delta\text{deg}_{\text{lat}})^2 + (\Delta\text{deg}_{\text{lon}})^2}$	Weight
ERCOT	26.458	0.033
FRCC	15.920	0.091
MRO	22.564	0.045
NPCC	4.802	1.000
RFC	5.261	0.833
SERC	14.021	0.117
SPP	23.206	0.043
WECC	38.604	0.015

^a Each region is assumed to be located at the average of the centers of area of the component states and provinces

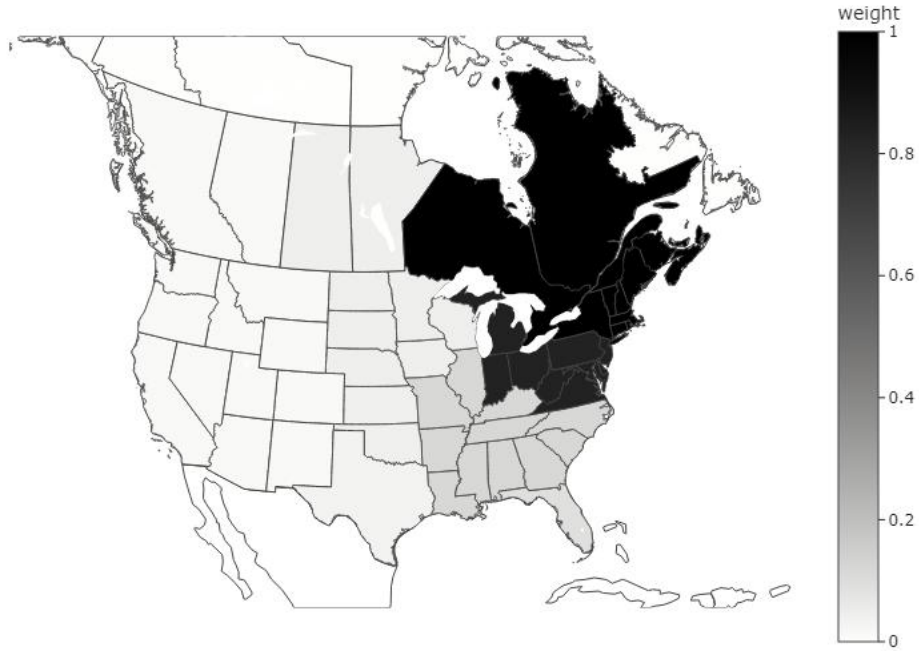


Figure 2-3: Calculated regression weights by region

2.3.2 Weighted averages

CPET uses (2.2) to calculate the mean failure rate within a group of components. Equation (2.2)

can be derived using weighted averaging, where each failure rate λ_i , expressed in component failures per year¹, is weighted by the in-service duration $T_i^{(I)}$ corresponding to that component, or

$$\bar{\lambda} = \frac{\sum_i T_i^{(I)} \lambda_i}{\sum_i T_i^{(I)}}. \quad (2.11)$$

Recognizing that the failure rate is equal to the number of failures N_i divided by the in-service duration, or $\lambda_i = N_i/T_i^{(I)}$, this becomes (2.2), repeated here:

$$\bar{\lambda} = \frac{\sum_i N_i}{\sum_i T_i^{(I)}}. \quad (2.2)$$

Equation (2.2) is a ratio of averages (RoA) since both the numerator and denominator are implicitly divided by the total number of components.

By changing the weights in (2.11) from $T_i^{(I)}$ to $w_i T_i^{(I)}$ and simplifying, (2.2) becomes

$$\bar{\lambda} = \frac{\sum_i w_i N_i}{\sum_i w_i T_i^{(I)}}, \quad (2.12)$$

allowing the inclusion of component weights into the mean failure rate calculation.

Similarly, the weighted mean repair rate $\bar{\mu}$, expressed in repairs per year², can be shown to be

$$\bar{\mu} = \frac{\sum_i w_i N_i}{\sum_i w_i T_i^{(O)}} \quad (2.13)$$

where N_i is the number of outages for component i , and $T_i^{(O)}$ is the total out-of-service time for component i .

Equations (2.12) and (2.13) maintain the original bias towards components that have been in service for a longer period of time, while allowing CPET to bias the failure and repair rates toward outage data that is more similar to the components for which the rates are being estimated.

2.3.3 Weighted least squares regression

CPET uses MATLAB's linear regression function `fitlm` to estimate the correlation of failure or repair rates with other variables. The linear regression model takes the form

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon} \quad (2.14)$$

where $\mathbf{y}$ is the response vector, $\boldsymbol{\beta}$ is the vector of coefficients, $\mathbf{X}$ is a matrix where each column is a vector of values for a predictor variable, and $\boldsymbol{\epsilon}$ is the error vector. MATLAB solves for $\boldsymbol{\beta}$ by minimizing the sum of squared errors (SSE), given by

¹ The failure rate is equivalent to the reciprocal of the mean time to failure (MTTF). Mean time between failures (MTBF), mean time to failure (MTTF), and mean time to repair (MTTR) may have different definitions depending on the source. Here they are used as defined in [20], that is, MTTF + MTTR = MTBF.

² The repair rate is the reciprocal of the mean time to repair (MTTR).

$$SSE = \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (2.15)$$

where y_i is the i^{th} observation, and $\hat{y}_i$ is the i^{th} calculated value. MATLAB allows weights to be added to observations used in `fitlm`. The calculation of the SSE is changed to

$$SSE = \sum_{i=1}^n w_i (y_i - \hat{y}_i)^2 \quad (2.16)$$

where w_i is the weight of the i^{th} value [21]. While weighted regression is typically used to bias the linear model toward certain data points to account for unequal variances, here weighting is used to bias the model toward data points that are more relevant to the desired utility's assets.

2.3.4 Illustration of weighted regression

Fig. 2.4 shows the effect of weighting on the linear regression. Fig. 2.4a shows the linear regression model between P1 failure rates and line length using only the New York Power Authority (NYPA) outage data. The usefulness of this model can be determined by calculating the statistical significance, or p-value, of the regression slope. The p-value is a statistical method which indicates the probability of obtaining the regression slope from a dataset with no correlation. The significance threshold was set to $p = 0.05$, corresponding to a 5% chance that the given regression equation was obtained from a dataset with no correlation, or conversely, a 95% probability that the data does in fact have a correlation. As seen in Table 2.4, the correlation between failure rate and line length in this dataset is not significant ($p > 0.05$).

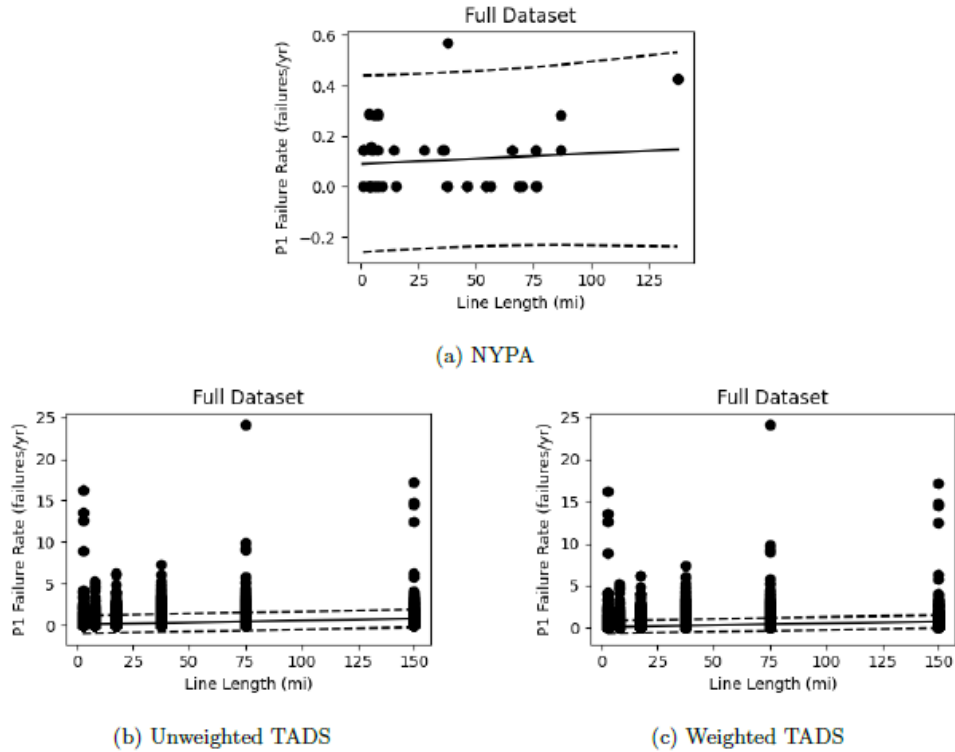


Figure 2-4: AC Line P1 Probability vs. Line Length

Performing linear regression on the TADS dataset, shown in Fig. 2.4b and Table 2.4, indicates a statistically significant relationship ($p < 0.05$) between line length and P1 failure rates. The amount of variation explained by the predictor variable, i.e., transmission line length, is quantified using the coefficient of determination (R^2). A higher value of R^2 indicates that the model accounts for more of the variation, while a lower value of R^2 indicates that there is more variation not explained by the model. Although this model has a low value for R^2 , its statistical significance indicates that transmission line length does explain some variation in failure rates.

Table 2-4: Linear regression statistics

Case	R2	p-value
NYPA	0.0107	0.508 92
Unweighted TADS	0.0728	≈ 0
Weighted TADS	0.0664	≈ 0

Figure 2.4c and Table 2.4 show the linear regression model generated from the TADS dataset using the weighted regression model described in Sections 2.3.1 and 2.3.3. While the change in the slope of the model is very small, the 95% confidence intervals are visibly narrower than they are in Fig. 2.4b. This occurred because weighting biased the regression function toward the Northeast Power Coordinating Council (NPCC) and Reliability First Corporation (RFC) data, which have tighter spreads, and away from the Midwest Reliability Organization (MRO) data, which contains more of the high P1 failure rates. (See Appendix C for P1 failure rates plotted by region.) This model shows stronger evidence that a relationship exists between line length and failure rate than in the utility data alone ($p < 0.05$), while remaining more tightly coupled to the data from the northeast part of the country around NYPA's assets.

2.4 Contingency probabilities

CPET was used to estimate the probabilities of P1 to P7 contingencies for NYPA assets, summarized in Tables 2.5 to 2.8. P3 and P6 events were excluded for this analysis.

2.4.1 Branch contingency probabilities

Transmission lines were grouped by voltage level to ensure differences in failure rates due to varying materials or construction and design methods between voltage classes are captured. It is reasonable to assume that the failure rate of a transmission line is correlated to its length, therefore linear regression was performed for transmission line P1 contingencies (S1–S2 transition rates) with respect to line length. CPET also uses this regression for P7, or common structure, contingencies (S1–S9 transition rates), since common structure rates are also assumed to correlate with line length. The other contingency types are related to bus faults, breaker faults, and protection faults, which are not correlated to the length of the transmission line, so linear regression was not performed for these contingency types. Table 2.5 shows the effects of grouping and of regression. All state probabilities vary from one voltage class to another, while

within a voltage class, only P1 and P7 state probabilities and mean failure rates³ λ_{12} vary significantly with line length and the other state probabilities and the mean repair rates⁴ μ_{21} remain fairly constant.

As mentioned previously, linear regression was not applied to P2, P4, or P5 contingencies; however, the state probabilities associated with these contingency types vary slightly within each voltage class due to differing line lengths. This is because the state probability of a state within a Markov model is a function of all the transition rates, not just the transition rates to and from that state, as seen from (2.7) and (2.9).

Table 2-5: Transmission Line Contingency Probabilities

ID	Length (mi)	P1 ($\times 10^{-6}$)	P2.1 ($\times 10^{-6}$)	P2.2 ($\times 10^{-6}$)	P2.3 & P2.4 ($\times 10^{-6}$)	P4 ($\times 10^{-6}$)	P5 ($\times 10^{-6}$)	P7 ($\times 10^{-6}$)	λ_{12} (failure/yr)	μ_{21} (repair/yr)
Voltage Class 1										
L-1	7.2	158.753	4.709	3.195	3.674	2.302	0.388	0.435	0.079	499.233
L-2	7.2	158.753	4.709	3.195	3.674	2.302	0.388	0.435	0.079	499.233
L-3	7.2	158.753	4.709	3.195	3.674	2.302	0.388	0.435	0.079	499.233
L-4	3.8	121.777	4.709	3.195	3.675	2.303	0.388	0.229	0.061	499.233
L-5	3.8	121.777	4.709	3.195	3.675	2.303	0.388	0.229	0.061	499.233
L-6	5.0	134.382	4.710	3.195	3.675	2.303	0.388	0.000	0.067	499.233
Voltage Class 2										
L-7	9.3	144.526	5.089	3.195	1.630	1.868	0.505	0.000	0.082	567.925
L-8	4.3	128.456	5.088	3.195	1.629	1.868	0.505	0.255	0.073	567.925
L-9	4.3	128.456	5.088	3.195	1.629	1.868	0.505	0.255	0.073	567.925
L-10	86.7	399.406	5.086	3.193	1.629	1.867	0.505	5.066	0.224	567.925
L-11	86.7	399.406	5.086	3.193	1.629	1.867	0.505	5.066	0.224	567.925
L-12	5.7	133.169	5.088	3.195	1.629	1.868	0.505	0.338	0.075	567.925
L-13	5.7	133.169	5.088	3.195	1.629	1.868	0.505	0.338	0.075	567.925
L-14	37.4	235.252	5.089	3.195	1.630	1.868	0.505	0.000	0.134	567.925
L-15	37.6	235.963	5.089	3.195	1.630	1.868	0.505	0.000	0.134	567.925
L-16	4.4	128.667	5.089	3.195	1.630	1.868	0.505	0.000	0.073	567.925

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³ CPET reports the S1–S2 transition rate as the mean failure rate.

⁴ CPET reports the S2–S1 transition rate as the mean repair rate.

Table 2.5 – *Continued from previous page*

ID	Length	P1	P2.1	P2.2	P2.3 & P2.4	P4	P5	P7	λ_{12}	μ_{21}
	(mi)	($\times 10^{-6}$)	($\times 10^{-6}$)	($\times 10^{-6}$)	($\times 10^{-6}$)	($\times 10^{-6}$)	($\times 10^{-6}$)	($\times 10^{-6}$)	(failure/yr)	(repair/yr)
L-17	15.2	163.702	5.089	3.195	1.630	1.868	0.505	0.000	0.093	567.925
L-18	27.2	202.204	5.089	3.195	1.630	1.868	0.505	0.000	0.115	567.925
L-19	6.4	135.261	5.089	3.195	1.630	1.868	0.505	0.000	0.077	567.925
Voltage Class 3										
L-20	46.1	247.273	6.906	3.195	4.094	3.363	1.161	0.000	0.132	534.890
L-21	54.3	284.118	6.903	3.194	4.093	3.362	1.161	4.911	0.149	534.890
L-22	54.3	284.118	6.903	3.194	4.093	3.362	1.161	4.911	0.149	534.890
L-23	13.9	120.979	6.906	3.195	4.095	3.364	1.161	0.000	0.065	534.890
L-24	75.8	363.732	6.905	3.194	4.094	3.363	1.161	0.000	0.195	534.890
L-25	69.8	339.937	6.905	3.195	4.094	3.363	1.161	0.000	0.182	534.890
L-26	0.8	69.646	6.907	3.195	4.095	3.364	1.161	0.000	0.037	534.890
L-27	35.3	204.810	6.906	3.195	4.094	3.363	1.161	0.000	0.110	534.890
L-28	37.2	212.164	6.906	3.195	4.094	3.363	1.161	0.000	0.114	534.890
L-29	35.9	207.103	6.906	3.195	4.094	3.363	1.161	0.000	0.111	534.890
L-30	75.8	363.495	6.905	3.194	4.094	3.363	1.161	0.000	0.195	534.890
L-31	45.8	245.850	6.906	3.195	4.094	3.363	1.161	0.000	0.132	534.890
L-32	0.7	68.986	6.906	3.195	4.094	3.363	1.161	0.063	0.037	534.890
L-33	0.7	68.986	6.906	3.195	4.094	3.363	1.161	0.063	0.037	534.890
L-34	68.3	340.110	6.902	3.193	4.092	3.362	1.161	6.185	0.179	534.890

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Table 2.5 – Continued from previous page

ID	Length (mi)	P1 ($\times 10^{-6}$)	P2.1 ($\times 10^{-6}$)	P2.2 ($\times 10^{-6}$)	P2.3 & P2.4 ($\times 10^{-6}$)	P4 ($\times 10^{-6}$)	P5 ($\times 10^{-6}$)	P7 ($\times 10^{-6}$)	λ_{12} (failure/yr)	μ_{21} (repair/yr)
L-35	68.3	340.110	6.902	3.193	4.092	3.362	1.161	6.185	0.179	534.890
L-36	3.2	78.980	6.907	3.195	4.095	3.364	1.161	0.000	0.042	534.890
L-37	3.2	78.980	6.907	3.195	4.095	3.364	1.161	0.000	0.042	534.890
L-38	7.6	96.144	6.907	3.195	4.095	3.364	1.161	0.000	0.051	534.890
L-39	65.3	322.544	6.905	3.195	4.094	3.363	1.161	0.000	0.173	534.890
L-40	76.5	366.428	6.905	3.194	4.094	3.363	1.161	0.000	0.196	534.890
L-41	1.4	71.624	6.907	3.195	4.095	3.364	1.161	0.000	0.038	534.890
Voltage Class 4										
L-42	56.0	216.913	5.462	3.195	3.162	2.258	0.512	0.000	0.114	523.193
L-43	137.6	562.594	5.460	3.194	3.161	2.257	0.512	0.000	0.295	523.193

In contrast to transmission lines, transformers are not reported with a “length” component. Regression is therefore not performed on the transformer outage data. Data is still grouped by high-side voltage, as different voltage classes may have different failure rates due to factors including different materials or design. As shown in Table 2.6, all the transformers within a voltage class have the same failure and repair rates, as well as state probabilities.

Table 2-6: Transformer Contingency Probabilities

ID	P1 ($\times 10^{-6}$)	P2.1 ($\times 10^{-6}$)	P2.2 ($\times 10^{-6}$)	P2.3 & P2.4 ($\times 10^{-6}$)	P4 ($\times 10^{-6}$)	P5 ($\times 10^{-6}$)	λ_{12} (failure/yr)	μ_{21} (repair/yr)
Voltage Class 2								
T-1	118.600	9.757	3.195	0.736	1.932	1.829	0.027	231.683
T-2	118.600	9.757	3.195	0.736	1.932	1.829	0.027	231.683
T-3	118.600	9.757	3.195	0.736	1.932	1.829	0.027	231.683
T-4	118.600	9.757	3.195	0.736	1.932	1.829	0.027	231.683
T-5	118.600	9.757	3.195	0.736	1.932	1.829	0.027	231.683
T-6	118.600	9.757	3.195	0.736	1.932	1.829	0.027	231.683
T-7	118.600	9.757	3.195	0.736	1.932	1.829	0.027	231.683
T-8	118.600	9.757	3.195	0.736	1.932	1.829	0.027	231.683
Voltage Class 3								
T-9	149.627	15.995	3.195	8.664	1.259	0.308	0.033	222.086
T-10	149.627	15.995	3.195	8.664	1.259	0.308	0.033	222.086
T-11	149.627	15.995	3.195	8.664	1.259	0.308	0.033	222.086
Voltage Class 4								
T-12	150.817	20.343	3.195	3.944	1.368	1.138	0.029	193.516
T-13	150.817	20.343	3.195	3.944	1.368	1.138	0.029	193.516
T-14	150.817	20.343	3.195	3.944	1.368	1.138	0.029	193.516
T-15	150.817	20.343	3.195	3.944	1.368	1.138	0.029	193.516

2.4.2 Generation contingency probabilities

CPET was also used to calculate mean failure rates λ_{12} and repair rates μ_{21} for generation, shown in Table 2.7, and for wind turbine generation, shown in Table 2.8. These failure rates were calculated from GADS and GADS-Wind data with no weighting applied. Both transmission and generation failure and repair rates are used for probabilistic calculations in Chapters 4 and 5.

Table 2-7: Generation contingency probabilities

Generation Class	P1	WEFORd	λ_{12} (failure/yr)	μ_{21} (repair/yr)
Fossil-Steam	0.044	0.055	42.257	203.000
Nuclear	0.132	0.169	7.400	70.149
Gas Turbine/Jet Engine	0.064	0.074	4.148	121.246
CC steam units	0.034	0.052	14.590	256.364
CC GT units	0.042	0.043	7.595	301.037
Pumped Storage/Hydro	0.069	0.071	3.171	71.385
CoG GT units	0.036	0.042	6.123	153.281
Combined Cycle Block	0.026	0.028	12.441	224.489
Co-generator Block	0.028	0.036	10.727	293.601
Internal Combustion Engines	0.043	0.061	15.928	147.603
CoG steam units	0.110	0.120	10.262	129.476
Miscellaneous	0.099	0.113	26.487	223.944
Fluidized Bed	0.020	0.047	39.418	241.030
Geothermal	0.055	0.056	11.620	361.561
Multi-boiler/Multi-turbine	0.090	0.094	39.887	238.641

Table 2-8: Wind turbine generation contingency probabilities

Wind Regime	EEFOR
1 – Seashore	0.084
2 – Plain	0.048
3 – Plateau	0.078
4 – Hills	0.054
5 – Mountain	0.080
6 – Ridge	0.040

2.5 Discussion

There are several instances where the data is anomalous and causes inconsistent results. These are described here, with the implemented adjustments.

1. Contingency types that did not occur in the dataset will cause the corresponding failure rate to be undefined. For small datasets, there is no information about that contingency type, so its Markov state is ignored. The inclusion of larger datasets resolves this issue, as the TADS and GADS datasets include all types of contingencies.
2. Reactance is used as a proxy for line length to fill in missing lengths in the network models. An effect of this calculation is that capacitive branches, e.g. equivalent branches in a reduced model that behave capacitively (from, for example, the model of a three-winding transformer), have a negative line length which may propagate into the failure rates. This is avoided by dropping capacitive branches from outage probability calculations.

In addition to the calculations discussed previously, CPET allows regression and pooling using any of the variables included in the outage data, including user-defined variables, as well as the effects of multiple variables at once. This provides additional flexibility for the utility to investigate

relationships between outage probabilities and other quantities, such as in-service duration and generation size or fuel type.

Probabilities calculated by CPET can be used as input to the probabilistic tools discussed later in this thesis. These tools provide additional methods of refining the probabilities obtained using CPET. For example, the tools discussed allow probabilities to be set for individual components, as well as for a group of components, providing a way to override the assigned group probability for components with extreme outage probabilities.

3. Contingency evaluation using traditional deterministic limits

3.1 Overview

Contingency analysis has traditionally been used to ensure the reliability of the BPS or a subsystem of the BPS by ensuring that the system being studied is able to undergo any and all contingencies without resulting in violations of specified performance criteria such as NERC's TPL-001-05 [1], summarized in Table 3.1, and NPCC's Reliability Reference Directory [22]. The term deterministic refers to the practice of defining acceptable operating conditions by whether they pass or fail network performance criteria for a specified set of contingencies, independent of the probabilities associated with those contingencies. As seen in Fig. 3.1, systems operating in a condition that do not meet the criteria are in an alert state and must be transitioned to a secure operating condition which satisfies the performance criteria [12]. Tools like PSS®E and Transmission Adequacy & Reliability Assessment (TARA) are used to run contingency analysis and perform checks against the performance criteria to indicate if any system problems are present.

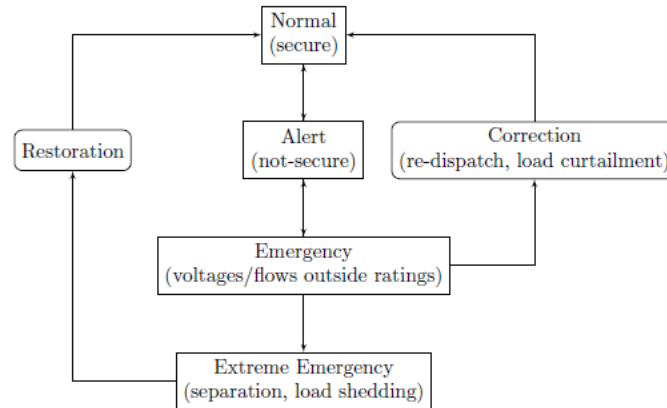


Figure 3-1: Power system operating state diagram, originally proposed in [23]

3.1.1 Deterministic contingency analysis

The deterministic approach to contingency analysis discussed in [4], [12] is outlined below.

1. Determine the base network configuration for the study. Power flow studies are prepared based on credible conditions during the time period of interest. This will usually include what are expected to be the worst conditions, as well as representative loadings through the period, e.g., typical severe, but credible cases for each season. The scenario will also include unit commitments and network configurations based on what is likely to occur.
2. Select the contingency set for the study. Due to the large number of components in the system, there are numerous contingencies to choose from, especially considering multiple element contingencies. This list is narrowed down by only considering “credible” contingencies, which are the contingencies that the utility or ISO considers reasonably likely to occur. Utilities and ISOs will likely have a standard contingency list used in and developed from past studies that can be modified as needed. Often, the majority of contingencies included are N-1 contingencies, involving the failure of only one component.

Table 3-1: Summary of TPL-001-5 Disturbance Performance Table, adapted from [1, Table 1]

Category	Description	Intrp. of Firm Transmission		Non-Cons. Load Loss	
		EHV	HV	EHV	HV
P0	(None) Normal system		No		No
P1	(Single) Loss of a single component		No		No
P2 (Single)—Loss of a single component due to protection failure					
P2.1	Opening of a line section w/o a fault		No		No
P2.2	Bus section fault	No	Yes	No	Yes
P2.3	Internal breaker fault (non-bus-tie breaker)	No	Yes	No	Yes
P2.4	Internal breaker fault (bus-tie breaker)		Yes		Yes
P3	(Multiple) Loss of generator unit followed by loss of a single component		No		No
P4 (Multiple)—Loss of multiple elements caused by a stuck breaker					
P4.1-4.5	Fault on component (non-bus-tie breaker)	No	Yes	No	Yes
P4.6	Fault on associated bus (bus-tie breaker)		Yes		Yes
P5	(Multiple) Fault plus non-redundant component of a protection system failure to operate	No	Yes	No	Yes
P6	(Multiple) Two overlapping single contingencies		Yes		Yes
P6	(Multiple) Common structure failure		Yes		Yes

3. Select the range of operating conditions over which the system will be analyzed. The study range will include ranges of load over which to analyze system performance.
4. Identify the limiting contingencies, which are the contingencies that first cause violations of the determined performance criteria as the system is stressed over the study range.
5. Identify the limiting operating conditions, which are those operating conditions in which the limiting contingencies first cause violations of the performance criteria. The limiting operating conditions will be the highest stressed operating conditions, and the set of limiting operating conditions will bound the space of acceptable operating conditions.
6. Summarize the study into tables or graphs that can be used by operators to make decisions in order to remain within the acceptable operating conditions.

3.1.2 Deterministic transfer studies

In addition to evaluating a normal operating condition, deterministic contingency analysis is also used in transfer studies, which stress the transmission system to find the maximum amount of power that can be transferred from one area to another while meeting the performance criteria. These studies are particularly useful in interconnections work, as the physical location of changes in generation and load affect the ability of the transmission lines to transfer power. For instance, adding generation in Manhattan would decrease the amount of power needed to be imported, whereas adding load in Manhattan will increase the amount of energy needing to be imported. Similarly, additional generation in upstate New York will need to be exported to the demand, whereas additional load can be locally supplied by the excess generation, freeing up transmission capacity.

3.1.3 PSS®E

The work presented in this thesis uses PSS®E to perform contingency analysis and violation checks. PSS®E performs contingency analysis using the AC contingency calculation (ACCC) module, which iterates through a provided contingency list and applies each contingency to the operating condition, recording the system performance and resetting the operating condition before continuing. ACCC reports tabulate the response of the system to each contingency and provide a way to export the results to excel for further processing.

PSS®E also contains another module called the Probabilistic Reliability Assessment Module (PRA) for post-processing ACCC results [24, Sec. 6.17]. As the name suggests, PRA is designed to perform probabilistic reliability assessments and is discussed in Chapter 5, but it is mentioned here since it also produces deterministic reports that summarize the ACCC results.

3.2 Case studies

The following example shows a typical analysis of a subsystem of the BPS using deterministic analysis.

3.2.1 NYPA subsystem load growth

A subsystem of NYPA's assets was analyzed using PRA to report the deterministic violations as the system become stressed due to increased load growth without corresponding capacity growth. Fig. 3.2 shows a simplified representation of this subsystem. The original model as received from NYPA, labeled Base, is a very lightly loaded system. To simulate load growth, the load in the system model was scaled to match the annual peak load, obtained from the New York Independent System Operator's (NYISO) *2023 Load & Capacity Data Report* [25, Table I-3], and generation was scaled to match the demand using a reserve dispatch method.

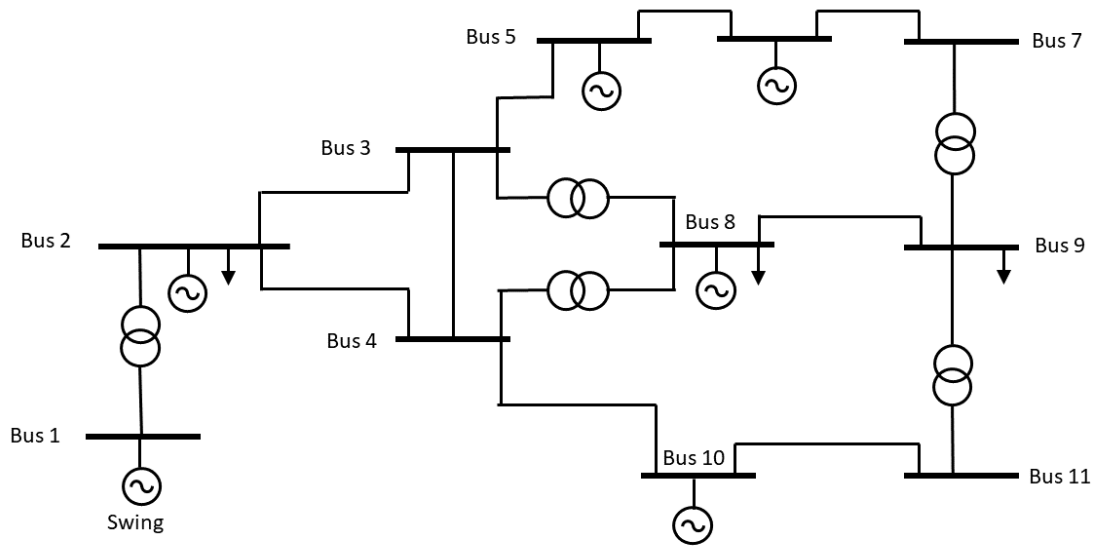


Figure 3-2: Simplified subsystem model for NYPA subsystem load growth

The low voltage violation threshold was set to 0.95 pu, and the overload threshold was set to 100 %. Post-contingency steady-state under-voltage and overload violations are shown in Table 3.2. As expected, the increase in load without a corresponding increase in capacity stressed the system and resulted in more violations. This analysis shows that at 667MW of load, the isolated subsystem was N-1 non-compliant according to [1, Table 1], since the post-contingency steady-state voltage is below the acceptable threshold, indicating a need for a different operating condition.

Table 3-2: Contingency Analysis Subsystem Results

Scenario	Load (MW)	Low Voltage			Overload		
		Min. Voltage (pu)	Num. of Ctg.	Worst Ctg.	Overload (%)	Num. of Ctg.	Worst Ctg.
Base	280	-	0	-	-	0	-
2015	667	0.9276	2	CTG_027	-	0	-
2020	750	0.9082	2	CTG_027	-	0	-
2025	893	0.8772	6	CTG_027	-	0	-
2030	1024	0.8414	33	CTG_027	-	0	-
2035	1095	0.8179	33	CTG_027	-	0	-
2040	1161	0.7924	33	CTG_027	106.1	2	CTG_028
2045	1194	0.7747	33	CTG_027	110.6	2	CTG_028
2050	1204	0.7689	33	CTG_027	112.4	2	CTG_027

3.2.2 Corrective action

A weakness of deterministic contingency analysis is demonstrated by the system shown in Fig. 3.3, which was derived from NYPA's reduced model. The transformer between Bus 2 and Bus 3 has been experiencing a high overload for an extended period of time.

One suggested solution to relieve this overload is to open the line from Bus 1 to Bus 2. As shown in Fig. 3.4, this will force power to flow along the remaining branches, eliminating the load on the transformer between Bus 2 and Bus 3. The maximum load decreased from 109% to 103 %, but there are now four overloaded lines. Deterministic analysis alone has no inherent capability to determine whether one large overload or four smaller overloads is preferable, as both scenarios contain violations. Without a way to compare these different quantities, it is left to the operators best judgment on whether to take preventative action or not. This case study is revisited in Chapter 5 where we present an approach which does provide a basis for identifying which of these situations is preferable.

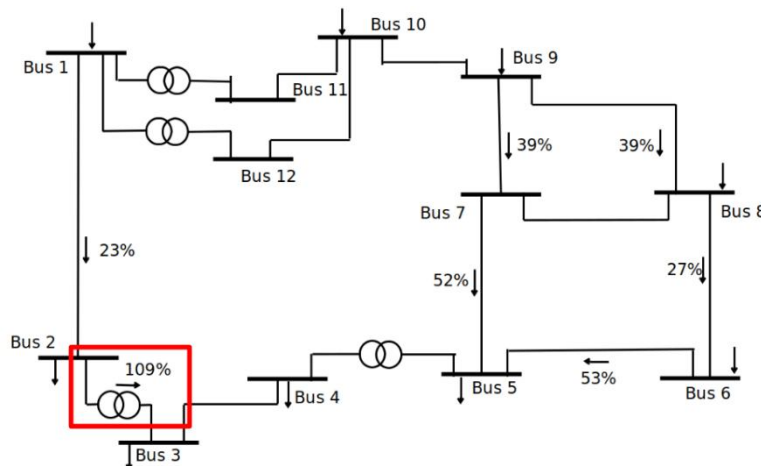


Figure 3-3: Original scenario

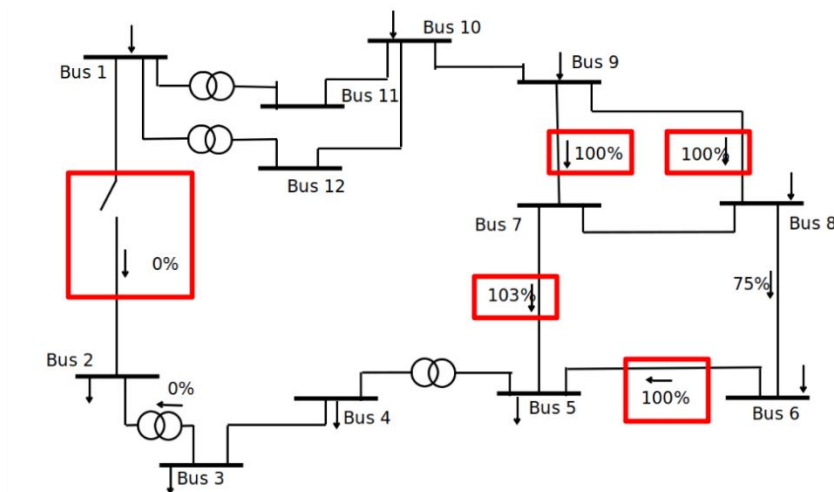


Figure 3-4: Simulation of preventive action

3.3 Discussion

The deterministic approach is well adapted to operational decision-making due to its low computation time (relative to other approaches) and the ability of the operators to know the current operating condition of the grid to a high degree of certainty. Deterministic contingency analysis enables operators to evaluate compliance with performance standards by testing the current operating condition against credible contingencies. Since the system must be secure against any credible contingency regardless of likelihood, the deterministic approach will indicate whether the current condition is acceptable or not, and if not, if adjustments need to be made. This clear indication of whether action should be taken is a useful feature of using deterministic criteria.

Deterministic contingency analysis is also beneficial in operation planning and system planning. Instead of merely identifying and avoiding insecure operating conditions, planners can identify solutions to the contingencies causing the violations. Within operational planning, this could involve adjusting maintenance schedules or unit commitment schedules, while in system planning, these corrections could include plans for new infrastructure.

While deterministic contingency analysis is useful in these time horizons, it does have some limitations. One of the largest limitations is that the effect of unequal probabilities are not considered in the system analysis. Smaller contingencies with higher probabilities may be ignored because they are not as severe, even though the disruptions or violations may have more impact over time due to their higher frequency. Additionally, many deterministic contingency analysis techniques do not take into account the severity of a contingency, only whether a violation occurred. This may cause near-violations to be overlooked, even though they may cause additional problems if not addressed, such as widespread heavy loading that does not result in any actual overloads. With a pass-fail analysis technique, violations may also be considered equally even if they have different severities.

Despite these drawbacks, deterministic criteria are still useful for aiding the decision-making process. Other assessments described in this thesis can be used alongside deterministic assessments to expand the information provided to the decision makers and enable them to obtain a complete view of the problem.

4. Traditional resource adequacy evaluation

4.1 Overview

Resource adequacy is focused on ensuring enough generation is available to meet the forecasted demand [26]. This is done by using the forced outage rates of generation within the system to calculate or estimate the probability that the available generation will be unable to meet the forecasted demand.

4.1.1 Contingency modeling

Resource adequacy tools are often grouped into analytical tools and simulation-based tools [26]. Analytical tools use mathematical theory to calculate the probability distribution of the installed capacity. This probability distribution is then convolved with the forecasted demand distribution to obtain the reliability index desired. This is often the loss of load expectation (LOLE), which is the number of time units that the demand will exceed the capacity and is often in days per year or hours per year. Other indices include loss of load probability (LOLP), which is the number of times the demand will exceed the capacity, and the expected unserved energy (EUE) which is the amount of energy not provided to the demand due to lack of capacity [27].

Simulation-based tools use Monte-Carlo randomization to run multiple simulations in parallel until system converges below a specified tolerance. Within each iteration, the tool steps through time adjusting the demand and applying contingencies to analyze how the system performs. Many of these iterations are then combined using statistical analysis to obtain probabilistic results. A benefit of this method is that each run is accessible, providing insight into the performance of the system under various conditions and worst-case scenarios. These tools calculate the same metrics as the analytical tools [26].

4.1.2 Generation modeling

Conventional Generation: Conventional thermal generation is modeled assuming no uncertainty in resource availability. Units are modeled with two or more capacity states, including full capacity, no capacity, and optionally reduced capacity. Each capacity state is assigned a probability, which is used by the tool to model contingencies, as described in Section 4.1.1 [28].

Variable Energy Resources (VER): VERs such as wind and solar plants cannot simply be modeled as a single generating unit. These energy sources are very sensitive to temporal factors and must be treated differently than conventional generation, especially as they account for more of the generation mix [29]. Solar energy is only produced during the day, and wind speeds and water availability can vary throughout the day depending on the weather. Because of these factors, VERs are usually modeled as negative load and are incorporated into the daily load profile use in resource adequacy [30]. The resulting “net-load” is then served by the remaining generation. This approach captures the time-dependent variability of and correlation between the load and energy output from wind and solar plants. Additionally, unlike conventional generation wind and solar plants are often composed of many small units, all interconnected to the BES at the same point of interconnection (POI). While the BES sees the aggregate energy supplied by the plant, outages do

not often take the entire plant offline. Rather, only individual turbines or photovoltaic (PV) panels will fail. A daily profile of generation includes the variability of the energy produced due to these individual outages, although it does neglect the probability of losing the entire plant due to a substation transformer failure at the POI [28].

4.1.3 Transmission modeling

As RA focuses primarily on ensuring enough generation capacity, various tools have modeled transmission in varying levels of detail.

AC Power Flow: The highest-fidelity transmission model is AC modeling. This models the system using the AC power flow equations and performs a full power flow to analyze the system response.

DC Power Flow: The DC power flow approximates the AC power flow by assuming that the transmission line resistance is negligible, bus voltage magnitudes remain at 1 p.u., and the angular separation across a branch, θ , is small so that $\sin \theta \approx \theta$ and $\cos \theta \approx 1$. This simplifies the power flow equations to

$$\mathbf{P} = \mathbf{B}'\boldsymbol{\theta} \quad (4.1)$$

where $\mathbf{P}$ is the vector of real power injections, $\mathbf{B}'$ is a modified bus-admittance matrix, and $\boldsymbol{\theta}$ is the vector of bus angles. Equation (4.1) can be directly solved for the bus angles $\boldsymbol{\theta}$, greatly reducing the computation time necessary [31].

Multiarea: Multiarea modeling divides the system into several smaller areas, each modeled as a “copper plate” with no impedance between generation and load, and transmission between areas is modeled as an interface with maximum power flow limits in each direction. The interface may or may not have a failure rate associated with it to capture transmission availability.

Generation Only: Another option is to not model transmission at all. This model is optimistic in that it completely ignores the effects of congestion on resource availability, but it will produce a lower limit on loss-of-load metrics for generation unavailability.

4.1.4 GE MARS

While a variety of software is used for probabilistic resource adequacy assessment, as shown in Table 4.1, this project uses GE Vernova’s Multi-Area Reliability Simulation (MARS) software⁵ as a representative tool for resource adequacy assessment. MARS is a well-known resource adequacy tool used by several ISOs and various utilities. The tool uses a multi-area model and performs a full sequential Monte Carlo simulation to calculate LOLE and EUE in addition to other outage statistics such as frequency and duration of loss of load [32]. MARS also allows modeling of other probabilistic factors such as maintenance scheduling and limited-resource generation modeling, e.g., the weather-dependence of resource availability for hydro, wind, and solar generation.

⁵ MARS is included as a module of GE’s PlanOS.

Table 4-1: Summary of RA tools across ISO/RTOs from [33, Table 2]

ISO/RTO	Approach	Tool(s)
CAISO	Deterministic	PSLF & TARA
ERCOT	Both	SERVM
ISO-NE	Probabilistic	MARS
MISO	Probabilistic	SERVM
NYISO	Probabilistic	MARS
PJM	Probabilistic	PRISM & MARS
RTE	Probabilistic	ANTARES
SSP	Probabilistic	SERVM

4.2 Case studies

4.2.1 NYPA subsystem load growth

The NYPA Subsystem Load Growth subsystem from Fig. 3.2 was analyzed with MARS. Forced outage rates for different types of generation were obtained using CPET (see Chapter 2), and as in Section 3.2, annual peak load data and annual energy data for the subsystem were obtained from [25, Table I-2, Table I-3]. In addition, MARS requires hourly load data for one year to estimate the daily load curves for each year of the simulation. This data was obtained from NYISO’s Real-Time Actual Load dataset from 2014 [34].

Since analysis with the full system would likely allocate one area per NYISO balancing area, the subsystem was modeled with one area to include the effect of reducing the network to a “copper sheet” model.

The subsystem used contains hydroelectric dam generation units which are modeled using forced outage rates (FORs) assuming no scarcity of water, and wind turbine generators which are modeled using equipment equivalent forced outage rates (EEFORs), FORs that include the effect of resource unavailability on the availability of the wind turbine. (See Appendix B for discussion on the EEFOR.) While these resources are modeled in this work using FORs of equivalent thermal units to match the modeling capabilities of other software used in this project and allow one-to-one comparison, VERs such as wind and solar energy should be modeled in resource adequacy using a net-load approach, discussed in Section 4.1.2, which incorporates the variability of resource availability throughout the day as well as the effects of individual unit outages within a plant [35], [36].

As the other software in use in this project does not allow for different rates for maintenance outages, maintenance outages were set to zero in MARS.

LOLE analysis was performed on the system on the same years analyzed in Section 3.2, and results are shown in Table 4.2. One wind farm was installed in 2016, resulting in a decreased LOLE from 2015 to 2020 despite the increase in load. As the load continues to increase without further increases in capacity, the system becomes more stressed, and the LOLE rises.

The goal of resource adequacy is to determine how much capacity is needed to decrease the LOLE to a selected threshold, commonly 0.1 day per year. This is done by adding capacity and rerunning the analysis until the LOLE is below the threshold.

Table 4-2: Resource adequacy subsystem results

Scenario	Load (MW)	LOLE (d yr ⁻¹)	LOLE (h yr ⁻¹)	LOEE (MW h yr ⁻¹)	Freq. (outg/yr)	Duration (h/outg)
Base	280	0.0000	0.0000	0.00	0.0000	0.0000
2015	667	0.0404	0.4737	35.50	0.0430	11.0174
2020	750	0.0326	0.2809	13.88	0.0371	7.5657
2025	893	0.1294	1.6855	139.30	0.1264	13.3373
2030	1024	0.5205	5.5304	469.45	0.6515	8.4888
2035	1095	1.1503	11.6685	931.27	1.5209	7.6724
2040	1161	1.8942	23.2835	1879.14	2.3079	10.0887
2045	1194	2.3700	29.5571	2716.33	2.8255	10.4608
2050	1204	2.6300	35.5478	3314.33	2.9633	11.9960

4.2.2 500-bus NYISO reduced model load growth

The 500-bus reduced system model was analyzed with MARS, using the same load data from NYISO [25], [34] as in Section 3.2. Table 4.3 shows the LOLE for each of NYISO's balancing areas. The LOLE can be seen to increase in each area as the system becomes stressed due to increased load growth without additional capacity. In contrast with the subsystem model, the NYISO system remains adequate through 2030, as the interconnected areas can help support the load in neighboring areas.

Table 4-3: Calculated connected LOLE

	WEST	GENESE	CENTRL	NORTH	MHK VL	CAPITL
2015	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2020	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2025	0.0001	0.0001	0.0000	0.0000	0.0000	0.0000
2030	0.0001	0.0004	0.0001	0.0000	0.0001	0.0000
2035	0.2976	0.8270	0.4394	0.0000	0.6955	0.0242
2040	15.2700	28.7900	10.7900	0.0100	25.8400	2.3900
2045	68.4100	85.1900	30.8200	0.0600	78.8100	6.7600
2050	101.2700	115.9800	42.5400	0.0600	110.1200	13.0700

Table 4.3 – Continued

	HUD VL	MILLWD	DUNWOD	NYC	LONGIL	NYISO
2015	0.0000	0.0004	0.0004	0.0004	0.0004	0.0004
2020	0.0000	0.0005	0.0005	0.0005	0.0005	0.0005
2025	0.0000	0.0239	0.0241	0.0244	0.0244	0.0244
2030	0.0001	0.0189	0.0191	0.0194	0.0194	0.0194
2035	0.0208	2.1280	2.1419	2.1488	2.1488	2.1488
2040	2.6700	32.7500	32.7800	32.7800	32.8100	32.8100
2045	10.6300	88.5500	88.6700	88.7100	88.7100	88.7300
2050	17.8800	118.7800	118.9100	118.9100	118.9300	118.9300

Table 4.4 provides a closer look at the load, capacity, planning reserve margin (PRM), and LOLE for each area. The importance of system connections is again illustrated. For example, GENESE has a negative PRM for each modeled year, indicating that its load is always greater than its generation. This is even more apparent in DUNWOOD which has no generation and must supply its load with only imports. However, due to its connections to WEST and CENTRAL which have excess generation, the LOLE for GENESE remains below the threshold of 0.1 day per year until 2040.

Table 4-4: Calculated indices

	Peak Load	Capacity	PRM	LOLE
Year				
NYISO				
2015	29 487.9698	35 450.5000	20.2202	0.0004
2020	28 998.4163	35 568.2000	22.6557	0.0005

Continued on next page

Table 4.4 – *Continued from previous page*

	Peak Load	Capacity	PRM	LOLE
Year				
2025	30 730.7560	33 676.5100	9.5857	0.0244
2030	31 163.0942	33 676.5100	8.0654	0.0194
2035	35 328.6401	33 676.5100	−4.6765	2.1488
2040	41 931.3380	33 676.5100	−19.6865	32.8100
2045	46 275.7657	33 676.5100	−27.2265	88.7300
2050	47 991.3669	33 676.5100	−29.8280	118.9300
WEST				
2015	2631.9995	3811.5900	44.8173	0.0000
2020	2404.9995	3811.5900	58.4861	0.0000
2025	2687.9995	3811.5900	41.8002	0.0001
2030	2651.9995	3811.5900	43.7251	0.0001
2035	3191.0000	3811.5900	19.4481	0.2976
2040	4011.0000	3811.5900	−4.9716	15.2700
2045	4472.9990	3811.5900	−14.7867	68.4100
2050	4645.0000	3811.5900	−17.9421	101.2700
GENESE				
2015	1925.9998	62.7700	−96.7409	0.0000
2020	1804.0000	62.7700	−96.5205	0.0000
2025	2140.0000	62.7700	−97.0668	0.0001
2030	2155.9995	62.7700	−97.0886	0.0004
2035	2703.0000	62.7700	−97.6778	0.8270
2040	3406.9990	62.7700	−98.1576	28.7900
2045	3808.0000	62.7700	−98.3516	85.1900
2050	3960.0000	62.7700	−98.4149	115.9800
CENTRL				
2015	2705.0000	6170.9100	128.1298	0.0000

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Table 4.4 – *Continued from previous page*

Year	Peak Load	Capacity	PRM	LOLE
2020	2752.0000	6170.9100	124.2336	0.0000
2025	2957.9995	6170.9100	108.6177	0.0000
2030	3418.9995	6170.9100	80.4888	0.0001
2035	4083.0000	6170.9100	51.1367	0.4394
2040	4808.0000	6170.9100	28.3467	10.7900
2045	5200.0000	6170.9100	18.6713	30.8200
2050	5338.9990	6170.9100	15.5818	42.5400
NORTH				
2015	666.9999	1879.7000	181.8141	0.0000
2020	749.9999	1957.4000	160.9867	0.0000
2025	892.9999	1957.4000	119.1938	0.0000
2030	1024.0000	1957.4000	91.1523	0.0000
2035	1094.9998	1957.4000	78.7580	0.0000
2040	1161.0000	1957.4000	68.5960	0.0100
2045	1193.9998	1957.4000	63.9364	0.0600
2050	1203.9998	1957.4000	62.5748	0.0600
MHK VL				
2015	1376.0000	760.5200	−44.7297	0.0000
2020	1344.9998	800.5200	−40.4818	0.0000
2025	1419.9998	908.3200	−36.0338	0.0000
2030	1510.9998	908.3200	−39.8862	0.0001
2035	1911.0000	908.3200	−52.4689	0.6955
2040	2353.0000	908.3200	−61.3974	25.8400
2045	2601.0000	908.3200	−65.0780	78.8100
2050	2695.0005	908.3200	−66.2961	110.1200
CAPITL				

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Table 4.4 – *Continued from previous page*

Year	Peak Load	Capacity	PRM	LOLE
2015	2293.9995	4358.5500	89.9979	0.0000
2020	2374.0000	4358.5500	83.5952	0.0000
2025	2414.9995	4396.1500	82.0352	0.0000
2030	2464.9995	4396.1500	78.3428	0.0000
2035	3133.9995	4396.1500	40.2728	0.0242
2040	3883.0000	4396.1500	13.2153	2.3900
2045	4317.0000	4396.1500	1.8334	6.7600
2050	4499.9990	4396.1500	−2.3078	13.0700
HUD VL				
2015	2151.0000	3445.5000	60.1813	0.0000
2020	2177.0000	3445.5000	58.2683	0.0000
2025	2114.0000	3459.9000	63.6660	0.0000
2030	2151.9995	3459.9000	60.7761	0.0001
2035	2444.0000	3459.9000	41.5671	0.0208
2040	3101.0000	3459.9000	11.5737	2.6700
2045	3503.0000	3459.9000	−1.2304	10.6300
2050	3711.0000	3459.9000	−6.7664	17.8800
MILLWD				
2015	617.0000	2103.5900	240.9384	0.0004
2020	666.0000	2103.5900	215.8544	0.0005
2025	616.0000	52.1000	−91.5422	0.0239
2030	618.9999	52.1000	−91.5832	0.0189
2035	695.9999	52.1000	−92.5144	2.1280
2040	813.9999	52.1000	−93.5995	32.7500
2045	874.0000	52.1000	−94.0389	88.5500
2050	895.9999	52.1000	−94.1853	118.7800

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Table 4.4 – *Continued from previous page*

Year	Peak Load	Capacity	PRM	LOLE
DUNWOD				
2015	1345.0000	0.0000	−100.0000	0.0004
2020	1351.9998	0.0000	−100.0000	0.0005
2025	1396.0000	0.0000	−100.0000	0.0241
2030	1367.0000	0.0000	−100.0000	0.0191
2035	1478.9998	0.0000	−100.0000	2.1419
2040	1601.0000	0.0000	−100.0000	32.7800
2045	1750.9995	0.0000	−100.0000	88.6700
2050	1825.0000	0.0000	−100.0000	118.9100
NYC				
2015	10 409.9980	8971.7700	−13.8158	0.0004
2020	9798.0000	8971.7700	−8.4326	0.0005
2025	11 079.9980	8971.7700	−19.0273	0.0244
2030	10 860.0000	8971.7700	−17.3870	0.0194
2035	11 669.9980	8971.7700	−23.1211	2.1488
2040	13 080.0000	8971.7700	−31.4085	32.7800
2045	14 430.0000	8971.7700	−37.8256	88.7100
2050	14 959.9961	8971.7700	−40.0283	118.9100
LONGIL				
2015	5125.9990	3885.6000	−24.1982	0.0004
2020	5326.0000	3885.6000	−27.0447	0.0005
2025	4950.0000	3885.6000	−21.5030	0.0244
2030	4981.9990	3885.6000	−22.0072	0.0194
2035	5343.0000	3885.6000	−27.2768	2.1488
2040	6604.9990	3885.6000	−41.1718	32.8100
2045	7288.9990	3885.6000	−46.6923	88.7100

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Table 4.4 – *Continued from previous page*

	Peak Load	Capacity	PRM	LOLE
Year				
2050	7524.9990	3885.6000	−48.3641	118.9300

4.3 Discussion

RA is useful for system planning since the primary goal of the analysis is to ensure enough generation to meet the forecasted load. Investments in generation can be planned to ensure that load is not lost due to a lack of generation. This type of analysis is especially beneficial for the current BPS since the transition away from fossil fuels means that predictable generation, like coal and gas, will be retiring, while VERs like wind and solar will be installed to replace them. Since capacity for VERs cannot be directly compared to capacity of other generation sources due to the increased variability and uncertainty in the resource availability, probabilistic tools like MARS help specify how much capacity from VERs is needed to replace the lost capacity of thermal plants while maintaining the same level of reliability.

Although transmission modeling in RA is often highly simplified, it can serve as a feasibility test to ensure enough generation to meet the demand. The RA model represents a best-case scenario with minimal congestion or transmission-related contingencies, which are the most common. Systems which cannot adequately supply the load without these additional constraints cannot be expected to perform well when these constraints are added. RA can help ensure that enough resources are modeled on a large scale, and other studies can refine these results by informing the placement of resources or investment and configuration of transmission to interconnect the resources.

While RA is not designed to perform transmission expansion planning, it may still be able to inform decisions about where transmission is needed. For example, it may be able to provide a measure of how much total transmission needs to be available between two areas, but the actual configuration and transmission within those areas needs to be determined using another assessment. RA may also be able to be incorporated as a feedback mechanism within another expansion tool. For instance, the resource mix from RA can be used in a transmission expansion tool, and the new transmission lines can then be added into the interface limits in the RA model. This decoupled process would allow faster computation in each step as it approaches a feasible solution. A similar process combining generation and transmission expansion planning tools and resource adequacy tools is described in [33].

Operational planning is not concerned with determining the installation or retirement of assets, but with how to effectively use the assets already in service. MARS includes the option of specifying maintenance schedules or maintenance frequencies, allowing insight into the effect on reliability due to operational planning decisions. The probabilistic nature of RA is useful to operational planning for many of the same reasons it is useful for system planning, as both decision horizons involve forecasting resource availability and demand; however, RA also cannot analyze

operational planning decisions about transmission lines, such as configuration or maintenance, due to the multi-area model.

There are additional challenges in applying RA to operations. Since decisions about committing and building units are made on a longer time-horizon than operation decisions, RA includes the effects of operator actions, namely curtailing load, which limits its use in informing those decisions. In addition, the loss of fidelity in transmission modeling results in approximations that are not acceptable in the real-time decisions made in operations. For example, the resource adequacy study shown in Table 4.2 indicates that the system is well below the LOLE threshold of 0.1 d yr^{-1} in 2015 and 2020, however, the deterministic results from Table 3.2 show that under-voltage problems are occurring during these years. The resource adequacy results indicated that there is enough generation within the area to supply the load, but the limited transmission model does not model the distance between generation and load and so overlooks the resulting voltage drop across the transmission lines.

Compliance with performance standards also requires modeling branch contingencies within the system. As the multi-area models used in many resource adequacy tools do not model transmission, aside from large area to area transfers, the results cannot indicate system compliance or non-compliance.

5. Risk-based contingency analysis

5.1 Overview

Risk-based contingency analysis uses the concept of risk to incorporate probabilities into a metric of reliability for the system. Risk refers to the combination of the impact or severity of an undesired outcome and the probability of that outcome [37]. For this project, the risk of event X is defined as

$$\text{Risk}(X) = \text{Pr}(X) \cdot \text{Sev}(X) \quad (5.1)$$

where $\text{Pr}(X)$ is the probability of X and $\text{Sev}(X)$ is a function that describes the severity of X . Depending on the nature of the analysis, X could be a particular contingency, an operating condition, or even the system infrastructure implementation.

5.1.1 Probability

Each event X has an uncertainty or probability associated with it. Contingency probabilities are related to the failure rates of specific components, which can be affected by external factors such as weather and maintenance frequency or internal factors such as the type of equipment. (Chapter 2 describes the calculation of contingency probabilities.) Operating condition probabilities are impacted by factors like short-term demand forecasts, which are also impacted by the weather, and maintenance schedules. The probability of implementing a particular infrastructure is influenced by long-term demand forecasts, as well as generation investments and retirements. While the calculation of probabilities related to operating conditions and system infrastructure plans is outside the scope of this project, it is useful to consider these uncertainties in addition to the contingency probabilities when considering system reliability.

As discussed in Chapter 2, the nature of these probabilities changes depending on the decisions being informed by the analysis. Short-term decisions, like determining an acceptable operating condition, will use transition probabilities, e.g. the probabilities that certain contingencies will occur in the next time period. Long-term decisions for adjusting the acceptable space of operating conditions will use steady-state probabilities, for instance, the percentage of time that the system is in a specific operating condition or experiencing a certain contingency.

5.1.2 Severity

The severity function in (5.1) can be defined in multiple ways. As with probability, each contingency, operating condition, system infrastructure implementation, or other event has an associated severity. The severity is often defined as a function of multiple events, for instance, the severity of a particular contingency given an operating condition. The severity function for operating conditions and system configurations can be defined as the calculated risk, so this chapter will focus on severity functions for contingencies. Two methods of calculating the severity of a contingency, the loss of load (LOL) approach and the quality of service (QOS) approach, are discussed here.

5.1.2.1 Loss of load approach

The LOL approach to calculating the severity of an event focuses on interruptions to consumer usage of power. At a system level, the LOL risk of an operating condition could be represented using the LOLE, as calculated in RA. The severity of the operating condition would be multiplied by the probability of operating in that operating condition to obtain the LOL risk. As discussed in Chapter 4, since the operating condition is not known, this method is more applicable to operational planning and system planning. Traditionally, this approach would neglect or simplify transmission line modeling.

Another way to quantify customer interruption is to perform contingency analysis with corrective actions. PSS®E enables this option, allowing violations to be resolved by various corrective actions, including transformer and shunt adjustments, generator redispatch, and load curtailment. Events causing load curtailment could be assigned a severity corresponding to the amount of load lost, and then used in the calculation of risk for that event.

A conservative approach to calculating an LOL index would be to only allow load curtailment as a corrective action. This would result in a higher risk index and would encourage more action to remedy or avoid system problems. A more realistic approach would be to use load curtailment only after other corrective actions have been exhausted, as disconnecting load is generally avoided if possible. This will allow some violations to be corrected and result in lower LOL indices. Even if corrective actions are not modeled, PSS®E will curtail load that is isolated due to the outage of a radial line or the creation of an island with insufficient generation reserves.

Power distribution networks are often analyzed using LOL severity functions such as the well known system average interruption duration index (SAIDI) and customer average interruption duration index (CAIDI) indices [38]. Versions of these indices could potentially be adapted for transmission systems, although several differences between transmission and distribution make the use of these indices more difficult, especially for short-term operational decisions. The distribution system is primarily a radial system, with one path for power to flow along to each customer, while the transmission system is a mesh design that can be reconfigured based on generation and loading profiles. This difference provides transmission operators more opportunities for real-time decisions than distribution operators. The SAIDI and CAIDI indices are therefore designed to evaluate the system and provide information for longer-term planning, as seen by the example usage of the indices in [38].

The LOL approach produces indices that have an easily understood meaning and are directly related to avoiding load curtailment. However, since load curtailment is the decision of an operator to avoid system collapse, it should not be modeled in studies to inform that decision. This consideration applies to both operations and operational planning. Long-term planning, however, does model the operator's decisions, so including load curtailment is more appropriate. The remainder of this chapter focuses on the QOS approach, which is more applicable on all three time horizons.

5.1.2.2 Quality of service approach

While interruption of service is an important aspect of reliability and one that should be considered in analyzing reliability, other problems may occur in response to a contingency that do not result in load interruption, such as low voltage or line overloads. Even though power is still delivered under these conditions, they degrade the QOS and so should be reflected in the reliability metric [39]. Additionally, system problems like overloads and voltage violations are often precursors to load loss if not handled properly.

Unlike the LOL approach which calculates a severity by directly aggregating lost load, the QOS approach deals with quantities of differing natures that cannot be directly added together to result in a severity function. PSS®E and Online Risk-Based Security Assessment Software (OL-RBSA), the two software tools used in this project for risk-based contingency analysis, provide different methods of converting low voltages and overloads to a metric that can be aggregated into a single severity.

5.1.3 On-line risk-based security assessment tool

OL-RBSA is a MATLAB tool developed at Iowa State University to quantify the risk of current or future operating conditions [40], [41]. The risk associated with an operating condition is given by a summation of (5.1) over the contingencies in that operating condition:

$$\text{Risk}(X) = \sum_i \text{Pr}(E_i) \cdot \text{Sev}(E_i|X) \quad (5.2)$$

where X is the operating condition, E_i is the i^{th} contingency, and $\text{Sev}(E_i|X)$ is a function that quantifies the severity of contingency E_i given operating condition X . OL-RBSA therefore incorporates both the probability and severity of the contingencies in its analysis of the operating condition.

5.1.3.1 Severity functions

Although many different severity functions could be used, OL-RBSA defines three different severity functions based on their usefulness to operators and planners [40, Sec II.A]. The severity function $\text{Sev}(E_i|X)$ is expressed as a summation of the severity function applied to each branch, that is

$$\text{Sev}(E_i|X) = \sum_j \text{Sev}(x_j|E_i, X) \quad (5.3)$$

where x_j is the value (e.g. bus voltage or branch loading) corresponding to the j^{th} component in operating condition X .

Discrete Severity Function: The discrete severity function for branch overloads is illustrated in Fig. 5.1a. The function is defined such that the function evaluates to one for a violation and evaluates to zero otherwise. The resulting risk is therefore an expectation of the number of violations observed on the system, or the expected violations (EV).

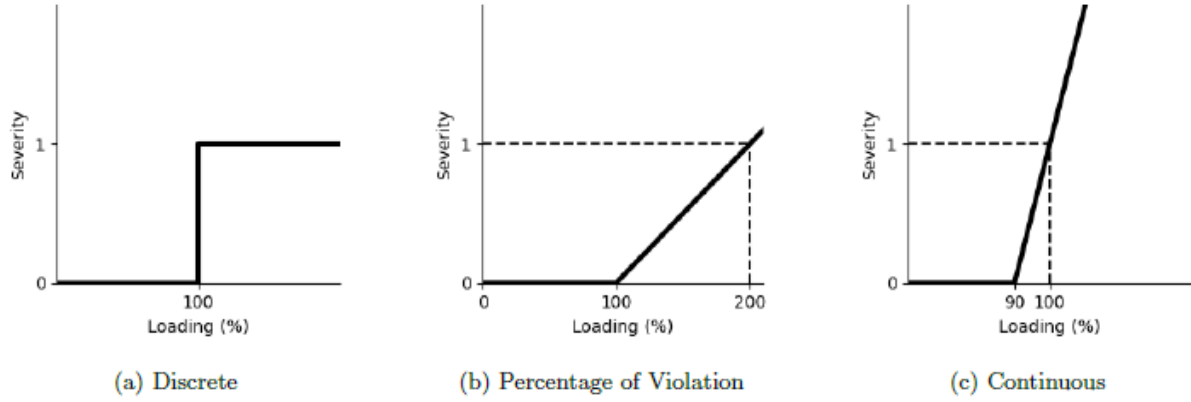


Figure 5-1: OL-RBSA overload severity functions

Percentage of Violation Severity Function: The percent of violation severity function for branch overloads is shown in Fig. 5.1b. The function measures the extent of the violation such that the function evaluates to zero at the deterministic limit and increases linearly as the extent of the violation increases. This is expressed as

$$\text{Sev}_{\min}(x) = \begin{cases} \frac{x_{\min} - x}{x_{\min}} & \text{for } x \leq x_{\min} \\ 0 & \text{for } x > x_{\min} \end{cases} \quad (5.4)$$

for minimum limit and

$$\text{Sev}_{\max}(x) = \begin{cases} \frac{x - x_{\max}}{x_{\max}} & \text{for } x \geq x_{\max} \\ 0 & \text{for } x < x_{\max} \end{cases} \quad (5.5)$$

for a maximum limit. The resulting metric is the expected percent violations (EPV).

Continuous Severity Function: The continuous severity function for branch overloads is shown in Fig. 5.1c. The function is defined such that the function evaluates to one at the deterministic limit and increases with the extent of the violation. This function has the added benefit that it captures an expectation of the number of violations, due to evaluating to one at the violation threshold, while also contributing risk to conditions that are approaching the violation limit. This metric is the expected weighted violations (EWV).

Other Severity Functions: While OL-RBSA does not currently implement other severity functions, the functions mentioned should not be considered a complete set. While the functions included in OL-RBSA are desirable for their simplicity and value as expectations, it would be reasonable to desire a severity function that does not vary linearly with voltage or load. The further the system is from the operating point the more severe each unit step is, so an exponentially increasing (or decreasing) function may better capture the severity.

5.1.3.2 Uncertainty

Two types of uncertainty are incorporated into OL-RBSA's calculation of risk [40]. The first type of uncertainty, the uncertainty of contingencies, is discussed in detail in Chapter 2. The second type is uncertainty in the operating condition. OL-RBSA models the operating condition at some future time t using a normal distribution with the mean of the distribution equal to the forecasted condition for each of three parameters causing this uncertainty: load distribution factors, load power factors, and generation distribution factors. These are assumed to be random and follow a multivariate normal (MVN) distribution. Performance measures such as loadability, bus voltage, and branch flow are calculated from this MVN distribution and also follow a normal distribution, as described in [40].

The different indices calculated by OL-RBSA represent different ways of handling uncertainty and severity, summarized in Table 5.1. These indices show some of the variation possible within probabilistic assessment. Different indices can be obtained from these by modifying the uncertainty parameters. For instance, in on-line assessment, the current operating condition is well known, so the operating condition uncertainty can be removed from the EWV index by setting the standard deviation on the operating condition uncertainty to a very small value. This narrows the normal distribution to values immediately around the mean. Other combinations can be obtained using similar methods.

Table 5-1: Summary of risk indices, adapted from [40]

Index Name	Uncertainty		Severity	
	Ctg	Op. Cond.	Num. Viol.	Level of Viol.
Worst-case	No	No	No	No
Violation-count	No	No	Yes	No
Expected Violations Count	Yes	No	Yes	No
Expected Violations	Yes	Yes	Yes	No
Expected Weighted Violations	Yes	Yes	Yes	Yes

5.1.3.3 Additional features

OL-RBSA also contains other tools for analyzing and visualizing system reliability.

Voltage Collapse and Cascading: In addition to low voltage and overload indices, OL-RBSA contains modules to calculate the risk of voltage collapse and cascading failures.

Failure-based Indices: OL-RBSA contains a module to calculate failure-based indices, including expected load lost due to low voltage or voltage collapse, probability of failure and time to failure for transformers, and probability of sag and time to sag for transmission lines. These indices require more detailed modeling of the physical structure and location of components in the system.

Sensitivities and Nomograms: Another feature of OL-RBSA is its calculation of risk sensitivities and nomograms. These provide additional information about how the system behaves around the operating condition. The sensitivities show how the risk indices change at each bus with real and reactive power injections and voltage set points, and the nomograms provide a visual representation of the relative levels of risk for nearby operating conditions.

5.1.4 PSS®E

PRA enables analysis of an operating condition probabilistically [24, Sec. 6.17]. The module uses the results from contingency analysis and outage statistics for the included contingencies to calculate probabilistic indices.

PRA allows the reporting of three distinct time-periods after the contingency: post-contingency happens immediately after the contingency, post-tripping follows any automatic tripping events, and post-corrective action occurs after corrective actions are performed. To enable these reports, the corresponding options must be provided to the ACCC solution module. Tripping events are used to model protection operation, automatic network configuration, and operator actions to avoid system collapse. Corrective actions are actions taken to alleviate system violations while optimizing the operating condition [24, Sec. 6.13, 6.15.7]. Since these actions are in response to the initial contingency, they represent decisions made based on the performance of the system in the post-contingency time period. While there is value in analyzing the performance of tripping events and corrective actions, the focus of this project is to inform those decisions and so only the post-contingency results are considered to avoid circular reasoning.

5.1.4.1 Reports

PRA has six different report types available, each in a deterministic and probabilistic format, as listed in Table 5.2. The deterministic reports return a summary of violations, organized by component or violation type, along with the number of contingencies matching each entry and the maximum and average violations that occurred. The probabilistic reports add the frequency (oc/y), duration (hour), and probability (hour/year) corresponding to each entry, as well as some measure of impact which varies depending on the report.

Table 5-2: PSS®E Probabilistic Reliability Assessment Module available reports

Deterministic	Probabilistic
System problem summary	System problem probabilistic indices
System loss of load	System load curtailment probabilistic indices
Bus loss of load	Bus load curtailment probabilistic indices
Branch flow overloading	Branch flow overloading probabilistic indices
Bus voltage violation	Bus voltage violation probabilistic indices
Contingency summary	Contingency summary with outage statistics

System Problem Summary: The system problem summary report gives an overview of the system, providing the number of contingencies that resulting in voltage violations, overloads, loss of load, or non-convergence, as well as the worst violation and corresponding contingency.

System Loss of Load: The system loss of load report identifies the amount of load lost. In the post-contingency time frame, this load is all dropped due to islanding, where a load or multiple loads are separated from the main system with insufficient generation resources. In this scenario, the ACCC module drops all load and generation in this island. Similar to the system problem summary, the system loss of load reports the number of contingencies resulting in each load curtailment level, and the worst violation and corresponding contingency.

Bus Loss of Load: The bus loss of load report presents the loss of load due to islanding by individual buses, reporting the load at the bus, the average and maximum curtailments at that bus, the number of contingencies affecting that bus, and the contingency resulting in the highest load curtailment. For the post-contingency time frame, lost load is calculated the same as for system loss of load.

Branch Flow Overloading: The branch flow overloading report shows the average and maximum loading for each monitored branch in the system. The report also shows the number of contingencies affecting the branch, as well as the contingency with the highest branch loading.

Bus Voltage Violation The bus voltage violation report shows the buses where the voltage is outside the specified range, or where the change in voltage exceeded deviation limits. The report shows the average and maximum violations, as well as the number of contingencies and the contingency with the worst violation.

Contingency Summary: The contingency summary report shows the maximum mismatch, total load curtailment, maximum branch loading, maximum voltage drop, maximum voltage rise, minimum voltage, and maximum voltage for each contingency.

5.1.4.2 Impact

PSS®E refers to both severity and risk as impact. Within the ACCC results used by PRA, impact refers to the severity of the contingency, either aggregated or separated by component. PRA multiplies these severities by the probabilities of the contingencies, and reports the risk associated with each contingency as impact. Hereafter, the terms risk-impact and severity-impact will be used to distinguish which concept is meant by impact.

Similar to OL-RBSA, several indices can be obtained from PRA's probabilistic reports. The probabilistic reports include the number of violations caused by a contingency. This can be obtained using the function shown in Fig. 5.2a, which is similar to OL-RBSA's EV. The probabilistic reports do include the risk-impact, shown in Fig. 5.2b, which similar to OL-RBSA's EPV. One major difference is that both the slope and violation thresholds (intercepts) of the severity functions can be modified in OL-RBSA, whereas PRA fixes the slope at $m = \pm 1$ and only

the violation threshold of the severity function can be adjusted.⁶ Appendix D compares voltage and overload severity functions for both OL-RBSA and PRA.

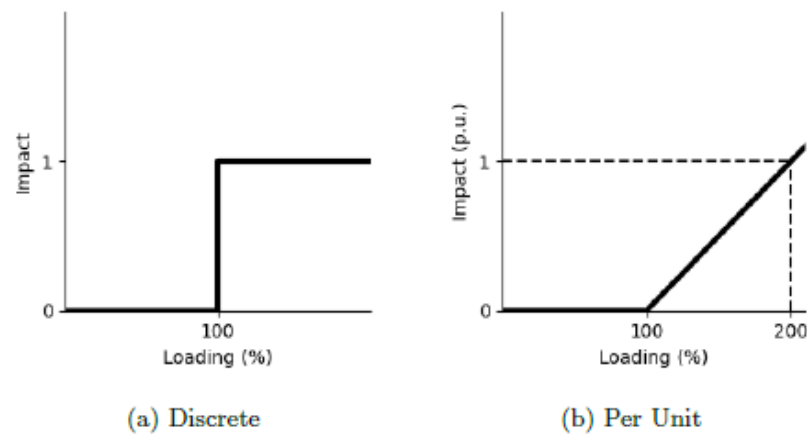


Figure 5-2: PRA overload severity function

5.1.5 Probabilistic contingency analysis

The probabilistic contingency analysis process follows the same steps as the deterministic contingency analysis process described in Chapter 3, with a few modifications to steps 2, 4, and 5 [12]:

2. Contingency selection is often done using state enumeration rather than a specified contingency list. Contingencies are assigned probabilities, and contingencies with a probability below a specified threshold are excluded from the analysis to limit the computational burden.
4. Instead of identifying limiting contingencies, the probabilistic index is calculated across the entire study range, resulting in an index value for each potential operating condition. The acceptable region is delimited by selecting a threshold for the index beyond which performance is considered unacceptable.
5. The limiting operating conditions are defined as those operating conditions with an index equal to the threshold specified. These operating conditions will form a boundary around the acceptable region.

The end result of both the deterministic and probabilistic processes is a bounded region of acceptable performance. This means that operators can use the probabilistic limits the same way as the deterministic limits.

⁶ For the overload severity function, PRA fixes the slope at $m = 1$.

5.2 Case studies

5.2.1 NYPA subsystem load growth

The NYPA Subsystem Load Growth subsystem from Section 3.2.1 was analyzed using risk-based contingency analysis. As seen in Tables 5.3 to 5.6, both PRA and OL-RBSA show the risk of the subsystem increasing as more load is added to the system, which is reasonable as the system is becoming more stressed. The probabilistic reports from PRA duplicate the deterministic results reported in Chapter 3, but add frequency, duration, probability, and risk-impact metrics.

Table 5-3: Risk-Based Contingency Analysis Subsystem PRA Under-Voltage Results

Scenario	Load (MW)	Freq. (oc/yr)	Duration (h)	Prob. (h yr ⁻¹)	Risk-Impact (pu)	Num. of Ctg.	Worst Viol. (pu)	Worst Ctg.
Base	280	-	-	-	-	0	-	-
2015	667	0.0580	100.0	5.8	0.24	2	0.93	CTG_027
2020	750	0.0580	100.0	5.8	0.47	2	0.91	CTG_027
2025	893	683.8612	10.0	6851.8	196.16	6	0.88	CTG_027
2030	1024	# ^a	10.0	26 660.6	1231.82	33	0.84	CTG_027
2035	1095	# ^a	10.0	26 660.6	2225.82	33	0.82	CTG_027
2040	1161	# ^a	10.0	26 660.6	3427.43	33	0.79	CTG_027
2045	1194	# ^a	10.0	26 660.6	4290.20	33	0.77	CTG_027
2050	1204	# ^a	10.0	26 660.6	4551.50	33	0.77	CTG_027

^a Values are larger than 1000 occurrences per year.

Table 5-4: Risk-Based Contingency Analysis Subsystem PRA Overload Results

Scenario	Load (MW)	Freq. (oc/yr)	Duration (h)	Prob. (h yr ⁻¹)	Risk-Impact (pu)	Num. of Ctg.	Worst Viol. (%)	Worst Ctg.
Base	280	-	-	-	-	0	-	-
2015	667	-	-	-	-	0	-	-
2020	750	-	-	-	-	0	-	-
2025	893	-	-	-	-	0	-	-
2030	1024	-	-	-	-	0	-	-
2035	1095	-	-	-	-	0	-	-
2040	1161	0.0580	100.0	5.8	0.32	2	106.05	CTG_028
2045	1194	0.0580	100.0	5.8	0.62	2	110.65	CTG_028
2050	1204	0.0580	100.0	5.8	0.71	2	112.40	CTG_027

Table 5-5: Risk-Based Contingency Analysis Subsystem OL-RBSA Low Voltage Results

Scenario	Load (MW)	EV (10^{-3})	EPV (10^{-6})	EWV (10^{-3})
Base	280	0.0000	0.0000	0.0066
2015	667	0.0132	0.2701	0.2365
2020	750	0.0132	0.5326	0.5141
2025	893	0.1573	3.2413	1.1442
2030	1024	0.9907	18.4592	2.3662
2035	1095	1.0385	31.9174	3.1249
2040	1161	1.1638	46.4552	3.9027
2045	1194	1.3233	56.0576	4.4162
2050	1204	1.4704	59.4704	4.5848

Table 5-6: Risk-Based Contingency Analysis Subsystem OL-RBSA Overload Results

Scenario	Load (MW)	EV (10^{-3})	EPV (10^{-6})	EWV (10^{-3})
Base	280	0.0000	0.0000	0.0000
2015	667	0.0000	0.0000	0.0000
2020	750	0.0000	0.0000	0.0000
2025	893	0.0000	0.0000	0.0000
2030	1024	0.0000	0.0000	0.0000
2035	1095	0.0000	0.0000	0.0000
2040	1161	0.0000	0.0000	0.0033
2045	1194	0.0000	0.0000	0.0055
2050	1204	0.0000	0.0000	0.0062

5.2.2 NYPA subsystem heavy load

A closer look into the highly stressed 2050 NYPA subsystem case study demonstrates several benefits of using a risk-metric calculation. Two runs were used in this study, one with the overload limit set to 100% and the other with the overload limit reduced to 90 %. Table 5.7 shows two branches that both have overload violations in different contingencies.

Table 5-7: Branch Overload Impact for 100% and 90% of Branch Loading (NYPA Subsystem 2050)

Ctg	Prob	LTE Rating	Loading		Severity-Impact (pu)		Risk-Impact (pu)	
	(h yr^{-1})		(MVA) ^a	(MVA) ^a	(%)	100 %	90 %	100 %
Line 10-11								
L-6-7	1230.8	277.0	279.37	100.86	0.0086	0.1086	10.5307	133.6107
T-7-9	2.9	277.0	316.37	114.21	0.1421	0.2421	0.4122	0.7022
Total							10.9428	134.3128
Line 6-7								
L-10-11	3591.0	277.0	275.18	99.34	0.0000	0.0934	0.0000	335.5057
T-9-11	2.9	277.0	315.25	113.81	0.1381	0.2381	0.4005	0.6905
Total							0.4005	336.1962

^a Loading characterized by MVA flow.

5.2.2.1 Effect of probability

Looking at Line 10-11 in Table 5.7, contingency T-7-9 results in a higher loading than contingency L-6-7, however, due to the much higher probability of contingency L-6-7 happening, the risk associated with contingency L-6-7 is more than an order of magnitude higher than the risk associated with contingency T-7-9. In deterministic assessment, contingency T-7-9 would have caused a performance criteria violation first, and so would be the limiting contingency. Contingency L-6-7 would not have been considered even though it contributes more risk.

5.2.2.2 Effect of non-violations

Table 5.7 also shows the effects of non-violations. Both branches have a violation for one of the transformer contingencies (T-7-9 and T-9-11), but only Line 10-11 has a violation for one of the line contingencies (L-6-7 and L-10-11). As seen in the 100% case, Line 10-11 has a higher risk due to the presence of two more severe violations. The 90% case, however, shows Line 6-7 with a higher risk due to the risk of a heavily loaded line from a high probability contingency. Even though Line 6-7 had lower severity contingencies, the probability of their occurrence caused Line 6-7 to have a higher risk. Comparing the 90% severity and risk for the line contingencies (442 and 443) also shows that even though contingency 10-11 is “passing” since it is not overloaded, due to its much higher probability, it still has a higher risk than contingency L-6-7 which is “failing.”

5.2.3 Corrective action

The corrective action case study from Section 3.2.2 was analyzed using probabilistic reliability. As mentioned previously, this case results in a choice between one large overload or several small overloads. The results from risk-based analysis, shown in Table 5.8, demonstrate that for this scenario, several lower overloads have less risk than one large overload, although the adjustment

does increase the risk of low voltage. The additional information from probabilistic assessment allows a decision to be made based on an order of magnitude estimation. The original configuration has an order of magnitude lower risk of low voltage and the same order of magnitude for overload risk, so this adjustment is likely not beneficial.

Table 5-8: Risk-impact of corrective action case study

Scenario	Risk-Impact (pu)	
	Low Voltage	Overload
Original	264.47	3134.29
Adjusted	2584.05	1753.21

5.3 Discussion

OL-RBSA was developed to address questions pertinent to operations, such as how close the system is to voltage collapse, or how many overloads there are and how bad they are [40]. Risk-based contingency analysis would provide some insight into the system regarding these questions by providing a metric that incorporates both the likelihood and extent of violations. By supplementing the information gained from the EMS and the results from deterministic contingency analysis, risk-based contingency analysis can help the operators make some of these traditionally subjective assessments with more confidence and insight into the system.

Since many performance criteria standards are still based on deterministic limits and require deterministic assessments, risk-based contingency analysis can be used to provide additional information about the area around the acceptable operating region. Fig. 5.3 shows a deterministic boundary *ABCDE*, obtained from four limiting contingencies, and three contours of equal risk. The addition of the equal-risk contours provides information about the operating space outside the deterministic boundary which is not normally obtained in deterministic analysis. For example, the contours around line *DE* are closer to each other, indicating that the risk increases rapidly as the boundary is approached, whereas those around line *AB* are spaced further apart, indicating that the risk more gradually. This additional information can help operators determine the best operating condition within the acceptable region that balances risk and reliability concerns with other factors such as economics.

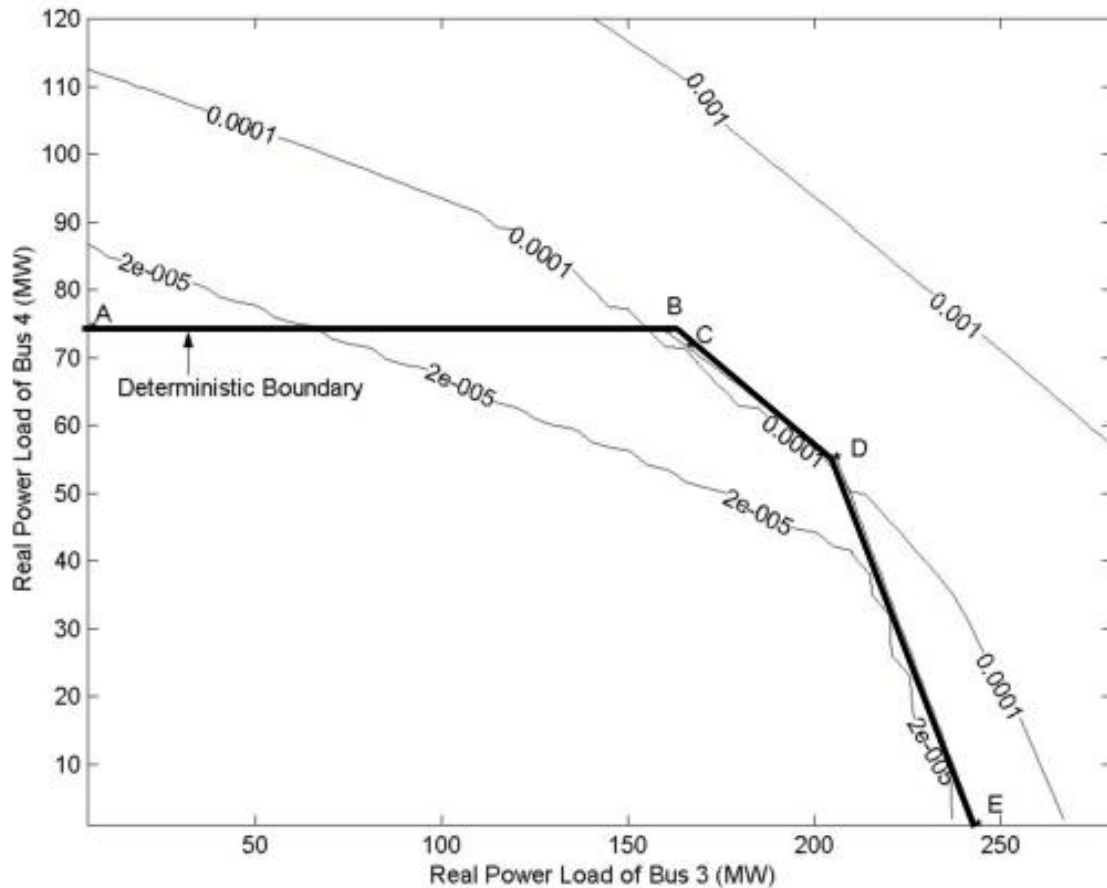


Figure 5-3: Nomogram with deterministic and probabilistic boundaries [12]

Operations planning decisions often have more uncertainty in the operating condition, as they have to forecast demand into the future. To be able to model this uncertainty, tools performing risk-based contingency analysis (RBCA) must either be able to include uncertainty into the load demand modeling, as discussed in Section 5.1.3.2, or results must be post-processed to add the uncertainty from the load into the risk metric. Operations planning can benefit from analyzing the risk of under-voltage or overload, and so can gain more insight into their decisions.

The additional information provided around deterministic limits and visualized in Fig. 5.3 is also beneficial in operational planning. Understanding how system risk behaves with changes in operating condition parameters can help operational planners determine the correct steps for operators to take in response to certain stress patterns within the system.

Long-term system planning largely uses RA to determine the investments that need to be made to ensure adequate generation. The probabilistic nature of this calculation is important, as the further into the future the decision is, the more uncertainty exists. While RA tools have been important in generation planning, it is not as informative for transmission planning, since most RA tools vastly simplify the transmission network. Risk-based contingency analysis performed by OL-RBSA and PRA uses a full AC transmission model, allowing for analysis of transmission expansions or retirements.

RBCA and PRA are not expansion planning tools or optimization engines, but they can be incorporated into expansion and optimization processes. For example, risk-based contingency analysis can be performed for each hour of an 8760 h production cost study. Risk from each component and contingency is accumulated into a risk for each hour, and then finally into a cumulative risk for each plan [42]. This process can be performed for each plan, allowing for comparison of the relative risk between proposed plans. Assigning a cost to risk and incorporating RBCA into the optimization feedback process allows optimization engines to include the cost of risk into the objective function as part of the operating cost and find an optimum balance between increasing investments to minimize risk and other operating costs and decreasing initial capital expenditures.

6. Conclusion

6.1 Summary

The work presented in this thesis compares three different assessments of calculating the reliability of the BPS and applies them to decisions made within operations, operational planning, and long-term planning. A high-level summary of insights provided by each assessment into various reliability related questions is provided in Table 6.1.

Transition probabilities and steady-state probabilities for NERC’s P1 to P6 contingencies are essential for resource adequacy assessment, risk-based contingency analysis, and other probabilistic reliability assessments. To calculate these probabilities, CPET was adapted for use on local data, allowing utilities and system planners to supplement local outage datasets with the national TADS and GADS datasets and obtain reasonable estimates of failure and repair rates for components within their area of responsibility.

6.1.1 Deterministic contingency analysis

Contingency analysis using deterministic limits has historically been used for calculating system reliability. One reason for this is the ease with which the assessment can be applied to decision-making problems. Given a defined operating condition and a list of contingencies, if the operating condition performs within criteria for all contingencies, no action needs to be taken, otherwise, some action should be taken [12]. Deterministic contingency analysis aligns well with short-term decisions, such as in operations or operations planning, as the analysis is done with the expected operating condition, and credible contingencies are simulated to ensure reliability in the upcoming hours or days. While other assessments are being incorporated into long-term planning, deterministic contingency analysis is still used to verify correct performance. Since long-term planning has a large uncertainty in the operating condition, deterministic contingency analysis is usually performed on selected operating conditions, such as summer and winter peak-load cases.

6.1.2 Resource adequacy assessment

Resource adequacy assessment is largely performed to perform long-term system planning decisions. The analysis ensures that sufficient infrastructure exists to minimize disturbances due to lack of resources. Metrics such as LOLE and EUE result from RA and are helpful in informing decisions related to investments or retirements, but these metrics include the assumption that the operator is curtailing load instead of other remediation schemes [12]. While maintenance scheduling decisions in operational planning are similar in nature to investment and retirement decisions and could benefit from RA assessment, the operator’s decisions would need to be removed from RA metrics to be appropriate for use in other operations or operational planning decisions.

Table 6-1: Insights into reliability-related questions

Question	Deterministic Contingency Analysis	Resource Adequacy	Risk-Based Contingency Analysis
How stressed is my system for this operating condition?	Proximity of operating condition to limiting contingencies	High loss of load metric due to system generation stress, but less information about congestion	Metric indicating system risk due to stress that can be compared across different types of system stress
How adequate are my resources for this operating condition?	Identification of problems due to inadequate generation or transmission	Metric indicating loss of load due to inadequate resources, not usually used for only one operating condition	Indication of problems or near-problems due to inadequate generation or transmission
How well will my planned system satisfy NERC criteria TPL-001-5?	Clear indication of whether the system passes or not	Minimal information as performance in response to specific contingency is not modeled	Risk threshold can approximate performance criteria, but current criteria are based on deterministic limits
How adequate is my planned system?	Operating conditions studied individually, adequate performance of all credible operating conditions determines system adequacy	Information about adequate generation across many simulated operating conditions, but less information about transmission	Operating conditions studied individually, information can be aggregated over operating conditions to obtain system adequacy

6.1.3 Risk-based contingency analysis

RBCA follows the basic steps of deterministic contingency analysis, and uses similar inputs to produce an output metric that can be used to delimit the space of acceptable operating conditions [12]. RBCA is therefore well-adapted to inform short-term decisions in operations and operational planning, providing additional insight into the deterministic analysis of system operating conditions, such as whether the deterministic boundary borders a high-risk or lower-risk region. In contrast to the deterministic assessment, RBCA calculates indices by aggregating risk rather than selecting the worst case. This allows uncertainties to be included using probability density functions, and enables more informative use in long-term planning, as operating condition uncertainties can be incorporated into the formulas for calculating risk [40].

6.2 Suggestions for future work

A more rigorous statistical method for “borrowing strength” from TADS and GADS should be incorporated into CPET’s calculations. This method should be able to utilize a zero distance for the target utility, as well as analyze other relationships between components in addition to proximity.

Future work with RBCA could include demonstrating its use in transmission expansion planning as a way to obtain an optimal solution in terms of risk, operational cost, and initial investment cost.

Appendix A: Contingency probability estimation tool calculations

Reference [16] describes the theory of CPET calculations in more detail, however the implementation of some major calculations are summarized here.

A.1 Line length calculation

A main feature of CPET is the ability to correlate failure and repair rates with line length using linear regression. As some system models do not include line length, it is necessary to estimate line length using typical impedance-per-mile data for different voltage classes. Since line impedances are included in the system models, lines can be assigned an estimated length based on their total impedance.

A.2 Theoretical failure rate calculations

This section summarizes CPET's failure transition rate calculations [16].

A.2.1 Submodel 1 – faulted component, protection working as designed

Submodel 1 corresponds to NERC P1 contingencies, where the fault occurs on a component and the protection works as designed. The failure transition rate is

$$\lambda_{ksp} = \frac{N_{ksp}}{T_{kp}^{(I)}} \quad (\text{A.1})$$

where N_{ksp} is the number of state s outages and $T_{kp}^{(I)}$ is the in-service duration for line k assigned to pool p .

A.2.2 Submodel 2 – common structure

Submodel 2 corresponds to NERC P7 common structure contingencies. This model assumes that the ratio of total common structure outages to total automatic outages is equal to the ratio of total common structure line length to total line length within same pool and the ratio of total common structure service duration to total line service duration. The transition rate is

$$\bar{\lambda}_{sp} = \frac{\sum_{k=1}^{K_p} N_{ksp}}{\sum_{k=1}^{K_{cp}} L_k \cdot \sum_{k=1}^{K_{cp}} T_{kp}^{(I)}} \quad (\text{A.2})$$

where K_{cp} is the total number of common structure lines in pool p , and L_k is the common structure line length of line k .

A.2.3 Submodel 3 – breaker/protection/bus section failure

Submodel 3 corresponds to NERC P2, P4, and P5 contingencies types. This submodule assumes that the service duration of each breaker and protection is the same as the line they protect, and that the number of breakers and protections is twice the number of transmission lines. This

assumption is accurate for straight buses, but underestimates for ring buses, breaker and a half, and double-bus-double-breaker configurations. The transition rate is

$$\bar{\lambda}_{sp} = \frac{C_{sp}}{\sum_{k=1}^{K_p} T_{kp}^{(I)}} = \frac{\sum_{k=1}^{K_p} N_{ksp}}{\sum_{k=1}^{K_p} T_{kp}^{(I)}} = \frac{\sum_{k=1}^{K_p} N_{ksp}}{2 \sum_{l=1}^{L_p} T_{lp}^{(I)}} \quad (\text{A.3})$$

where $T_{lp}^{(I)}$ is the in-service duration of line l assigned to pool p , $T_{kp}^{(I)}$ is the in-service duration of breaker k assigned to pool p , L_p is the total number of transmission lines assigned to pool p , C_{sp} is the total number of state s outages in pool p , and K_p is the total number of components (breakers) in pool p .

A.2.4 Submodel 4 – various

Submodel 5 contains various other failures not categorized in the other submodels. This submodel assumes that state S10 contains multiple contingencies due to common right-of-way, repair time of S10 will exceed repair time of single line, repair time of S10 will not exceed two single lines, total service duration of S10 will exceed line service duration, and total service duration of S10 will be less than twice line service duration due to protection misoperations. Using a factor of 1.5 to account for these assumptions, the transition rate is

$$\bar{\lambda}_{sp} = \frac{\sum_{k=1}^{K_p} N_{ksp}}{\sum_{k=1}^{K_p} T_{kp}^{(I)}} = \frac{\sum_{k=1}^{K_p} N_{ksp}}{1.5 \sum_{l=1}^{L_p} T_{lp}^{(I)}} \quad (\text{A.4})$$

where $T_{lp}^{(I)}$ is the in-service duration of line l assigned to pool p , $T_{kp}^{(I)}$ is the in-service duration of breaker k assigned to pool p , L_p is the total number of transmission lines assigned to pool p , and K_p is the total number of components (breakers) in pool p .

A.3 Theoretical repair rate calculations

This section summarizes CPET's repair transition rate calculations [16]. Since the repair rate does not depend on line length or the number of protection devices per line, most submodels use the repair transition rate

$$\bar{\mu}_{sp} = \frac{\sum_{k=1}^{K_p} N_{ksp}}{\sum_{k=1}^{K_p} T_{ksp}^{(O)}} \quad (\text{A.5})$$

where N_{ksp} is the number of state s outages, and $T_{ksp}^{(O)}$ is the outage duration for line k assigned to pool p .

Repair rate calculations for Submodel 5 retain the factor of 1.5 and are given by

$$\bar{\mu}_{sp} = \frac{\sum_{k=1}^{K_p} N_{ksp}}{1.5 \sum_{k=1}^{K_p} T_{ksp}^{(O)}} \quad (\text{A.6})$$

A.4 Implemented mean transition rates calculations

The transition rates implemented in CPET are shown in Table A.1 where

$$\sum_i l_i^{(c)} = \frac{\sum_i N_i^{(c)}}{\sum_i N_i} \sum_i l_i$$

$$\sum_i T_i^{(c)} = \frac{\sum_i N_i^{(c)}}{\sum_i N_i} \sum_i T_i^{(I)},$$

N_i is the number of events, $N_i^{(c)}$ is the number of auto events, $T_i^{(O)}$ is the outage duration in h, $T_i^{(I)}$ is the in service duration in h, and l_i is the line length miles.

The common structure model has the assumption that ratio of common structure events to single line events is equal to the ratio of common structure length and time to single line length and time, respectively. Mathematically, this is

$$\frac{\sum N_c}{\sum N} = \frac{\sum l_c}{\sum l} = \frac{\sum T_c}{\sum T} \quad (\text{A.7})$$

where X is a single line quantity, X_c is a common structure quantity.

The factor of 8760 h yr⁻¹ is necessary to account for different units provided in input data.

Table A- 1: Transition rate calculations implemented in CPET

Path	State	Mean Repair Rate $\bar{\mu}$ (repairs/yr)	Mean Failure Rate $\bar{\lambda}$ (failures/yr)
Submodel 1			
Single Component	S2	$\sum_i N_i / (\sum_i T_i^{(O)} / 8760 \text{ h yr}^{-1})$	$\sum_i N_i / \sum_i T_i^{(I)}$
Submodel 2			
Common Struct (Line)	S9	$\sum_i N_i / (\sum_i T_i^{(O)} / 8760 \text{ h yr}^{-1})$	$\sum_i N_i / \sum_i l_i^{(c)} / \sum_i T_i^{(c)}$
Common Struct (Xfmr)	S9	$\sum_i N_i / (\sum_i T_i^{(O)} / 8760 \text{ h yr}^{-1})$	$\sum_i N_i / \sum_i T_i^{(c)}$
Submodel 3			
Protection Failure	S7	$\sum_i N_i / (\sum_i T_i^{(O)} / 8760 \text{ h yr}^{-1})$	$\sum_i N_i / 2 / \sum_i T_i^{(I)}$
Stuck Breaker	S6	$\sum_i N_i / (\sum_i T_i^{(O)} / 8760 \text{ h yr}^{-1})$	$\sum_i N_i / 2 / \sum_i T_i^{(I)}$
Breaker Internal	S5	$\sum_i N_i / (\sum_i T_i^{(O)} / 8760 \text{ h yr}^{-1})$	$\sum_i N_i / 2 / \sum_i T_i^{(I)}$
Protection Misoperation	S3	$\sum_i N_i / (\sum_i T_i^{(O)} / 8760 \text{ h yr}^{-1})$	$\sum_i N_i / 2 / \sum_i T_i^{(I)}$
Submodel 5			
Various	S10	$\sum_i N_i / (\sum_i T_i^{(O)} / 8760 \text{ h yr}^{-1}) / 1.5$	$\sum_i N_i / \sum_i T_i^{(I)} / 1.5$

A.5 Markov model

The transition formula for a Markov model is given by

$$\boldsymbol{\pi}_{i+1} = \mathbf{P}\boldsymbol{\pi}_i \quad (\text{A.8})$$

where $\boldsymbol{\pi}_i$ is the initial state probability vector and $\mathbf{P}$ is the transition matrix

$$\mathbf{P} = \begin{bmatrix} \lambda_{11} & \lambda_{21} & \cdots & \lambda_{n1} \\ \lambda_{12} & \lambda_{22} & \cdots & \lambda_{n2} \\ \vdots & \vdots & \ddots & \vdots \\ \lambda_{1n} & \lambda_{2n} & \cdots & \lambda_{nn} \end{bmatrix} \quad (\text{A.9})$$

where λ_{ij} is the transition probability from state s_i to state s_j . The probability of remaining in state s_i is given by the transition rate

$$\lambda_{ii} = 1 - \sum_{\substack{j=1 \\ j \neq i}}^n \lambda_{ij} \quad (\text{A.10})$$

Defining the quantity

$$\lambda_i = \sum_{\substack{j=1 \\ j \neq i}}^n \lambda_{ij} \quad (\text{A.11})$$

and substituting into (A.8) and (A.9), we obtain

$$\boldsymbol{\pi}_{i+1} = \begin{bmatrix} 1 - \lambda_1 & \lambda_{21} & \cdots & \lambda_{n1} \\ \lambda_{12} & 1 - \lambda_2 & \cdots & \lambda_{n2} \\ \vdots & \vdots & \ddots & \vdots \\ \lambda_{1n} & \lambda_{2n} & \cdots & 1 - \lambda_n \end{bmatrix} \boldsymbol{\pi}_i \quad (\text{A.12})$$

Distributing,

$$\boldsymbol{\pi}_{i+1} = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 1 \end{bmatrix} \boldsymbol{\pi}_i + \begin{bmatrix} -\lambda_1 & \lambda_{21} & \cdots & \lambda_{n1} \\ \lambda_{12} & -\lambda_2 & \cdots & \lambda_{n2} \\ \vdots & \vdots & \ddots & \vdots \\ \lambda_{1n} & \lambda_{2n} & \cdots & -\lambda_n \end{bmatrix} \boldsymbol{\pi}_i \quad (\text{A.13})$$

Simplifying,

$$\boldsymbol{\pi}_{i+1} = \boldsymbol{\pi}_i + \begin{bmatrix} -\lambda_1 & \lambda_{21} & \cdots & \lambda_{n1} \\ \lambda_{12} & -\lambda_2 & \cdots & \lambda_{n2} \\ \vdots & \vdots & \ddots & \vdots \\ \lambda_{1n} & \lambda_{2n} & \cdots & -\lambda_n \end{bmatrix} \boldsymbol{\pi}_i \quad (\text{A.14})$$

Letting $\Delta\boldsymbol{\pi} = \boldsymbol{\pi}_{i+1} - \boldsymbol{\pi}_i$,

$$\Delta\boldsymbol{\pi} = \begin{bmatrix} -\lambda_1 & \lambda_{21} & \cdots & \lambda_{n1} \\ \lambda_{12} & -\lambda_2 & \cdots & \lambda_{n2} \\ \vdots & \vdots & \ddots & \vdots \\ \lambda_{1n} & \lambda_{2n} & \cdots & -\lambda_n \end{bmatrix} \boldsymbol{\pi}_i \quad (\text{A.15})$$

Setting $\Delta\boldsymbol{\pi} = \mathbf{0}$ and solving for the state probabilities vector $\boldsymbol{\pi}_i$ gives a set of steady-state probability vectors which does not change under $\mathbf{P}$. This solution space can be forced to be unique by requiring that the sum of state probabilities must equal one.

Appendix B: Contingency probability estimation tool error calculations

The EEFOR is an equivalent FOR that aims to incorporate resource unavailability and is calculated as

$$\text{EEFOR} = \frac{\text{FTH} + \text{EFDTH}}{\text{CTH} + \text{RUTH} + \text{FTH}} \quad (\text{B.1})$$

using forced turbine hours (FTH), equivalent forced derated turbine hours (EFDTH), contactor turbine hours (CTH), and resource unavailable turbine hours (RUTH).

While the EEFOR is used for wind energy resources in this work to allow one-to-one comparison with other software, wind and solar energy should be modeled using the net-load approach discussed in Section 4.1.2, which incorporates the variability of resource availability throughout the day as well as the effects of individual unit outages within a plant [35], [36].

Appendix C: Contingency probability estimation tool regional regression plots

Figure C-1 shows the P1 failure rate with respect to line length for each NERC reliability region.

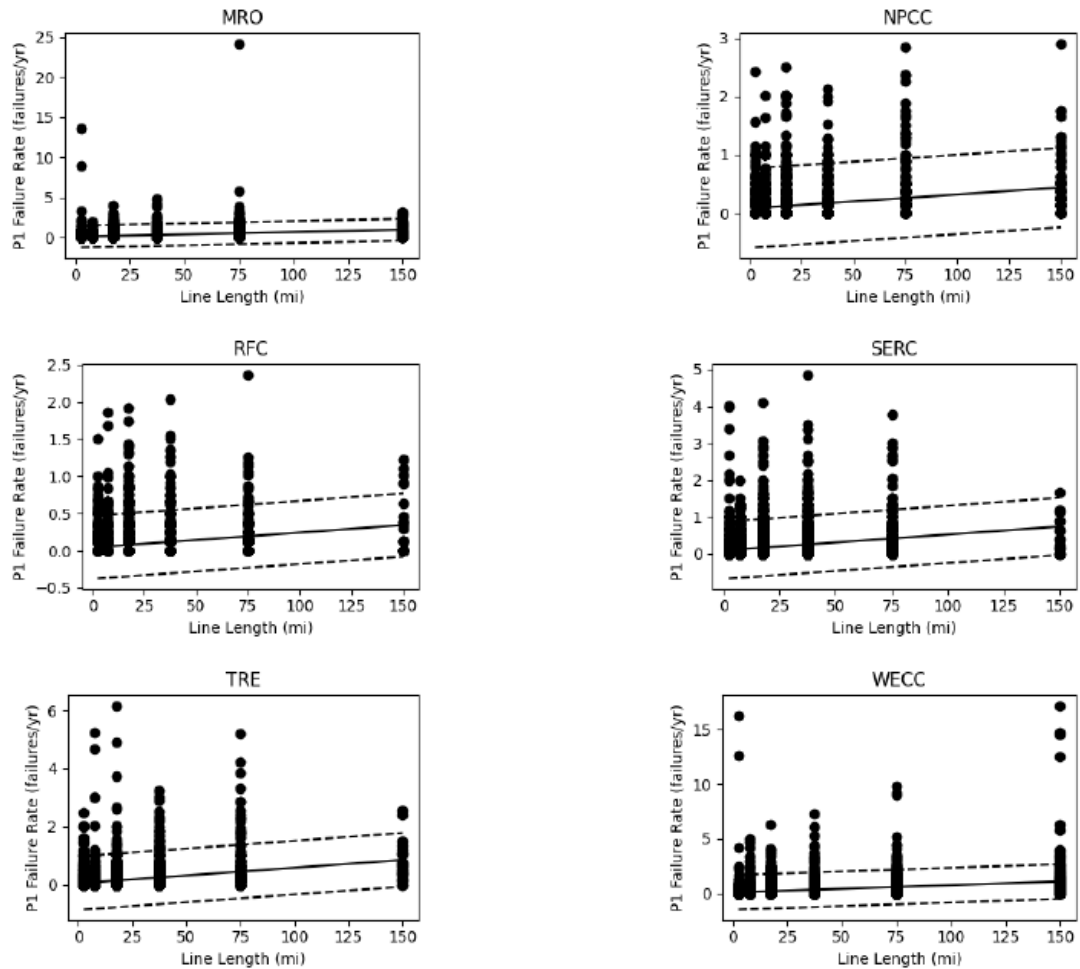


Figure C- 1: AC Line P1 probability vs line length by region

Appendix D: Severity functions

The first column of Figs. D.1 and D.2 shows a deterministic severity function which evaluates to unity if a violation occurs. The threshold for this violation can be specified in both PRA and OL-RBSA.

The second column combines the presence of a violation with the extent of that violation. OL-RBSA calculates these metrics by comparing the amount the threshold was exceeded to the value of the threshold, while PRA uses a fixed unity slope starting at the specified threshold. These metrics will only have values once a violation has occurred.

The third column shows custom metrics able to be defined in OL-RBSA. These can be any form of a ramp function, but it is useful to have the severity evaluate to unity at the threshold to represent an expectation of the number of violations, while still enabling non-violations to contribute to risk.

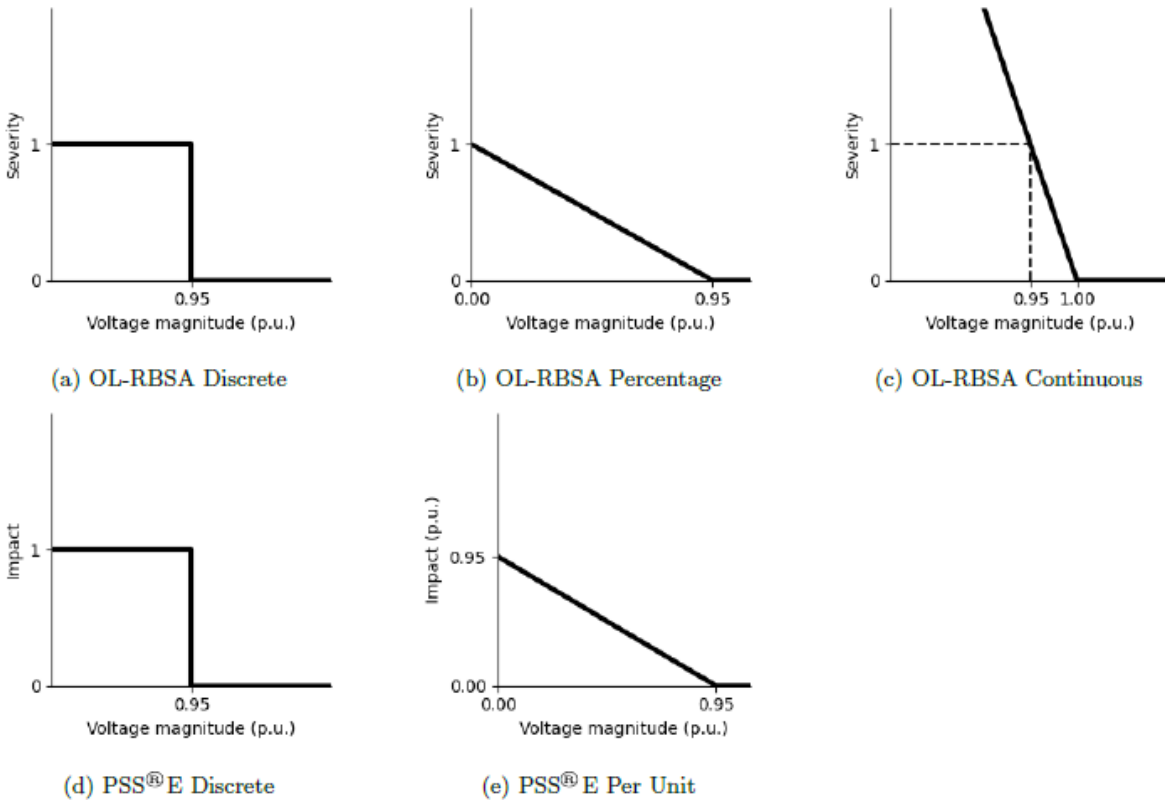


Figure D- 1: Voltage severity functions

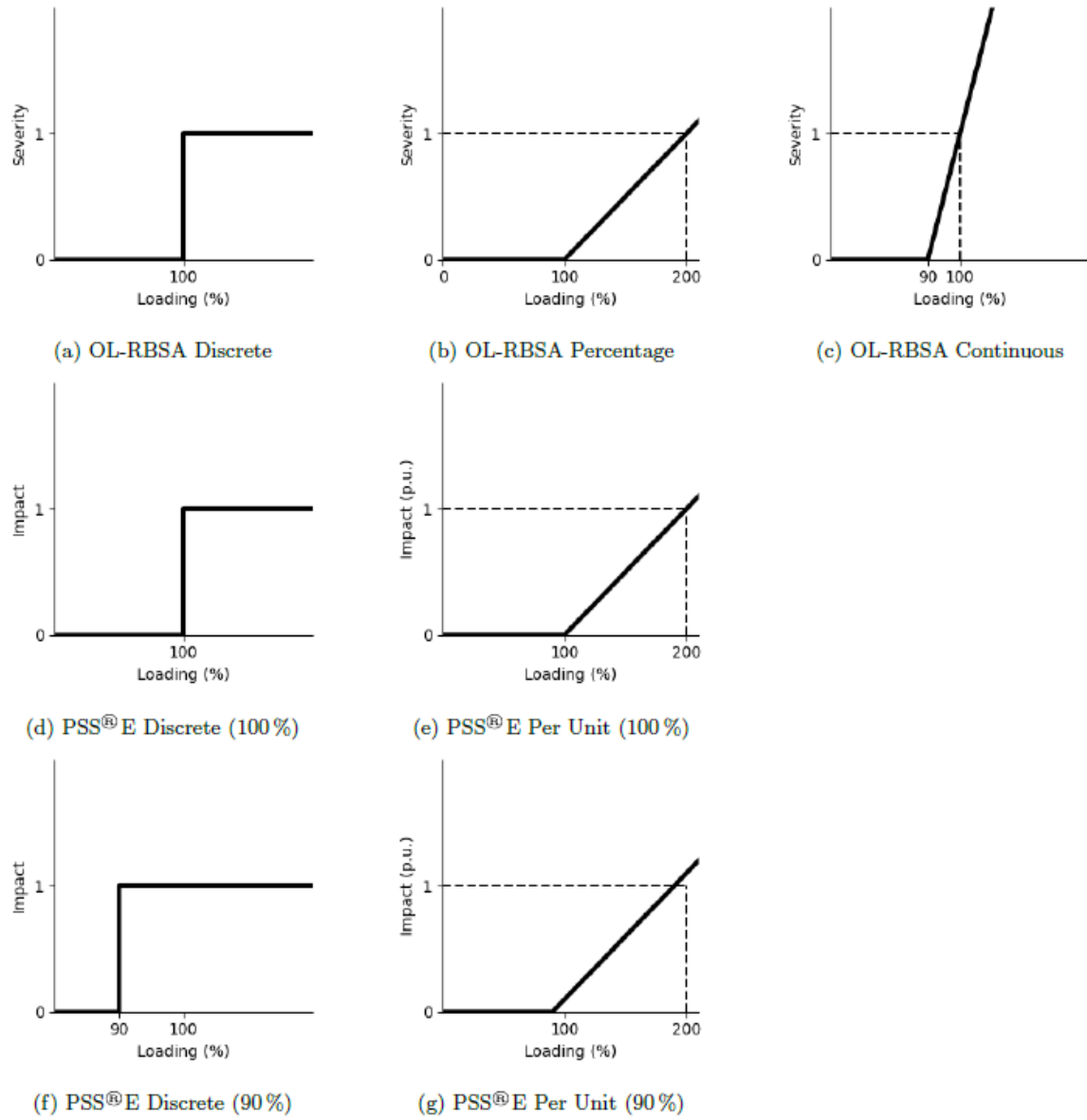


Figure D- 2: Overload severity functions

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