RELIABILITY AND RESILIENCY WORTH ASSESSMENT OF INVESTMENT IN POWER TRANSMISSION FACILITIES

A Thesis Submitted to the
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In Partial Fulfillment of the Requirements
For the Degree of Master of Science
In the Department of Electrical and Computer Engineering
University of Saskatchewan
Saskatoon, Canada

By
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ABSTRACT

Global initiative to reduce the carbon footprint from the environment is transforming the modern power system. Growing integration of uncertain and intermittent renewable energy source like wind generation and increased number of electric vehicles in automotive industry will create difficulties in balancing supply and demand. This will change the power flow in the system, which will create the congestion in the existing transmission line reducing the overall system reliability. There is ongoing research and development in smart grid resources such as energy storage, var compensator, dynamic line ratings and communication devices to increase the capability of existing line to alleviate the congestion and maintain the continuity of supply to the bulk load points. Further, the existing transmission infrastructures are vulnerable to extreme weather events, such as windstorms that are occurring more frequently. There is a growing need for appropriate investment in modern transmission resources to ensure reliable and resilient transmission systems in the changing scenario.

The value-based reliability assessment is necessary to justify the worth of any investment in the power system. The worth of investment comes from the reduced outage cost. Generally, generation facilities comprise the most capital investment for an electric utility. Therefore, the outage cost data available in published reports and past surveys associated with generation inadequacy. The customer power outage from insufficient generation mainly occurs during the peak demand period. However, the outages due to transmission resource failure can occur at other periods with specific probabilities. This thesis presents a methodology to estimate the cost of power interruptions originated from transmission component failures. The methodology proposes a sector periodic model for each customer sector to obtain the associated demand normalized outage costs.

Furthermore, the thesis utilizes the outage cost obtained from the methodology to evaluate the reliability and resiliency worth of investments in the transmission grid facilities and technologies. The thesis presents a method to assess the reliability worth of investments in advancing transmission technology to enhance the grid reliability. The thesis also presents a method to assess the resiliency worth of investing into the infrastructure hardening to improve grid resilience against extreme wind events.
ACKNOWLEDGEMENTS

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Finally, I want to thank my parents and my wife for their love and support.
DEDICATION

To my beloved parents, Laxmi Prasad and Purna Kumari,

and

To my wife, Asmita for her unwavering patience, compassion,

and most importantly her love.
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<thead>
<tr>
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<th>Description</th>
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<tbody>
<tr>
<td>AAR</td>
<td>Ambient Adjusted Ratings</td>
</tr>
<tr>
<td>ACSR</td>
<td>Aluminum Conductor Steel Reinforced</td>
</tr>
<tr>
<td>AMI</td>
<td>Advance Metering Infrastructure</td>
</tr>
<tr>
<td>CCDF</td>
<td>Composite Customer Damage Function</td>
</tr>
<tr>
<td>CDF</td>
<td>Customer Damage Function</td>
</tr>
<tr>
<td>CF</td>
<td>Cut-off load point</td>
</tr>
<tr>
<td>CVaR</td>
<td>Conditional Value at Risk</td>
</tr>
<tr>
<td>DER</td>
<td>Distributed Energy Resources</td>
</tr>
<tr>
<td>DLR</td>
<td>Dynamic Line Rating</td>
</tr>
<tr>
<td>DNC</td>
<td>Demand Normalized Cost</td>
</tr>
<tr>
<td>ECOST</td>
<td>Expected Cost of customer interruption</td>
</tr>
<tr>
<td>EDLC</td>
<td>Expected Duration of Load Curtailments</td>
</tr>
<tr>
<td>EDNC</td>
<td>Expected Demand Normalized Cost</td>
</tr>
<tr>
<td>EENS</td>
<td>Expected Energy Not Supplied</td>
</tr>
<tr>
<td>ELC</td>
<td>Expected Load Curtailed</td>
</tr>
<tr>
<td>ERCOT</td>
<td>The Electric Reliability Council of Texas</td>
</tr>
<tr>
<td>ESS</td>
<td>Energy Storage System</td>
</tr>
<tr>
<td>FACTS</td>
<td>Flexible AC Transmission System</td>
</tr>
<tr>
<td>HILP</td>
<td>High Impact Low Probability</td>
</tr>
<tr>
<td>HL</td>
<td>Hierarchical Level</td>
</tr>
<tr>
<td>IC</td>
<td>Interruption Cost</td>
</tr>
<tr>
<td>IEEE</td>
<td>Institute of Electrical and Electronics Engineers</td>
</tr>
<tr>
<td>kW</td>
<td>Kilowatt</td>
</tr>
<tr>
<td>L.F.</td>
<td>Load Factor</td>
</tr>
<tr>
<td>LOLF</td>
<td>Loss of Load Frequency</td>
</tr>
<tr>
<td>MTTR</td>
<td>Mean Time to Repair</td>
</tr>
<tr>
<td>MVA</td>
<td>Megavolt amperes</td>
</tr>
<tr>
<td>MW</td>
<td>Megawatt</td>
</tr>
</tbody>
</table>
MWhr  Megawatt Hour
NERC  North American Electric Reliability Corporation
NLC  Number of Load Curtailments
PJM  Pennsylvania-New Jersey-Maryland interconnection
Prob  Probability
RD  Representative Diurnal load profile
RTS  Reliability Test System
RW  Reliability Worth
SCDF  Sector Customer Damage Function
SPD  Sector Periodic Demand
VBRI  Value-Based Reliability Investment
CHAPTER 1: INTRODUCTION

1.1. Power system reliability

1.1.1. Reliability concept in power system

Power system reliability refers to the ability of an electrical power system to deliver electricity to consumers with acceptable quality minimizing the likelihood of outages. Power outages can affect daily operation of residential and industrial activities leading to major financial losses to the society. Therefore, power utilities have the responsibility to provide reliable power supply to their customers. The reliability of power supply can be enhanced by making appropriate investment in system facilities and operational resources. For example, adding redundancies in system components and increasing the generation reserve margin improves the reliability. However, the investment in system redundancies should be justified by the resulting improvement in reliability. The primary objective of an electric power system is to economically provide electric power to its customers while maintaining an acceptable level of reliability and complying with environmental obligations.

The Evaluation of a power system can be divided into system adequacy and security as shown in Figure 1.1. Adequacy deals with the availability of the power system infrastructure to meet its demand, while security deals with the ability of the power system to withstand a sudden disturbance. The North American Electric Reliability Corporation (NERC) defines system adequacy as the ability of the electric system to supply the aggregate electrical demand and energy requirements of the end-use customers, considering scheduled and reasonably expected unscheduled outages of system elements. System security is defined as the ability of the electric system to withstand sudden disturbances such as unanticipated loss of system components. The scope of this thesis is within the area of system adequacy.
1.1.2. **Functional Zone and Hierarchical level**

The power system can be divided into three major functional zones – generation, transmission and distribution. The reliability assessment can be performed at different hierarchical levels from the combination of these functional zones as shown in Figure 1.2. HL-I is concerned with the ability of the generation system to meet the overall load demand, HL-II is concerned with the ability of the generation and transmission system to collectively meet the demand at bulk load point. The HL-III includes all the three functional zones. This thesis is focused on HL-II adequacy assessment.

1.1.3. **Reliability assessment techniques**

The Reliability assessment of a power system can be performed using both deterministic and probabilistic approaches. The Deterministic N-1 criteria are widely used in transmission planning. The N-1 criterion requires the system be intact when the large single component fails to operate.
The deterministic approach does not incorporate the stochastic nature of power system arising from components failure and balancing the supply-demand. To circumvent the limitation of deterministic reliability assessment, a probabilistic assessment is introduced in the power system planning and operation. Probabilistic assessment approach can effectively represent the inherent random factors in the power system that impact the system reliability. This approach can provide quantitative reliability metrics that can be used to evaluate and compare different planning and operational options and their associated costs. There are two types of assessment methods – analytical and simulation to evaluate the probabilistic power system reliability approach.

An analytical method develops a mathematical model to closely represent the system characteristics and perform a numerical solution to evaluate reliability indices. The reliability assessment of bulk power systems must consider a multiplicity of factors, such as the failure and repair rates of equipment and operating practices, including economic generation scheduling, security controls, emergency controls, projected load variations, and maintenance schedules. These system characteristics can be represented with analytical models in the analytical technique [1]. By using the analytical technique, system contingencies, which may involve line failures, unit outages, or both, are first enumerated up to a certain level. To identify the contingencies that result in system failures, failure effects analysis is then conducted to test system contingencies against some predetermined criteria. The impact of each contingency on the system, such as line loading and bus voltages, is obtained by solving power flows. Based on the results of effects analysis, system reliability indices such as loss-of-load probabilities, frequencies, and durations can be calculated [2]. Example of analytical method includes Marko model, fault tree analysis etc.

A simulation method such as Monte-Carlo techniques estimate the reliability indices by simulating the actual process and stochastic behaviour of the system. The bulk power system reliability assessment problem is treated as a series of experiments in the Monte Carlo simulation technique. This technique consists of randomly sampling system states, testing them for acceptability, and aggregating the contribution of loss-of-load states to the reliability until the variations of reliability indices drop below pre-specified tolerances [3]. The simulation of selected system states is done with the use of load flows that consider generation dispatch and other pre-selected operating policies. Simulation results are distributions of the 20 variables of interest (i.e.,
circuit flows, voltage levels, energy curtailment, and so on). These results are utilized in the computation of appropriate reliability indices [4].

1.1.4. Value-based reliability investment

Value-based reliability investment assesses the worth of an investment in a power system network. It involves assessing the trade-off between investment cost of reliability enhancing measures and the customer outage cost in terms of reduced economic losses and improved customer satisfaction. The sum of investment cost and outage cost represent the societal cost and the target of value-based reliability is to achieve higher reliability with minimal societal cost as shown in Figure 1.3.

The analysis helps utilities to allocate resources efficiently to achieve the cost effective overall societal benefits. Furthermore, the approach considers regulatory requirements and compliance. Aligning reliability targets and performance standards with regulatory expectations is essential. Utilities must ensure that the cost of compliance with these regulations is justified by the value it delivers in terms of improved reliability and customer service. Finally, value-based reliability encourages innovation and technology adoption. By exploring new technologies and innovative solutions, utilities can enhance reliability in a cost-effective manner, ensuring that investments yield a positive return in terms of reliability value.

![Figure 1.3. Value-based reliability investment](image-url)
1.1.5. Customer outage cost

Customer outage costs in a power system encompass a wide spectrum of expenses incurred by individuals and businesses when electricity service is disrupted. These costs fluctuate based on several critical factors, notably the duration of the outage, the type of customers affected (Ex. residential, commercial, or industrial), the timing of the outage, the geographic location, seasonal variations. For instance, prolonged outages can result in significant financial losses for commercial and industrial entities due to halted production, revenue loss, and potential damage to equipment. Moreover, urban areas or regions with high economic activity might experience escalated costs during outages due to the concentration of businesses. Outages occurring during peak hours or crucial periods, such as extreme weather conditions, could escalate costs due to heightened demand or critical needs. Calculating outage costs involves evaluating direct expenses like lost revenue and productivity, as well as indirect costs such as equipment damage, and customer dissatisfaction.

The customer outage cost is estimated for various outage durations from different methods [5] such as customer survey, case studies of blackouts etc. The outage cost is normalized by customer demand and is represented in terms of demand normalized cost (DNC, $/kW). The demand normalized costs, from all the customer sectors within a load point, are weighted by the sector load compositions to form a composite customer damage function (CCDF).

1.1.6. Reliability indices used for reliability worth analysis in composite power system

The reliability worth of an investment is the reduction in customer outage cost in a power system after the investment. The reliability worth of an investment at a load point is given by (1.1a).

\[ \text{Reliability worth of investing at bus } K = ECOST_{K, before} - ECOST_{K, after} \quad (1.1a) \]

Where, \( ECOST_{K, before} \) and \( ECOST_{K, after} \) represents the expected cost of customer interruption (ECOST) at bus K before and after an investment is made. The ECOST at bus K is given by (1.1b).

\[ ECOST_K = \sum_{j \in V} L_{Kj} \times F_j \times C_{Kj}(D_{Kj}) \frac{MW}{kW} \frac{\$}{yr} \quad (1.1b) \]
Where, $L_{Kj}$, $F_j$, and $C_{Kj}(D_{Kj})$ represent the load curtailment, the frequency of occurrence, and the CCDF ($$/kW$$) as a function of a power outage of duration $D_{Kj}$$\text{(hours)}$ respectively for each failure scenario $j$ causing load curtailment at load point $K$ respectively. Also, $j \in V$ includes all failure scenarios which cause load flow violations – insufficient generation, line overloads, voltage violations and isolation of bus.

1.2. Power system Resilience

1.2.1. Resiliency concept in power system

Power system resilience is a critical concept in the field of the system infrastructure and its ability to supply energy when a significant physical disturbance occurs. It is the power system's ability to endure and recover from a wide range of disruptions, thus ensuring the uninterrupted delivery of electricity even in adverse conditions. These disruptions encompass natural disasters like hurricanes and earthquakes, as well as human-made challenges such as cyber-physical attacks. Resilient power systems achieve this by incorporating redundancy, maintaining robust physical infrastructure, swiftly restoring service, implementing advanced monitoring and control systems, bolstering cybersecurity measures, and ensuring effective planning and coordination between stakeholders.

Study of power system resilience has become the paramount importance in recent decades as the occurrence of extreme events such as hurricane and wildfire has increased significantly mainly due to global warming. Power system resilience study mainly deals with the analysing the potential impacts from an extreme event, quantifying the loss and implementing the effective measures against such events to reduce the impact and facilitate the swift recovery.

The resilience phases in power system can be divided into pre-event, during the event and post event. The power system resilience during the event and its phases can be presented as resilience trapezoid [6] as shown in Figure 1.5.
1.2.2. Power system Resilience metrics

The resilience metrics attempt to quantify the damage caused by the extreme event. A power system resilience is fairly a new academic research area and lacks the widely accepted metrics. Some of the metrics - Conditional Value at Risk (CVaR), expected energy not supplied (EENS), and FLEP model representing Resilience Trapezoid, which are in current research studies are summarized in [7].

1.2.3. Extreme events

Extreme events, often referred to as High Impact Low Probability (HILP) events, are naturally occurring or human-induced events with low probability of occurrence but possess the potential to substantially harm power system infrastructure, leading to disruptions or even a complete halt in electricity supply to consumers. Power system infrastructure is susceptible to a range of these extreme events including but not limited to extreme weather, cyber-physical attacks, seismic events, electromagnetic pulse etc. These extreme events, while infrequent, requires a heightened level of preparedness and resilience within the power sector to ensure continued and reliable energy delivery to consumers, particularly in the face of unexpected challenges. For
example, a hurricane in an area not only can have destructive impact on power system but also disturb the livelihood of human.

Power system resilience against an extreme event in a region depends on the probability of an occurrence of the extreme event and section of power system infrastructure exposed to the event. For example, a region with high probability of hurricane can severely damage the transmission and distribution section of power system, while a region with high probability of earthquake can damage the generation station such as nuclear power plant. It is therefore advisable to assess the power system resilience against specific types of events which has the highest probability of causing damage to the system infrastructure that is in the region.

Key components of power system resilience against extreme events include:

- Robust Infrastructure: Investing in strong and durable physical infrastructure, such as substations, transmission lines, and distribution systems, that can withstand the forces of nature, such as high winds, floods, or earthquakes.
- Redundancy: Incorporating backup systems, components, and diversified energy sources to reduce the risk of complete system failure during extreme events. Redundancy ensures that critical functions can continue to operate, even if some elements are compromised.
- Rapid Restoration: Developing efficient procedures and response plans to quickly restore power after an extreme event, reducing downtime and minimizing the impact on consumers and the economy.
- Advanced Monitoring and Control: Utilizing real-time monitoring, automation, and control systems to detect disturbances and respond rapidly to isolate and mitigate problems as effectively as possible.
- Cybersecurity: Implementing robust cybersecurity measures to protect the power system from cyber threats and attacks, safeguarding grid reliability and data security.
- Collaboration and Planning: Coordinating efforts and communication among various stakeholders, including utilities, government agencies, and emergency responders, is essential for a well-organized response to extreme events.

In summary, power system resilience against extreme events is fundamental for safeguarding the continuous supply of electricity, which is critical for public safety and economic stability.
Efforts in this domain involve a combination of technology, policy, and investment to ensure that the power system can endure and recover from the unexpected and rare challenges it may encounter. Resilience measures are crucial in ensuring that electricity remains available, even when confronted with unforeseen challenges and disruptions.

1.2.4. Extreme wind and its impact in power system resilience

Extreme wind events encompass various meteorological phenomena with high wind speeds that can significantly impact power systems. These events are characterized by strong winds that can lead to power outages, infrastructure damage, and operational challenges. The Beaufort scale is a system for classifying wind speeds based on observed conditions at sea or on land. It ranges from 0 (calm) to 12 (hurricane), with each category associated with specific wind speeds and descriptions of their effects. The Beaufort scale as presented in Table 1.1 can be used to understand the impact of wind on the physical system as follows [8].

<table>
<thead>
<tr>
<th>No.</th>
<th>Description</th>
<th>Wind speed</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>Calm</td>
<td>0–2</td>
</tr>
<tr>
<td>1</td>
<td>Light air</td>
<td>0.3–1.5</td>
</tr>
<tr>
<td>2</td>
<td>Light breeze</td>
<td>1.6–3.3</td>
</tr>
<tr>
<td>3</td>
<td>Gentle breeze</td>
<td>3.4–5.0</td>
</tr>
<tr>
<td>4</td>
<td>Moderate breeze</td>
<td>5.5–7.9</td>
</tr>
<tr>
<td>5</td>
<td>Fresh breeze</td>
<td>8–10.7</td>
</tr>
<tr>
<td>6</td>
<td>Strong breeze</td>
<td>10.8–13.8</td>
</tr>
<tr>
<td>7</td>
<td>High wind, moderate gale, near</td>
<td>13.9–17.1</td>
</tr>
<tr>
<td>8</td>
<td>Gale, fresh gale</td>
<td>17.2–20.7</td>
</tr>
<tr>
<td>9</td>
<td>Strong/severe gale</td>
<td>20.8–24.4</td>
</tr>
<tr>
<td>10</td>
<td>Storm, whole gale</td>
<td>24.5–28.4</td>
</tr>
<tr>
<td>11</td>
<td>Violent storm</td>
<td>28.5–32.6</td>
</tr>
<tr>
<td>12</td>
<td>Hurricane-force</td>
<td>≥ 32.7</td>
</tr>
</tbody>
</table>
Impacts of Extreme Wind on Power Systems:

- **Power Outages**: The most immediate and widespread impact of extreme wind events is power outages. Strong winds can bring down power lines, damage transformers, and cause other equipment failures, resulting in loss of electricity for customers.

- **Infrastructure Damage**: Extreme wind events can damage power infrastructure, including substations, transmission lines, and distribution equipment. This damage can be costly to repair and may require extensive rebuilding efforts.

- **Debris and Tree Damage**: Falling trees and debris, carried by strong winds, can impact power lines and equipment, causing outages. This is a common issue in regions with a significant tree canopy near power lines.

- **Safety Risks**: High winds pose safety risks to utility workers who must repair the damage and restore power. Wind-related injuries and fatalities can occur during response and recovery efforts.

- **Operational Challenges**: Extreme wind events can lead to challenges in power system operations, such as managing grid stability by switching to alternative power sources and coordinating restoration efforts.

1.3. **Power system Grid Facilities**

The power grid facilities are a vital component in electric power system, operating as a high-voltage network of power lines and substations that serve as the backbone for electricity transmission. It is designed for long-distance transportation of electricity, connecting power generation sources to substations closer to load centers. Operating at high voltage levels reduces energy losses, making it a cost-effective solution for transporting large quantities of power over extended distances. Transformers at substations facilitate the conversion of voltage levels, ensuring that electricity can be efficiently distributed to homes, businesses, and industries.

One of the transmission grid's primary objectives is to ensure the reliability and redundancy of the electricity supply. It incorporates multiple transmission lines and substations, allowing for backup options in case of equipment failures or unforeseen events. Load balancing is another critical function, ensuring that electricity flows efficiently across the network to prevent congestion.
and overloading. Transmission grids are often interconnected with neighboring grids, enabling the exchange of electricity between regions, enhancing reliability, and facilitating resource sharing. Real-time monitoring and control of the transmission grid occur from central control centers, where operators can manage the flow of electricity, reroute power as needed, and respond to disturbances to maintain grid stability. Ongoing grid expansion and upgrades are essential to meet changing energy generation patterns, demand growth, and evolving technologies. The transmission grid also plays a pivotal role in the integration of renewable energy sources, necessitating the construction of new transmission lines to connect remote renewable energy sites to urban load centers.

In addition to its operational functions, the transmission grid is designed to withstand emergencies and natural disasters. Grid operators should have a contingency plans and backup systems to restore power swiftly in case of outages. Economic efficiency and environmental considerations are integral to transmission grid projects, as they aim to minimize energy losses and environmental impacts while ensuring reliable power delivery. In summary, the power system transmission grid is the vital link in the electricity supply chain, ensuring efficient, reliable, and resilient power transmission for modern societies.

The transmission grid is owned and operated by transmission system operators (TSOs) in many countries. It is subject to regulation by relevant authorities to ensure that it functions reliably and efficiently. The transmission grid forms an essential part of the larger electrical grid, which also includes power generation facilities, distribution networks, and various other components to deliver electricity to end-users.

1.4. Research Motivations and Objectives

Utilities are required to meet net-zero carbon emissions in near future and are actively investing on renewable energy sources. The governments are encouraging to the public to use environment friendly energy in their daily activities such as electric vehicles for the transportation. The growth in intermittent and uncertain renewable resources such as wind [9] and rising share of electric vehicles in the automotive industry [10] will create a difficulty in balancing the supply and demand. Such change in generation and load pattern will also make the congestion in existing transmission network, making existing grid resources less reliable. Further, the increased
occurrences of HILP events such as extreme wind in a recent decade resulted in catastrophic destruction in grid resources leading to long outages and huge financial losses [11]. The transmission grid is mainly affected by extreme wind due to the long span and high exposure of overhead lines. Therefore, to maintain reliable power supply to the customers, utilities are investing into the transmission resources. The reliability and resiliency improvement of transmission system and finding the cost-effective investment option became imperative to the utilities.

Assessment of the reliability worth of an investment provides a method to analyze the financial aspects of the potential upgrades in a power system [12]. Understanding the resiliency worth of an investment is still under development and there is not widely accepted metrics yet. However, widely accepted assessment of reliability worth of an investment can be a starting point [7]. The reliability worth of an investment in power system is evaluated from the reduced outage cost. The outage costs before and after an investment are evaluated from the reliability indices such as frequency, duration and load loss of an outage and monetary equivalent of a power outage event for a customer using customer damage function (CDF). The reliability indices are evaluated from various reliability assessment techniques such as analytical and simulation methods [13]. The CDF is obtained from customer survey, case studies from historical blackouts etc. [5]. The evaluation of reliability and resiliency worths of investing into the transmission resources require the estimation of load loss in MW and CDF originating from the transmission component failure.

Significant work [5], [14] – [23] has been conducted to assess the reliability worth of investment in power systems at the HL-I level. Generation facilities require huge capital investment in expansion planning and therefore CDF estimation in a reliability worth assessment is primarily focused on generation inadequacy. The customer outage due to the generation component failure mostly occur during annual system peak and therefore CDF obtain for HL-I study is during that period. There are increased concerns of congestion in transmission lines due to recent changes in generation and load pattern and the transmission resilience against extreme wind as mentioned above. To cope these problems, there is ongoing research and development in new and smart technologies in power grid that can increase the reliability and resiliency of the transmission system. The reliability worth of an investment in transmission planning study presented in [21], [24] – [34] uses the similar CDF that was prepared for HL-I study. The
occurrence of power outages during periods other than annual system peak due to random failures of transmission component are very likely. The CDF to estimate the reliability worth of transmission resources also requires incorporating the outage cost due to those random failures. Therefore, a methodology is needed to develop CDF that was originated from transmission resource failure. The outage cost originated form the transmission component failure can also be utilized to evaluate the resiliency worth of an investment to improve the transmission resilience against extreme wind.

Based on the research motivation presented, this thesis aims to develop a methodology to obtain the cost of power outages originated from transmission system failures, and to utilize the resulting customer damage functions to assess the reliability and resiliency worth of an investment in transmission facilities and technologies. The specific objectives of this research are summarized below:

- To understand and apply the concepts of reliability and resiliency worth of investments in low-carbon power systems subjected to changing weather patterns.
- To develop a method to assess the outage cost incurred from transmission component failures in a power system.
- To quantify and analyze the reliability and resiliency worth of investing into transmission resources utilizing the customer outage cost originated from transmission system failures.

1.5. Thesis Organization

The manuscript-based thesis contains five chapters. The three body chapters of the thesis are based on the papers published or submitted or ready for submission. Each chapter has all the necessary information and references and can be read independently. Chapters are closely linked together to meet the overall objective of the thesis. The thesis is organized as following.

Chapter 1 is divided into three section to introduce the power system reliability, resiliency and grid facilities. In reliability section, it discusses the concept of reliability in different function zones and value-based reliability investment in a power system. The customer outage cost, and reliability indices used for the value-based reliability studies in composite power system are also briefly described. In resiliency section, it discusses the concept resiliency in power system and the
extreme event affects the different sections in the power system. The impact of the extreme wind is specifically described to understand its impact in resiliency of power system. A brief discussion on power system grid facilities is also provided to understand the importance of the power grid in the power system.

Chapter 2 is the paper titled “Analyzing Investment Strategies for Power System Resilience” [7]. This paper is published in the 2022 IEEE Power and Energy Society General Meeting (PESGM). This paper provides the discussion on understanding the resiliency against extreme event in different sections in the power system and how a resiliency worth analysis can be studied.

Chapter 3 is the paper titled “Interruption Cost Estimation for Value-Based Reliability Investment in Emerging Smart Grid Resources”, which is submitted to IEEE Transactions on Energy Markets, Policy and Regulation. This chapter present a novel methodology to estimate the customer outage cost incurred from the transmission components failures. The consideration of random failures of transmission component is incorporated in estimating the customer damage function.

Chapter 4 is paper titled “Reliability and Resiliency Worth of Investment in Power Transmission Resources” is ready to submit as Conference paper. This paper presents the reliability and resiliency worth analyses of investing the transmission resources by implementing the customer damage function originated from failure of transmission resources.

Finally, Chapter 5 presents the summary and conclusion of the thesis.
1.6. References


CHAPTER 2: ANALYZING INVESTMENT STRATEGIES FOR POWER SYSTEM RESILIENCE

2.1. Abstract

Extreme weather and other high impact low probability (HILP) events are occurring more frequently with increased severity on electric power systems. Even systems adequately designed to meet acceptable reliability standards are experiencing costly sustained outages due to HILP events. It is desired that power systems be resilient against such events. The engineering knowledge on power system resiliency is at an early stage, and considerable work is needed to achieve widely accepted standards, metrics, and guidelines for implementation. This paper presents a review of contributions made by researchers on resiliency models, evaluation methods and metrics, and analyzes the importance of power system resiliency in comparison to system reliability needs. The paper also investigates various strategies for resiliency improvement and the associated investment costs and presents useful arguments on how value-based resiliency investment can be addressed and implemented for societal benefits.

2.2. Introduction

The reliability of an electric power system is closely related to the optimal fulfilment of energy needs and the economic development of a society. Power outages can result in substantial direct and indirect financial losses to a society. It is therefore of utmost importance to make value-based investment in these systems to ensure reliable system planning and operation [1]. To meet

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established NERC Planning standard of reliability criteria, power systems are usually operated to withstand N-1 or N-2 contingencies [2]. Certain highly impactful but rare events, such as natural disasters or cyber-attacks, however, can cause widespread power outages resulting from multiple contingencies and cascading failures. These high impacts low probability (HILP) events have been noticeably increased both in frequency and impacts due to climate change within the past decade. The average number of disaster events has more than doubled in the last 5 years compared to that over the last four decades in US alone [3]. Power systems which would otherwise be highly reliable are experiencing costly sustained outages due to HILP events. Therefore, the resiliency of power systems against such events is receiving increased attention in both the power industry and in academia.

The motive of this paper is to analyze the importance of power system resiliency in comparison to the need for reliability. The paper presents reviews of selected resiliency models proposed in existing literature and presents research findings on resiliency evaluation techniques and relevant metrics. The paper also investigates various strategies for resiliency improvement and the associated investment costs. The paper then proposes a forum for a value-based resiliency investment and presents useful arguments on how it can be addressed and implemented. The discussion includes the need for different resiliency investment strategies for generation, transmission, and distribution systems due to the difference in its infrastructure and the geography of location, as well as their exposure and vulnerability to the different types of extreme events.

2.3. Understanding Power System Resiliency

It is desired that a power system be able to withstand or quickly recover from HILP hazards, such as extreme weather, floods, landslides, seismic events and cyber-physical attacks. Achieving this will require coordinated efforts with the national preparedness system across prevention, protection, mitigation, response, and recovery [4]. The IEEE defines resilience as “The ability to withstand and reduce the magnitude and/or duration of disruptive events, which includes the capability to anticipate, absorb, adapt to, and/or rapidly recover from such an event” [5]. Different resilience stages and actions taken during an extreme event can be divided into three parts: preventive, restorative and adaptive as represented graphically by the resilience triangle [6] as shown in Figure 2.1.
Power system resiliency can be categorized into the constituent segments of generation, transmission, and distribution sub-systems. The vulnerability of a power system against HILP events increases as we go downstream from the generation to the distribution level [7] due to the increased exposure of the system elements to such events. Most of the research in this field are, therefore, concentrated at the distribution system level. Moreover, the nature and the extent of the impacts at the different power system segments are event specific. It is noticeable that generation stations with indoor installations can be highly vulnerable to earthquakes and landslides, whereas, transmission and distribution systems are more susceptible to tornado and hurricanes as most of the infrastructure are located outdoors. The probability of occurrence of HILP events depends on the geographic location, and the impacts of these events also depend on the characteristics of physical structure of the power system present at those locations. The resiliency of a power system is highly dependent on the type of HILP event and system characteristics. For example, a system that is resilient against cyber-physical attacks may not be resilient against extreme weather, and vice versa. So, it is reasonable to assess a system’s resiliency against a particular type of extreme event. Also, different events cause different types of damages in a system. For example, a hurricane can damage towers and overhead lines, whereas cyber-attacks can create false measurements at the control centers and lead to system shutdown.

The extent of damage to the different segments of a power system can be a result of a direct or an indirect impact of an HILP event. For example, an earthquake at a generation station causes
a damage with a direct impact to the generation segment, whereas damages to several transmission and distribution lines by a hurricane can cause the generation system to be out of service and result in an indirect impact to the generation segment. In this case, the generation system can be severely financially impacted even though it was designed to be resilient against such events.

The amount of damage caused by HILP events will depend on the ability of the system to withstand the destructive forces, and the restoration and recovery time. These damages can cause significant financial losses, such as the loss of utility revenue, cost of emergency measures taken, cost of repair and restructuring work, cost of recovery, and the outage cost to the customers [3]. The monetary impacts of HILP events can often influence the gross municipal product (GMP), and the gross regional product (GRP) [8]. The indirect economic impacts are relatively difficult to assess but can be far reaching and cause a wide range of social disturbances.

In summary, power system resiliency study requires the knowledge of the likelihood of extreme events in the region, the type of HILP events with relatively high probabilities, the geographic distribution of the power system infrastructure and their vulnerability to such events, the direct and indirect impact of the HILP events at the different segments of the power system, and the extent of damages that can occur from the occurrence of such events.

2.4. Resiliency Evaluation

Both qualitative and quantitative assessment methods have been used to understand and interpret the resiliency of a power system. Qualitative methods are used to understand a situation in order to develop a proper quantitative model of the system. Qualitative resilience analyses are carried out using methods such as: in-depth interview with experts, focus group workshops, a review available from literature and reports, individual ratings to address personal, business, governmental, and infrastructure aspects of resilience, etc [9], [10]. Qualitative evaluation is done based on preparedness, mitigation, response and recovery capabilities of power system such as availability of trained repair personnel, existence of proper emergency plan, etc. Resilience scoring matrix and analytical hierarchy process (AHP) can be used to model qualitative findings into comparable entities to get clearer perspective of evaluation [11], [12].

Quantitative analysis, on the other hand, uses numerical data in different measurement techniques, such as semiquantitative, deterministic and probabilistic approaches [9]. The inherent
unpredictability associated with the intensity of severe events, the resultant loss in system performance, and the effects of utilities' efforts to improve grid resilience should be reflected by the resilience metric [13].

Although there is no universally accepted metric to quantify resilience several efforts have been made to develop the metrics. Since resilience is concerned with HILP events, Ref. [6], [14] uses conditional value at risk (CVaR) as the resilience metric, which models the tail of probability density function of HILP. The percentage of lines offline is used as infrastructure indices and loss of load frequency (LOLF, occ/year) and expected energy not supplied (EENS, MWh/yr) are used as operational resilience indices in [15]. A novel resilience metrics FLEP, based on the resilience trapezoid as shown in Figure 2.2 is proposed in [16], [17]. The FLEP metric is time-dependent and represents the speed (F) and depth (L) to which the resiliency of the power grid drops in phase I, how long the system resides in the derated state in phase II (E), and the promptness with which the system recovers in phase III (P). The study in [17] also introduces another metrics dependent on FLEP, which measures the area of the trapezoid where smaller area of the trapezoid represents more resilient system. The study in [18] measures the expected probability of interruption (EPI), expected outage duration (EOD), and expected energy not supplied (EENS) for the load points in the distribution system and for the overall system to quantify the resilience with and without the presence of distributed energy resources (DER) in the system. The reduced value of these indices with the presence of DER in the system confirms the improved resiliency of the system. The study

![Figure 2.2. The multi-phase resilience trapezoid [21].](image)
in [19] measures resiliency using two categories of metrics: based on power quality and based on monetary impacts. The power quality-related metrics are total customer hours of outage (h), total customer energy not served (kWh), and total and average number of customers experiencing outages. The metrics based on monetary impact are total loss of utility revenue ($), total outage costs ($), and total avoided costs ($).

2.5. Resiliency Improvement Strategies

Resilience enhancement of a power system aims to make the system more robust, resourceful, rapidly recoverable, and adaptive to the past event learnings as shown in Figure 2.3 [20]. Different enhancement strategies can be categorized into either infrastructure planning or operational management strategies as shown in Figure 2.4 [21]. Resilience enhancement planning strategies mainly involve infrastructure hardening and other long-term planning strategies that are carried out in anticipation of a potential future catastrophic event. On the other hand, operational management strategies for resilience mitigation are undertaken upon warning of an imminent HILP event, or during the occurrence of the event. These strategies can include the collection and analyses of real time system data as the event unfolds in order to minimize the extent of disruption and expedite recovery measures.

![Diagram](image)

Figure 2.3. Integrated decision framework for resilience enhancement [21].
2.5.1. Infrastructure planning/hardening

This strategy includes improving the physical condition of the system and making power system structures, such as water dam, transmission towers, cables and conductors, more robust so that the system is less susceptible to potential extreme events. Also, the adaptation capability is an important part of long-term resilience planning as it provides the ability to deal with similar scenarios in the future [6], [22], [23].

Infrastructure resilience enhancement reduces the physical impact of the catastrophic events and prevents the incapacitation of large parts of a power grid. It should however be noted that hardening measures that are very effective to a specific threat may have a negative effect in a different situation [6], [22]. For example, undergrounding cables can have high resilience towards windstorm, but will have reduced resilience to earthquakes, flooding and landslides resulting in longer repair and recovery times. It is therefore important to understand the geological conditions, climate, and the surrounding environment of the site before making decisions on resiliency improvement strategies. Some of the Infrastructure hardening practices [6], [22], [23] are listed below:

- Undergrounding distribution and transmission lines
- Elevating Substations
- Poles and structure upgrade
- Rerouting transmission lines to area less affected by extreme weathers
• Management of vegetations
• Design of redundant transmission and distribution system

2.5.2. Operational management

Operational management includes those set of control actions taken just before and during an extreme event in order to minimize the damage to the power system. It helps to improve the observability, controllability, and operational flexibility of the system during disruption in order to mitigate resilience degradation and enable fast recovery and restoration. An operational resilience management facilitates the system to ‘bend’ rather than ‘break’ during hazard, so that system can recover quickly and efficiently [22]. Some operational enhancements strategies [23]-[27] are listed below:

• Distributed Energy Systems and Decentralized Control
• Demand site management
• Preventive control (e.g., preventive generation rescheduling)
• Network reconfiguration
• Microgrids
• Advance and adaptive restoration
• Adaptive wide-area protection and control schemes (e.g., defensive, and controlled islanding of affected areas)
• Advance Visualization and Situation Awareness Systems, Disaster Response and Risk Management

Utility should consider the cost and benefits of investment in system resilience through both infrastructure planning and operational management. Infrastructure hardening generally yields more effective resilience improvement compared to an operational management strategy, but at a higher cost. It should also be noted that investment in energy generation or storage facilities at the customer-end can also minimize the impact of the outages, although these measures do not make the power system more resilient.
2.6. Resilience Investment

Resiliency improvements in power systems can be heavily investment-centric. A proper worth of enhancement should be analyzed before any investment decision is made. As the cost and worth of resilience investment against rare events are not yet defined, established value-based reliability investment models can be taken as reference starting point. Figure 2.5 shows how the investment costs and customer interruption costs can be traced to deduce a reliability planning criterion to achieve minimal societal cost [28].

![Value-based reliability approach](image)

Figure 2.5. Value-based reliability approach.

The cost of power interruptions due to either reliability events or HILP events depend on a range of factors as the impacts can be direct or indirect, economic or social, and short term or long term [29]. These impacts need to be identified, assessed and quantified to develop the metrics to assess the worth of investment. Customer damage functions and interrupted energy assessment rates have been extensively used [30] to quantify reliability worth. In comparison to reliability studies, the value-based resiliency studies should consider a much longer planning horizon to account for the rare but destructive events.

Planning and infrastructural hardening though effective often requires a relatively large investment. Moreover, resilience investment for one type of extreme event can make the system more vulnerable to another type of extreme event. For example, undergrounding of transmission lines is costly, but makes system more resilient against windstorms. This will however make the system more vulnerable to earthquakes. A holistic approach should therefore be used to assess the
worth of such investment over a foreseeable future period. On the other hand, investment in operational measures are decided during or just before the occurrence of an extreme event, and the worth of such investments are more comprehensible. These investments are generally more affordable and less effective than system hardening costs as shown in Figure 2.6 [22]. An optimal combination of these two strategies should be investigated to obtain a hybrid investment approach that yields minimum societal costs in the aftermath of an HILP event.

![Figure 2.6. A conceptual comparison of cost versus the effectiveness of resilience engineering approaches [22].](image)

### 2.7. Conclusion

This paper presents discussions of the importance of power system resiliency in addition to the need for maintaining system reliability. The paper presents reviews of selected resiliency models proposed in existing literature and presents research findings on resiliency evaluation techniques and relevant metrics. It is concluded that power system resiliency study requires the knowledge of the likelihood of extreme events in the specific region, the type of HILP events with relatively high probabilities, the geographic distribution of the power system infrastructure and their vulnerability to such events, the direct and indirect impact of the HILP events at the different segments of the power system, and the extent of damages that can occur from the occurrence of such events. The paper investigates various strategies for resiliency improvement and the associated investment costs. The discussion includes the need for different resiliency investment strategies for generation, transmission, and distribution systems due to the difference in its
infrastructure and the geography of location, as well as their exposure and vulnerability to the
different types of extreme events. The paper presents an analyses of past works on power system
resiliency to offer useful arguments and discussions on how value-based resilience investment
studies can be performed for the overall societal benefits.
2.8. References


CHAPTER 3: INTERRUPTION COST ESTIMATION FOR VALUE-BASED RELIABILITY INVESTMENT IN EMERGING SMART GRID RESOURCES

3.1. Abstract

Growing uncertainty in supply and demand in power systems cause significant challenges in maintaining the supply reliability at affordable costs. Power grids are expected to undergo substantial transformations to address these challenges with upgrades and integration of emerging smart technologies that require significant investment costs. A value-based reliability assessment of these grid technologies is necessary to justify the worth of these investments. A key parameter required in such assessment is the cost of power interruptions originated from transmission system failures. The interruption cost data available in published reports and past surveys relate to generation inadequacy, since generation facilities comprise the most capital-intensive investment of an electric utility. Customer interruptions due to lack of generation mainly occurs due to generation failures during the peak demand period. Whereas, the interruptions due to transmission component failures can occur at other periods with specific probabilities. This paper presents a methodology to estimate the cost of outages originated from transmission asset failures, which proposes a sector period model for each customer sector to obtain associated demand normalized interruption costs. The proposed method can also be used to decide investment in grid resiliency enhancement against extreme weather that mainly impact the grid network facilities.

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3.2. Introduction

Modern electric power grids are undergoing substantial changes to address upcoming environmental compliance challenges while maintaining supply reliability. The replacement of fossil-fired firm generation by intermittent and uncertain renewable energy sources, and the electric transformation of the automotive industry will cause increasing difficulty in balancing the electric supply and demand in future power systems. There is ongoing research and development in new and smart technologies in energy storage, power electronics, digital and communication devices that can increase the capability of power systems to continuously meet consumer demands. Long-term system planning requires optimal selection and allocation of these technologies in the bulk power grid and the necessary network upgrades to comply with existing and future environmental regulations and targets. System planners require appropriate methodologies and assessment tools to determine optimal investment on these bulk power system facilities to maintain acceptable reliability at affordable costs. The value-based reliability investment (VBRI) method analyzes the cost and worth of reliability investment in order to justify the investment in new resources, facilities and/or system upgrades. This method can be used with necessary modification or extension to address system-specific investment decision problems.

The VBRI approach requires comparative study of two aspects of system adequacy and economics, and the resulting cost/worth analysis [1] is done to estimate the expected investment benefits in decision making. The adequacy cost is the investment cost needed to achieve a certain level of reliability. Whereas the adequacy worth is the benefit derived by the utility, consumer, and the society in the form of reduced power outage or interruption cost. It quantifies the monetary losses incurred by electricity customers due to the unreliability of the power system. An adequacy assessment is not usually conducted on the entire power system but is done at the various sub-systems or hierarchical levels (HL) as shown in Figure 3.1. HL-I assessment considers only the generation system and its ability to meet the overall system demand. HL-II or bulk system adequacy refers to the existence of adequate generation and transmission facilities to meet the bulk load requirements distributed throughout the grid network. HL-I VBRI assessment helps make the investment decision on appropriate and adequate generation resources to minimize the overall societal cost, i.e. the sum of the investment cost and the outage cost as shown in Figure 3.2 [2]. Similarly, HL-II VBRI studies can be done to make investment decisions on transmission facilities
while considering both the generation and the transmission systems. VBRI assessment techniques for HL-I and HL-II are illustrated in [2].

![Composite Power System](image1)

**Figure 3.1. Composite Power System**

![Value-based reliability investment approach](image2)

**Figure 3.2. Value-based reliability investment approach.**

Significant work [3]–[12] has been done on VBRI methods and their applications at the HL-I level. Generation facilities comprise the most capital-intensive investment of an electric utility in expansion planning. The interruption cost estimation in a value-based reliability assessment is therefore primarily focused on generation inadequacy. The interruption cost can be estimated using various techniques [13], such as analytical methods, case studies of blackouts and from customer
surveys. Among these methods, customer surveys [14]–[20] provide the most reliable information related to the usage of electricity and the impact of power outage on the different categories of electricity customers. The customer survey is designed primarily to obtain relevant information to assess the monetary losses associated with various frequency and duration of power outages at different times of the day and year. The customers are categorized into different sectors, such as residential, commercial, industrial, etc. The survey data is used to estimate the interruption cost in $/interruption for each customer sector for a range of interruption durations. This value is then normalized by the sector load demand to obtain the demand normalized cost (DNC) in $/kW. The DNCs of a customer sector calculated for the selected outage durations form a customer damage function (CDF) [21] for that customer sector. The CDFs of all the different customer sectors are aggregated to obtain the composite customer damage function (CCDF) [1], which can then be used in alternate HLI expansion plans to determine the corresponding outage costs. The cost of interruption during the system peak becomes the deciding factor in determining the capacity reserve needed above the peak demand [22]. The interruption costs are therefore normalized by the peak demand in VBRI assessment at the HL-I level. The CDFs thus obtained are not suitable for VBRI assessment of transmission or distribution systems and facilities.

Transmission planning usually follows HL-I expansion planning, and make use of deterministic reliability methods, such as the North American Reliability Corporation’s N-1 planning criteria [23]. The rapid growth in renewable/intermittent generation and expected growth of electric vehicles will significantly increase uncertainties in line loadings and net demands at the bulk load points. There are considerable efforts and activities [24] among electric utilities and research institutions to adopt probabilistic reliability methods that recognize these uncertainties in HL-II system planning and decision making. An appropriate VBRI must be conducted to determine HL-II reliability criteria that yield minimum societal costs. The increased variability and uncertainty in the bulk electric systems require additional support resources and emerging smart technologies to operate the system in a reliable manner. For example, various types of energy storage systems, voltage support devices, and smart-grid technologies to acquire and process relevant system data for operational management of power supply and demand will be expected to be deployed throughout the network. A VBRI assessment at the HL-II level will be necessary to justify the cost and worth of deploying these new technologies into the bulk system network. Also, the increase in frequency of extreme weather events in past decades due to climate change [25] as
well as other extreme events like cyber-physical attacks and seismic events have impacted the grid facilities due to their exposure to these events [26] causing catastrophic losses [27], [28]. The cost and worth of hardening the grid infrastructure against such adverse events requires an appropriate HL-II VBRI assessment.

There has been limited work on VBRI at the transmission system level. A VBRI approach is illustrated in [29], [30] to make expansion planning decision on a composite generation and transmission system. Ref. [31] presents a methodology to determine optimum probabilistic reliability criterion for grid expansion planning to meet a specified level of reliability at the lowest cost. A VBRI approach is introduced in [32] for determining optimal reliability criteria considering load bus reserve rate in long term load forecast for optimal transmission systems expansion planning with minimal costs for society. An application of value-based reliability model is presented in [33] for a transmission capital projects in a real transmission system with feasible transmission reinforcement alternatives that provides a reliable electricity at the lowest possible rate. Ref. [34] proposes a VBRI approach to determine line upgrades to alleviate transmission congestion and maintain reliability of a bulk system integrated with large-scale wind power. Ref. [35] describes the reliability worth scheme for multiple dispatch scenario using binary disjunctive techniques and screening strategies. A multi-stage planning of transmission system to minimize overall societal cost is proposed in [36] based on the metaheuristic Ant Colony Optimization. These studies, however, use a customer outage cost model that was prepared for HL-I, which is not appropriate for outage cost estimation associated with transmission-related outages. Customer interruptions due to transmission-related outages are not confined to the peak load period as in HL-I but can occur at other times with a relatively high probability depending on weather patterns and loading conditions of individual lines at different times of the day and season. It should further be noted that the cost of power outage can vary widely at different times of the day and season. For example, the power interruption cost to a commercial customer during business hours is much higher than that outside of business hours. Also, the cost of a power interruption to a residential customer is generally low during a mild spring evening when compared to a hot summer afternoon. The outage cost model for HL-II can therefore be very different from the model obtained for HL-I. Ref. [37] provides estimates of customer damage functions that can be applied to calculate interruption costs per event by season, time of day, day of week for various electricity customers in the United States. However, in [37], the outage cost was normalized by the average demand
and unable to obtain a demand normalized cost of a power interruptions for a range of possible load demands in the study period. Ref. [38] proposes a VBRI methodology for transmission expansion planning by using of customer surveyed outage cost data and historical annual load profiles divided into summer period, winter period and off-peak period. This study lacks the consideration of diurnal load variation as power outage cost at different times of the day can vary considerably as mentioned above. It is therefore important to recognize the impact of transmission system originated failures on customer interruptions, estimate the frequency and duration of their occurrence at different times of a day, season and year, and develop a VBRI methodology to incorporate them in a bulk system reliability model.

This paper presents a methodology to develop a composite customer damage function (CCDF) for VBRI assessment of a bulk electric power system that considers customer interruptions arising from transmission system originated failures. The proposed method incorporates the probability of a power outage occurrence at different times of the day and year, and the impact of the time of occurrence and duration of outage on the customer interruption cost.

3.3. Estimation Of Interruption Costs arising from Transmission System originated Failures

This section describes the methodology to estimate the cost of interruptions incurred at the bulk load points due to forced outages of components of a bulk power system. As earlier mentioned, the customer interruption costs obtained from previous works [29]–[36] are mainly applicable to the determination of optimal investment in generation capacity reserves in a power system. It should be noted that the system capacity reserve is the difference between the total installed capacity and the system peak load. The interruption costs are therefore associated with power outages that occur during the system peak load as generating unit failures during other periods are less likely to contribute to power outages. A new approach is proposed in this paper that considers the fact that power outages arising from the failures of bulk system components, such as transmission lines or devices connected to the bulk power grid, can occur at any time of the day or year with a probability that can be estimated from past performance data. The new approach also recognizes the fact that the energy consumption patterns vary significantly depending on the type of electricity customer, and so do the interruption costs. For example, a residential customer load is characterized by a specific diurnal and seasonal variation pattern,
whereas an industrial customer load is more or less constant throughout the year. The bulk system customers are divided into different sectors, such as industrial, residential, commercials, farm, etc. The proposed methodology consists of (1) developing a sector periodic demand model, and (2) developing an integrated interruption cost model, in order to obtain the cost of interruption originated from HL-II components.

3.3.1. Sector Periodic Demand Model

The interruption costs in VBRI assessment are expressed as demand normalized costs (DNC), and therefore, the proposed method utilizes a periodic demand model to estimate the demand normalized interruption costs for the bulk system customer sectors. Figure 3.3 shows the steps involved to obtain the sector periodic demand (SPD) model for a bulk system. The proposed model is designated as the SPD model in this paper.

![Diagram of sector periodic demand model](image)

**Figure 3.3. Development of a sector periodic demand model.**

The first step of the methodology is to identify the major customer sectors in a bulk system. Electricity consumers are classified into various customer sectors depending on their end use applications. Typically, customers within a specific sector share similar needs for electricity and are affected similarly by power outages. Residential, commercial and industrial sectors are a
significant part of a bulk system load. However, specific customer sectors, such as farm or oil sectors, may exist in bulk systems based on the region they operate.

The next step is to obtain the historical load data for each customer sector identified in the previous step. The acquisition of customer sector load data is a part of utility load research [39], [40], which is used to analyze cost-of-service, load forecasting, load management technologies and other system planning related activities. In recent years, customer sector load data can be obtained from advanced metering infrastructure (AMI) in various time intervals. The proposed methodology in this paper utilizes the hourly interval load data expressed in kilowatts (kW) as given by (3.1).

\[ D_i = \{H_{i,h} | i = 1, 2, \ldots d \text{ and } h = 1, 2, \ldots, 24\} \]  \hspace{1cm} (3.1)

Where, the daily load profile, D is a set of 24-hourly loads H, and d is the total number of days of historical data used in the analysis.

Adequacy assessment in system planning utilizes annual reliability indices, and therefore, the evaluation period is typically one year. The sector load data obtained is then grouped into N periods, such that the diurnal loads with identical profiles are grouped into one period as described in (3.2).

\[ \{D_{i,p=1,2,\ldots,N}\} \in \{D_i\} | \mu(D_{i=j}) \approx \mu(D_{i\neq j}) \text{ and } med(D_{i=j}) \approx med(D_{i\neq j}) \text{ for } j = 1, 2, \ldots, d \]  \hspace{1cm} (3.2)

Where, functions \( \mu() \) and \( med() \) evaluates the mean and median of \( D_i \).

The proposed methodology then determines a representative load profile for each of the N periods. The bulk system reliability indices are highly sensitive to the peak load since the system is vulnerable to customer outages due to generation failures during minimum reserve conditions and to transmission failures during line congestion. The load profiles in a period are therefore represented by one load profile \( RD_p \) with the highest peak load as shown in (3.3). The representative load profile is then sorted in descending order.

\[ RD_p = D_{i=k,p} | \max(\{H_{k,h}\}) > \max(\{H_{i\neq k,h}\}) \]  \hspace{1cm} (3.3)

The contribution of transmission system failures to customer outages is highly dependent on the network structure and configuration, and such outages can occur during the off-peaks hours as
well. The next step of the proposed methodology is therefore to sub-divide the N periods into peak and off-peak periods. The cut-off load point, \( CF_p \), between peak and off-peak sub-period in each of the N periods as shown in Fig. 3b is determined from (3.4).

\[
CF_p = 0.9 \times \max(\{H_h\}) \mid H_h \in RD_p
\]  

(3.4)

The peak load, \( L_p \), is next determined as the representative load for the peak sub-period \( p \) as shown in (3.5). The probability of occurrence of the representative load \( L_p \) is given by (3.6).

\[
L_p = \max(\{H_{i,h}\}) \mid H_{i,h} \in RD_p
\]

(3.5)

\[
\text{Prob}_p = \frac{|\{H_{i,h}|H_{i,h} \in \{D_{i,p}\}, H_{i,h} \geq CF_p\}|}{d \times 24}
\]

(3.6)

The load profiles \( D_{i,N+1} \) in the \((N+1)\)th demand period is next obtained by aggregating load data from the N off-peak sub-periods as given by (3.7). The outages during off-peak sub-periods are due to random failures of bulk system components. The average load given by (3.8) is therefore taken as the representative load, \( L_{N+1} \) in the \((N+1)\)th period. The probability of occurrence of the representative load \( L_{N+1} \) is given by (3.9).

\[
D_{i,p=N+1} = \bigcup_{p=1}^{N}\{H_{i,h}|H_{i,h} \in \{D_{i,p=1,2,...,N}\}, H_{i,h} < CF_p\}
\]

(3.7)

\[
L_{p=N+1} = \frac{1}{|\{H_{i,h}|H_{i,h} \in \{D_{i,p=N+1}\}\}|} \sum_{H_{i,h} \in \{D_{i,p=N+1}\}} H_{i,h}
\]

(3.8)

\[
\text{Prob}_{p=N+1} = \frac{|\{H_{i,h}|H_{i,h} \in \{D_{i,p=N+1}\}\}|}{d \times 24}
\]

(3.9)

Finally, the ‘N+1’ step discrete probability distribution obtained from the representative load level and its associated probability derived from (3.5), (3.6), (3.8) and (3.9) from the SPD model as shown in (3.10).

\[
\{(L_p, \text{Prob}_p) \mid p = 1,2, \ldots, N + 1\}
\]

(3.10)
3.3.2. Integrated Interruption Cost Model

This section describes the methodology to develop the interruption cost model for each customer sector that can be integrated with the SPD model described in Section A. The interruption cost incurred to a customer sector due to bulk component failure depends on the magnitude of the load curtailed and the duration of the interruption. As the magnitude of the load varies with time with a specific characteristic for a customer sector, it will be necessary to determine the interruption cost as a function of time of day, time of year, and the interruption duration. This information can be extracted from a customer survey [18] of all the customer sectors within the power system. The statistical estimation method [14], [15], [16] is applied to get the interruption cost \( IC_p \) at each of the ‘N+1’ periods \( p \) of the SPD model for a range of outage durations as shown in (3.11).

\[
IC_p = \{ic_{p,t} | t = 1, 2, ..., T \} \tag{3.11}
\]

Where, \( ic_{p,t} \) is the interruption cost in $/interruption for an outage of duration \( t \) during the load period \( p \). The outage duration, \( t = 1, 2, ..., T \), representing 1 minute, 20 minutes, 1 hour, 2 hours, 4 hours, 8 hours, 24 hours [14], [15], [16], [41], [42] are usually considered in these studies.

The interruption cost is then normalized by the representative load for each period of the SPD model. The demand normalized cost \( DNC_{p,t} \) in $/kW is obtained from (3.12),

\[
DNC_{p,t} = \left\{ \frac{ic_{p,t}}{L_p} \right\} \text{ for } p = 1 \text{ to } N+1 \text{ and } t = 1 \text{ to } T \tag{3.12}
\]

The expected demand normalized cost \( EDNC_t \) for an outage duration \( t \) is next obtained from (3.13) by taking the weighted sum of all the DNC calculated for all the N+1 demand periods of the SPD model.

\[
EDNC_t = \sum_{p=1}^{N+1} (\text{Prob}_{p,t} \times DNC_{p,t}) \tag{3.13}
\]

The customer damage function (CDF) is the expected demand normalized cost as a function of the interruption duration. The CDF for a sector, SCDF, is given by (3.14),

\[
SCDF = \{EDNC_1, EDNC_2, ..., EDNC_t, ..., EDNC_T \} \tag{3.14}
\]
The composite customer damage function (CCDF) at a bulk load point is calculated by weighting the SCDF from (3.14) by load compositions (peak load and energy consumptions percentages) of customer sectors as given by (3.15).

\[
CCDF = \left[ \sum_{m=1}^{M} (EDNC_{m,t} \times wf_{m,t}) \right]_{t=1}^{T}
\]

(3.15)

Where, \( m = 1,2, ..., M \) denotes the participating customer sectors and, \( wf_{m,t} \) is weighting factor for a customer sector at the load point such that [41]:

\[
wf_{m,t} = \begin{cases} 
\frac{L_{peak,m}}{L_{peak}} & \text{for } t < 1 \text{ hour} \\
\frac{E_m}{E} & \text{for } t \geq 1 \text{ hour}
\end{cases}
\]

Where, \( L_{peak,m} \) and \( E_m \) are the annual peak load and energy consumption of Sector \( m \) respectively, and \( L_{peak} \) and \( E \) are the annual peak load and energy consumption of the overall system.

Finally, the monetary equivalence of power loss is expressed as expected cost of customer interruptions (ECOST) as given by (3.16).

\[
ECOST_k = \sum_{i=1}^{NC} L_{ki} \times F_i \times C_i(D_i) \frac{MW}{kW} \frac{\$/yr}{}
\]

(3.16)

Where, \( L_{ki}, F_i \) and \( C_i(D_i) \) represents the magnitude (MW), frequency (occ/year) and CCDF (\$/kW) of an outage of duration \( D_i \) from contingency \( i \) at load point \( k \) respectively. Also, \( NC \) represents the total number of outages leading to the power interruptions at load point \( k \).

### 3.4. Illustration of the Methodology

The section describes the illustration of the methodology using the load data from the Saskatchewan province in Canada, and the outage cost data from the survey [43] conducted by the University of Saskatchewan for generation adequacy assessment. Subsections A and B respectively illustrate the development of the SPD model and the integrated interruption cost model.
3.4.1. Obtaining the SPD Model

The initial step of the methodology requires identifying the major electricity customer categories based on their end-use applications. Residential, Industrial, Commercial, and Farm customers were identified as the major categories in the province of Saskatchewan. Historical hourly variation of the load data for each identified customer sector are shown in Figure 3.4 in per unit of the respective peak values. The annual load profile for each sector is then divided into periods having similar diurnal load profiles. Fig. 4 shows that the Residential and Farm sectors are divided into 4 seasonal periods since the diurnal load profiles for these customer sectors had reasonable similarity as assessed from (3.2). The diurnal load profiles of the Industrial and Commercial sectors were found to be similar throughout the year.

The next step is to observe the diurnal load variation in each period and further sub-divide into peak and off-peak periods. Figure 3.5 shows the sub-division using a cut-off factor of 0.9 per unit of the peak load in that period. The figure shows that the Commercial sector is divided into two periods that are represented by the peak and average loads in the respective periods calculated using (3.5) and (3.8) respectively, and the probabilities of the encountering the two periods is calculated using (3.6) and (3.9) respectively. Figure 3.5 also shows that diurnal variation in the Industrial load is insignificant, and therefore, was not sub-divided. Therefore, the industrial sector load consists of only one period and is represented by the peak load.

Figure 3.4. Annual load profiles for the identified customer sectors.
Figure 3.5. Diurnal load variation of Commercial and Industrial sectors.

Figure 3.6 shows the diurnal load profiles for the Residential and Farm sectors in the 4 seasonal periods. The seasonal periods for the Residential and Farm sectors are similarly further sub-divided into peak and off-peak periods as shown in the figure. The representative load and its probability are similarly calculated using (3.5) and (3.6) respectively.

The off-load sub-periods in the Residential sector are grouped together into one period and the representative load and its probability are calculated using (3.8) and (3.9) respectively. The load and corresponding probabilities for the different periods of the Farm sector is obtained similarly. The SPD model thus obtained is shown in Table 3.1.

Figure 3.6. Periodic load models for the Residential and Farm sectors.

Table 3.1. SPD Model

<table>
<thead>
<tr>
<th>Period</th>
<th>Load (p.u. of sector peak)</th>
<th>Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Residential</td>
<td>Winter peak</td>
<td>1.0000</td>
</tr>
</tbody>
</table>

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### 3.4.2. Obtaining the Integrated Interruption cost model

The data obtained from the outage cost survey [43] conducted in the year 2017 for Saskatchewan electricity customers are used to illustrate the interruption cost model. The cost per interruption data obtained for 6 different outage durations as shown in Table 3.2 are used in this study. The interruption cost data from the survey are converted to the 2023 price equivalence using the inflation calculator in [44]. It should be noted that the interruption cost data for all the required time periods and outage durations were not directly available from the 2017 survey since it was targeted to obtain data for generation planning. The data in Table 3.2 therefore pertains to the winter peak period which can be expressed as shown in (3.11). An approximate cost estimation method as described in this section was followed to indirectly obtain the relevant interruption costs incurred at other periods of the years.

**Table 3.2. Interruption Cost ($/Int) data from the 2017 Survey (in 2023 $)**

<table>
<thead>
<tr>
<th>Sector</th>
<th>1 min</th>
<th>20 mins</th>
<th>1 hr</th>
<th>4 hrs</th>
<th>8 hrs</th>
<th>24 hrs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Residential</td>
<td>0.00</td>
<td>0.54</td>
<td>4.06</td>
<td>45.52</td>
<td>92.78</td>
<td>352.07</td>
</tr>
<tr>
<td>Farm</td>
<td>1.83</td>
<td>8.06</td>
<td>13.98</td>
<td>24.32</td>
<td>26.83</td>
<td>52.37</td>
</tr>
<tr>
<td>Commercial</td>
<td>29.69</td>
<td>87.81</td>
<td>237.21</td>
<td>1194.95</td>
<td>1920.18</td>
<td>2312.68</td>
</tr>
<tr>
<td>Industrial</td>
<td>252912.00</td>
<td>417959.00</td>
<td>822855.00</td>
<td>2719105.00</td>
<td>5239916.00</td>
<td>15431217.00</td>
</tr>
</tbody>
</table>
The next step is to normalize the sector interruption cost by the load demand at each time period of the SPD model to obtain the DNC using (3.12). Table 3.3 shows the annual peak loads of the different customer sectors considered in the study.

Table 3.3. Sector Annual Peak Load, kW

<table>
<thead>
<tr>
<th>Sector</th>
<th>Residential</th>
<th>Farm</th>
<th>Commercial</th>
<th>Industrial</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sector peak (kW)</td>
<td>2.0461</td>
<td>2.7000</td>
<td>8.1000</td>
<td>99780.0000</td>
</tr>
</tbody>
</table>

The SPD model of the industrial sector consists of only one period as shown in Table 3.1. The DNC of the industrial sector obtained using (3.12) is shown in Table 3.4.

Table 3.4.Industrial DNC, $/kW

<table>
<thead>
<tr>
<th>Period</th>
<th>1 min</th>
<th>20 mins</th>
<th>1 hr</th>
<th>4 hrs</th>
<th>8 hrs</th>
<th>24 hrs</th>
</tr>
</thead>
<tbody>
<tr>
<td>One period</td>
<td>2.53</td>
<td>4.19</td>
<td>8.25</td>
<td>27.25</td>
<td>52.51</td>
<td>154.65</td>
</tr>
</tbody>
</table>

Residential, Farm and Commercial sectors have more than one load period in the SPD model. The interruption cost data for periods other than the winter peak period were not available from the survey [43] results. The approximate cost estimation method to obtain the interruption costs for the other periods in the SPD model is illustrated for the residential sector. Similar approach was used for the other remaining sectors.

The 2017 survey also obtained data on preparatory action costs of 5 alternative electric supply shown in Table 3.5, and 6-point Likert Scale shown in Table 3.6 to reflect the undesirability of power outages in different outage scenarios. The 4-hour outage duration undesirability Likert Scale for weekly and monthly outage frequency during different seasonal periods obtained from the survey are shown in Table 3.7. These data are used in the approximate method to estimate the interruption costs during other periods of the SPD model. It should be noted that the residential sector has five periods in the SPD model as shown in Table 3.1.

Table 3.5. Preparatory Action Costs from the Survey

<table>
<thead>
<tr>
<th>Actions</th>
<th>No Action</th>
<th>Provide Minimal lighting</th>
<th>Provide Full lighting and LED TVs</th>
<th>Lighting, TVs and small appliances (Fan)</th>
<th>Full household load</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost ($/hr.)</td>
<td>0.0</td>
<td>1.0</td>
<td>6.0</td>
<td>12.0</td>
<td>25.0</td>
</tr>
</tbody>
</table>
Table 3.6. 6-Point Likert Scale from the Survey

<table>
<thead>
<tr>
<th>Undesirability Scale</th>
<th>None</th>
<th>Low</th>
<th>Moderate low</th>
<th>Moderate high</th>
<th>High</th>
<th>Extremely undesirable</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
</tr>
</tbody>
</table>

Table 3.7. Likert Scale (4 Hours Duration) for various Scenarios

<table>
<thead>
<tr>
<th>Likert Scale (4 hours)</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>Cost, $/int</th>
</tr>
</thead>
<tbody>
<tr>
<td>Winter peak (weekly)</td>
<td>4</td>
<td>3</td>
<td>5</td>
<td>14</td>
<td>35</td>
<td>162</td>
<td>82.28</td>
</tr>
<tr>
<td>Winter peak (monthly)</td>
<td>11</td>
<td>22</td>
<td>39</td>
<td>41</td>
<td>53</td>
<td>57</td>
<td>45.97</td>
</tr>
<tr>
<td>Winter off-peak (weekly)</td>
<td>6</td>
<td>12</td>
<td>15</td>
<td>31</td>
<td>45</td>
<td>113</td>
<td>65.82</td>
</tr>
<tr>
<td>Spring peak (weekly)</td>
<td>14</td>
<td>12</td>
<td>35</td>
<td>50</td>
<td>51</td>
<td>61</td>
<td>47.70</td>
</tr>
<tr>
<td>Summer peak (weekly)</td>
<td>10</td>
<td>30</td>
<td>39</td>
<td>51</td>
<td>37</td>
<td>56</td>
<td>43.30</td>
</tr>
<tr>
<td>Fall peak (weekly)</td>
<td>10</td>
<td>13</td>
<td>24</td>
<td>58</td>
<td>55</td>
<td>62</td>
<td>48.92</td>
</tr>
</tbody>
</table>

The 6-point Likert scale is reduced to 5-point scale by merging Scale 3 (moderate low) and Scale 4 (moderate high) together. This is done to match the 5-point scale to the 5 preparatory action costs. The interruption costs for the different seasonal periods listed on the first Column of Table 3.7 are estimated by the weighted average of the preparatory actions cost per hour by the undesirability rating of the customer responses. The last column of Table 3.7 shows the interruption costs estimated using the approximate method. Equation (3.17) shows the calculation of the interruption cost of a 4-hour outage occurring monthly during the winter peak period. It can be seen that this value is close to the 4-hour interruption cost for residential sector shown in Table 3.2, and is therefore, used as the interruption data for the winter peak period of the proposed model.

\[
\text{Cost/\text{int}} = \frac{4\text{hr}}{1\text{hr}} \times \frac{(11 \times 0 + 22 \times 1 + (39 + 41) \times 53 \times 12 + 57 \times 25)}{11 + 22 + (39 + 41) + 53 + 57} = 45.97
\]  

(3.17)

Table 3.7 data shows that the monthly occurring outage cost is 56% of the weekly outage cost. This ratio can be used to estimate the 4-hour outage cost data shown in Table 3.8 for the remaining peak periods of the proposed residential SPD model. Similarly, Table 3.7 shows that the winter off-peak cost is 80% of the winter peak data. The outage during the off-peak period is therefore estimated to be 80% of the peak period. Since all the off-periods are merged together in
the SPD model, the average sum of the off-peak costs as calculated in (3.18) is used as the 4-hour outage cost for the off-period in the SPD model.

$$\text{Off-peak} = \frac{45.97 + 26.71 + 24.25 + 27.40}{4} \times 80\% = 24.87$$ (18)

Table 3.8. Interruption Cost of 4-hour Outage during the Peak Periods of the Residential Sector

<table>
<thead>
<tr>
<th>Period</th>
<th>(2023, $/int)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Winter peak</td>
<td>45.97</td>
</tr>
<tr>
<td>Spring peak</td>
<td>26.71</td>
</tr>
<tr>
<td>Summer peak</td>
<td>24.25</td>
</tr>
<tr>
<td>Fall peak</td>
<td>27.40</td>
</tr>
<tr>
<td>Off-peak</td>
<td>24.87</td>
</tr>
</tbody>
</table>

The next step is to calculate the interruption cost for outage durations other than 4-hour. Table II shows the interruption costs for outage durations of 1 min, 20 mins, 1 hr, 8 hrs and 24 hrs are 0.0%, 1.2%, 8.9%, 203.8%, and 773.5% respectively of 4-hour duration for residential sector. The calculated outage costs as expressed by (3.11) during the periods of residential SPD model is shown in Table 3.9.

Table 3.9. SPD Model Interruption Cost for Residential

<table>
<thead>
<tr>
<th>Period</th>
<th>1 min</th>
<th>20 mins</th>
<th>1 hr</th>
<th>4 hrs</th>
<th>8 hrs</th>
<th>24 hrs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Winter peak</td>
<td>0.00</td>
<td>0.55</td>
<td>4.09</td>
<td>45.97</td>
<td>93.69</td>
<td>355.58</td>
</tr>
<tr>
<td>Spring peak</td>
<td>0.00</td>
<td>0.32</td>
<td>2.38</td>
<td>26.71</td>
<td>54.43</td>
<td>206.60</td>
</tr>
<tr>
<td>Summer peak</td>
<td>0.00</td>
<td>0.29</td>
<td>2.16</td>
<td>24.25</td>
<td>49.42</td>
<td>187.57</td>
</tr>
<tr>
<td>Fall peak</td>
<td>0.00</td>
<td>0.33</td>
<td>2.44</td>
<td>27.40</td>
<td>55.84</td>
<td>211.94</td>
</tr>
<tr>
<td>Off-peak</td>
<td>0.00</td>
<td>0.30</td>
<td>2.21</td>
<td>24.87</td>
<td>50.69</td>
<td>192.37</td>
</tr>
</tbody>
</table>

A similar approach was used to obtain the interruption costs shown in Table 3.10 for the Farm and Commercial sectors. Since the only data available from the survey for the Farm and Commercial sectors are the interruption cost data shown in Table 3.2, these cost data are taken as the base values to approximate the costs in Table 3.10 using a linear approximation from the residential cost data shown in Table 3.8.
Table 3.10. SPD Model Interruption Cost for Farm and Commercial

<table>
<thead>
<tr>
<th>Period</th>
<th>Farm</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Winter peak</td>
<td>1.83</td>
<td>8.06</td>
<td>13.98</td>
<td>24.32</td>
<td>26.83</td>
<td>52.37</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Spring peak</td>
<td>1.06</td>
<td>4.68</td>
<td>8.12</td>
<td>14.13</td>
<td>15.59</td>
<td>30.43</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Summer peak</td>
<td>0.97</td>
<td>4.26</td>
<td>7.38</td>
<td>12.84</td>
<td>14.17</td>
<td>27.65</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Fall peak</td>
<td>1.09</td>
<td>4.80</td>
<td>8.33</td>
<td>14.49</td>
<td>15.99</td>
<td>31.20</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Off-peak</td>
<td>0.99</td>
<td>4.36</td>
<td>7.56</td>
<td>13.16</td>
<td>14.52</td>
<td>28.34</td>
<td></td>
<td></td>
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<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Commercial</td>
<td>Peak</td>
<td>29.69</td>
<td>87.81</td>
<td>237.21</td>
<td>1194.95</td>
<td>1920.18</td>
<td>2312.68</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Off-peak</td>
<td>16.03</td>
<td>47.52</td>
<td>128.32</td>
<td>646.47</td>
<td>1038.81</td>
<td>1251.18</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The interruption costs are then normalized by the sector demand during each period of the SPD model obtained by multiplying the per unit demand by the sector annual peak load in Table 3.3. The sector DNCs calculated using (3.12) for Residential, Farm and Commercial are presented in Table 3.11.

Table 3.11. Residential, Farm And Commercial DNCs, $/kW

<table>
<thead>
<tr>
<th>Period</th>
<th>Residential</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Winter peak</td>
<td>0.00</td>
<td>0.27</td>
<td>2.00</td>
<td>22.47</td>
<td>45.79</td>
<td>173.78</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Spring peak</td>
<td>0.00</td>
<td>0.21</td>
<td>1.57</td>
<td>17.62</td>
<td>35.90</td>
<td>136.26</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Summer peak</td>
<td>0.00</td>
<td>0.16</td>
<td>1.18</td>
<td>13.30</td>
<td>27.10</td>
<td>102.85</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Fall peak</td>
<td>0.00</td>
<td>0.17</td>
<td>1.26</td>
<td>14.11</td>
<td>28.76</td>
<td>109.16</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Off-peak</td>
<td>0.00</td>
<td>0.27</td>
<td>1.97</td>
<td>22.22</td>
<td>45.29</td>
<td>171.88</td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Farm</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Winter peak</td>
<td>0.68</td>
<td>2.99</td>
<td>5.18</td>
<td>9.01</td>
<td>9.94</td>
<td>19.40</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spring peak</td>
<td>0.51</td>
<td>2.26</td>
<td>3.91</td>
<td>6.81</td>
<td>7.51</td>
<td>14.67</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Summer peak</td>
<td>0.57</td>
<td>2.52</td>
<td>4.37</td>
<td>7.60</td>
<td>8.39</td>
<td>16.37</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Fall peak</td>
<td>0.43</td>
<td>1.91</td>
<td>3.32</td>
<td>5.77</td>
<td>6.36</td>
<td>12.42</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Off-peak</td>
<td>0.66</td>
<td>2.92</td>
<td>5.06</td>
<td>8.80</td>
<td>9.71</td>
<td>18.95</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Commercial</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Peak</td>
<td>3.67</td>
<td>10.84</td>
<td>29.29</td>
<td>147.52</td>
<td>237.06</td>
<td>285.52</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Off-peak</td>
<td>3.00</td>
<td>8.89</td>
<td>24.00</td>
<td>120.93</td>
<td>194.32</td>
<td>234.04</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Next, the sector customer damage function (SCDF) is formed from the expected DNCs for each sector. The industrial sector has one load period and therefore the expected DNC is same as
the data in Table 3.4. The expected DNCs for Residential, Farm and Commercial sectors are obtained by (3.13). The SCDF as described in (3.14) are presented in Table 3.12.

Table 3.12. Sector Customer Damage Function (SCDF), $/kW

<table>
<thead>
<tr>
<th>Sector</th>
<th>1 min</th>
<th>20 mins</th>
<th>1 hr</th>
<th>4 hrs</th>
<th>8 hrs</th>
<th>24 hrs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Residential</td>
<td>0.00</td>
<td>0.27</td>
<td>1.96</td>
<td>22.09</td>
<td>45.03</td>
<td>170.90</td>
</tr>
<tr>
<td>Farm</td>
<td>0.65</td>
<td>2.89</td>
<td>5.02</td>
<td>8.72</td>
<td>9.63</td>
<td>18.79</td>
</tr>
<tr>
<td>Commercial</td>
<td>3.05</td>
<td>9.02</td>
<td>24.36</td>
<td>122.75</td>
<td>197.25</td>
<td>237.57</td>
</tr>
<tr>
<td>Industrial</td>
<td>2.53</td>
<td>4.19</td>
<td>8.25</td>
<td>27.25</td>
<td>52.51</td>
<td>154.65</td>
</tr>
</tbody>
</table>

The composite customer damage functions (CCDF) for the all load points are finally calculated using (3.15). The composite power system consists of multiple load points with unique load composition. Therefore, the CCDFs will vary from one load point to another depending upon the composition of the customer sectors at a given load point. Figure 3.7 shows the 17 load points of the IEEE-RTS 24-bus system, which has an annual peak demand of 2850 MW and a load factor of 61.4%. Table 3.13 shows the load sector composition for two selected load points, 4 and 14 that are assumed to illustrate the method. The CCDF obtained at these load points are shown in Figure 3.8. A composite system reliability assessment of the test system will yield the frequency, duration and the load curtailment at each load point. These load point indices are then used in (3.16) to calculate the ECOST of the system. The decision to invest in a new transmission resource should then be justified by the reduction in ECOST due to the implementation of the new resource.

Table 3.13. Assumed Sector load composition at two Load Points in IEEE RTS 24 Bus System

<table>
<thead>
<tr>
<th>Sector</th>
<th>Peak demand %</th>
<th>Energy consumption %</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Load point 4</td>
<td>Load point 14</td>
</tr>
<tr>
<td>Residential</td>
<td>40%</td>
<td>19%</td>
</tr>
<tr>
<td>Farm</td>
<td>15%</td>
<td>10%</td>
</tr>
<tr>
<td>Commercial</td>
<td>30%</td>
<td>25%</td>
</tr>
<tr>
<td>Industrial</td>
<td>15%</td>
<td>46%</td>
</tr>
</tbody>
</table>
Figure 3.7. IEEE-RTS 24 bus system load points.

Figure 3.8. CCDF at two different load points of the IEEE RTS system.
3.5. Conclusions

Substantial investments in transmission resources will be required to address the growing challenges of maintaining the reliability of power grids, stemming from the rising penetration of intermittent renewable energy sources and the growth in electric vehicles causing increased uncertainty in load profiles across the load centers. Ongoing research and development in smart technologies, such as energy storage, power electronics, and digital communication devices, provide opportunities for enhancing the capabilities of the transmission system. The appropriate investment in the selected emerging technologies, should however, enhance the grid network reliability and mitigate the cost of power outages. The methodology proposed and illustrated in this paper can be used by grid reliability planners to estimate the cost of outages originated from transmission facilities. The outage costs obtained from the proposed method can also be used to decide investment in grid resiliency enhancement against extreme weather that mainly impact the grid network facilities.

The paper presents and illustrates the methodology to estimate the outage costs originated from transmission component failures using data obtained from an outage cost survey conducted in the year 2017 in the Canadian province of Saskatchewan. Since past outage cost survey were all focused on outages due to lack of generation supply, the paper illustrates approximations required due to lack of data needed to calculate outage costs originated from transmission failures. The paper shows that the amount of customer data required increases with the number of periods in the SPD model for the customer sector. The industrial sector SPD model has only one period, and therefore, the data from other existing surveys can be adequately utilized. The industrial and residential sectors account for over 80% of the total system load in most power systems, and therefore, concentrated efforts are required to plan appropriate survey questionnaire for the residential sector in order to obtain useful data to assess the transmission originated outage costs. New surveys that incorporate these recommendations will yield realistic outage costs that can then be used in value-based reliability or resiliency investment in emerging technologies and transmission facilities.
3.6. References


CHAPTER 4: RELIABILITY AND RESILIENCY WORTH INVESTMENT IN POWER TRANSMISSION RESOURCES

4.1. Abstract

Electric power transmission grids are undergoing substantial changes to accommodate low-carbon technologies in order to meet established and upcoming environmental compliance regulations and guidelines. Large scale integration of renewable generation and electric vehicles will substantially increase uncertainty in supply, demand and line loadings, and cause significant challenges in maintaining the reliability of the power grid. Further, the escalating frequency of occurrence of extreme weather events have raised concerns about grid resilience against such events. Transmission planners strive to address these challenges and achieve reliable, resilient and cost-effective power network by efficiently investing in new technologies and processes and implementing them to minimize power outage costs. This paper investigates the reliability and resiliency worth of investments in the transmission grid facilities and technologies. The paper presents a method to assess the reliability worth of investment in advancing transmission technology to enhance the grid reliability. Investing into such technology can alleviate the grid congesti in short planning horizon. An illustration of assessing the reliability worth of investing into Dynamic Line Ratings (DLR) technology is presented in the paper. Further the paper also presents a method to assess the resiliency worth of investing into the infrastructure hardening to bolster grid resilience against extreme wind events. The methodologies presented in the paper employ probabilistic composite system reliability assessment methods using contingency enumeration techniques to analyze reliability indices of the IEEE RTS 24 bus system.

1 Ready for submission to a publication
4.2. Introduction

The power transmission network is a vital infrastructure of a modern power system that enables efficient and reliable delivery of the electricity from the power generation sources to the distribution networks connected to its bulk load points [1]. A sustainable economic growth of a nation requires a reliable and resilient electrical transmission network that can effectively integrate diverse sustainable energy sources and green technologies. The transition towards renewable generation has introduced a new level of complexity to the power grid [2]. Additionally, increasing frequency and regional shift of high-impact low-probability (HILP) weather events such as extreme winds and snow storms over the past decades [3] has threatened the overall grid infrastructural integrity [4].

The growing integration of renewable energy sources, such as wind power [5] into the electricity grid causes significant difficulties in balancing the supply and demand in power systems. Unlike conventional power generation, renewable sources are inherently intermittent and geographically dispersed, leading to fluctuations in power output based on weather conditions and time of day. This variability combined with the growing uncertainty in demand [6] caused by electric vehicles poses challenges for the grid planner to maintain system reliability. To accommodate renewable energy penetration and load growth, utilities need to expand or strengthen the transmission network at a pace to match the changes in generation and load demand [7], [8]. Any investment made to expand or upgrade the transmission network should also be justified by the resulting reliability worth in terms of reduced outage cost. Transmission upgrades can be done in many different forms, such as under-grounding an overhead line, elevating the voltage of the line, replacing the line to increase ampacity, implementing dynamic line rating (DLR) technology to increase ampacity, installing flexible ac transmission system (FACTS) devices for var compensation, integrating energy storage systems (ESS), etc. Ref. [9] presents the reliability worth of multiple capital projects such as building a new line and rebuilding existing line in a practical transmission system using contingency enumeration in a probabilistic reliability assessment technique and outage cost data obtained from a customer damage function (CDF). Value-based planning of addition of new lines and grid reinforcements are presented in [10] based on N-1 security criterion. The authors in [10] employ linear optimization to minimize the sum of investment cost and outage cost based on assumed outage cost values. Reliability worth of investing in static Var compensator for corrective control is studied in [11] using chronological
Monte Carlo Simulation based on the net present value of the expected outage cost, investment cost and operation cost. Ref. [12] presents reliability worth of remedial action based on optimizing the control mode and settings of a unified power flow controller. Reliability worth of investing in compressed air energy storage in a transmission congested wind integrated power system is presented in [13] using a Sequential Monte Carlo Simulation. A time series simulation technique is presented in [14] to evaluate the reliability worth of energy storage in a wind-integrated power system. Ref. [15] presented a case study of implementing ambient adjusted ratings (AAR) technology in the Argentinean transmission network. The reliability impact of implementing DLR technology in wind power integrated power grids is assessed in [16] using a sequential Monte Carlo simulation approach to model the time dependencies of line ratings and wind speeds. Both the papers [15], [16] discuss the financial benefits obtained from the DLR technology in terms of increased wind power absorption and reduced emissions. The reliability worth assessment in the above discussed papers utilize the demand normalized outage cost obtained for generation adequacy studies, which is related to outage costs occurred due to inadequate generation that occurs during the system peak load. Ref. [17] presents the methodology and illustration of the CDF obtained for transmission originated failures that can occur at different times of day and year with system specific probabilistic characteristics. In this paper, the reliability worth of investing into the transmission resources is illustrated utilizing the CDF estimated in [17].

HILP weather events have resulted in catastrophic destruction of grid infrastructure, leading to extended outages and inconvenience for customers and also imposing significant financial and asset losses for utilities [18]. The structural integrity of the grid facilities is crucial for power system resilience, and utilities are prioritizing investments in strengthening the grid infrastructure to withstand extreme weather events and natural disasters [19]. This can involve measures such as infrastructure reinforcement, redundancy and diverse pathways, emergency response and recovery plans, microgrids, and grid modernization [20]. By enhancing the structural resilience of the grid, utilities can minimize downtime, reduce the risk of widespread outages, and ensure a prompt recovery from disruptions. Improving the infrastructural resilience requires huge investment cost in the transmission system while the likelihood of such event occurring is quite low. Therefore, resiliency worth of investing in transmission infrastructure is becoming the important field of research for both academia and utility industries. A duration dependent outage cost model is implemented in [21] to show consideration of interruption cost that varies with outage duration.
can influence the investment choices for value-based resiliency investment decision. A comparison of resiliency worth of investment is presented in [3] using a long term average indicator like Expected Energy Not Supplied (EENS) and a risk indicator like Conditional Value At Risk (CVaR). A Mixed-Integer Program (MIP) is used to determine the best investment in transmission system to improve the power system resilience using the historical data to predict the impact of natural disasters in a region [22]. A Monte-Carlo simulation based power system infrastructure upgrades is proposed in [23] using fragility curves of transmission tower, line and transformer to predict the possible failure scenario as the wind speed and the concept of CVaR to reduce the impact of an impending extreme event. In these literatures, simulation method is used to assess the impact of extreme event in terms of MW or MWhr loss that is comparable to reliability assessment technique with the focus on rare and destructive nature of extreme event. In this paper, the resiliency worth of an investment into the transmission resources is presented by utilizing the customer outage cost function obtained for customer interruptions originated from transmission component failures [17].

The IEEE Reliability Test System (IEEE-RTS) 1996 [24] is used in this work to conduct the reliability and resiliency worth assessment studies. This paper illustrates a contingency enumeration method for a probabilistic assessment of various power outage scenarios originated from transmission grid failures. Section 4.3 of this paper presents the reliability worth analysis of a composite power system. Section 4.4 describes the steps to calculate the composite customer damage function at the different load points in the IEEE-RTS using the sector customer damage function developed in [17]. Finally, reliability and resiliency worth studies in the IEEE-RTS testing system is presented in Sections 4.5 and 4.6 respectively.

4.3. Composite Power System Reliability Worth Analysis

The reliability analysis in a composite power system involves the consideration of components failures or contingencies from both generation and transmission system. The failure scenarios are studied for optimal power flow which utilizes optimal dispatch of generating units, assessment of power flow on transmission system components, alleviation of network violations, and load curtailment if required. The basic modeling approach of composite power system is shown in Figure 4.1 [25]. The two state Markov Model for Generation, Transmission, and the Load
as shown in Figure 4.2 [25] is used to form a risk model containing various contingencies with probabilistic reliability indices – probability of a failure (P), frequency of a failure (occurrence/year) (F), and duration of a failure (hours/year) (D). The load flow of a power system network under each contingency can be solved using different solution methods, such as Network Flow, DC Load Flow, and AC Load Flow, to evaluate load curtailment. The Load curtailment is a reliability index that shows the intensity of power outages in MW. The composite power system reliability is studied at each load bus and therefore the reliability indices are also obtained for each load bus as given by (4.1a) – (4.1e) [25]. The evaluation period of a power system reliability study is usually done for 1 year period and therefore the obtained reliability indices are for annual period.

Probability of failure = \( \sum_{j \in V} P_j \times P_{Kj} \) \hspace{1cm} (4.1a)

Where, j is an outage condition in the network, \( P_j \) is the probability of existence of outage j, \( P_{Kj} \) is the probability of the load at bus K exceeding the maximum load that can be supplied at that bus during the outage j, and \( j \in V \) includes all contingencies which cause load flow violations – insufficient generation, line overloads, voltage violations and isolation of bus.

\text{Number of load curtailments (NLC)} = \sum_{j \in V} F_j \times P_{Kj} \hspace{1cm} \text{(occ/yr)} \hspace{1cm} (4.1b)

Where, \( F_j \) is the frequency of occurrence of outage j.

\text{Expected duration of load curtailments (EDLC)} = \sum_{j \in V} F_j \times D_{Kj} \hspace{1cm} \text{(hrs/yr)} \hspace{1cm} (4.1c)

Where, \( D_{Kj} \) is the duration in hours of a load curtailment arising due to the outage j at bus K.

\text{Expected load curtailed (ELC)} = \sum_{j \in V} F_j \times L_{Kj} \hspace{1cm} \text{(MW/yr)} \hspace{1cm} (4.1d)

Where, \( L_{Kj} \) is the load curtailment at bus K to alleviate line overloads arising due to the contingency j.

\text{Expected energy not supplied (EENS)} = \sum_{j \in V} L_{Kj} \times F_j \times D_{Kj} \hspace{1cm} \text{(MWhr/yr)} \hspace{1cm} (4.1e)

Where, \( D_{Kj} \) is the duration of a load curtailment \( L_{Kj} \).
In this paper, the reliability analysis of a composite power system is conducted using PSSE software version 34 [26]. The contingencies are obtained from the outage level definition of 1G + 4L with contingency frequency > 0.000001. The obtained contingencies are fed into PSSE as user defined contingency. PSSE provides contingency analysis tool with following stages for load curtailments:

• Post Contingency: A contingency that causes separation (or islanding) of a portion of the network in which the island has insufficient generation to meet the load.

• Post Tripping: A contingency that initiates a trip event in which the trip sequence causes load to be shed.

• Post Corrective Actions: A contingency that has an overload or voltage violation after redispatch and tripping and for which corrective actions involving load curtailment have been specified.

The reliability worth assessment requires an equivalent outage cost for all the expected load curtailed for an outage as given by (4.1d). A composite customer damage function (CCDF), which is basically an outage cost as a function of outage duration for a load point. CCDF is utilized to estimate the expected cost of customer interruption (ECOST) as given by (4.2a).

\[
ECOST_K = \sum_{j \in V} L_{K_j} \times F_j \times C_{K_j}(D_{K_j}) \frac{MV}{kW} \text{$/yr}$
\]  

(4.2a)
Where, $C_{Kj}(D_{Kj})$ represents the CCDF ($$/kW$$) as a function of a power outage of duration $D_{Kj}$ for each contingency $j$ at load point $K$ respectively.

The reliability worth of an investment is the reduced customer interruption cost in a power system after the investment. Therefore, reliability worth of an investment at a load point $K$ is given by (4.2b).

$$RW_K = ECOST_{K, before} - ECOST_{K, after}$$  \hspace{1cm} (4.2b)

Where, $ECOST_{K, before}$ and $ECOST_{K, after}$ represents the expected cost of customer interruption at bus $K$ before and after an investment.

Since the reliability indices are calculated for an annual evaluation period, the reliability worth evaluated from (4.2b) gives the annual cost saving for the customers at bus $K$. The annual outage cost saving provided by (4.2b) will be available for the duration of the operating years of a technology or upgrade.

### 4.4. Composite Customer Damage Function

This section presents the system and load points CCDFs for the IEEE RTS system. The IEEE Reliability Test System (RTS) 1996 is used in power system for reliability research work [24]. It was developed by the Reliability Test System Task Force of the Application of Probability Methods Subcommittee. The single line diagram of the One Area IEEE-RTS is shown in Figure 4.3. The One Area test system consists of 32 generating units located at 10 generator buses, 10 load buses, 33 transmission lines and 5 transformers at 138kV and 230kV voltage levels. The installed total capacity is 3405 MW and system peak load is 2850 MW. There are 17 load points in the system as shown in the Figure 4.3.
Figure 4.3. IEEE-RTS 24 bus single line diagram.
IEEE-RTS System and load point CCDFs are evaluated using the sector customer damage function (SCDF) that was prepared for transmission originated failure in [17] as shown in Table 4.1 and assumed customer sector load composition in the IEEE RTS system as shown in Table 4.2. The steps involve to obtain the CCDFs system wide and at different load point are also described in [17]. Table 4.3 shows the calculated system CCDF for this load composition.

Table 4.1. Sector customer damage function

<table>
<thead>
<tr>
<th>Sector</th>
<th>1 min</th>
<th>20 mins</th>
<th>1 hr</th>
<th>4 hrs</th>
<th>8 hrs</th>
<th>24 hrs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Residential</td>
<td>0.00</td>
<td>0.27</td>
<td>1.96</td>
<td>22.09</td>
<td>45.03</td>
<td>170.90</td>
</tr>
<tr>
<td>Farm</td>
<td>0.65</td>
<td>2.89</td>
<td>5.02</td>
<td>8.72</td>
<td>9.63</td>
<td>18.79</td>
</tr>
<tr>
<td>Commercial</td>
<td>3.05</td>
<td>9.02</td>
<td>24.36</td>
<td>122.75</td>
<td>197.25</td>
<td>237.57</td>
</tr>
<tr>
<td>Industrial</td>
<td>2.53</td>
<td>4.19</td>
<td>8.25</td>
<td>27.25</td>
<td>52.51</td>
<td>154.65</td>
</tr>
</tbody>
</table>

Table 4.2. Assumed load composition in the system

<table>
<thead>
<tr>
<th>Sector</th>
<th>Peak demand %</th>
<th>Energy consumption %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Residential</td>
<td>25%</td>
<td>18%</td>
</tr>
<tr>
<td>Farm</td>
<td>10%</td>
<td>7%</td>
</tr>
<tr>
<td>Commercial</td>
<td>17%</td>
<td>19%</td>
</tr>
<tr>
<td>Industrial</td>
<td>48%</td>
<td>56%</td>
</tr>
<tr>
<td>Total</td>
<td>100%</td>
<td>100%</td>
</tr>
</tbody>
</table>

Table 4.3. IEEE RTS System CCDF

<table>
<thead>
<tr>
<th>Dur.</th>
<th>1 min</th>
<th>20 mins</th>
<th>1 hr</th>
<th>4 hrs</th>
<th>8 hrs</th>
<th>24 hrs</th>
</tr>
</thead>
<tbody>
<tr>
<td>IEEE RTS System</td>
<td>1.80</td>
<td>3.90</td>
<td>9.95</td>
<td>43.17</td>
<td>75.66</td>
<td>163.82</td>
</tr>
</tbody>
</table>

Similarly, CCDFs at each load point is calculated using the load composition at each load bus. The load composition at every bus can be obtained by assigning the peak load for the different sectors at each load bus and then calculating the sector peak load and energy consumption percentages. The following steps and equations (4.3a) – (4.3d) involved to calculate load composition at each load bus is explained in [27]. The sector allocation at the load buses must meet two conditions as presented in (4.3a).

\[
\sum_{All\ sectors} \text{Sector peak at bus } k = \text{Peak load at bus } k
\]

\[
\sum_{All\ buses} \text{Bus peak of sector } m = \text{System peak of sector } m
\]

(4.3a)
The peak load percentage of a given sector at bus $k$ can be calculated by (4.3b).

$$\text{Sector peak load \% at bus } k = \frac{\text{Sector peak load at bus } k}{\text{Total peak load at bus } k} \times 100 \quad (4.3b)$$

Next, the sector load factor at each bus is calculated from the system load factor as given by (4.3c).

$$\text{Sector L.F.} = \frac{\text{Sector energy \%}}{\text{Sector peak load \%}} \times \text{System L.F.} \quad (4.3c)$$

Where, System L.F. = 61.40\% for IEEE-RTS.

The energy consumption percentage of a given sector at bus $k$ is calculated as given by (4.3d).

$$\text{Sector energy consumption \% at bus } k = \frac{\text{Sector L.F.} \times \text{Sector peak load at bus } k}{\sum_{\text{All Sectors}} \text{Sector L.F.} \times \text{Sector peak load at bus } k} \times 100 \quad (4.3d)$$

Table IV shows the assumed sector peak load at each load bus in the test system. This table is created by following the conditions as given by (4.3a) where column “Total (MW)” in the Table 4.4 shows the bus load data at each load point. Next, the sector peak load and sector energy consumption percentages at each load point are calculated using (4.3b) and (4.3e) and the obtained values are shown in Table 4.5 and 4.6 respectively. The calculated CCDF at each load point for the test system is shown in Table 4.7.

Table 4.4. Assumed sector peak load at IEEE RTS load points

<table>
<thead>
<tr>
<th>Load point</th>
<th>Industrial</th>
<th>Residential</th>
<th>Commercial</th>
<th>Farm</th>
<th>Total (MW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>16.20</td>
<td>54.00</td>
<td>37.80</td>
<td>0.00</td>
<td>108.00</td>
</tr>
<tr>
<td>2</td>
<td>0.00</td>
<td>63.54</td>
<td>33.47</td>
<td>0.00</td>
<td>97.01</td>
</tr>
<tr>
<td>3</td>
<td>0.00</td>
<td>90.00</td>
<td>90.00</td>
<td>0.00</td>
<td>180.00</td>
</tr>
<tr>
<td>4</td>
<td>11.47</td>
<td>37.00</td>
<td>25.53</td>
<td>0.00</td>
<td>74.00</td>
</tr>
<tr>
<td>5</td>
<td>10.65</td>
<td>46.15</td>
<td>14.20</td>
<td>0.00</td>
<td>71.00</td>
</tr>
<tr>
<td>6</td>
<td>24.00</td>
<td>62.00</td>
<td>20.00</td>
<td>30.00</td>
<td>136.00</td>
</tr>
<tr>
<td>7</td>
<td>25.00</td>
<td>56.25</td>
<td>43.75</td>
<td>0.00</td>
<td>125.00</td>
</tr>
<tr>
<td>8</td>
<td>42.75</td>
<td>76.95</td>
<td>42.75</td>
<td>8.55</td>
<td>171.00</td>
</tr>
<tr>
<td>9</td>
<td>52.50</td>
<td>70.88</td>
<td>42.88</td>
<td>8.75</td>
<td>175.01</td>
</tr>
<tr>
<td>10</td>
<td>58.50</td>
<td>78.98</td>
<td>47.78</td>
<td>9.75</td>
<td>195.01</td>
</tr>
<tr>
<td>13</td>
<td>172.25</td>
<td>26.50</td>
<td>35.78</td>
<td>30.48</td>
<td>265.01</td>
</tr>
<tr>
<td>14</td>
<td>135.80</td>
<td>17.46</td>
<td>9.70</td>
<td>31.04</td>
<td>194.00</td>
</tr>
<tr>
<td></td>
<td>Industrial</td>
<td>Residential</td>
<td>Commercial</td>
<td>Farm</td>
<td></td>
</tr>
<tr>
<td>----</td>
<td>------------</td>
<td>-------------</td>
<td>------------</td>
<td>------</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>15.00%</td>
<td>50.00%</td>
<td>35.00%</td>
<td>0.00%</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>0.00%</td>
<td>65.50%</td>
<td>34.50%</td>
<td>0.00%</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>0.00%</td>
<td>50.00%</td>
<td>50.00%</td>
<td>0.00%</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>15.50%</td>
<td>50.00%</td>
<td>34.50%</td>
<td>0.00%</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>15.00%</td>
<td>65.00%</td>
<td>20.00%</td>
<td>0.00%</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>17.65%</td>
<td>45.59%</td>
<td>14.71%</td>
<td>22.06%</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>20.00%</td>
<td>45.00%</td>
<td>35.00%</td>
<td>0.00%</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>25.00%</td>
<td>45.00%</td>
<td>25.00%</td>
<td>5.00%</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>30.00%</td>
<td>40.50%</td>
<td>24.50%</td>
<td>5.00%</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>30.00%</td>
<td>40.50%</td>
<td>24.50%</td>
<td>5.00%</td>
<td></td>
</tr>
<tr>
<td>13</td>
<td>65.00%</td>
<td>10.00%</td>
<td>13.50%</td>
<td>11.50%</td>
<td></td>
</tr>
<tr>
<td>14</td>
<td>70.00%</td>
<td>9.00%</td>
<td>5.00%</td>
<td>16.00%</td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>80.00%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>20.00%</td>
<td></td>
</tr>
<tr>
<td>16</td>
<td>75.00%</td>
<td>5.00%</td>
<td>0.00%</td>
<td>20.00%</td>
<td></td>
</tr>
<tr>
<td>18</td>
<td>80.00%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>20.00%</td>
<td></td>
</tr>
<tr>
<td>19</td>
<td>80.00%</td>
<td>5.00%</td>
<td>0.00%</td>
<td>15.00%</td>
<td></td>
</tr>
<tr>
<td>20</td>
<td>70.00%</td>
<td>10.00%</td>
<td>5.00%</td>
<td>15.00%</td>
<td></td>
</tr>
</tbody>
</table>

Table 4.5. Sector peak load percentages at each load point

<table>
<thead>
<tr>
<th></th>
<th>Industrial</th>
<th>Residential</th>
<th>Commercial</th>
<th>Farm</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>18.89%</td>
<td>38.87%</td>
<td>42.24%</td>
<td>0.00%</td>
</tr>
<tr>
<td>2</td>
<td>0.00%</td>
<td>55.02%</td>
<td>44.98%</td>
<td>0.00%</td>
</tr>
<tr>
<td>3</td>
<td>0.00%</td>
<td>39.18%</td>
<td>60.82%</td>
<td>0.00%</td>
</tr>
<tr>
<td>4</td>
<td>19.52%</td>
<td>38.86%</td>
<td>41.62%</td>
<td>0.00%</td>
</tr>
<tr>
<td>5</td>
<td>20.20%</td>
<td>54.01%</td>
<td>25.80%</td>
<td>0.00%</td>
</tr>
<tr>
<td>6</td>
<td>24.14%</td>
<td>38.49%</td>
<td>19.27%</td>
<td>18.10%</td>
</tr>
<tr>
<td>7</td>
<td>24.60%</td>
<td>34.16%</td>
<td>41.24%</td>
<td>0.00%</td>
</tr>
<tr>
<td>8</td>
<td>31.36%</td>
<td>34.84%</td>
<td>30.04%</td>
<td>3.76%</td>
</tr>
<tr>
<td>9</td>
<td>36.82%</td>
<td>30.68%</td>
<td>28.81%</td>
<td>3.68%</td>
</tr>
<tr>
<td>10</td>
<td>36.82%</td>
<td>30.68%</td>
<td>28.81%</td>
<td>3.68%</td>
</tr>
<tr>
<td>13</td>
<td>71.42%</td>
<td>6.78%</td>
<td>14.21%</td>
<td>7.58%</td>
</tr>
<tr>
<td>14</td>
<td>77.83%</td>
<td>6.18%</td>
<td>5.33%</td>
<td>10.67%</td>
</tr>
<tr>
<td>15</td>
<td>86.96%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>13.04%</td>
</tr>
</tbody>
</table>

Table 4.6. Sector energy consumption percentages at each load point
Table 4.7. Load point CCDFs

<table>
<thead>
<tr>
<th>Load point / Dur</th>
<th>1 min</th>
<th>20 mins</th>
<th>1 hr</th>
<th>4 hrs</th>
<th>8 hrs</th>
<th>24 hrs</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.45</td>
<td>3.92</td>
<td>12.61</td>
<td>65.58</td>
<td>110.73</td>
<td>195.99</td>
</tr>
<tr>
<td>2</td>
<td>1.05</td>
<td>3.29</td>
<td>12.04</td>
<td>67.37</td>
<td>113.51</td>
<td>200.89</td>
</tr>
<tr>
<td>3</td>
<td>1.53</td>
<td>4.65</td>
<td>15.58</td>
<td>83.31</td>
<td>137.61</td>
<td>211.45</td>
</tr>
<tr>
<td>4</td>
<td>1.44</td>
<td>3.90</td>
<td>12.51</td>
<td>64.99</td>
<td>109.85</td>
<td>195.48</td>
</tr>
<tr>
<td>5</td>
<td>0.99</td>
<td>2.61</td>
<td>9.01</td>
<td>49.10</td>
<td>85.81</td>
<td>184.82</td>
</tr>
<tr>
<td>6</td>
<td>1.04</td>
<td>2.83</td>
<td>8.35</td>
<td>40.31</td>
<td>69.76</td>
<td>152.29</td>
</tr>
<tr>
<td>7</td>
<td>1.57</td>
<td>4.12</td>
<td>12.75</td>
<td>64.87</td>
<td>109.65</td>
<td>194.40</td>
</tr>
<tr>
<td>8</td>
<td>1.43</td>
<td>3.57</td>
<td>10.78</td>
<td>53.45</td>
<td>91.77</td>
<td>180.11</td>
</tr>
<tr>
<td>9</td>
<td>1.54</td>
<td>3.72</td>
<td>10.84</td>
<td>52.50</td>
<td>90.34</td>
<td>178.52</td>
</tr>
<tr>
<td>10</td>
<td>1.54</td>
<td>3.72</td>
<td>10.84</td>
<td>52.50</td>
<td>90.34</td>
<td>178.52</td>
</tr>
<tr>
<td>13</td>
<td>2.13</td>
<td>4.30</td>
<td>9.87</td>
<td>39.07</td>
<td>69.32</td>
<td>157.23</td>
</tr>
<tr>
<td>14</td>
<td>2.03</td>
<td>3.87</td>
<td>8.37</td>
<td>30.04</td>
<td>55.18</td>
<td>145.57</td>
</tr>
<tr>
<td>15</td>
<td>2.15</td>
<td>3.93</td>
<td>7.83</td>
<td>24.83</td>
<td>46.92</td>
<td>136.93</td>
</tr>
<tr>
<td>16</td>
<td>2.03</td>
<td>3.73</td>
<td>7.60</td>
<td>24.60</td>
<td>46.54</td>
<td>137.11</td>
</tr>
<tr>
<td>18</td>
<td>2.15</td>
<td>3.93</td>
<td>7.83</td>
<td>24.83</td>
<td>46.92</td>
<td>136.93</td>
</tr>
<tr>
<td>19</td>
<td>2.12</td>
<td>3.80</td>
<td>7.72</td>
<td>25.27</td>
<td>48.07</td>
<td>141.92</td>
</tr>
<tr>
<td>20</td>
<td>2.02</td>
<td>3.84</td>
<td>8.35</td>
<td>30.13</td>
<td>55.41</td>
<td>146.59</td>
</tr>
</tbody>
</table>

4.5. Reliability Worth of an Investment in Transmission System

This section evaluates the reliability worth of investing in ambient adjusted ratings (AAR), a DLR technology, to improve the reliability of the IEEE RTS 24 bus system. AAR technology enables estimation of line ratings daily, hourly or more frequently based on ambient air temperature. Other environmental data such as wind speed and solar radiation are considered as fixed worst-case possible [15]. Usually, the AAR is implemented for step temperature distribution for example, in ERCOT and PJM, AARs are implemented using temperature step of 5-degree Fahrenheit and 5-degree Celsius respectively [28]. In this section, AAR is implemented on by considering the ambient air temperature data from the Saskatchewan, Canada. Then the CCDF
data from Table VII is utilized to estimate the worth of the AAR technology in different system configurations.

4.5.1. Step ambient temperature distribution and conductor’s capability

The historical ambient air temperature data in Saskatchewan province is first obtained. The obtained data shows that ambient temperature range in the province is usually +40 to -40 degree Celsius. The conductor capability is calculated within this ambient temperature range. Then, the temperature from 40 to -40 degree Celsius are grouped by 10-degree step. The obtained Step ambient temperature distribution is presented in Table 4.8.

Table 4.8. Step ambient temperature distribution

<table>
<thead>
<tr>
<th>Temperature(°C)</th>
<th>Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>40</td>
<td>0.001004</td>
</tr>
<tr>
<td>30</td>
<td>0.050685</td>
</tr>
<tr>
<td>20</td>
<td>0.210224</td>
</tr>
<tr>
<td>10</td>
<td>0.219512</td>
</tr>
<tr>
<td>0</td>
<td>0.217024</td>
</tr>
<tr>
<td>-10</td>
<td>0.187015</td>
</tr>
<tr>
<td>-20</td>
<td>0.078183</td>
</tr>
<tr>
<td>-30</td>
<td>0.033775</td>
</tr>
<tr>
<td>-40</td>
<td>0.002579</td>
</tr>
</tbody>
</table>

Next, the conductor capability is calculated for each ambient temperature in Table 4.8. The corresponding conductor capability at each temperature step is calculated using the (4.4a) – (4.4e) as in the IEEE Std 738 [29]. Data other than ambient temperature, that are considered for the worst-case scenario in this study are presented in Table 4.9, which are given in the IEEE Std 738. The equations (4.4a) – (4.4e) are evaluated in SI unit. In this paper, the steady state conductor temperature is considered for 75 degrees Celsius, and the steady state current rating is given by (4.3a) evaluates the current rating for this steady state temperature.

\[
\text{Steady State current rating (I)} = \sqrt{\frac{q_c + q_r - q_s}{R(T_{avg})}} \text{ Amp}
\] (4.4a)

Where, \(q_c, q_r, \text{ and } q_s\) are convection heat loss, radiated heat loss, and solar heat gain respectively. The \(R(T_{avg})\) is the resistance per meter of a conductor at temperature \(T_{avg}\). The formulas for these quantities are given by (4.4b) – (4.4e).
\[q_c = K_{angle} \cdot \left[1.01 + 1.35 \cdot N_{Re}^{-0.52}\right] \cdot k_f \cdot (T_S - T_a) \text{ W/m} \quad (4.4b)\]

Where, \(T_S\) and \(T_a\) are steady state maximum continuous conductor temperature and ambient temperature in °C and,

\[K_{angle} = 1,\]

\[k_f = 2.424 \cdot 10^{-2} + 7.477 \cdot 10^{-5} \cdot T_{film} - 4.407 \cdot 10^{-9} \cdot T_{film}^2, \quad \text{here, } T_{film} = \frac{T_S + T_a}{2}\]

\[N_{Re} = \frac{D_0 \cdot \rho_f \cdot V_w}{\mu_f}, \quad \text{here, } D_0 = \text{conductor outer diameter}, \ V_w = \text{wind velocity}\]

\[\rho_f = \frac{1.293 - 1.525 \cdot 10^{-8} \cdot H_e + 6.379 \cdot 10^{-9} \cdot H_e^2}{1 + 0.00367 \cdot T_{film}}, \quad \text{here, } H_e = \text{line elevation}\]

\[\mu_f = \frac{1.458 \cdot 10^{-6} \cdot (T_{film} + 273)^{1.5}}{T_{film} + 383.4}\]

\[q_r = 17.8 \cdot D_0 \cdot \varepsilon \cdot \left[\frac{(T_S + 273)}{100}^4 - \left(\frac{(T_a + 273)}{100}\right)^4\right] \text{ W/m} \quad (4.4c)\]

Where, \(\varepsilon = \text{emissivity}\)

\[q_s = \alpha \cdot Q_{se} \cdot \sin(\theta) \cdot D_0 = 0.5 \cdot 1027. \sin(76.22^\circ) \cdot D_0 \text{ W/m (worst case)} \quad (4.4d)\]

\[R(T_{avg}) = \left[\frac{R(T_{high}) - R(T_{low})}{T_{high} - T_{low}}\right] \cdot (T_{high} - T_{low}) + R(T_{low}) \quad (4.4e)\]

Where, \(R(T_{high})\) and \(R(T_{low})\) are conductor resistances per meter at \(T_{high}\) and \(T_{low}\) temperatures respectively.
Table 4.9. Worst condition data considered to calculate conductor capabilities

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wind speed, $V_w$</td>
<td>0.61 m/s</td>
</tr>
<tr>
<td>Emissivity, $\varepsilon$</td>
<td>0.5</td>
</tr>
<tr>
<td>Solar Absorptivity, $\alpha$</td>
<td>0.5</td>
</tr>
<tr>
<td>Max allowable continuous conductor Temp, $T_s$</td>
<td>75°C</td>
</tr>
<tr>
<td>Azimuth of line, $Z_l$</td>
<td>90°</td>
</tr>
<tr>
<td>Latitude</td>
<td>50°</td>
</tr>
<tr>
<td>Solar altitude (Hc) is calculated at 11:00 am on June 10 (Day 161), N</td>
<td>161</td>
</tr>
<tr>
<td>Line elevation, $H_e$</td>
<td>0 m</td>
</tr>
<tr>
<td>Kangle</td>
<td>1</td>
</tr>
<tr>
<td>Hour angle at 11:00am, $\omega$</td>
<td>-15°</td>
</tr>
<tr>
<td>Solar heat flux (heat intensity) for clear air at sea level, $Q_s$</td>
<td>1027 W/m²</td>
</tr>
<tr>
<td>Solar azimuth constant, $C$</td>
<td>180°</td>
</tr>
</tbody>
</table>

The transmission lines in the IEEE RTS have two MVA ratings i.e. 175 MVA for 138kV lines and 500 MVA for 230kV lines. These ratings are assumed to be at worst ambient temperature i.e. 40°C. The conductors’ current ratings in the test system are 1268A and 2174A for 175 MVA and 500 MVA conductors respectively at 40°C. The ACSR conductors that are available in the market are identified for both ratings by using the standard rating datasheet from [30]. This datasheet has ACSR current rating with ambient temperature of 25°C and steady state maximum continuous conductor temperature of 75°C. The rating 2174A is found to be larger than the maximum rating at 25°C of the conductors in [30]. Therefore, parallel conductor is considered for both MVA ratings, which gives the rating of 2x634A (175MVA) and 2x1087A (500MVA) at 40°C. Table 4.10 presents the selected standard ACSR conductors from the datasheet that matches the current ratings for both type of conductors in the test system. Table 4.10 also presents the standard rating at 25°C, calculated rating at 40°C and conductor properties such as diameter and resistance per meter of the selected standard conductors.

Table 4.10. IEEE RTS conductor matching with standard ACSR

<table>
<thead>
<tr>
<th>IEEE RTS Conductor</th>
<th>Selected ACSR conductor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conductor type 1 (175 MVA at 138kV):</td>
<td>Conductor “Grossbeak”:</td>
</tr>
<tr>
<td>- Current rating for single conductor is 1268A at 40°C</td>
<td>- Standard current rating at 25°C is 789A</td>
</tr>
<tr>
<td>- Current rating for parallel conductors is 2x634A at 40°C</td>
<td>- Calculated current rating at 25°C is 791A</td>
</tr>
<tr>
<td></td>
<td>- Calculated current rating at 40°C is 640A</td>
</tr>
<tr>
<td></td>
<td>- Resistance at 20°C, $R(20°C) = 8.760\times10^{-5}$ Ω/m</td>
</tr>
</tbody>
</table>
• The ACSR conductor is selected with current rating nearby 634A at 40°C, which is “Grossbeak”

- Resistance at 75°C, $R(75°C) = 10.761 \times 10^{-5} \Omega/m$
- Outer diameter, $D_0 = 0.025171$ m

Conductor type 2 (500 MVA at 230kV):
• Current rating for single conductor is 2174A at 40°C
• Current rating for parallel conductors is 2x1087A at 40°C
• The ACSR conductor is selected with current rating nearby 1087A at 40°C, which is “Lapwing”

Conductor “Lapwing”:
• Standard current rating at 25°C is 1354A
• Calculated current rating at 25°C is 1358A
• Calculated current rating at 40°C is 1090A
• Resistance at 20°C, $R(20°C) = 3.543 \times 10^{-5} \Omega/m$
• Resistance at 75°C, $R(75°C) = 4.560 \times 10^{-5} \Omega/m$
• Outer diameter, $D_0 = 0.038202$ m

The steady state current rating and capability for step ambient temperature distribution for selected two ACSR conductors are calculated by using (4.4a) – (4.4e) with conductor properties from Table 4.10 and worst condition data from Table 4.9. Table 4.11 shows the calculated capabilities with varying step ambient temperature for both conductors. Among these two capabilities at each step ambient temperature, the minimum rise in capability is chosen for each step temperature change as shown in Table 4.11.

Table 4.11. ACSR calculated current rating and capability at various ambient temperature

<table>
<thead>
<tr>
<th>Temperature</th>
<th>Lapwing</th>
<th>Grossbeak</th>
<th>Conductor capability</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Amp</td>
<td>capability</td>
<td>Amp</td>
</tr>
<tr>
<td>40</td>
<td>1090</td>
<td>100%</td>
<td>640</td>
</tr>
<tr>
<td>30</td>
<td>1276</td>
<td>117%</td>
<td>745</td>
</tr>
<tr>
<td>20</td>
<td>1435</td>
<td>132%</td>
<td>835</td>
</tr>
<tr>
<td>10</td>
<td>1576</td>
<td>145%</td>
<td>915</td>
</tr>
<tr>
<td>0</td>
<td>1703</td>
<td>156%</td>
<td>988</td>
</tr>
<tr>
<td>-10</td>
<td>1820</td>
<td>167%</td>
<td>1056</td>
</tr>
<tr>
<td>-20</td>
<td>1928</td>
<td>177%</td>
<td>1118</td>
</tr>
<tr>
<td>-30</td>
<td>2030</td>
<td>186%</td>
<td>1177</td>
</tr>
<tr>
<td>-40</td>
<td>2125</td>
<td>195%</td>
<td>1232</td>
</tr>
</tbody>
</table>
The reliability worth of AAR technology is the reduced ECOST by investing into the technology as given by (4.2b). Therefore, the transmission line capability in IEEE RTS system is adjusted according to the change in capability with 9 steps ambient temperature distribution to build 9 IEEE RTS scenarios. Then, the risk model is built according to two state Markov model for each scenario to obtain the reliability indices as described in section 4.3. The reliability worth of AAR technology in IEEE RTS system is investigated for various system cases as described in the following subsection.

### 4.5.2. Case Study

The improvement of reliability by increasing the capability of transmission line is dependent on the line congestion condition. Transmission line installation or upgrades are usually time consuming and high costing projects for the utilities and may not always keep with the growing load demand. In such scenario, the transmission network will be congested and show low reliability performance in comparison to rest of the power system. Such weak transmission networks can be benefited from the AAR technology to increase its reliability performance. Following IEEE RTS system cases with varying line congestion are studied to evaluate the reliability worth of implementing the AAR technology to the grid.

**Case 1: Base case**

This case study is performed for base case generation, transmission and load data of the IEEE RTS 24 bus system. The following reliability indices for the system and one of the low reliable load points are obtained.

<table>
<thead>
<tr>
<th>System</th>
<th>NLC</th>
<th>ELC</th>
<th>EENS</th>
<th>EDLC</th>
<th>ECOST, $</th>
</tr>
</thead>
<tbody>
<tr>
<td>Without AAR</td>
<td>0.06399084</td>
<td>1.821680135</td>
<td>19.33579</td>
<td>0.790510464</td>
<td>162,501.76</td>
</tr>
<tr>
<td>With AAR</td>
<td>0.06327363</td>
<td>1.806522241</td>
<td>19.1812</td>
<td>0.780011061</td>
<td>161,212.06</td>
</tr>
<tr>
<td>Reliability worth, $</td>
<td>1,289.70</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 4.12. System annual indices with and without the AAR
Table 4.13. Load point (bus 3) annual indices with and without AAR

<table>
<thead>
<tr>
<th>System</th>
<th>NLC</th>
<th>ELC</th>
<th>EENS</th>
<th>EDLC</th>
<th>ECOST, $</th>
</tr>
</thead>
<tbody>
<tr>
<td>Without AAR</td>
<td>0.052666117</td>
<td>0.188014091</td>
<td>1.910360567</td>
<td>0.615587807</td>
<td>21,833.55</td>
</tr>
<tr>
<td>With AAR</td>
<td>0.05251912</td>
<td>0.186730661</td>
<td>1.897898682</td>
<td>0.614005419</td>
<td>21,694.36</td>
</tr>
<tr>
<td>Reliability worth, $</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>139.18</td>
</tr>
</tbody>
</table>

Case 2: RTS system with congested transmission lines

The congested transmission system means there is less capability available to deliver the power to the load points during various outage scenarios. To simulate the line congestion in the test system the load and generation of the base case test system is increased by 25% and 50%. The reliability worth for each increment is evaluated for system and one of the low reliable load points.

Case 2.1: 25% growth in load and generation

Table 4.14. System annual indices with and without the AAR

<table>
<thead>
<tr>
<th>System</th>
<th>NLC</th>
<th>ELC</th>
<th>EENS</th>
<th>EDLC</th>
<th>ECOST, $</th>
</tr>
</thead>
<tbody>
<tr>
<td>Without AAR</td>
<td>0.09667469</td>
<td>2.865496558</td>
<td>32.30098</td>
<td>1.244243765</td>
<td>266,147.94</td>
</tr>
<tr>
<td>With AAR</td>
<td>0.09593239</td>
<td>2.831737059</td>
<td>31.89943</td>
<td>1.232131494</td>
<td>262,975.92</td>
</tr>
<tr>
<td>Reliability worth, $</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>3,172.02</td>
</tr>
</tbody>
</table>

Table 4.15. Load point (bus 3) annual indices with and without AAR

<table>
<thead>
<tr>
<th>System</th>
<th>NLC</th>
<th>ELC</th>
<th>EENS</th>
<th>EDLC</th>
<th>ECOST, $</th>
</tr>
</thead>
<tbody>
<tr>
<td>Without AAR</td>
<td>0.082183311</td>
<td>1.373388227</td>
<td>18.24432</td>
<td>1.07626616</td>
<td>178,823.10</td>
</tr>
<tr>
<td>With AAR</td>
<td>0.081478105</td>
<td>1.351250072</td>
<td>17.87803</td>
<td>1.063310682</td>
<td>175,741.65</td>
</tr>
<tr>
<td>Reliability worth, $</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>3,081.45</td>
</tr>
</tbody>
</table>

Case 2.1: 50% growth in load and generation

Table 4.16. System annual indices with and without the AAR

<table>
<thead>
<tr>
<th>System</th>
<th>NLC</th>
<th>ELC</th>
<th>EENS</th>
<th>EDLC</th>
<th>ECOST, $</th>
</tr>
</thead>
<tbody>
<tr>
<td>Without AAR</td>
<td>0.189640545</td>
<td>6.964692431</td>
<td>77.74306113</td>
<td>2.425664559</td>
<td>640,557.27</td>
</tr>
<tr>
<td>With AAR</td>
<td>0.178218389</td>
<td>6.452557736</td>
<td>72.84300757</td>
<td>2.336247374</td>
<td>598,546.23</td>
</tr>
<tr>
<td>Reliability worth, $</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>42,011.04</td>
</tr>
</tbody>
</table>
Table 4.17. Load point (bus 3) annual indices with and without AAR

<table>
<thead>
<tr>
<th>System</th>
<th>NLC</th>
<th>ELC</th>
<th>EENS</th>
<th>EDLC</th>
<th>ECOST, $</th>
</tr>
</thead>
<tbody>
<tr>
<td>Without AAR</td>
<td>0.114142871</td>
<td>4.325062573</td>
<td>51.28690879</td>
<td>1.404248938</td>
<td>533,569.39</td>
</tr>
<tr>
<td>With AAR</td>
<td>0.10998436</td>
<td>4.082264837</td>
<td>48.8445093</td>
<td>1.361969477</td>
<td>506,361.98</td>
</tr>
<tr>
<td>Reliability worth, $</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>27,207.42</td>
</tr>
</tbody>
</table>

The case study presented above shows that the worth of investing AAR technology increases as the transmission line gets more congested. The annual system reliability worth has increased from $1,289.70 for base case to $42,011.04 for 50% load and generation growth case. Also, annual reliability worth of AAR technology for one of the low reliable load points (bus 3) has increased from $139.18 to $27,207.42 for same change is line congestion condition.

The investment cost of the technology is proportional to the number of lines, therefore reliability worths of investment in the technology for load bus 3 is higher than that for whole system for congested transmission network. AAR implementation in the whole system requires technology upgrades to 31 transmission lines. While AAR implementation in the selected transmission lines to improve the reliability at load bus 3 requires the technology upgrades to only 6 transmission lines i.e. line nos. 2, 6, 11, 18, 23, 28 in Figure 4.3. The reliability worth percentage and investment cost percentage for bus 3 with respect to system wide upgrade for 50% growth case can be calculated as following.

Reliability worth percentage of bus 3 with respect to system wide upgrade =

\[
\frac{27,207}{42,011} \times 100\% = 64.8\%
\]

Investment cost percentage of bus 3 with respect to system wide upgrade =

\[
\frac{6 \text{ lines}}{31 \text{ lines}} \times 100\% = 19.4\%
\]

Above results shows that the 64.8% of the reliability worth can be achieved from only investing 19.4% of overall system investment cost in the technology. Therefore, the AAR
technology can provide higher reliability worth with minimal investment cost if it is implemented to improve the reliability of less reliable load points.

Besides the cost savings from the reduction in customer outages, there are other benefits that can be associated to the reliability worth investment of the AAR technology. For example, improvement of the power carrying capability through an existing transmission line can allow to integrate more renewable resources such as wind and solar to the system. This can help to reduce the net carbon footprint from the utility. Environmental incentives are not evaluated in the paper and is left for the utility to assess further. Such incentives are specific to the environmental policy in the region and are an important aspect to incorporate into the reliability worth analysis.

4.6. Resiliency Worth of an Investment in Transmission System

In this section, the resiliency worth of improving the resiliency of transmission grid against extreme wind is evaluated utilizing the Three Wind State Failure Rates Model [31] in the transmission resources. The wind speed increases drastically during the extreme wind conditions and otherwise reliable transmission grid may face an infrastructure failure resulting lower grid resiliency. Therefore, a higher failure rate of transmission resource can be observed during the extreme wind condition than normal wind speed.

4.6.1. Extreme Wind Failure Rates Model for Transmission Resources

Ref. [31] illustrates the calculation of failure rates during the Normal, Adverse and Major Adverse weathers from average failure rates of transmission resources. The same method is used to calculate the failure rate during Extreme wind speeds from average failure rates of transmission resources. The wind speeds, $S_w$ (m/s), are first grouped into extreme wind scenarios as shown in Figure 4.4 based on Beaufort scale [32] as given by (4.5a). In Figure 4.4, $t_i^e$ represents the duration in hours of $i^{th}$ extreme wind event respectively in T years period.

$$Extreme\ Wind\ Speed, S_w^e : 24.4 > S_w$$

(4.5a)
Figure 4.4. Chronological wind speeds with extreme wind

If $N_e$ is total no of occurrences of extreme wind event in T years period, then total average duration in hours of extreme wind event is given by (4.5b).

Average duration (hour) of Extreme wind event, $\text{dur}_e = H_e/N_e$  \hspace{1cm} (4.5b)

Where, $H_e = \sum_{i=1}^{N_e} t_i^e$ is the total duration of extreme event in T years period.

The Probability of a extreme wind event for a yearly period is given by (4.5c).

Probability of Extreme wind state, $P_e = \frac{H_e}{H}$  \hspace{1cm} (4.5c)

Where H is total hours in T years period i.e. $H = T \times 8760$

The relationship between average failure rate and extreme wind state failure rates are given by (4.5d). The graphical representation of the relationship is shown in Figure 4.5.

$$\lambda^e = \frac{\lambda_{avg} F_e}{P_e}$$  \hspace{1cm} (4.5d)

Where, $\lambda_{avg}$ is average failure rate of a transmission resource, failures/year, $\lambda^e$ is failure rate of a transmission resource during extreme wind, and $F_e$ is the fraction of total failures occurring during extreme wind.
During the extreme wind event condition, repairing the damaged transmission line is difficult and therefore average repair time or mean time to repair (MTTR) of the transmission lines will be extended by the extreme wind duration. The MTTR of the transmission line during the extreme event can be given by (4.5e).

\[
\text{MTTR}^e = \text{MTTR}^a + \text{dur}_e
\]  

(4.5e)

Where, \(\text{MTTR}^a\) is average repair time in hours of the transmission resources.

4.6.2. Extreme wind state model from historical wind data

A historical wind data is obtained in order to capture trend of extreme wind states over the long period. A 20-year period from 2003 to 2022 hourly wind speed with 50m wind rose data [33] is obtained to estimate the failure rate. Average duration and probability of an extreme wind event in the 20 years-period wind data are evaluated by using (4.5b) and (4.5c) respectively and are presented in Table 4.18.

Table 4.18. Extreme wind state model from historical wind data

<table>
<thead>
<tr>
<th>Wind State</th>
<th>Duration</th>
<th>Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Extreme</td>
<td>2.17 hours</td>
<td>0.00092979</td>
</tr>
</tbody>
</table>

Figure 4.5. Failure rate representation of extreme wind state
4.6.3. Extreme Wind State failure rates for IEEE-RTS transmission lines

The base reliability data (failure rate and repair time) of generator units and transmission lines of the IEEE RTS 24 bus system can be found in [24]. The failure rates and repair time of transmission lines in IEEE-RTS during extreme wind event can be calculated by using (4.5d) and (4.5e). Fraction of total failures occurring during extreme wind, Fe, is assumed to be 4% [31]. Table 4.19 shows calculated failure rates and repair time of the transmission lines in the test system. Since, transformer is also equally exposed to extreme wind the failure rate and repair time of transformer during the extreme wind event is similarly calculated. Table 4.20 shows the extreme wind state failure rate and repair time for transformer in the test system. The IEEE RTS system has two cables lines 1 and 10 and the failure rate and repair rate of these cables are not changed during the extreme wind event.

Table 4.19. IEEE RTS Transmission lines failure rate and repair time during extreme wind event

<table>
<thead>
<tr>
<th>Transmission lines</th>
<th>$\lambda^e$, failures/year</th>
<th>MTTR$^e$, hours</th>
<th>Transmission lines</th>
<th>$\lambda^e$, failures/year</th>
<th>MTTR$^e$, hours</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.24</td>
<td>18.17</td>
<td>23</td>
<td>16.35</td>
<td>13.17</td>
</tr>
<tr>
<td>2</td>
<td>21.94</td>
<td>12.17</td>
<td>24</td>
<td>14.20</td>
<td>13.17</td>
</tr>
<tr>
<td>3</td>
<td>14.20</td>
<td>12.17</td>
<td>25</td>
<td>17.64</td>
<td>13.17</td>
</tr>
<tr>
<td>4</td>
<td>16.78</td>
<td>12.17</td>
<td>26</td>
<td>17.64</td>
<td>13.17</td>
</tr>
<tr>
<td>5</td>
<td>20.65</td>
<td>12.17</td>
<td>27</td>
<td>17.64</td>
<td>13.17</td>
</tr>
<tr>
<td>6</td>
<td>16.35</td>
<td>12.17</td>
<td>28</td>
<td>15.06</td>
<td>13.17</td>
</tr>
<tr>
<td>7, 14, 15, 16, and 17</td>
<td>0.86</td>
<td>770.17</td>
<td>8</td>
<td>15.49</td>
<td>13.17</td>
</tr>
<tr>
<td>9</td>
<td>14.63</td>
<td>12.17</td>
<td>30</td>
<td>13.77</td>
<td>13.17</td>
</tr>
<tr>
<td>10</td>
<td>0.33</td>
<td>37.17</td>
<td>31</td>
<td>23.23</td>
<td>13.17</td>
</tr>
<tr>
<td>11</td>
<td>12.91</td>
<td>12.17</td>
<td>32</td>
<td>15.06</td>
<td>13.17</td>
</tr>
<tr>
<td>12</td>
<td>18.93</td>
<td>12.17</td>
<td>33</td>
<td>15.06</td>
<td>13.17</td>
</tr>
<tr>
<td>13</td>
<td>18.93</td>
<td>12.17</td>
<td>34</td>
<td>16.35</td>
<td>13.17</td>
</tr>
<tr>
<td>18</td>
<td>17.21</td>
<td>13.17</td>
<td>35</td>
<td>16.35</td>
<td>13.17</td>
</tr>
<tr>
<td>20</td>
<td>17.21</td>
<td>13.17</td>
<td>37</td>
<td>14.63</td>
<td>13.17</td>
</tr>
<tr>
<td>21</td>
<td>22.37</td>
<td>13.17</td>
<td>38</td>
<td>19.36</td>
<td>13.17</td>
</tr>
<tr>
<td>22</td>
<td>21.08</td>
<td>13.17</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 4.20. IEEE RTS Transformers failure and repair rates in during extreme wind

<table>
<thead>
<tr>
<th>Transformers</th>
<th>$\lambda^e$, failures/year</th>
<th>MTTR$^e$, hours</th>
</tr>
</thead>
<tbody>
<tr>
<td>7, 14, 15, 16, and 17</td>
<td>0.86</td>
<td>770.17</td>
</tr>
</tbody>
</table>
4.6.4. Resiliency worth of upgrading system infrastructure

Overhead transmission lines have long spans and are highly exposed to the extreme winds. The exposure of these lines to extreme winds can be reduced by upgrading to underground cables. However, undergrounding the cable is capital intensive and therefore must be justified by resiliency worth of investment. Similar to reliability worth analysis described in section 4.3, the resiliency worth analysis is performed by developing the system risk model with two state Markov model and calculation of the reliability indices. The only difference from the reliability analysis is that the failure rate and repair time considered for transmission lines and transformers are during the extreme wind event as presented in Tables 4.19 and 4.20. The resiliency worth of investing into the underground cable is evaluated by calculating the ECOST before and after the line upgrade to underground cables as shown in Table 4.21.

Table 4.21. Reliability indices of IEEE RTS base case and Cable upgrade during extreme wind

<table>
<thead>
<tr>
<th>System</th>
<th>NLC</th>
<th>ELC</th>
<th>EENS</th>
<th>EDLC</th>
<th>ECOST, $</th>
</tr>
</thead>
<tbody>
<tr>
<td>RTS Base Case</td>
<td>7.73</td>
<td>287.81</td>
<td>1,354.08</td>
<td>42.34</td>
<td>13,730,211.29</td>
</tr>
<tr>
<td>Cable upgrade</td>
<td>5.78</td>
<td>220.24</td>
<td>1,021.09</td>
<td>31.00</td>
<td>10,356,420.28</td>
</tr>
</tbody>
</table>

Resiliency worth of upgrading the two lines to underground cable given that an extreme wind event occurred = (13,730,211.29 − 10,356,420.28) = $3,373,791.01

The average lifespan of underground transmission cable is between 40 to 60 years [34]. Assuming the 50 years be an average lifespan of the underground cable then,

The expected Resiliency worth of the upgrade during the lifespan of Cable = 50 × 3,373,791.01 = $168,689,550.5

4.7. Conclusion

Power system transmission grids are evolving to meet the environmental compliance. The rapid development and integration of renewable generation and growth in electric vehicles are changing load demand and line loading causing the congestion in the transmission grid. Smart grid technologies such as ESS, FACTS, DLR etc. are implemented to alleviate those congestion to maintain the reliability of the transmission system. In the past, reliability worth of investing into
these technologies are analyzed by utilizing demand normalized cost developed for the generation adequacy studies, which is related to outage cost incurred due to inadequate generation that occurs during the system peak demand. Power outage due to the failure of transmission components can occur anytime in a day and year with system specific probabilistic characteristics. Therefore, the outage cost originating from the transmission components failure is utilized in this paper to evaluate the reliability worth of investing into DLR technology in a transmission system. A comparison reliability worth of investment in DLR technology for a load point and overall system is also presented. The result suggested that investing this technology into the transmission line to improve the reliability of the low reliable load point can provide cost effective solution. Additionally, the improvement of line loading capability can allow the higher penetration of renewable generation and can help to meet environment compliance for the utility. The reliability worth of DLR technology can also incorporate the potential environment compliance incentive from the government in addition to the reduce power outage cost. Further, the high number of extreme weather events during recent decade are causing the catastrophic destruction to the transmission grid. An investment to the underground cable can increase the resiliency of the transmission grid against extreme weather, however the investment cost of the cable is very high and should be justified by the resiliency worth analysis. This paper also presented an evaluation of resiliency worth of an investment against extreme wind by utilizing the outage cost originated from the transmission component failure. The overall resiliency worth of investing into underground cable is estimated for the average lifespan of the cable.
4.8. Reference


CHAPTER 5: SUMMARY AND CONCLUSIONS

Global environmental concerns are driving the growing adoption of renewable energy sources like wind generation alongside the expanding use of electric vehicles. Integration large nos. of intermittent and uncertain wind generation and the electric vehicles into the existing transmission grid will cause the difficulty in balancing supply and load due to the congestion in the power grid, which can lower the reliability of overall power system. Therefore, there is research and development in smart power grid facilities like energy storage, dynamic line rating, protection and communication devices etc. that can alleviate the line congestion by increasing the capability of existing network. A considerable portion of the capital budget is now being allocated to invest in these emerging power grid technologies to improve the reliability of power grid. Further, in recent years, there has been a reported increase in extreme weather events like windstorm damaging large part of transmission grids resulting huge financial losses. Hence, there is also a growing concern to invest in power infrastructure to enhance the resilience of the power system. Investments in power grid facilities and infrastructure to improve the reliability and resiliency of the power system are capital intensive and must be justified by the cost-benefit analysis. The assessment of reliability worth of an investment has been a useful tool to justify the cost and benefit of an investment in power system. However, the resiliency worth of an investment is still in research progress and similar approach of reliability worth of investment is utilized to assess the resiliency worth of an investment.

The reliability worth of an investment comes from the reduced power outage cost. The power outage cost is evaluated from the customer outage cost. This thesis explored the understanding of resiliency worth of an investment, the past approach of obtaining the outage cost to evaluate the reliability worth of an investment and the development of novel models and methodologies to obtain outage cost mainly originating from the transmission component failures. Also, an
illustration is provided to utilize the obtained customer outage cost from the proposed model to evaluate the reliability and resiliency worth of investments in power grid facilities.

The thesis examined different approaches in enhancing power system resilience and their respective investment costs. It delved into the necessity of different investment strategies for enhancing resilience in power generation, transmission, and distribution systems, considering their unique infrastructures, geographical locations, and susceptibility to various extreme events. It also explored how resiliency worth of an investment can be assessed motivated from the past studies of reliability worth of an investment to maximize societal benefits.

The past studies on reliability worth of an investment in transmission resources utilizes the customer outage cost that was mainly prepared for the evaluation of the reliability worth of an investment to increase the generation reserve margin. The customer outage cost prepared for this assessment is evaluated during the system annual peak demand period, where likelihood of occurrence of power outage is very high due to insufficient generation. The use of the past customer outage cost was helpful, however, random occurring transmission component failure can cause power outages at a load point any time in a year and the thesis argued the estimation of customer outage cost during those periods other than the system annual peak is also equally important to incorporate outage cost mainly incurred from the transmission outages. The methodology is proposed how to get a load period model to incorporate the outage cost from the transmission resource failures and obtaining the customer outage cost is illustrated from the past customer survey data. The obtained customer outage cost can also be utilized to evaluate the resiliency worth of an investment in transmission resources.

The reliability and resiliency worths of investments are studied by utilizing the customer outage cost obtained form the proposed methodology and illustration. The results from the case studies in reliability worth of investing in dynamic line rating technology shows the reduced outage cost is an annual saving and the overall reduction in outage cost is come from the overall operating period of the technology. In addition to the reduced outage cost, environmental benefits by adding more greener energy resources like wind into the transmission grid can be accommodated with the increased transmission capability. The resiliency worth of investing in transmission infrastructure is illustrated by upgrading the overhead line to underground cables, and the overall resiliency worth comes from the reduced outage cost from the operational period of the cables.
In conclusion, this thesis proposed a methodology to obtain the customer outage cost mainly incurring from the transmission component failure and an illustration is presented to estimate those cost from the past customer survey. The obtained customer outage cost will help the utility planner to analyze the cost and benefits of cost intensive investment in transmission grids to improve the reliability and resiliency of the transmission network. The improved reliability and resiliency of transmission resource will help to transform the modern power system to achieve a sustainable future.