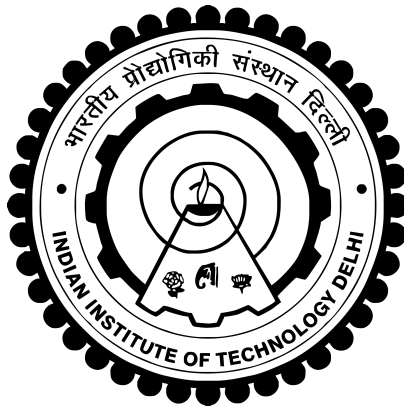


QUANTIFYING AND ENABLING RESILIENCE FOR DER-RICH POWER DISTRIBUTION SYSTEMS

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QUANTIFYING AND ENABLING RESILIENCE FOR DER-RICH POWER DISTRIBUTION SYSTEMS

by

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Submitted

*In fulfillment of requirements of degree of **Doctor of Philosophy**
to the*



**INDIAN INSTITUTE OF TECHNOLOGY DELHI
HAUZ KHAS, NEW DELHI-110016, INDIA
APRIL, 2026**

Dedicated to the ones who taught me to dream and persevere,
my Papa & Mumma,
Śrī Pradeep Kumar Sajwan & Śrīmatī Anita Sajwan
and my husband,
Manoj Kumar Singh
for his constant support and encouragement

CERTIFICATE

This is to certify that the thesis entitled “**Quantifying and Enabling Resilience for DER-Rich Power Distribution Systems**”, being submitted by **Samridhi Sajwan** to **Indian Institute of Technology, Delhi** is a record of bonafide research work carried out under my supervision and I consider it worthy for consideration of the award of the degree **Doctor of Philosophy** in Electrical Engineering. The results obtained here have not been submitted to any other University or Institute for the award of any degree or diploma.

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Place:

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This thesis is not just a result of academic effort; it is a reflection of the support, love, and strength I received from those who walked this journey with me. To each of you - thank you.

— Samridhi Sajwan

Abstract

The ineptitude of distribution grids in maintaining supply during low-probability events has highlighted the importance of resilience in power distribution systems (PDS). Currently, resilience is an unbounded concept with no universally accepted definition or standard metric. Although distributed energy resources (DERs) have emerged as a crucial element in supplying power during outages, thereby enhancing resilience, present studies lack the abstraction for resilience-driven restoration, considering the impact and application of DERs in a PDS. DERs are sometimes behind-the-meter sources, working in either grid-forming (GFR) or grid-following (GFL) mode, which introduces greater variability in operational decision-making. Thus, it is necessary to consider the diverse modes of operation and the time- and weather-dependent availability of DERs in restoration over the time horizon. Therefore, it is crucial for the scientific community to propose a formal resilience metric and strategy for effective resilience-driven operation, encompassing immediate restoration in uncertain low-probability scenarios.

To address these issues, the work in this thesis presents a comprehensive solution to support utilities in resilient planning and operations. Firstly, it introduces a novel Integrated Resilience Assessment Metric (IRAM) to support real-time operations in DER-rich distribution systems. Following this, it proposes a two-stage optimization algorithm for resilience-driven system restoration, considering load prioritization based on event duration, impacts, and resource management. The two-stage Power and Energy Restoration Algorithm (PERA): (i) maximizes power to critical loads (CLs), and (ii) optimizes power and energy to all loads, considering DER intermittency over the time horizon. Next, it aims to scrutinize the impact of various vulnerable events on the resilience of a DER-rich PDS. A comprehensive tri-stage architecture is developed for vulnerability assessment, supporting robust data analysis through interfacing online and offline modes. Finally, it develops an approach to capture and quantify the intensity of damage from uncertain weather events and suggests optimal strategies for a resilient and cost-effective PDS.

Key Words: Critical loads, Distributed energy resources, Distribution system restoration, Extreme weather event, Multi-constraint optimization, Operational redundancy, Resilience metric.

सारांश

कम संभावना वाली घटनाओं के दौरान विद्युत आपूर्ति बनाए रखने में वितरण ग्रिडों की अक्षमता ने विद्युत वितरण प्रणाली (पीडीएस) में रेज़िलिएंस के महत्व को उजागर किया है। वर्तमान में, रेज़िलिएंस एक अपरिभाषित अवधारणा है, जिसकी कोई सार्वभौमिक रूप से स्वीकृत परिभाषा या मानक मापदंड (मैट्रिक) नहीं है। यद्यपि डिस्ट्रीब्यूटेड एनर्जी रिसोर्सेज (डीईआर) बाधित परिस्थितियों में विद्युत आपूर्ति प्रदान कर रेज़िलिएंस बढ़ाने में एक महत्वपूर्ण तत्व के रूप में उभरे हैं, फिर भी वर्तमान शोध कार्यों में पीडीएस में डीईआर के प्रभाव और अनुप्रयोग को ध्यान में रखते हुए रेज़िलिएंस-आधारित रिस्टोरेशन के लिए आवश्यक अमूर्तता (अब्स्ट्रैक्शन) का अभाव है। डीईआर कभी-कभी मीटर के पीछे स्थित स्रोत होते हैं, जो या तो ग्रिड-फॉर्मिंग (जीएफआर) या ग्रिड-फॉलोइंग (जीएफएल) मोड में कार्य करते हैं, जिससे संचालन संबंधी निर्णयों में अधिक परिवर्तनशीलता उत्पन्न होती है। अतः समय और मौसम पर निर्भर उपलब्धता एवं संचालन के विविध तरीकों को रिस्टोरेशन प्रक्रिया में समय क्षितिज के साथ ध्यान में रखना आवश्यक है। इसलिए, वैज्ञानिक समुदाय के लिए यह अत्यंत आवश्यक है कि वे अनिश्चित, कम संभावना वाली परिस्थितियों में त्वरित रिस्टोरेशन को शामिल करते हुए प्रभावी रेज़िलिएंस-आधारित संचालन के लिए एक औपचारिक रेज़िलिएंस मैट्रिक और स्ट्रेटेजी प्रस्तावित करें।

इन चुनौतियों के समाधान के लिए, इस शोधकार्य में यूटिलिटीज़ को लचीले नियोजन और संचालन में समर्थन देने हेतु एक समग्र समाधान प्रस्तुत किया गया है। सबसे पहले, यह डीईआर-युक्त पीडीएस में वास्तविक समय संचालन के लिए एक नवीन एकीकृत रेज़िलिएंस मूल्यांकन मापदंड (आईआरएएम) प्रस्तावित करता है। इसके पश्चात, यह घटना की अवधि, प्रभावों और संसाधन प्रबंधन के आधार पर लोड प्राथमिकता को ध्यान में रखते हुए, रेज़िलिएंस-आधारित सिस्टम रिस्टोरेशन के लिए एक द्वि-चरणीय ऑप्टिमाइज़ेशन एल्गोरिदम प्रस्तावित करता है। यह द्वि-चरणीय पावर और एनर्जी रिस्टोरेशन एल्गोरिदम (पीईआरए): (i) क्रिटिकल लोड्स (सीएल) को अधिकतम शक्ति प्रदान करता है, और (ii) समय क्षितिज पर डीईआर की अनियमितता को ध्यान में रखते हुए सभी लोड्स के लिए शक्ति और ऊर्जा का अनुकूलन करता है। इसके बाद, यह विभिन्न संवेदनशील घटनाओं के प्रभाव का डीईआर-समृद्ध पीडीएस की रेज़िलिएंस पर विश्लेषण करने का लक्ष्य रखता है। एक व्यापक त्रि-स्तरीय संरचना कमजोरियों के मूल्यांकन हेतु विकसित की गई है, जो ऑनलाइन और ऑफलाइन मोड्स के इंटरफेस के माध्यम से मजबूत डेटा विश्लेषण को सक्षम बनाती है। अंत में, यह अनिश्चित मौसमीय घटनाओं से होने वाली क्षति की तीव्रता को पकड़ने और मापने की एक विधि विकसित करता है तथा एक लचीली और लागत-कुशल पीडीएस के लिए सर्वोत्तम स्ट्रेटेजीज़ सुझाता है।

कुंजी शब्द: महत्वपूर्ण लोड्स, वितरित ऊर्जा संसाधन, वितरण प्रणाली पुनर्स्थापन, अत्यधिक मौसमीय घटनाएँ, बहु-बंधन अनुकूलन, परिचालन पुनरावृत्ति, लचीलापन मापदंड।

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Nomenclature

Acronyms/Abbreviations

AC	Attack Complexity
AHP	Analytical Hierarchical Process
ANSI	American National Standards Institute
AV	Attack Vector
BOI	Bus Observability Index
CCL	Connectivity to Critical Loads
CDF	Cumulative Distribution Function
CL	Critical Load
CLPU	Cold Load Pick Up
CVE	Common Vulnerability Exposure
CVR	Conservation Voltage Reduction
CVSS	Common Vulnerability Scoring System
DER	Distributed Energy Resources

DG Diesel Generator

DLAM Damage-level Assessment Matrix

DMS Distribution Management System

DSO Distribution System Operator

DTMC Discrete Time Markov Chain

ELs Essential Loads

ENS Electric power Not Supplied

EPS Electric Power Supplied

ETAP Electrical Transient and Analysis Program

GFL Grid-following

GFR Grid-forming

IBDR Inverter-based DERs

IEC International Electrotechnical Commission

IEEE Institute of Electrical and Electronics Engineers

IRAM Integrated Resilience Assessment Metric

MDP Markov Decision Process

MILP Mixed-integer Linear Programming

MLE Maximum Likelihood Estimation

MVAr Mega Volt-Amperes Reactive

MWs Megawatts

NRS Network Redundancy Score

OMS Outage Management System

PCC Point of Common Coupling

PDF Probability Density Function

PDS Power Distribution System

PERA Power and Energy Restoration Algorithm

PMU Phasor Measurement Units

PR Privileges Required

PSO Particle Swarm Optimization

SLDA System-level DER Availability

SN SubNetwork

SORI Summation of Redundancy Index

SRS Source Redundancy Score

SS Sectional Switch

SW Switch

TLS Tie-line Switch

UI User Interaction

VulnAT Vulnerability Assessment Tool

ZIB Zero Injection Buses

List of Symbols

α_i Real-time DER availability

β Degree of connectivity

Ω_{SS} Sectional switch vector

Ω_{TLS} Tie-line switch vector

θ Load angle

φ_i Operational mode of i^{th} DER

C_{avb} Average betweenness centrality

C_{avc} Average closeness centrality

C_{avd} Average degree centrality

f_{sc} Operational flexibility score

$k_{i,PSO}^{th}$ PSO-defined unique solutions (paths) supplying CL

N_t Total time duration

N_{DER} Number of redundant sources

N_{sc} Network redundance score

P Active Power

P_G Total power generation

P_L Total load demand

P_{DER}	Output Active Power of DER
P_{loss}	PDS losses
P_{mis}	Power mismatch
Q	Reactive Power
Q_{DER}	Output Reactive Power of DER
r	Line resistance
r_{sc}	Operational redundancy score
R_s	Integrated resilience score
S_i	Total power)
S_{sc}	Source redundance score
S_{sc}	Source redundance score
t_{int}	Time when the disruption has hit the system
t_{rec}	Time when the system has recovered with remedial measures
t_{res}	Time when system has fully restored to normal operation
t_{sc}	Topological robustness score
t_{sys}	Time where system operates at normal condition
w_{R1}	Weight associated with operational redundancy
w_{r1}	Weight associated with network redundancy
w_{R2}	Weight associated with operational flexibility

w_{r2}	Weight associated with source redundancy
w_{R3}	Weight associated with topological robustness
w_{si}	DER-associated weight
w_{t1}	Weight associated with average betweenness centrality
w_{t2}	Weight associated with average closeness centrality
w_{t3}	Weight associated with average degree centrality
x	Reactance

Chapter 1

Introduction

1.1 Motivation

Recent high-impact blackouts have exposed the vulnerabilities of modern power systems, particularly in low-resilience grids with increasing renewable penetration. For instance, the Iberian Peninsula blackout in April 2025 resulted in the loss of approximately 60% of the region's power generation within seconds, driven by a lack of system inertia and limited interconnection capacity. Similarly, extreme weather events continue to strain the distribution systems worldwide. In Victoria, Australia, storm-related outages in February 2024 affected over 77,000 customers, reinforcing the need for improved grid resilience and weatherproofing strategies. Argentina also experienced severe outages due to heavy rainfall, leaving over 44 million people without power.

These events emphasize that traditional reliability-driven planning is insufficient in the face of such operational and environmental challenges. Thus, the objective of a resilient power system has become prominent over the years. According to the literature, 90% of disruptive events originate from a PDS [1]. A PDS consists of many critical assets that require an uninterrupted power supply. This has made critical infrastructure a concern and motivates the development of a resilient infrastructure that ensures continuous supply [2]- [3]. However, resilience is an unbounded concept with no universally accepted definition. The National Infrastructure Advisory

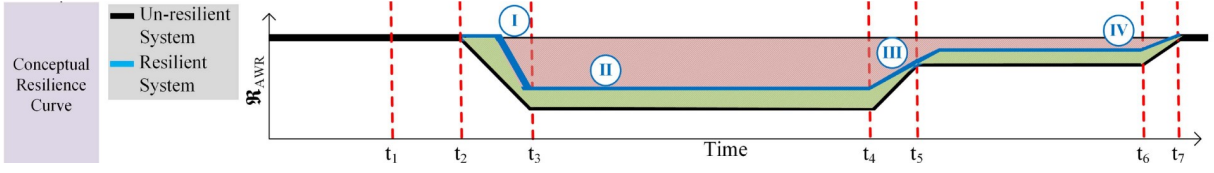


Figure 1.1: Conceptual Resilience Curve.

Council states that a resilient system must be robust, adaptable, and resourceful with an immediate recovery [4]. Also, the Department of Energy defines resilience as the ability of a utility to recover, respond, and be prepared to mitigate disruptions [5]. Even international platforms such as CIGRE Working Group C4.47 [6] and IEEE Taskforce [7] are actively working towards precise definitions of resilience. However, no common attributes or standardized characteristics currently exist to establish a comprehensive definition. Also, various studies offer a definition of resilience in this regard, and several authors have attempted to extract the resilience metric using diverse factors [8]- [9]. But, defining resiliency in distribution systems is critical due to its radial topology and low redundancy; however, to summarize, “the main attributes of a resilient utility are rapid recovery, anticipation, adaptability, and absorbance”. The above-cited references make it evident that the concept of resilience is required for a utility. Although the studies lack the abstraction of a resilience metric-driven restoration considering the impact of DERs, as outlined below:

- Resilience is a multi-constraint formulation that adopts DER integration to ensure an uninterrupted supply over a time horizon to the CLs, affecting operational constraints.
- A resilience-metric-driven restoration is required for operational decisions while optimizing power and energy during partial or main feeder islanding.
- Quantifying operational resilience by considering the impacts and challenges in a DER-enabled restoration is required to improve the resilience of a DER-rich PDS.

A distribution system is considered DER-rich when a substantial portion of the total load demand is supplied by DERs. In this work, DER penetration is quantified as the ratio of total installed DER capacity to the total system load demand. Higher DER penetration increases the availability

of local generation resources, enhances operational flexibility, and supports improved restoration strategies during contingencies. As a result, systems with higher DER penetration exhibit improved resilience performance under disturbance conditions. The integration of DER or forming microgrids has been the imperative highlight for a self-healing and resilient PDS [10]. In [11]-[12], the authors emphasized optimal microgrid scheduling and provided optimization techniques to model a resilient microgrid. These studies contribute to developing a resilient PDS; however, DERs rely on time-dependent availability and their active mode of operation. Thus, a resilience study with real-time performance analysis of DERs needs to be explored for field implementation. However, the utilization of advanced technology and intelligent devices (such as microgrids, electric vehicles, smart meters, DERs, mobile energy resources, etc.) enhances the PDS's resilience, but may introduce cyber challenges [13] in a system. Advancements in communication networks make a PDS more prone to cyber-physical vulnerabilities [14] and open the door for researchers to build a resilient power infrastructure. Thus, there is a need to analyze the severity-based impact and establish a resilient network against cyber-physical vulnerabilities in a PDS.

Further, in extreme events, there could be multiple outages, and diesel generators, microgrids [15], and DERs [16] are required to enhance resilience. Even IEEE standard 1547 [17] encourages load restoration using DG with intentional islanding. Most studies have introduced hardening measures, including diesel generator integration [18], deployment of backup diesel generators and TLSs [19], uncertainty modeling [20], and multi-level feeder restoration by DERs [21], to enhance resilience. However, there has been a limited study suggesting the restoration based on the damage level of the PDS. A detailed formulation must model the impact, analyze the damage, and suggest remedial actions for a resilient PDS.

The objective of this thesis is to contribute to knowledge and advancements in the aforementioned research areas, with a focus on integrating DERs to build a secure, reliable, and resilient PDS. By addressing challenges related to real-time DER availability, DER operation/control modes, and power and energy optimization over the time horizon, this research aims to promote sustainable and efficient energy solutions, enhance grid resiliency, and facilitate the transition to-

wards a more resilient and sustainable power infrastructure. Specifically, this thesis:

- Introduces a multi-stage operational resilience metric that integrates impact and challenges with DERs in the evolving distribution grids. In the case studies, DER penetration is varied by integrating 1 to 4 DER units, representing different levels of integration from low to relatively high penetration.
- Develops a resilience-driven service restoration strategy that optimizes power and energy beyond critical loads and adapts to real-time system states and resource availability.
- Models wind-induced damage-based restoration framework to guide the operator with an optimal solution under an extreme weather event.
- Assesses system vulnerability under cyber-physical disturbances to strengthen decision-making during critical events.

The metrics and strategies proposed in this thesis aim to equip system operators with practical, real-time restoration strategies that are adaptive, cost-effective, and scalable across diverse system conditions and disruption scenarios.

1.2 Existing Works and Major Research Gaps

The existing literature have identified the following challenges in the resilience assessment and restoration of DER-integrated distribution networks:

1.2.1 Inadequate Resilience Quantification

The existing literature lacks a universal, standardized resilience metric that can consistently quantify and compare the resilience of power distribution systems across varied operating scenarios. Most studies rely on static redundancy-based indices or reliability-focused metrics that are inadequate to capture the real-time operational capability of the system during and after disruptive events. Moreover, there is no commonly accepted framework that systematically measures resilience across different network topologies, event severity, or restoration stages. This limitation

restricts system operators and planners from making meaningful comparisons between restoration strategies and system configurations under uncertain and evolving conditions.

Inputs from various researchers and industrialists have advanced the understanding of resilient distribution systems. The authors in [3] provided a comprehensive review of power system resilience, summarizing current practices, key challenges, and future directions across both transmission and distribution networks. They emphasized that resilience lacks a universal definition and standardized quantification method, with most existing frameworks being system-specific and fragmented.

The authors in [22] proposed a probabilistic resilience assessment framework for power distribution systems under various weather scenarios using Monte Carlo simulations and time-to-event models. Their study evaluates both structural resilience (network connectivity) and service resilience (energy delivery) during extreme weather events. However, while providing a probabilistic evaluation, the study does not offer a standardized, universally applicable resilience metric capable of capturing system performance in real-time. Similarly, several researchers addressed the role of DERs in enhancing network resilience. Some have utilized the multi-microgrid concept to supply high-priority loads and assess resilience using various methods [23]- [24]. The authors in [23] analyzed the impact of DER penetration levels and introduced a quantitative resilience metric based on several influencing factors. Building on this, [25] employed the analytical hierarchical process and percolation theory to define resilience as a multi-criteria decision-making problem, incorporating various topological factors for short-term planning. Additionally, data aggregation techniques such as the Choquet integral [24] and weighted mean methods have been applied for non-additive multi-criteria resilience computations. However, these approaches do not incorporate real-time performance analysis of DERs in resilience metrics, limiting their applicability for practical field implementation. Among the diverse methodologies, only a few studies have addressed the challenges associated with DER-oriented restoration strategies [26].

Hence, there is a critical need to develop a universal, standardized, and real-time resilience metric that can consistently evaluate power distribution systems across diverse operating conditions.

Such a metric should effectively capture the dynamic impacts of DER integration and support meaningful comparisons of restoration strategies. This would enable system operators and planners to make timely, data-driven decisions for enhancing system resilience. Addressing this gap is essential for building more robust and adaptive future power networks.

1.2.2 Limited Consideration of DER's Impact and Challenges

The increasing integration of DERs, including the adoption of microgrids [27]– [28], has been a critical focus for achieving self-healing and resilient PDS [10]. Several studies have emphasized optimal microgrid scheduling and proposed various optimization techniques to model resilient microgrid operations [11]– [12]. These efforts significantly contribute to enhancing PDS resilience. However, DERs introduce unique challenges due to their time-dependent availability and active modes of operation. Specifically, the integration of renewable energy sources often degrades the voltage profile within the distribution grid [29].

The author in [30] attempted to define a resilience metric that accounts for behind-the-meter generation challenges, yet comprehensive real-time performance analysis of DERs for field implementation remains underexplored. Behind-the-meter DERs [31] present additional complexity in system visibility and controllability. Furthermore, DERs such as solar and wind resources may operate in either GFM or GFL modes. GFM-DERs typically maintain voltage and frequency during islanding events, whereas GFL-DERs follow grid voltage and frequency references and may operate as dispatchable units or as negative loads depending on their configuration.

While the operational modes of DERs (GFM, GFL, or hybrid) significantly influence system performance, most existing resilience studies oversimplify these aspects. The dynamic interaction of DERs, their availability, and their power injection capability over time remains insufficiently captured in many restoration strategies. Existing approaches often rely on static assumptions and do not adequately address the weather-driven variability and the real-time operational behavior of DERs, which are crucial for accurate resilience assessment.

Also, as modern distribution grids evolve into active distribution networks, the massive penetra-

tion of DERs introduces significant voltage regulation challenges [32]. Traditional voltage control devices, such as voltage regulators and on-load tap changers, are insufficient to manage the high variability introduced by DERs. CVR has emerged as a promising strategy to improve PDS efficiency by reducing power consumption, minimizing losses, and maintaining voltage profiles [33]. Some studies have implemented CVR by controlling legacy voltage regulation devices [34]; however, these approaches often lack integration with voltage-responsive loads and do not fully consider the impact of real-time DER variability.

Hence, there is a need to develop a restoration strategy that holistically models the diverse operational characteristics of DERs, focusing on their control modes (grid-forming, grid-following, and hybrid capabilities), time-varying availability, and real-time MW capacity. Restoration frameworks must integrate resilience metrics and support dynamic, prioritized load restoration while explicitly considering practical constraints such as switching device statuses, load priorities, and DER operational uncertainties. Additionally, incorporating CVR with voltage-responsive loads and real-time DER availability is essential to achieving an efficient, resilient, and field-ready PDS restoration approach. Addressing these aspects will significantly contribute to advancing practical deployment and resilience quantification in DER-enabled power distribution systems.

1.2.3 Weather-Dependent Restoration and Damage-Level Assessment

Existing literature has widely adopted fragility curve-based assessments to estimate the failure probability of distribution system components under extreme weather events such as hurricanes and storms. However, most of these studies rely on static fragility models that do not capture the real-time evolution of weather dynamics or the progression of system damage during an event [35]-[36]. Restoration strategies in previous works are primarily designed for offline analysis or proactive planning, which limits their applicability in supporting real-time, event-driven restoration decisions. Although stochastic modeling techniques, including Monte Carlo simulations and MDP, have been utilized to simulate uncertainties in system damage and repair processes [22]-[37], these models largely focus on proactive planning rather than reactive, adaptive restoration based

on real-time system conditions.

Additionally, several existing methodologies integrate system hardening measures, such as deploying tie-line switches and backup DERs, to improve system resilience under extreme weather scenarios [19], [21]. However, most of these approaches overlook the spatial variation in wind speeds and localized damage patterns during extreme events, often assuming uniform damage across the entire network, which can lead to inaccurate resilience assessments and suboptimal restoration. Further, many conventional restoration frameworks trigger standard repair or hardening actions irrespective of the actual damage severity [38], potentially resulting in inefficient resource allocation and increased restoration costs. Dynamic restoration strategies that adjust in real time based on updated resilience scoring or evolving system states remain underexplored in the existing literature.

Another key limitation is the lack of methodologies that develop damage-level dependent decision frameworks capable of adjusting the restoration sequence and resource deployment based on real-time weather data and system damage assessment. Moreover, inter-dependencies between critical assets such as poles and distribution lines during simultaneous outages are rarely considered, which can significantly influence system behavior and restoration priorities. Current studies also provide limited approaches for the integration of hybrid datasets combining empirical, historical, and simulated damage records to develop realistic, real-time fragility models that better represent the evolving system state.

Additionally, few studies attempt to integrate fragility-based damage modeling with real-time DER coordination to achieve adaptive, probabilistic restoration in multi-event scenarios. Most existing methods still offer static restoration sequences without coupling probabilistic cost-based decision-making with damage-driven restoration.

This thesis directly addresses these gaps by proposing a damage-based stochastic restoration framework that incorporates real-time wind speed inputs, hybrid fragility curve modeling, and probabilistic damage evaluation. The developed approach dynamically adapts restoration strategies based on the evolving system state, cost, and damage severity, providing a real-time, resilience-

enhancing solution for power distribution systems affected by extreme weather events.

1.2.4 Limited Resiliency-Driven Vulnerability Assessment

Modern PDSs are increasingly exposed to cyber-physical vulnerabilities, particularly with the growing penetration of smart devices, communication layers, and DERs [39]. Several studies have emphasized the need to ensure cyber-physical resilience in transmission systems, proposing various cybersecurity strategies and impact quantification frameworks [40]- [41]. While these studies provide valuable insights at the transmission level, their applicability to distribution systems, which directly cater to CLs, remains limited. Some researchers introduced cyber-physical resilience metrics, primarily focused on microgrids, that often assume static threat models and overlook severity-based impact analysis [23]- [24]. Existing frameworks tend to classify and detect events using intrusion detection systems or machine learning methods [42], but they largely neglect the severity-driven, event-specific remedial decision-making essential for real-time operations. Further, studies such as [43] enhanced microgrid resilience through cybersecurity measures but did not sufficiently address the potential cascading impact of medium-severity cyber events, which can escalate if left unaddressed. While tools like the CVSS [44] are often employed to assess vulnerabilities, most prior work used them as generic indicators without providing actionable, severity-specific recovery strategies [45]. Additionally, despite the availability of advanced event detection tools, the literature lacks a comprehensive tri-stage architecture that can classify, identify, and manage both cyber and physical events in real-time with adaptive resilience quantification.

To address these research gaps, this thesis proposes a severity-based VulnAT that integrates a tri-stage architecture for event classification, identification, and management, specifically tailored for DER-rich PDS. Unlike prior studies, this work does not restrict attention to high-severity events but also considers medium-severity vulnerabilities that, if ignored, could undermine system resilience. Leveraging CVSS for vulnerability scoring, the proposed methodology introduces centroid-based partition clustering and Jaccard similarity-based event pattern recognition to recommend both proactive and post-event remedial actions. Furthermore, this approach combines

graph theory-based topological robustness and operational flexibility to develop a comprehensive resilience quantification metric that can guide real-time decision-making. The proposed framework is validated through extensive case studies on a modified IEEE-33 bus system under various cyber-physical attack scenarios, demonstrating its effectiveness in enhancing the resilience of power distribution systems.

∴ Given the state-of-the-art, the following research questions arise:

1. How can a universal and comprehensive resilience metric be developed to consistently quantify and compare the resilience of DER-rich power distribution systems across diverse operating conditions?
2. How can the real-time availability, operational uncertainties, and control mode transitions of DERs be effectively integrated into a resilience-driven service restoration strategy?
3. How can a damage-based stochastic restoration framework be designed to dynamically incorporate real-time weather-dependent failures and probabilistic system uncertainties for effective restoration planning?
4. How can a severity-driven vulnerability assessment tool be developed for cyber-induced physical events to quantify system impact and recommend event-specific, real-time remedial actions?

Although existing studies have contributed significantly to resilience assessment and restoration of distribution systems, their applicability is often constrained by inherent modeling assumptions, such as static system representation, limited consideration of DER operational dynamics, or focus on isolated resilience aspects. These limitations arise from the original objectives of the methods, which were not intended for real-time, DER-rich operational environments. Consequently, these approaches cannot be directly extended to capture the complex interactions between system topology, DER behavior, and operational constraints. This gap motivates the need for a unified and dynamic framework, as proposed in this thesis, which integrates multiple resilience

attributes and supports real-time decision-making in DER-rich power distribution systems. In this thesis, the author's intent is to extend the existing research by providing comprehensive solutions to these challenges through the development of resilience metric-driven frameworks, real-time restoration strategies, and cyber-physical vulnerability assessment methods tailored for DER-integrated power distribution systems.

1.3 Scopes and Common Assumptions

- The PDS is modeled with limited sectional switches at selected branches to maintain radiality and enable service restoration.
- DERs, including solar PV and wind turbines, are considered with uncertain, weather-dependent, and time-varying availability. Their real-time operating modes are assumed to be known as per scenario definitions.
- A three-tier load priority structure is adopted: CLs, ELs, and non-ELs. Load control is enabled through smart meters, with shedding or restoration decisions based on this priority.
- For wind-induced damage modeling, the PDS is assumed to experience uniform wind conditions, and all poles/lines share identical fragility curves unless specified. These curves are probabilistically modeled with 95% confidence intervals to capture uncertainty due to aging, type, and environmental factors.
- In the absence of known initial physical conditions of poles/lines, all components are assumed identical. However, the developed models allow the incorporation of actual component conditions and spatially varying weather profiles when data is available.
- The real-time wind speed is assumed to be known during damage-based restoration analysis. The cost of hardening or retrofitting components is treated as scenario-specific and may vary with system context

1.4 Basic Definitions

- **Resilience** refers to the power system's ability to anticipate, absorb, adapt to, and rapidly recover from disruptive events such as extreme weather conditions or cyber-physical attacks. It focuses on system performance during and after the event rather than solely on failure prevention.
- **Operational Resilience** is the system's capability to maintain CL availability through adaptive real-time control and restoration actions during and following extreme events.
- **Critical Load** refers to high-priority community-level or essential loads that must be restored and maintained during service disruptions. These typically include hospitals, emergency services, and public infrastructure.
- **Distributed Energy Resources** are small-scale, grid-connected energy sources such as solar PV units, wind turbines, DGs, and battery energy storage systems that contribute to local power generation and enhance power system resilience.
- **Vulnerability Assessment** is the process of identifying, classifying, and quantifying the severity of cyber-induced or physical events based on their potential impact on the operational resilience and stability of the power distribution system.
- **Fragility Curve** represents the probability of failure of a system component as a function of external stress parameters, such as wind speed. It is widely used to model weather-dependent failures and system damage probabilities in resilience studies.
- **Common Vulnerability Scoring System** is a standardized open framework for assessing the qualitative and quantitative severity of vulnerabilities, which provides a consistent basis for vulnerability scoring across different systems.

1.5 Objectives of the Thesis

Drawing on the motivation established through contemporary state-of-the-art and the identified research gaps, the following objectives have been formulated to guide the study in addressing

these critical areas and contributing meaningfully in this domain:

- To develop a comprehensive, multi-stage operational resilience metric that incorporates real-time, uncertainty-aware modeling of DERs and supports optimal service restoration in DER-rich distribution systems.
- To formulate a DER-centric restoration framework that enhances both power and energy resilience using the proposed metric, under varying load priorities and event impacts.
- To design a vulnerability assessment tool for cyber-induced physical threats using an existing resilience framework, enabling the classification and severity evaluation of events in renewable-integrated distribution systems.
- To propose a damage-based stochastic restoration framework under wind-induced extreme events, leveraging probabilistic fragility models to enable effective post-event decision-making.

1.6 Major Contributions of the Thesis

The major contributions of this thesis are summarized as follows:

- A unified resilience assessment framework is proposed for DER-rich distribution systems, integrating multiple aspects of system performance into a single analytical structure, unlike conventional approaches that treat them independently.
- A novel Integrated Resilience Assessment Metric (IRAM) is developed based on operational redundancy, operational flexibility, and topological robustness, enabling a comprehensive and scalable quantification of system resilience.
- A resilience-driven optimal restoration methodology is formulated, which incorporates load prioritization and efficient utilization of DERs to enhance restoration performance under contingency conditions.
- A structured vulnerability assessment tool (VulnAT) is introduced to evaluate system performance under different disturbance scenarios.

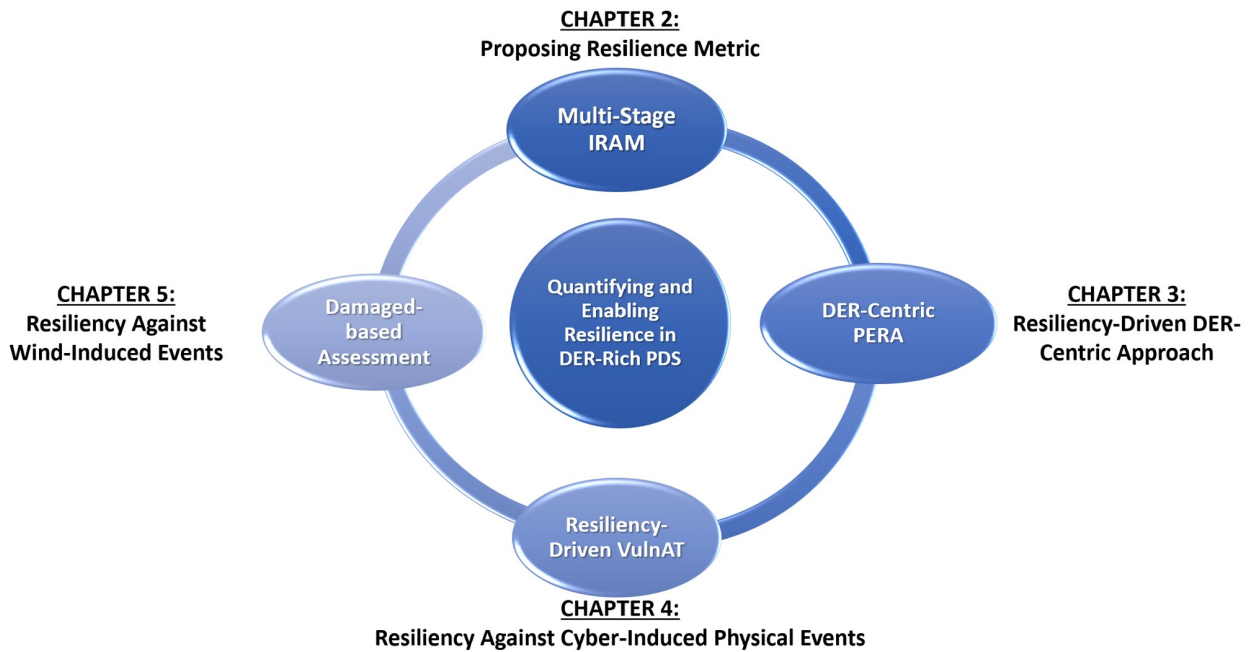


Figure 1.2: Chapter Linkage Diagram.

- A damage-based stochastic restoration framework is developed to model the impact of uncertain extreme events, enabling realistic representation of system damage and recovery processes.
- The proposed methodologies are validated through extensive simulations, demonstrating improved resilience in terms of restoration efficiency, cost-effectiveness, and adaptability compared to existing approaches.
- The thesis provides an integrated perspective by linking resilience assessment, vulnerability analysis, and restoration strategies, which is not addressed collectively in existing literature.

The interrelationship among the chapters and the progression of the proposed work are illustrated in Fig. 1.2. Each of the above contributions is presented in the respective chapters of this thesis and is supported by corresponding peer-reviewed publications.

1.7 Brief Overview of the Work Done

The research presented in this thesis focuses on quantifying and enhancing the operational resilience of distribution systems rich in DERs. As modern distribution networks increasingly integrate IBRs such as solar PV and wind turbines, their complexity and vulnerability to disturbances have grown substantially. This necessitates the development of advanced resilience metrics and restoration strategies capable of managing uncertainties inherent in DER availability and cyber-physical risks, while ensuring reliable and efficient service restoration during extreme events.

1.7.1 Developing a multi-stage operational resilience metric

The first major contribution of this work introduces a multi-stage operational resilience metric tailored for DER-rich distribution systems. Unlike existing resilience metrics that primarily emphasize static or planning-time assessment, this metric incorporates real-time system states and DER operational modes, including GFL and GFR. The metric captures system robustness, redundancy, and resource availability dynamically, enabling quantification of resilience under various operational scenarios. The proposed resilience metric is based on three key components, namely operational redundancy, operational flexibility, and topological robustness, which collectively influence system resilience. The relative importance of these components is incorporated through an appropriate weighting approach. This metric serves as the foundation for the subsequent development of an optimal service restoration framework, formulated as a multi-constraint optimization problem. The restoration problem accounts for the limited number of sectionalizing switches to maintain radiality, real-time availability of DERs influenced by stochastic weather-dependent generation, and load prioritization schemes that differentiate CLs, ELs, and non-ELs. The optimization objective balances restoration speed, load served, and operational constraints, with resilience metric maximization guiding decision-making. This approach enables service restoration that adapts to real-time DER status, ensuring high-priority loads receive uninterrupted supply even during multi-stage restoration processes.

1.7.2 Formulating a DER-centric restoration framework

Building on this resilience-driven restoration framework, the thesis further proposes a DER-centric power and energy restoration approach to enhance system resilience from an operational perspective. Recognizing that DERs operate in diverse control modes and their availability varies with environmental conditions, the restoration algorithm integrates multi-constraint optimization with a real-time DER dispatch model. The proposed method ensures the effective utilization of DERs in forming stable microgrid islands, providing grid-supportive services. Additionally, the method incorporates energy management strategies to optimally allocate DER power output over restoration horizons, maximizing service continuity while minimizing the need for load shedding. By dynamically adjusting DER dispatch based on operational resilience metrics, the approach improves overall network robustness against cascading failures and prolonged outages.

1.7.3 A vulnerability assessment tool for cyber-induced physical threats

The thesis also addresses the critical challenge of cyber-physical vulnerabilities in renewable-rich distribution systems. Given the increasing dependence on advanced communication infrastructure such as PMUs and SCADA systems for real-time monitoring and control, these cyber interfaces introduce new attack surfaces that can compromise system stability and safety. The research develops a resiliency-driven vulnerability assessment tool that combines qualitative and quantitative measures to evaluate cyber-physical threats. Leveraging frameworks such as the CVSS and integrating advanced machine learning classifiers for event detection and classification, the tool assesses the severity and criticality of cyber-induced physical attacks within distribution networks. It goes beyond conventional detection by quantifying the impact of events on physical operations, offering severity-based prioritization for remediation actions. This novel vulnerability assessment framework incorporates uncertainty modeling to account for the stochastic nature of cyber threats and their propagation through network components, enhancing situational awareness and enabling proactive defense strategies.

1.7.4 Proposing a damage-based stochastic restoration framework

Complementing these developments, the thesis explores damage-based stochastic restoration techniques specifically addressing weather-induced disruptions, with a focus on wind-related events. Recognizing that strong winds cause component failures, such as line outages and pole collapses, due to mechanical stresses and external hazards, the work employs hybrid fragility curves constructed from diverse datasets to model component failure probabilities accurately. These curves incorporate factors such as equipment age, type, environmental exposure, and confidence intervals reflecting modeling uncertainty. The stochastic restoration framework uses these damage assessments to prioritize restoration actions dynamically, employing MDP to handle the inherent uncertainties of extreme weather events. This approach supports adaptive resource allocation, where restoration measures are recalibrated as real-time damage information becomes available. Additionally, the framework integrates DERs and microgrid islanding to provide a localized power supply during outage conditions, enhancing resilience by reducing dependence on the main grid.

Throughout the thesis, advanced mathematical modeling techniques underpin the proposed methods, including MILP for optimization, hierarchical decision-making for multi-stage restoration, and probabilistic modeling for uncertainty quantification. The research also pays special attention to practical constraints such as radiality preservation, switch operation limits, and load priority categorization, ensuring that the solutions are implementable in real-world distribution systems. The large-signal stability implications of integrating GFL and GFR are analyzed to guarantee stable operation during restoration transitions.

Collectively, this work significantly advances the state-of-the-art in power distribution system resilience by integrating novel resilience metrics, DER-aware restoration algorithms, cyber-physical vulnerability assessment tools, and weather-dependent stochastic damage models. The proposed approaches provide system operators with actionable insights and decision support tools to maintain critical services during extreme events and emerging threats, thereby supporting the transition toward smarter, more flexible, and resilient energy infrastructures.

1.8 Thesis Outline

Chapter 1 comprehensively examines key elements, including motivation, literature review, identified research gaps, scopes, assumptions, basic definitions, research objectives, and overall outline. This chapter discusses each aspect in detail to lay a strong conceptual foundation and sets the contextual foundation for the propositions in the subsequent chapters.

Chapter 2 proposes a novel integrated resilience assessment metric to support real-time operations in DER-rich distribution systems.

Chapter 3 proposes a two-stage optimization algorithm for resilience-driven system restoration by considering load prioritization based on event duration, impacts, and resource management.

Chapter 4 scrutinizes the impact of various vulnerable events on the resilience of a PDS, and develops a comprehensive tri-stage architecture for vulnerability assessment, supporting robust data analysis on interfacing online and offline modes.

Chapter 5 develops an approach to capture and quantify the damage intensity of uncertain weather events and suggests optimal results for a resilient and cost-effective power distribution system.

Chapter 6 summarizes the thesis and suggests future endeavors.

Chapter 2

Proposed Multi-Stage Operational Resilience Metric

2.1 General

The rising frequency of high-probability occurrences and the lack of a universal resilience metric have transformed the research paradigm to focus on quantifying resilience for the purpose of facilitating adaptive restoration. Consequently, a resilience-driven strategy is essential for efficient operations, including prompt recovery in unpredictable situations. Nonetheless, DERs have become an essential component for resilient distribution networks; nonetheless, their integration increases uncertainty in operational decision-making. This research introduces a novel IRAM to support real-time operations in DER-rich PDSs. This multi-stage metric significantly contributes in developing a formal resilience-driven solution in evolving distribution grids. The significant contributions of this chapter can be enumerated as follows:

1. Proposed a novel multi-stage IRAM utilizing comprehensive attributes- operational redundancy, operational flexibility, and topological robustness. The attribute-based computed resilience score utilizes the AHP and weighted graph theory to evaluate the priority-based pairwise criteria weights, and suggest the most optimal restorative measure based on itera-

tive optimization.

- (a) Evaluated NRS utilizes modified particle swarm optimization to solve the network flow problem and suggest the most optimal switching vector based on the frequency of the nodes in redundant paths supplying the CLs. The computed SRS optimizes for system-level DER availability that provides an estimate ensuring the uptime guarantee of a DER-rich PDS.
 - (b) Developed algorithm for operational flexibility- utilizes a load-controlling strategy to ensure higher availability of power to CLs even with reconfiguration in load shedding.
 - (c) Evaluated topological robustness score utilizes weighted graph theory to compute the average centrality indices, indicating the best network topology for resilient PDS.
2. Developed attribute-based IRAM is the first attempt to quantify the resilience metric-driven restoration, including the real-time impact and application of GFR and GFL DERs in the resilience metric.
- (a) Proposed work utilizes multi-factor-based DER services for short-term planning to support operational resilience. It considers real-time and weather-dependent DER availability and participates in the multi-stage restoration to suggest the most optimal resilient measure.
 - (b) Developed approach quantifies the resilience based on the operation and control modes of integrated DERs. It executes the operation of GFR- and GFL-DERs in various events and confirms the highest power restoration to establish a flexible, robust, and resilient DER-rich PDS.

2.2 Resilience Quantification and Restoration Strategy

This section provides a detailed overview of the proposed system architecture, including the formulation of the multi-stage resilience metric, the optimization-based restoration framework, and

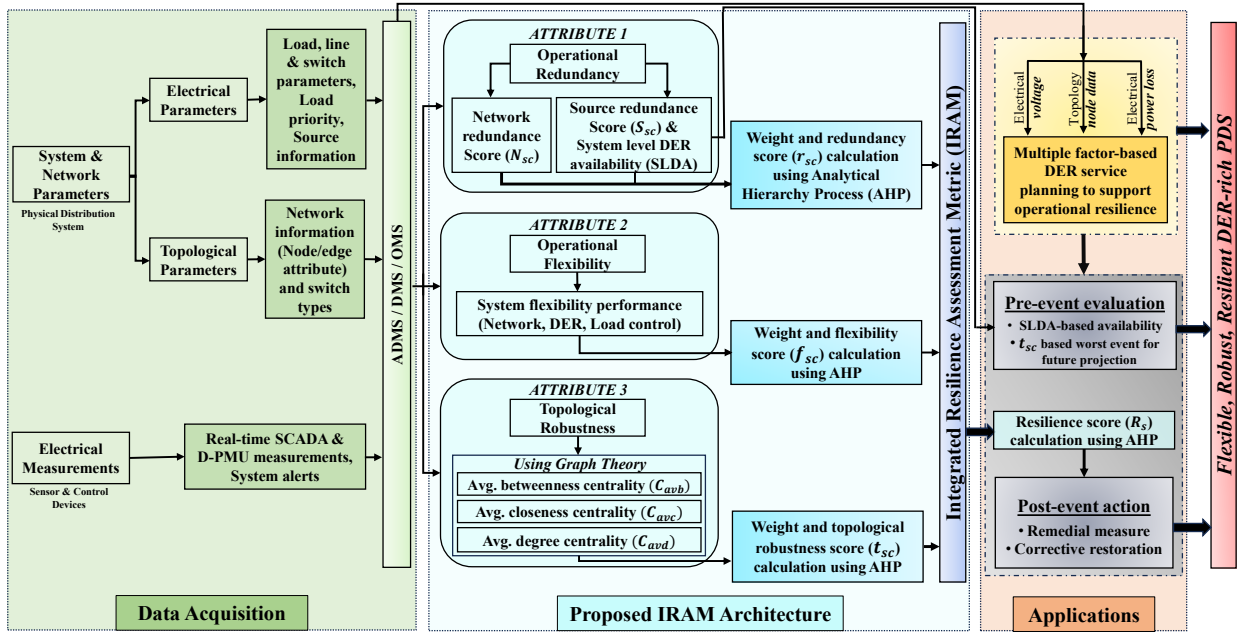


Figure 2.1: Detailed Overview of the Proposed Architecture to Compute the Resilience Score.

the operational considerations for DERs in grid-forming and grid-following modes.

2.2.1 System Architecture

The proposed attribute-based metrics bring insight into a resilience tool- IRAM that acquires only physical data and electrical measurements to perform the analysis, as shown in Fig. 2.1. The electrical parameters consist of the physical data of components; however, the topology has been defined with an undirected graph $G(N, E)$, where N is the nodes or buses, and E represents the number of edges or branches in PDS one-line. The electrical measurement feeds the real-time data from sensors and control devices to the DMS, or Advanced DMS, or OMS. This data is then fed to the proposed IRAM architecture that processes the available data to evaluate an integrated resilience score. The attributes in IRAM are explained with their significance below.

2.2.2 Operational Redundancy

A radial PDS is employed with redundant sources and switches to supply downstream loads in contingent operations. The methodologies explored in the past utilize DERs as redundant sources at random locations [46]- [47]. The following considerations narrow down the possibilities for DER services to support operational resilience in a DER-rich PDS.

DER Planning and Analysis for Operational Resilience

DERs, diesel generators, or storage are added to a PDS as a part of pre-event planning or preparedness to supply the CLs in extreme events. However, the location of DERs in real-time is unknown to us. This study devises strategic considerations to plan DER operations, supporting operational resilience.

Consideration 1: Penetration of DERs in a PDS is a significant concern for voltage violations, making voltage regulation a challenge. This work reviewed various voltage control techniques for a distribution grid [29] and thus worked to optimize the voltage. The proposed algorithm optimizes the voltage regulation and places a DER in a PDS to improve the voltage violation and maintain it within the $\pm 5\%$ range.

Consideration 2: To ensure the utmost utilization of the redundant source, a DER gets placed at the bus having the highest β and is farthest from the main feeder. β is the number of links between a parent and child node (i.e., all connected nodes). Also, this consideration uses a graphical cutset methodology to improve resilience. It picks up a central node, which is an equidistant node from each CL and has the highest β , and places a DER.

Consideration 3: A DER is supposed to be placed on a bus with the objective of reducing the PDS losses, given as:

$$P_{loss} = \frac{r_{ij} (P_i P_j + Q_i Q_j) \times \cos(\theta_i - \theta_j)}{V_i V_j} + \frac{r_{ij} (Q_i P_j - P_i Q_j) \times \sin(\theta_i - \theta_j)}{V_i V_j} \quad (2.1)$$

where r_{ij} is the resistance of the line between buses i and j ; P_i, Q_i and P_j, Q_j are the active and reactive power at buses i and j , respectively; V_i, V_j are the voltage magnitudes; and θ_i, θ_j are the voltage phase angles at buses i and j .

Above considerations are necessary to plan the DER services strategically and evaluate the network and source redundancy.

Evaluation of Network and Source Redundancy

Network and source redundancy are two distinct segments required to maintain operational redundancy in a system. Network redundancy is defined as the ability to scrutinize the optimal resilient path, maintaining the radiality based on the frequency of the node. It acts as a novel contribution that involves the path, node, and network in a single score and is evaluated as:

$$N_{sc} = w_{Ni} \sum_{i=1}^{N^{path}} k_{i,PSO}^{th} \quad (2.2)$$

Equation 2.2 follows the spanning tree protocol, IEEE 802.1D specification, with the main requirement of radial networks utilizing redundant paths. For this purpose, a modified PSO algorithm has been developed to obtain the best switch configuration. Solving a non-linear problem with approximations in a smaller system does not impact the results much. However, this study deals with a large number of control variables with mixed integers; thus, it uses PSO instead of traditional mathematical optimization. The variable $k_{i,PSO}^{th}$ defines the summation of each k_i path supplying the CL in the unique solution, and w_{Ni} is the associated weight representing the fraction of CLs supplied with the unique solution. Here, i denotes the path index, and N^{path} represents the total number of feasible paths. The unique solution refers to the set of connected branches forming a path from the source to the CLs. The developed PSO scrutinizes feasible solutions out of all the possible solutions based on the following criteria:

1. Paths forming a loop with connected branches from the source to CL violate the radiality constraint and are disregarded as infeasible solutions.

2. Paths that do not fulfill the ENS or do not supply the minimal CL power at the time of interruption are straightaway rejected.

Among the feasible solutions, the unique solution meets the criteria of maximum electric power supplied, energizing all CLs, while maintaining the radiality. The $k_{i,PSO}^{th}$ for the unique solution is computed by:

$$k_{i,PSO}^{th} = \frac{\text{Common branches in } k_i \text{ unique solution}}{\# \text{branches in } k_i \text{ unique solution}} \quad (2.3)$$

where k_i represents the i^{th} path connecting the source to the CLs, and the numerator denotes the number of common branches in the unique solution. This study assigns w_{Ni} weight to each path, which is computed based on the ratio of CLs supplied to all the loads for $k_{i,PSO}^{th}$. Another weight is assigned to the connected DERs concerning their modes of operation and control while evaluating the source redundancy. However, this approach evaluates the SLDA to intensify practical application. Including SLDA in the pre-event analysis provides an estimate for a fault-tolerant PDS, ensuring high availability.

$$SLDA(\%) = 1 - \frac{\sum_{i=0}^{N_{DER}} S_i(1 - \alpha_i)}{\sum_{i=0}^{N_{DER}} S_i} \quad (2.4)$$

where S_i is the power rating of the i^{th} DER, α_i represents the availability factor, and N_{DER} is the total number of DERs. In the case of batteries, S_i (total power) depends on the discharging profile, and SLDA might not accurately estimate system availability. SLDA plays a vital role in the aftermath of an event while evaluating the source redundancy.

$$S_{SC} = \sum_{i=0}^{N_{DER}} \varphi_i \cdot SLDA_i \quad (2.5)$$

$$\varphi_i = \begin{cases} 0, & \text{DER not connected / GFL DER not connected to GFR DER} \\ w_{si}, & \text{GFR DER connected / GFL DER connected to GFR / convertible} \end{cases} \quad (2.6)$$

where S_{SC} represents the source redundancy score; φ_i represents the operational status weight of the i^{th} DER, and $SLDA_i$ denotes the corresponding availability. The weight associated with

Algorithm 1: Utilize and maximize operational redundancy

Input: Location of CLs, ELs, Non-ELs
 Specification of TLSs, SSs
 Operational modes and availability of DERs

1. Update $\Omega_{TLS} \leftarrow \text{create_initial_swarm}()$
2. Update $\Omega_{SS} \leftarrow \text{open_SSs } \forall \text{ branches}$
3. **for** each bus $\in n$ **do**
4. Plan DER services
5. DER 1 : GFR $\leftarrow \max \beta_i \quad i \forall n$
6. DER 2 : GFL $\leftarrow \text{voltage regulation}$
7. DER 3 : GFL $\leftarrow \min P_{loss}$
8. **end**
9. $N_{sc} \leftarrow [\Omega_{TLS}], [\Omega_{SS}], w_{Ni}$
10. **SLDA** $\leftarrow \text{availability of DERs } (\alpha)$
11. $S_{sc} \leftarrow \varphi_i, SLDA$
12. $r_{sc} \leftarrow w_{ri}, N_{sc}, S_{sc}$

Maximizing Redundancy

Computing Redundancy

the operational mode of the i^{th} DER is given by w_{si} . Here, the value of φ_i is 0 if the DER is not connected, else the value varies. Theoretically, a GFR-DER is a source of energy that acts as an independent grid in islanding, whereas a GFL acts as a current source. The GFR-DERs are dispatchable and operate as voltage sources, keeping frequency and voltage maintained in islanding. Meanwhile, GFL-DERs typically operate by following the grid voltage and frequency. Thus, the islanded SN having the GFL-DER must be connected to the SN with a GFR to supply loads. Henceforth, the value of φ_i is 1 if the integrated GFL is connected to another SN having GFR, or if the GFL can convert to GFR-DER. The weight w_{si} depends on the active mode of operation of each DER. This methodology allocates a higher weight to GFRs than GFL and utilizes AHP to conduct the sensitivity analysis and evaluate the criteria weights with the aggregate impact of each DER.

Algorithm 1 successfully establishes a redundant PDS by evaluating NRS and SRS. It plans for DER services with respect to the considerations and assigns their modes of operation to visualize real-time operation. For the IEEE 33-bus system (used in this study), it plans for three DERs. However, Algorithm 1 is not system-specific and would suggest a different number of DERs depending on the system, considering the criteria or resilience analysis. While computing

the operational redundancy, it also evaluates SLDA to define the system's availability for pre-event preparedness. Thus, algorithm 1 computes and maximizes the operational redundancy, assisting the operator in restoring the DER-rich PDS.

2.2.3 Operational Flexibility

A flexible network can expand or contract its boundaries in case of any uncertain event [48]. Power systems have the capability to adjust demand and supply flexibly, which can be maintained by DERs in outages. Authors in [24] presented a similar resilience-driven methodology to restore the CLs via distributed generation. However, this study develops a flexible load-controlling strategy, where the operational flexibility score is computed based on the network reconfiguration and the DERs supplying the CLs, during the duration N_t , where:

$$N_t = \begin{cases} t_{sys} & \text{system with no interruption} \\ t_{int} & \text{system under disruptive state} \\ t_{res} & \text{system restored via remedial actions} \\ t_{rec} & \text{system in fully recovered state} \end{cases} \quad (2.7)$$

Reconfiguration using Spanning Tree Protocol

This study develops a practical algorithm for reconfiguration with three objectives, which are: (i) minimum supply to CLs, (ii) maximize the load energized, and (iii) maintain the operational constraints, respecting the impact of GFL/GFR DERs. The algorithm scans the PDS at frequent intervals and observes power flow during N_t . It evaluates the ENS at t_{int} by:

$$ENS = 1 - \sum_{t=0}^{N_t} P_{L_{i,t}} \quad (2.8)$$

It follows a stepwise procedure to recover the ENS (summation of interrupted energy) in various stages. Problem formulation for each stage involved in the process is shown in Section 3. After estimating ENS, algorithm 2 reconfigures the network and generates an optimal TLS vector

Algorithm 2: Algorithm to establish operational flexibility at t_{int}

Input: Location of CLs, ELs, Non-ELs, SN with event

Input: $\int_{t_{int}}^{t_{rec}} ENS$, Status of TLS & SS

```

1. Run PSO  $\ni N_t = t_{int}$ 
2. Update ( $V_{new}, \delta$ )
3.  $\mu (P_{best}, G_{best})$ 
4. Update ( $[\Omega_{TLS}], [\Omega_{SS}]$ )
5. for  $N_t = t_{int} \leftarrow$  internal window do
6.   if  $P_i \geq \sum_{i=0}^{i-1} P_i - P_{LL(i-1,i)} - P_{L(i)}$  then
7.     continue
8.   end
9.   else
10.    Goto SN and integrate DER
11.    if (DER  $\leftarrow$  GFL) do
12.      continue
13.       $\sum(P_G + P_{DER}) \geq \sum(P_L + P_{LOSS})$  do
14.        end
15.      else
16.        Update ( $[\Omega_{TLS}], [\Omega_{SS}]$ )
17.        Connect DER  $\leftarrow$  GFR
18.      end
19.      Compute  $P_{mis}$ 
20.      for  $t_{int} \leq t \leq t_{rec} \leftarrow$  internal window do
21.         $P_{mis} \cong 0$ 
22.        shed  $P_{L_{max}}$ 
23.        if  $P_{L_{max}} = P_{Non-EL}$  then
24.          shed  $P_{Non-EL}$ 
25.          jump next in the list
26.        else if  $P_{L_{max}} = P_{EL}$  then
27.          shed  $P_{EL}$ 
28.          jump next in the list
29.        else
30.          jump out of the list
31.          check backup DER availability
32.          if (backup DER available) then
33.            connect DER  $\leftarrow$  GRF
34.          end
35.        end
36.      end
37.    end
38. end

```

Table 2.1: Parameters for Critical, Essential, and Non-essential Loads

Load buses	Priority level	Location
Critical	High	7, 14, 24
Essential	Moderate	4, 8, 18, 25, 30, 32
Non-Essential	Low	2, 3, 5, 6, 9, 10, 11, 12, 13, 15, 16, 17, 19, 20, 21, 22, 23, 26, 27, 28, 29, 31, 33

(Ω_{TLS}) serving the maximum load with minimum losses. The resultant network may disturb the radial topology of the PDS. So, the unique solution suggested by the PSO algorithm opens some desired SSs to maintain the radiality. Thus, the iterative optimization yields the best switching vectors with (Ω_{TLS}) and (Ω_{SS}).

Flexible Load Control with Diverse Modes of DERs

This stage introduces an optimal load control strategy to establish operational load flexibility in a PDS. For real-time analysis, this study divides the load into CLs, ELs, and Non-ELs, as shown in Table 2.1. Up to this stage, algorithm 2 has already attained primary supply with optimal re-configuration and suggests connecting DERs (initially considered disconnected). Although DERs improve the system availability [48], it has a time and weather-dependent supply. The challenge is to provide a constant amount of power during a disruption. Thus, this study devises DER services and plans three DERs at nodes 6, 13, and 30, which supply on closing SW1, SW2, and SW3, as shown in Fig. 2.2. Algorithm 2 (lines 9-38) specifies that a DER of a disrupted SN gets integrated into the PDS if the updated switching vector fails to meet the expected P_L (line 1-8). The supremacy of this approach is the consideration of DER availability, which is impacted by weather-dependency, and the type of DER [49], affecting the operation in islanding mode. The algorithm integrates the DERs on checking the type and mode of operation, as given in Table 2.2. A GFR-DER can provide a continuous supply in voltage control mode, whereas the algorithm updates the switching in the case of GFL-DER (operating in MVar mode). Additionally, for a practical overview, the algorithm inspects for DER convertibility and suggests connecting the GFL-DER if it is convertible. However, if there is no supply at t_{int} or the DER gets into discharging, there will

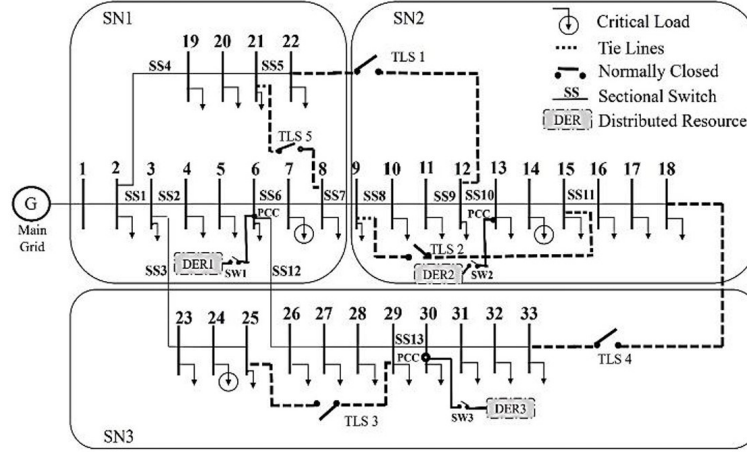


Figure 2.2: Modified IEEE 33 bus PDS with Tie-lines and Inverter-based DER.

Table 2.2: Source Specifications with the Control mode of DER

Source	PCC	Capacity (MW)	SN	Mode
DER 1	6	2.844	SN1	GFR (Backup)
DER 2	13	0.743	SN2	GFL
DER 3	30	2.320	SN3	GFL

be a power mismatch. The condition to verify the power mismatch P_{mis} is given as:

$$P_{mis} = \begin{cases} 0, & \text{if } (P_{G_t} + P_{DER_t} - P_{L_t}) \geq 0 \\ 1, & \text{if } (P_{G_t} + P_{DER_t} - P_{L_t}) < 0 \end{cases} \quad \forall t \in N_t \quad (2.9)$$

If $P_{mis}=1$, there is a risk of an unplanned outage unless the load shedding starts. Thus, this approach develops a priority list of loads likely to be shed to provide a continuous supply to CLs. It starts shedding loads in the SN with the highest demand. If that load is a CL or EL, it sheds the next on the list. This cyclic process of restoration and shedding makes it an intelligent load-controlling strategy and adds a valuable aspect.

Another aspect of intelligent load control is the connection of the backup DER in the worst scenarios. If a DER of a disrupted SN fails to supply the CLs, the GFR-DER works as a backup to the CLs. The algorithm first checks for the availability of backup and integrates it to provide a continuous supply to CLs, even in load shedding. This capability sets a higher tolerance limit to

the PDS so that it remains resilient and supplies CLs in the worst case.

2.2.4 Topological Robustness

A resilient infrastructure should be capable of monitoring and controlling the power flow between various nodes in a PDS. Once the connection between nodes is established, coordination must be maintained between the operator and the system to take corrective actions immediately. Thus, evaluating selected attributes allows topological robustness to be maintained up to a desired level. This study utilizes graph theory to assess the robustness via centrality indices and compute C_{avb} , C_{avc} , and C_{avd} for each event. Further, it suggests the most optimal unique solution as the remedial measure, satisfying all the criteria and facilitating the system's recovery to normal operating conditions. All the suggested unique solutions are feasible; however, the path with the highest topological score t_{sc} establishes higher interconnection with enhanced robustness. The following text briefly explains the significance of each measure. C_{avb} is the measure of node dependency on one another, given as:

$$C_{avb}(k) = \frac{\sum_{i=1, i \neq j}^n \sum_{j=1}^n \frac{d_{ij}(k)}{d_{ij}}}{n} \quad (2.10)$$

where the shortest path between node i and j is given by d_{ij} , and $d_{ij}(k)$ represents those paths that pass through node k . n is the total number of buses. (2.10) represents that a higher node dependency provides the maximum scope of disconnection. C_{avc} represents closeness between nodes. The higher the closeness, the faster the flow of information in a PDS. It is defined as:

$$C_{avc}(k) = \frac{\sum_{i=1, i \neq k}^n \sum_{k=1}^n \frac{1}{d(i,k)}}{n} \quad (2.11)$$

where $d(i, k)$ is the average distance between each pair of nodes; $d(k, i)$ is the number of nodes connected to k . Lastly, C_{avd} is the number of connections of a particular node with others. It can be referred to as the degree of a particular node and defined as:

$$C_{avd}(k) = \frac{\sum_{i=1}^n \sum_{k=1}^n d(k, i)}{n} \quad (2.12)$$

Table 2.3: Pairwise Criteria Weights for all Parameters

w_i for	S_{sc}	t_{sc}	IRAM
w_{i1}	0.5	0.171	0.537
w_{i2}	0.168	0.550	0.267
w_{i3}	0.33	0.277	0.195

Moreover, as a part of pre-event planning, these indices can be utilized to project the worst events, thus suggesting a topologically robust measure, as explained in section 4.

2.3 Multi-constraint Resilience-Oriented Formulation

2.3.1 IRAM: Defining Metrics and Scores

Resilience-oriented Operational Redundancy Score

This study evaluates network and source redundancy independently to maintain a redundant PDS. Mathematically, the operational redundancy is the weighted sum of NRS and SRS, where the weights are computed by the AHP [50] [34]. Table 2.3 shows pairwise criteria weights assigned based on the aggregate impact of each DER on the PDS, where w_{i1} , w_{i2} , and w_{i3} represent different weights with i as s , t , and R , respectively.

$$r_{sc} = w_{r1}N_{sc} + w_{r2}S_{sc} \quad (2.13)$$

This study assigns an equal weight to both (network and source redundancy) due to equal relevance. The proposed operational redundancy evaluation covers all aspects, including TLSs and GFR/GFL-DERs operability at various instants.

Resilience-oriented Operational Flexibility Score

The flexibility score f_{sc} represents the fraction of CLs supplied in the interval N_t , where N and n are the total loads and CLs, respectively. This score expresses the availability of CLs and aids in

Table 2.4: Pairwise Comparative Weights for Centrality Indices

	C_{avb}	C_{avc}	C_{avd}	Criteria Weights
C_{avb}	0.330	0.570	0.750	0.1706
C_{avc}	0.166	0.285	0.061	0.5500
C_{avd}	0.500	0.143	0.188	0.2786

formulating the metrics to observe the resilience enhancement in PDS with the suggested remedial measures.

$$f_{sc} = \left\{ \frac{\sum_{i=1}^{N_t} \int_{t_{\text{int}}}^{t_{\text{rec}}} n_{i,t} dt}{\sum_{i=1}^{N_t} \int_0^{t_{\text{rec}}} n_{i,t} dt} \right\} \quad (2.14)$$

Resilience-oriented Topological Robustness Score

This methodology computes the comparative weight for each index as w_{t1} , w_{t2} and w_{t3} , using AHP. Thus, the topological robustness score is given by,

$$t_{sc} = w_{t1}C_{avb} + w_{t2}C_{avc} + w_{t3}C_{avd} \quad (2.15)$$

Table 2.4 exhibits the detailed computation of criteria weights for each parameter, aggregating their impact on the PDS.

2.3.2 Computation of Resilience Score for IRAM

This study integrates the weighted sum of three key attributes: operational redundancy, operational flexibility, and topological robustness, to quantify system resilience based on the impact and application of DERs. These attributes are interrelated and collectively influence the system's overall resilience.

The relative importance of each attribute is incorporated through user-defined weights determined using the AHP. AHP is a structured decision-making method that prioritizes and ranks criteria based on their significance. In this work, AHP is employed to systematically evaluate the

contribution of each attribute and integrate them into a unified resilience metric. The integrated score represents the overall resilience of the system by capturing the combined effect of these attributes under the given operating conditions. Here, redundancy maintains an efficacious level of primary resilience in the planning stage; thus, r_{sc} has been given a higher weight than f_{sc} and t_{sc} .

$$\text{IRAM: } R_S = w_{R1}r_{sc} + w_{R2}f_{sc} + w_{R3}t_{sc} \quad (2.16)$$

$$R_S = w_{R1}(w_{r1}N_{sc} + w_{r2}S_{sc}) + w_{R2} \left(\frac{\sum_{i=1}^N \int_{t_{\text{int}}}^{t_{\text{rec}}} n_{i,t} dt}{\sum_{i=1}^N \int_0^{t_{\text{res}}} n_{i,t} dt} \right) + w_{R3}(w_{t1}C_{avb} + w_{t2}C_{avc} + w_{t3}C_{avd}) \quad (2.17)$$

The significance of the proposed IRAM is a step towards a formal solution. The characteristics of the IRAM, highlighting the efficacy of the approach can be briefly pointed out as follows:

- Operational redundancy, flexibility, and robustness are the prime attributes of a resilient PDS. This approach computes network and source redundancy that provides alternate restorative paths for maximum recovery. Moreover, the continuous supply to CLs with the load control strategy allows PDS to adapt to extremes.
- Multiple factor-based DER planning services narrow the possibility of having DERs to support operational resiliency.
- Application of DERs concerning their service availability, type, and operation and control modes strengthens the on-field implementation of the proposed IRAM architecture.
- The multi-stage IRAM evaluates each necessary attribute numerically, enhancing the system's security and preparedness to ensure a resilient DER-rich PDS.

2.4 Experimental Validation and Resilience Evaluation

This section implements the algorithm on a benchmark IEEE 33 bus radial PDS, operating at 12.65 kV with active and reactive demand of 3.72 MW and 2.3 MVar, respectively, with 285 control variables. The control variables include voltage adjustments, load management, switching operations with TLS or SS, and DER connection. The IEEE test systems used in this study are

widely recognized benchmark distribution networks and are extensively adopted in power system research for validation and comparative analysis. These systems provide a standardized platform to evaluate the effectiveness of proposed methodologies under controlled conditions. Although originally developed to represent typical distribution systems in the United States, the structural characteristics of these test systems, such as radial topology, load distribution, and operational constraints, are sufficiently generic to emulate practical distribution networks, including those in India. Therefore, the proposed framework and insights derived from the analysis remain applicable to Indian distribution systems with appropriate adaptation of system parameters. Furthermore, this study models the algorithm on MATLAB/MATPOWER 6.0 to obtain the switch configuration. The ease of implementation to handle the nonlinearity and suitability for iterative optimization provide a certain edge with PSO. It uses a binary notation to update the particle position and generate the optimal switching vector as the unique solution. It later calls the power flow from the ETAP software to compute the resilience score. This significantly reduces the execution time, instead of making it computationally intensive. ETAP 19.0.1 has been used to simulate the events, and Cytoscape-v3.10.1 has been used to develop the undirected graph. Cytoscape analyzes the topology via the graph extracted from PDS's one-line to measure the importance of nodes/edges. This study exhibits various single and multiple events mentioned in Table 2.5. Moreover, the case study details the impact of events on each attribute in the integrated metrics and evaluates the resilience. Key findings from the case studies include:

1. The proposed approach achieves 97% system restoration under extreme event scenarios.
2. The IRAM-based restoration consistently outperforms traditional strategies in terms of resilience score and load restoration time.
3. The incorporation of real-time DER availability and operational flexibility significantly enhances system robustness and adaptive response capabilities.

Table 2.5: Pre-event Analysis with DER Availability

Events	DER availability (α_n)	SLDA (%)	Impact on Rs
E-I: 4-5	$\alpha_1 = \alpha_2 = \alpha_3 = 1$	100	0.2201
E-II: 12-13	$\alpha_1 = \alpha_2 = 1; \alpha_3 = 0.2$	68.58	0.3107
E-III: 3-23	$\alpha_1 = 1; \alpha_2 = \alpha_3 = 0.9$	94.85	0.3094
E-IV: 5-6, 6-26, 6-7	$\alpha_1 = 1; \alpha_2 = \alpha_3 = 0.98$	98.97	0.2282
E-V: 8-9, 21-22, 29-30	$\alpha_1 = 1; \alpha_2 = \alpha_3 = 0.8$	89.63	0.3128
E-VI: 8-9, 3-23, 2-19	$\alpha_1 = \alpha_2 = \alpha_3 = 1$	100	0.2298

2.4.1 Scenario 1: Computing Scores for Single Outage Event

The modified test system underwent diverse events to analyze the performance under various conditions. It has been observed that each event has different switching vectors and restoration alternatives. All the events and suggested switch configurations are not expressed here. However, the most resilient unique solution that best fits the criteria with maximum recovery, minimum shedding, and maintaining real-time grid operability has been explained. For better understanding, all the feasible paths to recover CL in the first event are presented in detail, and the significance of resilient unique solution is verified quantitatively.

a) The first event (E-I) hits a line connecting buses 4 and 5. Algorithm 2 yields the optimal reconfiguration on closing TLS 25-29 and 12-22 and opening SS2. The PSO segregates three feasible solutions out of six possible paths supplying the CLs:

Path 1. Ω_{TLS} : [25-29, 12-22] and Ω_{SS} : [3-4]

Path 2. Ω_{TLS} : [25-29, 8-21] and Ω_{SS} : [6-7]

Path 3. Ω_{TLS} : [12-22, 8-21] and Ω_{SS} : [9-10]

The solution represents the switch vector indicating the closing of TLSs and opening of SS to maintain the radiality in the restored PDS. These feasible solutions increase the level of redundancy and are used to compute the NRS. However, the PSO suggests the unique solution as the resilient path with maximum EPS at t_{int} , i.e., Path 1. It shows a flexible performance on restoring 97.2% of loads, supplying all CLs, and out of the three feasible solutions, Path 1 has the highest t_{sc} . The

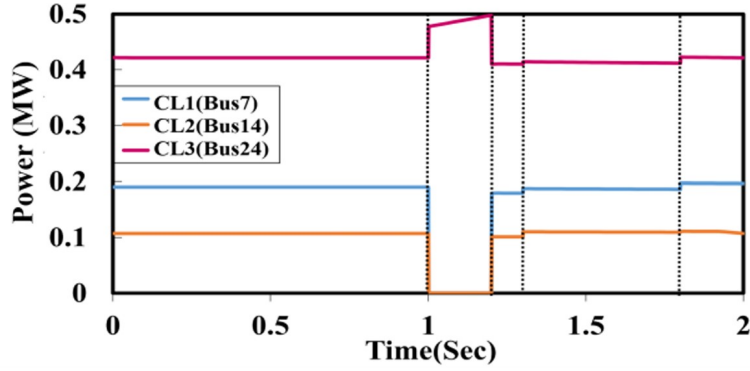


Figure 2.3: MW Restoration at Critical Load with Suggested Measure in Event-I.

highlight of this solution discloses:

- The developed algorithm provides a unique solution that recovers not only the maximum CLs but also produces a switch vector that has the capability to retrieve the maximum power while maintaining the radiality. Fig. 2.3 illustrates the load increment in a step-by-step pattern, gradually restoring service after t_{int} with the updated switching vector.
- The cost-effectiveness of the approach has been observed with the backed MWhr of 97.2% at t_{res} with the suggested Ω_{TLS} and Ω_{SS} . Algorithm 1 does suggest allocating DERs; however, a complete recovery at t_{rec} has been achieved without DER services. Thus, IRAM proves its significance by producing a resilient and cost-effective result with only TLSs.

b) A similar event in SN2 (E-II) is considered a minor disruption of downstream loads to bus 13, which made CL at bus 14 out of service. Algorithm 2 delivers an effective result while maintaining radiality with 100% recovery by closing TLS 9-15. Table 2.6 exhibits a more impactful event for E-II to verify the effectiveness of the approach in real-time on-field scenarios. It considers a disruption at line 12-13, followed by grid islanding that eventually distributes the PDS into 3 SNs with no supply.

In this case, the developed algorithm integrates all three DERs in their respective SNs. To ensure the working of GFL-DERs, the algorithm updates Ω_{TLS} and Ω_{SS} , and restores the ENS at t_{int} . The actual on-field situation comes up with the DER availability challenge. Thus, this study

Table 2.6: Post-event Control Actions for Multiple Events Supporting Operational Resilience

Event	Operational mode of active DERs	Scores			IRAM (R_s)	Suggested switch reconfiguration (Ω_{TLS} : NO _{normally opens} , Ω_{SS} : NC _{normally close})		Power Supply (%)		
		r_{sc}	f_{sc}	t_{sc}				t_{int}	t_{res}	t_{rec}
E-I	-	0.147	1	0.668	0.4762	Ω_{TLS} : [25-29, 12-22]	Ω_{SS} : [3-4]	41.5	97.2	100
E-II	DER1: GFR and Backup DER2: GFL DER3: GFL	0.684	1	0.682	0.7649	Ω_{TLS} : [-]	Ω_{SS} : [-]	0	99.8	100
E-III	-	0.187	1	0.647	0.4936	Ω_{TLS} : [25-29]	Ω_{SS} : [-]	74.5	96.2	100
E-IV	DER1: GFR	0.324	1	0.648	0.5678	Ω_{TLS} : [8-21, 25-29, 12-22]	Ω_{SS} : [11-12]	46.6	98.9	100
E-V	DER2: GFL converts to GFR	0.528	1	0.688	0.6831	Ω_{TLS} : [18-33, 12-22]	Ω_{SS} : [-]	65.1	100	100
E-VI	DER1: GFR	0.809	1	0.646	0.8274	Ω_{TLS} : [18-33, 25-29, 8-21]	Ω_{SS} : [-]	33.6	92.4	100

considers that with 100% restoration at t_{res} , DER3 faces an availability challenge. The simulation assumes 20% availability of DER3. Hence, the algorithm suggests shedding the load of SN3. According to the priority list, Non-ELs start shedding until the P_{mis} becomes 0. Thus, in this case, all non-ELs followed by ELs have been shed to supply the CL. The P_{shed} is 0.77, indicating 77.29% of loads shed in SN3. The highlight of this solution discloses:

- The developed algorithm provides 100% recovery by the suggested unique solution, and no DER connection until required. DERs are integrated when there is no surplus supply having $P_{mis} \neq 0$. In the case of isolated SNs, the connected DERs supply all the loads in their respective SNs. The switch configuration gets updated in the case of GFL-DERs. The intelligent load-controlling strategy plays a role if any DER meets the availability challenge. However, the developed architecture has the capability to supply the CLs even in load shedding.

c) Event at line 3-23 (E-III) disconnects SN3 from the main grid and degrades the EPS to 74.52% with one CL unserved. However, algorithm 2 immediately restored the PDS by closing TLS 25-29, and a recovery of 96% has been made at t_{res} .

Remark 1: The computed resilience score (R_s) depends on source redundancy (S_{sc}), i.e., real-time DER availability. The presence of operational redundancy improves the evaluation. However, integrating DERs may not be economical, but it enhances the operational profile. For instance, the integrated score in E-I reflects 100% recovery by the updated switching. However, the voltage profile can be improved by integrating DER1, as shown in Fig. 2.4. The proposed IRAM considers

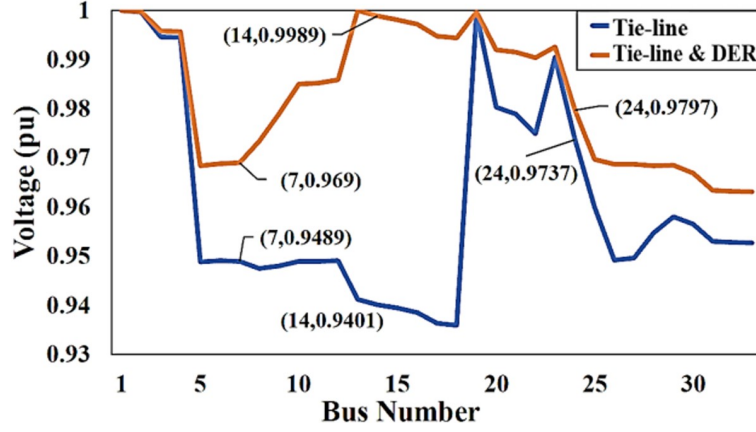


Figure 2.4: Bus Voltage with Updated Switching Vector and DER Connection.

these impacts and applications to compute the resilience score.

Remark 2: Topological robustness demands a better understanding of network topology to produce effective results for short-term planning to support operational resilience. The evaluated centrality indices help in computing the topological robustness to compute the resilience score. Besides that, the developed approach can assist in projecting the worst events and warn the operator to plan. It has been noted that the worst event has the maximum C_{avb} and minimum C_{avc} (explained in section 2). For example, E-I reported to be the least aware scenario with 0.1228 C_{avc} and 0.2425 C_{avb} , and a simultaneous warning can be generated. Meanwhile, E-II with disruption at 12-13 has the best awareness with 0.1484 C_{avc} and 0.1959 C_{avb} . Thus, besides operational analysis, topological robustness can be used to minimize the impact of events on PDS.

2.4.2 Scenario 2: Computing Scores for Multiple Outage Events

Among various simulated scenarios, this thesis presents three distinct events attempting to simulate the on-field scenarios with load shedding, SN formation, use of GFR- and GFL-DERs, conversion of a GFL-DER, and DER availability issues.

Event E-IV isolates bus 6 and disintegrates 46.6% of the load, involving 2 CLs unserved. Algorithm 2 suggests closing three TLSs while opening SS9. The step-by-step improvement in

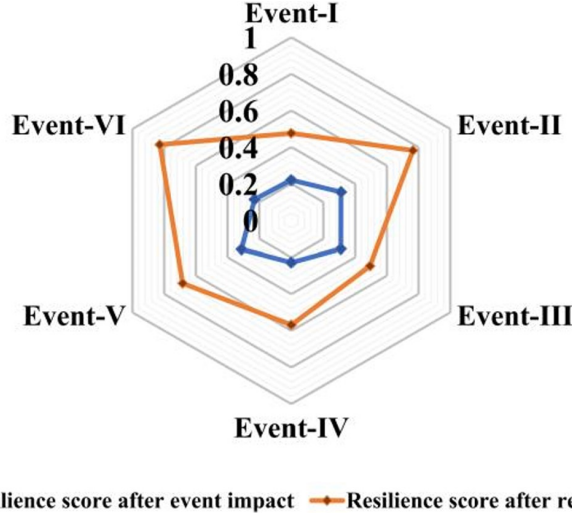


Figure 2.5: Resilience Improvement with Suggested Operational Decisions.

EPS with suggested Ω_{TLS} , Ω_{SS} , and DERs, and the resilience enhancement with the suggested measure are shown in Fig. 2.5.

- The proposed methodology recovers all the buses (including the isolated bus 6) at t_{rec} , ensuring 100% load supply.
- Results with $\pm 5\%$ voltage deviation, even with DER penetration, indicate the efficacy of the proposed methodology.

E-V considers a sequence of events disconnecting SN2 from the main grid, with only 65% of EPS at t_{int} . At first, Algorithm 2 suggests the switch vectors; however, the SN is isolated in this event and does not get restored. Thus, DER2 is integrated to maximize the EPS. Since DER2 operates in GFL mode, the algorithm checks for its convertibility. Whenever possible, the GFL is operated in GFR mode to ensure a fully restored PDS. In the worst case, if redundant switches and sources fail to fulfill the ENS, the operator is advised to restore CL in SN2 via additional battery storage or on-field assistance. In this case, one GFR (converted from GFL) has been in active mode, but if two GFRs operate at a time, then the one with the higher φ_i in S_{sc} is considered as leading. The last real-time possibility is explored in E-VI, where the disruption splits the PDS into three SNs with grid islanding. The algorithm suggests integrating DER1 as the PDS fails to recover from the suggested switch vector. After connecting DER, the configuration gets updated,

and the PDS fully restores the ENS. Hence, the proposed IRAM can adapt to the worst and deliver a flexible, robust, and resilient DER-rich PDS.

2.5 Outcomes

This chapter presents a novel multi-stage Integrated Resilience Assessment Metric (IRAM) to enable a resilient DER-rich distribution system. The chapter is based on the publications [P1]. The developed metric correlates multiple comprehensive attributes- operational redundancy, flexibility, and topological robustness to compute the integrated resilience score. The developed algorithms incorporate real-time characteristics of DERs in the resilience metric and suggest the optimal restorative measure utilizing iterative optimization. The first algorithm computes and maximizes the operational redundancy by determining the network and source redundancy score. It computes system-level DER availability for short-term planning to support operational resilience. The second algorithm introduces a load-controlling strategy to ensure higher availability of critical loads even in load-shedding. The operational flexibility score results from the optimized switching vector and DER integration, supplying at least a minimum of CLs as the optimal operational measure. The third attribute, topological robustness, utilizes graph theory to compute the average centrality indices that ensure the most optimal resilient path considering the network topology. The proposed IRAM incorporates 285 control variables participating in three stages- optimizing for switching, load management, control strategies, and operational modes.

Compared to the previous studies, the proposed architecture fits better for on-field applications given the time- and weather-dependent DER availability, planning and analysis for DER services, operation- and control-mode consideration of DERs, and decision-making capability in extremes. Implementing GFL and GFR DERs in grid-connected and islanding modes provides an edge to this study. Moreover, the proposed resilience metric represents a significant contribution, as it paves the way for developing formal resilience metric-driven strategies and generalized algorithms for enhancing resilience in DER-rich PDSs.

The effectiveness of the proposed IRAM is validated through case studies, in which resilience

scores approach unity under optimal operating conditions, indicating high system resilience. The results demonstrate improved critical load supply and enhanced system performance under varying DER availability and network conditions, thereby confirming the capability of the proposed framework for real-time resilience assessment.

The complexity of continuous tracking of grid behavior under uncertain scenarios and guiding adaptive decision-making for service restoration and DER dispatch served as the motivation for the subsequent chapter of this thesis.

Chapter 3

A DER-Centric Approach Considering Metric-Driven Assessment

3.1 General

Existing literature supports the integration of distributed resources in a PDS to restore CLs using mixed-integer linear programming [51]- [52], semidefinite programming [53], reinforcement learning [54], deep reinforcement learning with quadratic programming [55], probabilistic modeling [56], etc. The reinforcement learning-based restoration or robust optimization approaches require extensive training under specific system dynamics, increasing the computational complexity, especially on larger PDSs. Modern distribution grids are already complex due to the high inclusion of DERs, transforming them into an Active Distribution Network. The massive integration of DERs leads to voltage fluctuation and makes voltage regulation a challenge in PDS [32].

Traditionally, voltage regulators, tap-changing transformers, etc., have maintained the voltage in a specified range. However, it fails to handle the high variability that comes with integrating multiple DERs. Thus, CVR is one of the technical challenges that need to be modeled to increase the efficiency of a DER-enabled PDS [33]. Formulating the CVR objective adheres to power consumption reduction, loss minimization, and feeder voltage regulation. Some approaches imple-

mented CVR in a PDS, intending to reduce power consumption by controlling the legacy voltage control devices [34]. This study models the voltage-responsive loads for CVR and optimizes a healthy voltage profile with DER integration.

Moreover, DERs are sometimes behind-the-meter sources [31]. Also, solar and wind resources may operate in either GFR or GFL mode. The GFR-DERs are dispatchable and operate as voltage sources, keeping frequency and voltage maintained in islanding. Meanwhile, GFL-DERs typically operate by following the grid voltage and frequency. Depending on the underlying technology and control architecture, they may be dispatchable or operate as negative loads. The restoration considering the operational constraints and uncertainties in a DER-rich PDS, has been cited in [46]. Based on the literature review, the research gaps are outlined here:

- Existing literature partially captures the challenges of DERs on operational resilience, considering types of DER (grid-following/grid-forming/grid-following with grid-forming capability) and their diverse modes of operation; variable weather-dependent availability; real-time MW capacity over the time horizon.
- It lacks metrics-driven restoration while optimizing the power and energy to strategically restore by prioritizing loads in a DER-rich PDS.

3.1.1 Key Contributions

This work presents a two-stage power and energy restoration algorithm (PERA), considering the challenges and applications of inverter-based DERs in modern distribution grids. The suggested solution delivers an optimal result that benefits the customer and the utility. The key contributions of this work are:

- Proposed a novel two-stage resilience-driven restoration algorithm to (i) maximize the power to CLs, and (ii) optimize the power and energy to all loads considering DER intermittency over the time horizon.
 - Developed first stage utilizes penalty function in particle swarm optimization to handle the constraints, considering the degree of violation on solving the non-linear op-

timization. The problem formulation considers network flow constraints and calls for power flow to optimize the discrete variables involving switch reconfiguration in a binary state. The optimal reconfiguration maximizes the network redundancy based on the number of nodes in redundant paths from the source to CLs. The source includes existing transmission-distribution interface and distributed energy resource (DERs), including (a) GFR-DERs, (b) GFL-DERs, and (c) GFL-DER with GFR capability.

- Developed second stage optimizes power and energy of all the loads considering DER intermittency at different time steps. The operational measure gets modified following a time interval (15 minutes for this study). However, depending on the operating conditions, each step may not result in an action. The developed formulation also considers power consumption reduction by implementing voltage-responsive loads to optimize the energy.
- Computed and utilized the resilience score to derive the optimal restorative measure, supporting operational resilience in a DER-rich distribution system. It utilizes priority-based pairwise criteria weights to quantify the weighted resilience score characterized by comprehensive attributes- operational redundancy, operational flexibility, and topological robustness.
- Modeled and validated PERA using multiple case studies on balanced and unbalanced DER-rich distribution systems. The formulation integrates (i) diverse operation and control modes and (ii) time- and weather-dependent availability of DERs in the metric to yield the optimal resilience-driven restorative measure.

3.1.2 Assumptions

- PDS is equipped with limited SS at the suggested branches to maintain the radiality.
- The proposed PERA is applicable to all DERs, including solar, wind, etc. The real-time availability and modes of DER are unknown; thus, assumed as given in Table 3.1. The

Table 3.1: Source Specification With the Control Mode of DER

DER	PCC	Capacity (MW)	Control Modes of IB-DERs
DER 1	6	2.15	GFL-DER with GFR capability
DER 2	13	0.62	GFL-DER with GFR capability
DER 3	30	1.32	GFL-DER with GFR capability

Table 3.2: Parameters: Critical, Essential, and Non-essential Loads

Load buses	Priority	Location
Critical	High	7, 14, 24
Essential	Moderate	4, 8, 18, 25, 30, 32
Non-Essential	Low	2, 3, 5, 6, 9, 10, 11, 12, 13, 15, 16, 17, 19, 20, 21, 22, 23, 26, 27, 28, 29, 31, 33

availability of solar PV units and wind turbines may vary depending on the weather and time of day.

- This study divides the loads into three categories, same as in Chapter 2, where CLs are identified based on their importance to network operations and have the highest priority (as given in Table 3.2). The EL have medium priority, whereas non-ELs have the least priority. Upon energy optimization, non-ELs are shed first, and then ELs are shed to maintain a continuous supply to CLs.
- All loads are connected to smart meters and can be restored/shed with respect to their priority.

3.2 Framework of Proposed PERA and Resilience Metric

The multi-constraint two-stage PERA has been developed for evolving distribution grids with high penetration of IBDRs. Fig. 3.1 illustrates the architecture with a detailed implementation of power and energy optimization for resilience-oriented restoration over the time horizon. The proposed framework obtains necessary information, such as weather data based DER availability, and various system parameters. Later, it scans the active distribution network at different time steps, $\tau=\{t_{dis}, t_{res}, t_{rec}\}$, where t_{res} includes the restoration time of both the stages as $\{t_{st1}, t_{st2}\}$ -to

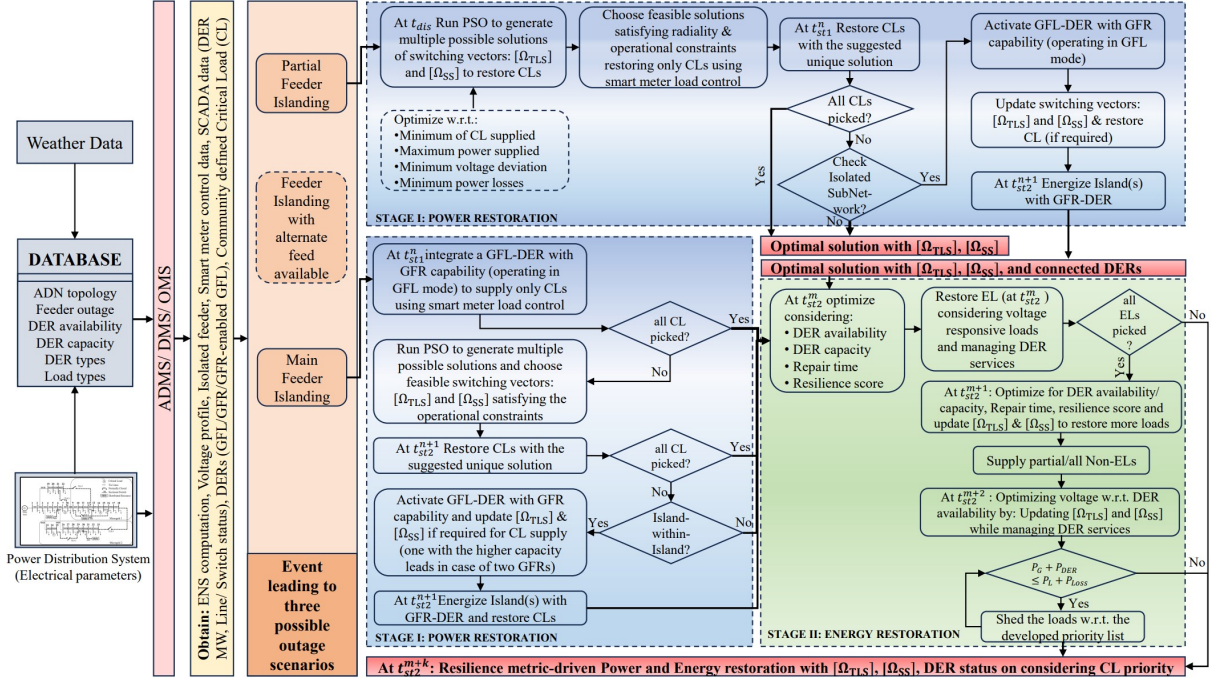


Figure 3.1: Detailed Overview of Proposed Power and Energy Restoration Algorithm (PERA).

derive a resilience-metric driven restoration. The event interrupts the supply at t_{dis} and starts restoring at t_{res} . t_{rec} represents the time of an actual grid-connected PDS, which either depends on repair time or the fault-clearing time. Stage I restores the power to CLs in two steps, defined as $\{t_{st1}^n, t_{st1}^{n+1}\}$, whereas the power and energy restoration of all the loads is optimized in stage II in $\{t_{st2}^m, \dots, t_{st2}^{m+k}\}$. This process allows the operator to maximize and manage the restoration by observing the real-time DER intermittency over the time horizon, i.e., till t_{st2}^{m+k} .

3.2.1 Stage I- Power Restoration

This study formulates the power restoration problem for three possible events causing either partial or main grid islanding. It strives to restore the CLs upon optimizing (i) voltage variations, (ii) power supplied to CLs, (iii) radial reconfiguration with minimum losses, and (iv) maximum service restoration considering operation and control modes of DER.

Network reconfiguration with TLSs is a traditional and effective way to restore the ENS dur-

Algorithm 1: Optimal network configuration for restoration

Input: Possible switching combinations $\leftarrow$ swarm_size
Input: Penalty weights for violation $\leftarrow (\omega_{VD}, \omega_{CL}, \omega_r, \omega_{loss})$
Output: Optimal switching configuration $\leftarrow gbest(\Omega_{TLS}),$
Power_restored (P_{opt})

Initialization: iteration count; particle velocity (v); inertia weights ($\omega_{max}, \omega_{min}$); cognitive and social coefficient ($c1, c2$); $pbest, gbest, fpbest, fgbest$; fitness function (ζ); tieline switches (TLSs); critical loads (CLs)

```
1: while max_iteration do
2:   Update  $\omega \leftarrow \omega_{max}, \omega_{min}$ 
3:   Update  $v \leftarrow \omega, c1, c2$ 
4:   Update particle position  $x \leftarrow$  clamp to 0/1
5:   Solve equations in (27-36) with optimal power flow
6:   func.1 { $P_{opt}, switch\_conf\_opt, num\_switch\_opt, loss$ }
7:   for  $i = 1: size(x, 1)$  do
8:     Loop through all  $x(i, :)$  switch combinations
9:     Evaluate sum ( $x(i, :)$ ) to determine opened switches
10:    for  $j = 1: size(TLSs, 1)$  do
11:      find ( $TLSs == TLSs(j)$ )
12:      Update branch switch status
13:      if all ( $abs(P_{mismatch}) < 1e^{-3}$ ) then
14:        Update output
15:      end if
16:    end for
17:  end for
18:  func.2 { $topology\_violation$ }
19:  for  $i = 1: n_{bus}$  do
20:     $C_B \leftarrow$  Initialize_bus_list
21:    Implement recursive Depth first search to trace buses
22:    Check for loops in connected branches
23:    radial = all(buses_explored) && ~loop
24:    Update topology_violation  $\leftarrow$  clamp to 0/1
25:  end for
26:  for  $i = 1: length(CLs)$  do
27:    if ~ismember(CLs)  $\leftarrow$  Checking_CL_existence then
28:      Penalty for missing CL
29:    end if
30:    if  $V_D < min\_volt \parallel V_D > max\_volt$  then
31:      Penalty for voltage deviation at CL
32:    end if
33:  end for
34:  for  $i = 1: size(TLSs, 1)$  do
35:     $\zeta(i) \leftarrow (\omega_{VD}, \omega_{CL}, \omega_r, \omega_{loss})$ 
36:  end for
37:  Update { $pbest, fpbest$ }
38:  Update { $gbest, fgbest$ }
39:   $gbest \leftarrow switch\_conf\_opt$ 
40: end while
```

ing a disruption. The deployment of TLSs and remote terminal units is preferred for advanced automation, and the investment is even looked at by the US Department of Energy [57]. Various researchers have presented methodologies to reconfigure the PDS and restore the ENS. Some studies produce the result for switching using dynamic programming [58], genetic algorithm [59], etc., for conventional PDS without DERs. However, a distribution system is no longer radial with the introduction of DERs, due to reverse power flow [60]. Thus, this chapter proposes an algorithm to generate the switching vectors with TLS $[\Omega_{TLS}]$ and SS $[\Omega_{SS}]$, respecting the voltage and power constraints in a PDS. Algorithm 1 is a significant part of PERA, which utilizes PSO to generate the optimal switch reconfiguration, suggesting the path to restore the CLs. Particularly, a SN, which is the islanded part of a feeder, communicates with other SN via TLSs, such that each CL gets supplied by only one source in a radial active distribution network. Thus, $[\Omega_{SS}]$ delivers the set of opened switches to maintain the radiality while restoring the CLs with the suggested TLS vector $[\Omega_{TLS}]$. Moreover, solving a non-linear problem with approximations in a smaller system does not impact the results much. However, this study deals with a large number of control variables with mixed integers, and thus, Algorithm 1 uses penalty-based constraint handling by particle swarm optimization instead of traditional mathematical optimization. The ease of implementation to handle the nonlinearity and suitability for the iterative optimization provide a certain edge with PSO in resilience-driven restoration. It takes the penalty weight for (i) voltage violation (w_{VD}), (ii) minimum of CL not supplied (w_{CL}), (iii) radiality violation (w_r), and (iv) increased loss (w_{loss}) as the inputs, and the switching combination as the search space. The penalty weights are used in the computation of the fitness function to derive the most optimal reconfiguration ($g_{best} : switch_conf_opt$), resulting from function 1 ($func.1$) along with the restored load (P_{opt}). Function 2 ($func.2$) verifies a radial PDS and updates the topology violation in a binary variable, i.e., 1 if there is no violation and 0 if it is non-radial. It uses the same binary notation to update the particle position and generate the optimal switching vector as the unique solution. It later calls the power flow from the ETAP software to compute the resiliency of the PDS. This algorithm is capable of providing flexible results with multiple redundant paths to restore the CLs at each time

step. Further, this study addresses the restoration of an electrical island with a CL. In such cases, PERA connects the GFL-DER that has the capability to supply the CLs as a GFR-DER. The proposed algorithm (PERA) even addresses the restoration in the case of substation or main feeder islanding. The instant implementation of the first stage restores the power to CLs, considering the operation and control modes of DERs in partial outages and grid islanding scenarios.

Operation and control Mode of Connected DERs

In a DER-rich PDS, it is crucial to observe the operation and control-based working, as IBDR can operate in four modes. A GFR-DER operates as an independent energy source, while a GFL operates more like a current source. Therefore, a SN with a GFL-DER necessitates connection to another SN equipped with a GFR-DER to supply the loads. The significance of each DER is determined by its active control mode and is defined by the respective operation. This approach assigns a higher weight to GFR-enabled GFL-DERs over the GFL because of their capability to convert to a GFR and operate independently in islanding. The assigned weights also have an influence of the operation mode of DER. This study considers that the GFR-DERs operate in voltage-control mode while the GFL-DERs operate in MVar-control mode. The GFR-DERs keep the voltages constant with a constant active power flow while having a variable reactive power output. Whereas the GFL-DERs have a constant active and reactive power flow while operating in MVar-control mode. The control system automatically adjusts the excitation to maintain the VArS regardless of the MWs during t_{st2}^{m+k} . Thus, the inclusion of the operation and control mode of DER provides a real-time on-field edge to this study.

3.2.2 Stage II- Energy Restoration

Real-time constraints over the time horizon characterize the restoration in the second stage. Upon updating the optimal solution to supply the CLs in stage I, stage II provides flexibility to the operator to optimize the power and energy to restore more loads beyond the CL. It formulates voltage-responsive loads and regulates feeder voltages to reduce the power consumption to supply

ELs/non-ELs. The developed strategy benefits the customers and utilities by restoring more loads beyond CL. It restores the loads on scanning the PDS in a gradual manner at multiple time steps $\{t_{st2}^m, t_{st2}^{m+1}, t_{st2}^{m+2}\}$. At t_{st2}^m , it immediately restores the ELs on optimizing (i) time- and weather-dependent DER availability, (ii) real-time DER MW capacity, (iii) associated repair time, and (iv) resilience score. The power and energy are continuously monitored at an interval of 15 minutes, which is variable and can be set according to the grid operator. The optimization results deliver maximum load restoration while considering DER intermittency over the time horizon.

DER Resource Management Over the Time Horizon

DERs have a limited reserve that may even lead to load shedding after the restoration. Thus, a detailed optimization of energy is required to benefit the utilities and customers. Stage II utilizes voltage-responsive loads to reduce the load consumption and maximize the load restoration. Moreover, resource management considers the issues due to uncontrolled DER output and the impact on voltage level, power flow limits, and management of distribution grids. The developed approach observes the active distribution network at an interval of 15 minutes after t_{st2}^1 , and allows for restoring/shedding the desired load based on the expected variability. Thus, it provides flexibility to the operator to look several steps ahead and take restoration measures based on the DER availability and energy requirement over the time horizon.

Cold Load Pick Up

CLPU emerges due to the surge in power demand following an extended outage. This sudden surge in the load poses a significant challenge for utilities to estimate the CLPU with numerous renewables installed in the distribution network. The DERs make the load demand surpass the pre-outage cutoff power during CLPU. Thus, there is a need to reduce the significant rise in line currents during restoration in a DER-rich distribution system [61]. The developed load restoration strategy steadily energizes the loads at t_{res} , based on the priority. This gradual increase in load aids in reducing the shoot in the peak of the load demand at t_{res} and energizes the restoration depending on the outage duration for time τ .

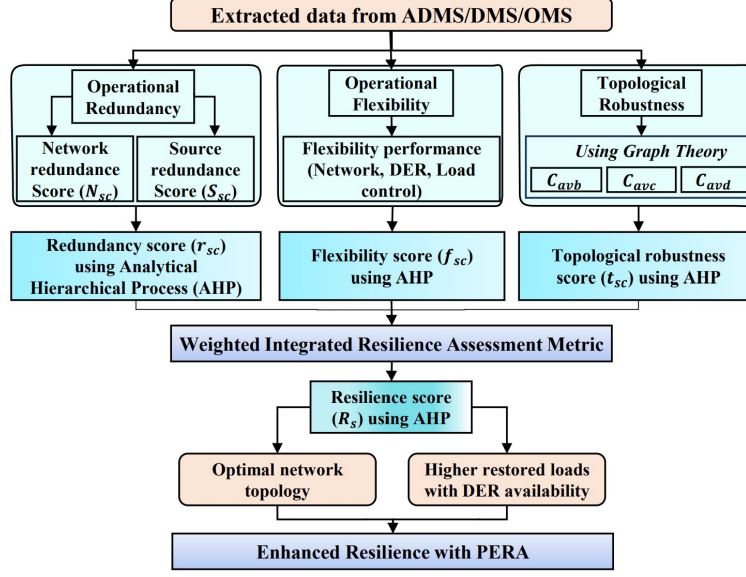


Figure 3.2: Schematic of Integrated Resilience Assessment Metric.

3.2.3 Resilience Metric

The developed operational resilience metric is taken from Chapter 2, to drive the optimal solution by the proposed PERA. This metric correlates various operational attributes and quantifies an integrated resilience score supporting operational redundancy, operational flexibility, and topological robustness. The Resilience Score (R_S) is a normalized index ranging from 0 to 1, where $R_S = 0$ represents minimum resilience and $R_S = 1$ indicates maximum resilience of the system. It is important to note that similar levels of load restoration may result in closely spaced R_S values, as the score also captures the combined effect of operational redundancy, operational flexibility, and topological robustness under different operating conditions. Fig. 3.2 briefly illustrates the computation of the metric and its utilization in a DER-rich PDS. For an overview, this section explains the utilized attributes in brief for a proper understanding. The evaluation of network and source redundancy scores ensures operational redundancy by supplying all the CLs via the unique solution. It comes into the role after an event has occurred. The network redundancy score involves the restoring path, frequency of nodes in the redundant path from source to load, and network radiality in a single computed score. The N_{sc} is evaluated as:

$$N_{sc} = \sum_{i=1}^{N_{\text{path}}} w_{Ni} k_{i_{PSO}}^{th} \quad (3.1)$$

where w_{Ni} is the weight associated with each unique solution defining the ratio of CLs supplied to all the loads for $k_{i_{PSO}}^{th}$. Here $k_{i_{PSO}}^{th}$ represents the summation of each path involved in the unique solution, restoring the CLs, and computed as:

$$k_{i_{PSO}}^{th} = \frac{\text{Common branches in } k_i \text{ unique_solution}}{\# \text{ branches in } k_i \text{ unique_solution}} \quad (3.2)$$

The estimation of source redundancy based on the DERs and their availability makes this approach distinctive. It computes the SLDA to support the pre-event preparedness and quantifies the source redundancy score to support the operational resilience. The computation of SLDA requires the real-time availability of DERs that get multiplied with a computed weight to determine the S_{sc} , as in (3.4).

$$SLDA(\%) = 1 - \frac{\sum_{i=0}^{N_{DER}} S_i (1 - \alpha_i)}{\sum_{i=0}^{N_{DER}} S_i} \quad (3.3)$$

$$S_{sc} = \sum_{i=0}^{N_{DER}} \varphi_i \cdot SLDA_i \quad (3.4)$$

The detailed description of each variable has been given in Chapter 2.

The second attribute is operational flexibility, which ensures a flexible performance in supplying a higher number of CLs. This score delivers the availability of CLs in the formulated metrics, resulting from the optimized switching and DER integration. Further, topological robustness ensures the awareness with the best network topology evaluated with three centrality indices. The graph theory-based C_{avb} , C_{avc} , and C_{avd} are given respective weights to evaluate the weighted topological robustness score. These weights are computed via the same process as in Chapter 2 and are given in Table 3.3.

The developed resilience metric is the same as that utilized in Chapter 2. It integrates the weighted sum of all the attributes to evaluate the resilience score. These weights are subjective and can be computed via the analytical hierarchical process as per the system requirement.

$$\text{Resilience Score : } R_S = w_{R1} r_{sc} + w_{R2} f_{sc} + w_{R3} t_{sc} \quad (3.5)$$

Table 3.3: AHP-based Pairwise Criteria Weights for Attributes

w_i for	S_{sc}	t_{sc}	R_s
w_1	0.5	0.171	0.537
w_2	0.168	0.550	0.267
w_3	0.33	0.277	0.195

$$R_S = w_{R1} (w_{r1}N_{sc} + w_{r2}S_{sc}) + w_{R2} \left\{ \frac{\sum_{i=1}^N \int_{t_{int}}^{t_{rec}} n_{i,t} dt}{\sum_{i=1}^N \int_0^{t_{res}} n_{i,t} dt} \right\} + w_{R3} (w_{t1}C_{avb} + w_{t2}C_{avc} + w_{t3}C_{avd}) \quad (3.6)$$

Here r_{sc} , f_{sc} , and t_{sc} represent the operational redundancy, operational flexibility, and topological robustness, with the associated weights w_{R1} , w_{R2} , and w_{R3} , respectively. Equation 3.6 gives the expanded form of the integrated metrics, where the weighted scores of N_{sc} and S_{sc} accumulate to operational redundancy (r_{sc}); and the weighted score of avg betweenness centrality, avg closeness centrality and avg degree centrality accumulates to topological robustness (t_{sc}). The flexibility score f_{sc} represents the fraction of CLs supplied in interval N_t , where N and n are the total loads and CLs, respectively.

3.3 Resilience-Oriented Problem Formulation

In a three-phase system, the nonlinear relationship between the measurement quantities and the mutual coupling between the phases results in non-linearity. This study denotes three phases a, b, c by phase p , and the set of phases on bus i as θ_i . The formulated problem aims to satisfy the objective and optimize multiple constraints involved in restoration. This section briefly explains the involvement of each parameter and mathematically models the three-phase power flow to deliver a resilient DER-rich PDS.

3.3.1 Multi-constraint optimization

PDS loss index to observe the power balance

Minimizing the PDS losses is not the primary objective of this study. However, the losses are directly connected to the extra cost of generation required to compensate for loads. Thus, minimizing losses may improve the reliable power supply [62] and is considered in this study. It is defined as:

$$P_{L,ij} = \frac{(r_{ij} (P_i P_j + Q_i Q_j) \times \cos(\theta_i - \theta_j))}{V_i V_j} \quad (3.7)$$

where $P_{L,ij}$ represents the PDS losses and θ is the load angle. P_L is required to approximate the unbalance in power with P_{jk} and Q_{jk} accumulates to S_{jk} ; $S_{jk}^{pp}(t) = P_{jk}^{pp}(t) + jQ_{jk}^{pp}(t)$. On introducing squared voltage and current, i.e., $v_k = V_k^2$ and $i_k = I_k^2$, the complex power flow is given as:

$$S_k = V_k I_k^* \longrightarrow i_k = \frac{P_k^2 + Q_k^2}{v_k} \quad (3.8)$$

Voltage Deviation Index

Optimizing the voltage profile is a challenging task in the evolving distribution systems. With the increase in electric vehicles or IBDRs, there is a need to model the impact of voltages on the network. It is achieved by optimizing the voltages within ANSI or IEC limits [63]. This study optimizes for a healthy voltage profile and maintains it within an acceptable range of $\pm 5\%$ under all operating conditions. The assistance in voltage violation handling with the DER penetration provides an edge to the utility in developing a resilient, reliable, and robust PDS, achieving complete voltage control. The valid equations concerning this constraint, while approximating the unbalance in voltage is given as:

$$V_j - V_k = Z_k I_k \quad (3.9)$$

Now, on multiplying both sides by the complex conjugate, we obtain Ohm's law squared:

$$V_k V_k^* = (V_j - z_k I_k) (V_j - z_k I_k)^* \quad (3.10)$$

$$v_k = v_j - 2r_{jk}P_{jk} - 2x_{jk}Q_{jk} + (r_{jk}^2 + x_{jk}^2) i_{jk} \quad (3.11)$$

where the voltage at line j is feeding bus j from its parent bus i . For each line, let the phase current be I_{ij}^p and the phase impedance be z_{ij} .

DER Restoration Unavailability

A GFL-DER with GFR capability is expected to perform in islanded mode during an extreme event. Let us consider that α_{DER}^k is the availability of the k^{th} DER in an active distribution network. Thus, the effective restoration unavailability is defined as the sum of the failure of a SN multiplied by the individual unavailability [51], evaluated as:

$$U_{res} = \sum_{i=1}^{N^{DER}} \left((1 - \alpha_{DER}^i) \sum_{i=1}^N \varphi_i^{DER} \right) \quad (3.12)$$

Restoration Time

It is the maximum duration for which the CLs are supplied by DER. This time must be more than the repair time to maximize resilience in a PDS. The repair time is the total time taken by the PDS to bounce back to the grid-connected. This time is the summation of the time taken by the repair crew to clear the fault or the time required for manual/automatic switching to restore the PDS. Equation 3.13 describes the maximum restoration time by the DERs, which is defined as the ratio of the capacity of the DER to the CL supplied. P_{DER} is the energy of a particular DER and P_i is the power served to i^{th} CL by a particular DER.

$$T_{res}^{DER} = \frac{P_{DER}}{\sum_{i=1}^{CL} P_i} \quad (3.13)$$

$$T_{rep}^{max} + T_{crew}^{max} < T_{res}^{DER} \quad (3.14)$$

Equation 3.14 formulates the time frame to observe the restoration, where T^{max} is defined as the maximum time taken to repair the active distribution network or by the crew, which must be comparably less than the DER availability/restoration time.

Voltage-Dependent Load Modeling

The ZIP load model is the most frequently accepted load model, which is a combination of constant impedance (Z), constant current (I), and constant power (P). Typically, the voltage control systems

rely on PQ load models, which reflect the connected loads having constant real and reactive power. The PQ model does not account for the sensitivity of loads to voltages, which is crucial to observing the voltage regulation in a DER-rich distribution grid. Here, an equivalent voltage-control load model has been adopted to visualize the voltage-responsive loads. The author in [34] defines $CV R_p$ and $CV R_q$ as the CVR factors for active and reactive power reduction, evaluated as,

$$CV R_P = \frac{dP_{\text{load}}^p}{P_0^p} \frac{V_0}{dV^p} \ \& \ CV R_Q = \frac{dQ_{\text{load}}^p}{Q_0^p} \frac{V_0}{dV^p} \quad (3.15)$$

Thus, with the consideration $v^p = (V^p)^2$, the voltage-dependent load model with CVR coefficients used in this chapter is given by (3.16)-(3.17), where the per-phase rated consumption of load at nominal voltage V_0 is defined as P_0^p and Q_0^p .

$$P_{\text{load}}^p(V) = P_0^p + CV R_P \frac{P_0^p}{2} \left(\left(\frac{v^p}{V_0^2} \right) - 1 \right) \quad (3.16)$$

$$Q_{\text{load}}^p(V) = Q_0^p + CV R_q \frac{Q_0^p}{2} \left(\left(\frac{v^p}{V_0^2} \right) - 1 \right) \quad (3.17)$$

3.3.2 Operational Constraints

$$\text{Objective: } \max \sum_{i=0}^{N_t} EPS(t) \quad (3.18)$$

$$\max R_s \quad (3.19)$$

$$\min \sum_{i=0}^{N_t} S_{\text{shed}}^k(i(t)) \quad \forall t \in [t_{\text{dis}}, t_{\text{res}}] \quad (3.20)$$

Subject to:

$$\sum_{j \rightarrow k} P_{jk}^{pp}(t) = P_{ij}^{pp}(t) + P_{DER_j}^p - P_{L,ij}^{pp} - P_{\text{load},j}^p \quad (3.21)$$

$$\sum_{j \rightarrow k} Q_{jk}^{pp}(t) = Q_{ij}^{pp}(t) + Q_{DER_i}^p - Q_{L,ij}^{pp} - Q_{\text{load},j}^p \quad (3.22)$$

$$(S_{jk}^{pp}(t))^2 = (P_{jk}^{pp}(t))^2 + (Q_{jk}^{pp}(t))^2 \quad \forall j, k \in n \quad (3.23)$$

$$S_{jk}^{pp}(t) = V_j^p(t) I_{jk}^{pp}(t) \quad (3.24)$$

$$v_k = v_j - 2r_{jk}P_{jk} - 2x_{jk}Q_{jk} + (r_{jk}^2 + x_{jk}^2) i_{jk} \quad (3.25)$$

$$I_{jk}^{pp} \leq I_{jk}^{pp, \text{rated}} \quad (3.26)$$

$$0.95 \leq v_j^p(t) \leq 1.05 \quad (3.27)$$

$$Q_{DER,k}^p \geq -\sqrt{\left(S_{DER,k}^{\text{rated},p}\right)^2 - \left(P_{DER,k}^p\right)^2} \quad (3.28)$$

$$Q_{DER,k}^p \leq \sqrt{\left(S_{DER,k}^{\text{rated},p}\right)^2 - \left(P_{DER,k}^p\right)^2} \quad (3.29)$$

$$T_{\text{rep}}^{\text{max}} + T_{\text{crew}}^{\text{max}} < T_{\text{res}}^{DER} \quad (3.30)$$

Equations (3.21)-(3.30) describe the constraints involved in maximizing the load restoration given by the EPS and the resilience of the network. Constraints (3.21)-(3.22) denote the branch flows, which are to be verified for each SN or island individually. The following constraint maintains the rated kVA capacity of the load. Transformers have specified kVA capacity, while lines have thermal limits defined by their ampacity. Constraints (3.25)-(3.27) describe the rated current and voltages, where the healthy network maintains the voltage within an acceptable range of $\pm 5\%$ under all operating conditions. The reactive power limits of DER are given by (3.28)-(3.29). Equation (3.30) defines the restoration time, which should be more than the maximum repair time $T_{\text{rep}}^{\text{max}}$ required for automatic or manual switching and the $T_{\text{crew}}^{\text{max}}$ which is required by the crew to clear the fault.

3.4 Case Study and Result Discussion

This section demonstrates the resilience-driven restoration by the proposed PERA. The implementation on balanced IEEE 33 and unbalanced 123 bus radial PDSs verifies the efficacy of the proposed PERA on different bus sizes. The optimization algorithm (Algorithm 1) is modeled on MATLAB/MATPOWER 6.0, and ETAP 19.0.1 is utilized to implement various outage scenarios. This study develops an undirected graph of the PDS one-line on Cytoscape v3.10.1 to examine the topology. Further, it calls the power flow solution from ETAP and the graph theory results

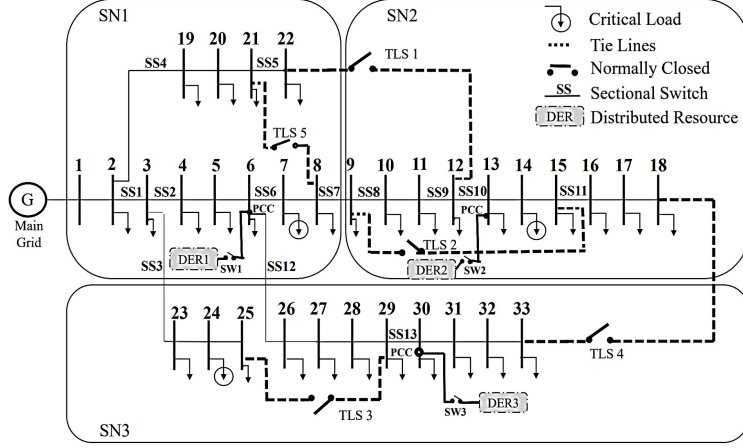


Figure 3.3: Modified IEEE 33 Bus Radial Distribution System.

Table 3.4: Pre-event Analysis with DER Availability

Case	DER availability (α_n)	% P_{CL} at t_{dis}	Impact on Rs
I: 4-5	$\alpha_1 = \alpha_2 = 0.95; \alpha_3 = 0$	33.3	0.220
II: 12-13 & Islanding	$\alpha_1 = 0.95; \alpha_2 = \alpha_3 = 0.2$	0	0.311
III: 5-6, 6-26, 6-7	$\alpha_1 = \alpha_3 = 1; \alpha_2 = 0$	33.3	0.228
IV: 8-9, 21-22, 29-30	$\alpha_1 = \alpha_2 = 0.5; \alpha_3 = 1$	66.3	0.312
V: 8-9, 3-23, 2-19	$\alpha_1 = 0; \alpha_2 = \alpha_3 = 0.7$	33.3	0.229

from Cytoscape to evaluate the integrated resilience score. The following study exhibits various scenarios to validate an effective restoration by PERA in DER-rich PDS.

3.4.1 Performance of PERA on Balanced 33-bus PDS

Fig. 3.3 illustrates the modified IEEE 33 bus PDS operating at 12.65 kV with 3.72 MW and 2.3 MVar of active and reactive demand, respectively, with three DERs (initially operating in GFL mode). The system underwent various single and multiple events to analyze the performance of the proposed PERA. This chapter presents some selected events with their suggested remedial measures due to space restrictions. However, it details the resilient unique solution that best fits the criteria with maximum recovery and minimum shedding and maintains real-time grid operation. For a better understanding, the possible solutions for the first event are presented, and the significance of the resilient unique solution is explained here.

Table 3.5: Post-Event Recovery for Multiple Events on Modified IEEE 33 Bus System

Case	Stage I (Suggested reconfiguration)	Stage II (Updated reconfiguration)	Load Recovery (%)			Scores			R_s
			t_{dis}	t_{st1}^n	t_{st2}^{m+k}	r_{sc}	f_{sc}	t_{sc}	
I	$\Omega_{TLS}:[12-22]$	$\Omega_{TLS}:[12-22, 25-29]$	39.4	51.2	100	0.83	1	0.67	0.843
		$\Omega_{SS}:[3-4, 7-8]$							
II	$\Omega_{TLS}:[18-33]$	$\Omega_{TLS}:[18-33]$	0	16.6	100	0.81	1	0.63	0.827
		$\Omega_{SS}:[-]$							
III	$\Omega_{TLS}:[8-21]$	$\Omega_{TLS}:[8-21, 25-29, 18-33]$	44.6	52.9	94.1	0.83	1	0.63	0.825
		$\Omega_{SS}:[11-12]$							
IV	$\Omega_{TLS}:[-]$	$\Omega_{TLS}:[18-33, 12-22]$	63.1	66.3	100	0.8	1	0.78	0.845
		$\Omega_{SS}:[-]$							
V	$\Omega_{TLS}:[25-29, 18-33]$	$\Omega_{TLS}:[25-29, 18-33, 8-21, 12-22]$	45.6	62.6	41.5	0.84	1	0.67	0.848
		$\Omega_{SS}:[-]$							

Table 3.6: Load Restored at Each Iteration

Iteration	Load Restoration (%)				
	Case: I	Case: II	Case: III	Case: IV	Case: V
1	51.2	16.6	52.9	66.3	62.6
2	74.1	20.1	59.4	79.9	70.2
3	93.5	52.3	94.1	100	97.4
4	100	100	94.2	100	100

The first case considers an event hitting the line connecting buses 4 and 5. As a result, SS2 between buses 3 and 4 disconnects. The availability of DERs, connectivity to CLs, and the resilience score at the time of interruption are detailed in Table 3.4. At t_{dis} , the PDS is equipped with TLSs and DERs to restore the supply. Thus, at t_{st1}^1 , the algorithm scrutinizes the feasible solutions based on the (i) paths restoring the maximum loads while supplying a minimum CL power and (ii) paths not forming a loop from source to load. The three feasible solutions among multiple possible solutions are:

Path 1. $\Omega_{TLS} : [25 - 29, 8 - 21]$ and $\Omega_{SS} : [3 - 4]$

Path 2. $\Omega_{TLS} : [25 - 29, 12 - 22]$ and $\Omega_{SS} : [3 - 4]$

Path 3. $\Omega_{TLS} : [12 - 22, 8 - 21]$ and $\Omega_{SS} : [9 - 10]$

These solutions represent the optimal switching vectors that indicate closed TLSs and opened SSs to restore the network. More number of feasible solutions increase the level of redundancy and are used to compute the network redundancy. In this case, Algorithm 1 picks Path 1 as the unique solution to restore the CLs by closing TLS 12-22. PERA optimizes the energy and maximizes the restored load in stage II by implementing voltage-responsive loads. Table 3.5 summarizes the suggested switching vectors in Stage I and the updated reconfiguration in Stage II for all the simulated cases. For example, in case I, all CLs are supplied by closing TLS 12-22. The network reconfiguration remains the same while restoring the ELs at t_{st2}^1 . The algorithm restored all the loads after t_{st2}^2 with DERs working as GFL in MVAR-mode. The DER availability gets affected (on the next iteration) after a 15-minute interval at t_{st2}^3 , where α_3 becomes 0- indicating zero availability of DER3. Since there was no effect of unavailability on the loads, thus, there was no load shedding.

Table 3.6 delivers the results for load restoration at each iteration. The proposed model shows its supremacy in restoring all the loads on optimizing energy over the time horizon. Furthermore, to verify the efficacy of the proposed PERA in islanding, case II considers a disconnection of the line between bus 12 and 13, followed by grid islanding. The PERA immediately scrutinized for convertible DERs and operated DER1 in GFR mode. The integration of DER1 supplied all the CLs, except at bus 14 (due to the electrically isolated SN). Thus, at t_{st1}^2 , Algorithm 1 maximizes the power to CLs on closing 18-33. At t_{st2}^1 , PERA verifies for DER availability and observed $\alpha_2=\alpha_3=0.2$. However, upon optimizing the energy with respect to real-time DER availability/capacity, repair time, and operating voltage, the PDS is fully recovered at t_{rec} .

This work demonstrated three multiple-outage cases, depicting different scenarios to demonstrate the on-field performance of the proposed restoration algorithm (PERA) in electrical islands, isolated SNs, load shedding, the utilization of GFR/GFL-DER, and energy optimization over the time horizon. Case III simulated a sequence of events that isolated bus 6 and disconnected 53.3% of the load. There was an instant bounce back, recovering all the unserved CLs by the suggested reconfiguration in stage I. This switching vector gets updated in stage II while recovering the other

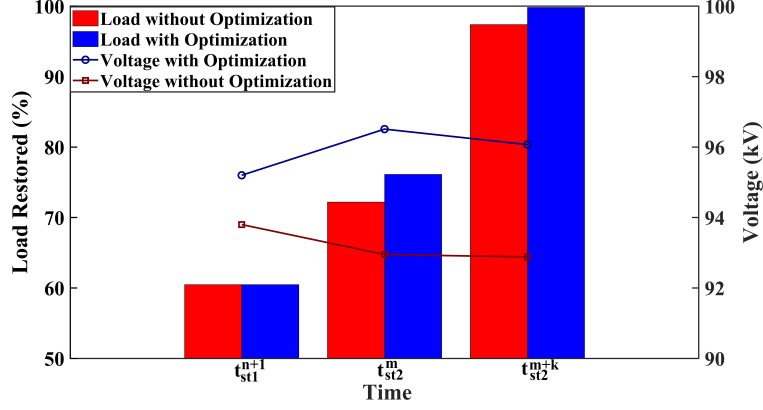


Figure 3.4: Maximizing Load Restoration on Optimizing Constraints in Case-V.

loads. The gradual picking up of loads at t_{sta}^b allows the utility to maximize the restoration while reducing the peak in the inrush current from CLPU consideration. Further, case III observed an unavailability issue at t_{st2}^1 with $\alpha_2=0$ and not enough power to restore the loads. Algorithm 1 suggested connecting TLS 18-33 and 25-29 to recover the ELs and non-ELs while implementing the CVR. The next case, case IV, represented the recovery in an electrically isolated SN. Since the isolated SN has a GFL-DER, PERA checked for the DER convertibility. The system observed a full recovery upon DER conversion and TLS connection. A load-shedding scenario has been demonstrated in the last case where the PDS observed $\alpha_1=\alpha_2=\alpha_3=0$ at t_{st2}^{m+k+1} . This started the shedding of loads with respect to the developed priority list. Hence, all the non-ELs were shed along with an EL at bus 25 in order to supply the CLs. Fig. 3.4 demonstrates the restoration of maximum possible loads with 41.5% of power supplied even with the load-shedding at t_{st2}^{m+3} .

Remark 1: The proposed PERA implements the load restoration in two stages, where the time of restoration is defined as $t_{res}=t_{st1}^n+t_{st2}^{m+k}$, with $n=[1,2]$ and $k=[1,2,3,...]$. n represents the iteration giving the optimal solution for stage I, and $m+k$ is the step delivering a resilient recovery following the iterative optimization in stage II, as shown in Fig. 3.5.

Remark 2: PERA optimizes the power and energy at different time steps on considering the DER resource management over the time horizon. It models the voltage-responsive loads to maximize the restoration beyond CLs for implementing power consumption reduction, loss minimiza-

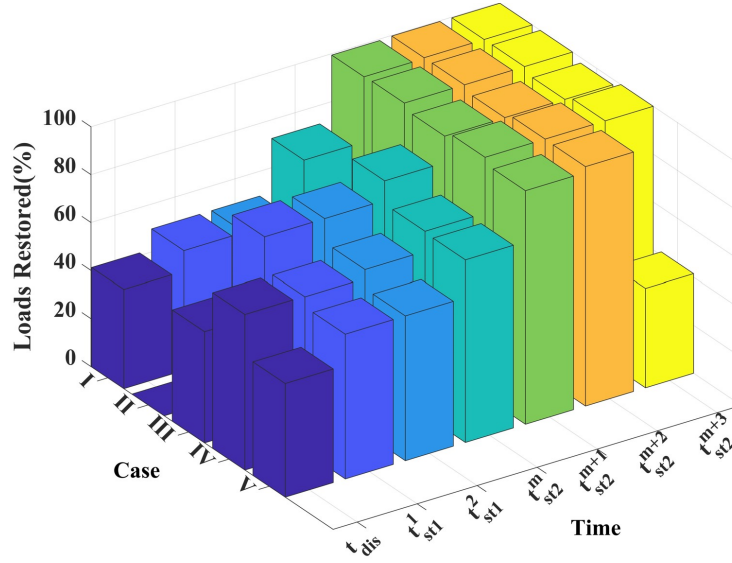


Figure 3.5: Temporal Analysis of Load Restoration in Single and Multiple Events.

tion, and feeder voltage regulation. The developed priority-based load list benefits the customer and utilities in restoring the maximum possible load even after the shedding. This capability of the PERA to cope with the load shedding while supplying the CLs sets a high tolerance for a resilient infrastructure. Fig. 3.6 authenticates the efficacy of the PERA by demonstrating the improvement in the resilience score of a DER-rich PDS.

3.4.2 Performance of PERA on Unbalanced 123-bus PDS

The proposed restoration tool has also been thoroughly tested on a large, unbalanced modified 123-bus feeder, operating at a nominal voltage of 4.16 kV as shown in Fig. 3.7. The system is considered to have twelve three-phase switches as per the IEEE PES feeder data [64], and four added IBDRs at node 4, 26, 86, and 60. All IBDRs are initially considered to be in grid-connected mode and operating as GFL-DERs. It is assumed that among the four, DER1, DER2, and DER3 have the capability to serve as GFR-DERs. For a rigorous analysis, this section simulates and compares the performance of the PDS under the same disruptive events as in [51]. Author in [51] (i) didn't consider the possibility of an alternate feed (besides substation) to supply the CLs, (ii) utilized

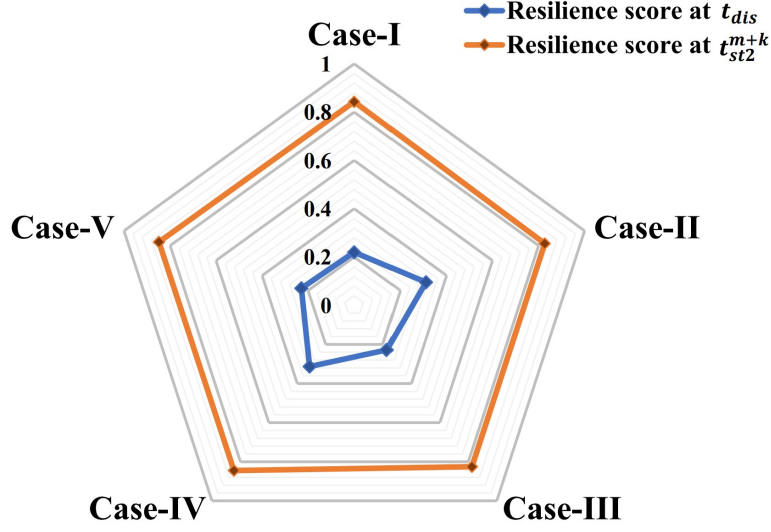


Figure 3.6: Improved Resiliency with PERA on DER-rich 33-bus System.

only DERs (no tie-lines) to restore the CLs, and (iii) suggested service restoration to only CLs. This work considers the same location and specification of DERs/CLs for an unbiased comparison. However, it considers TLSs and alternate feeds for a realistic on-field scenario. It successfully restored the same number of CLs with fewer DERs, and optimized power and energy on observing the DER intermittency. This strategy operates the three-phase switches as TLS for restoring power to CLs.

Event Resulting to Partial Feeder Islanding

The first case considered a minor disruption at lines 18-13 and 52-152 with equal availability of DERs. The simulated case considered $\alpha_1=\alpha_2=\alpha_3=\alpha_4=0.95$. The optimal results on implementing PERA suggested connecting DER2 as GFR (operating in voltage-control mode) and closing TLS 151-300 to maximize the CL restoration. The event affected 82% of CL at t_{dis} with 9 CLs not supplied. The proposed restoration strategy successfully restored the power to CLs and non-CLs at t_{st2}^5 . This iterative optimization of power and energy continued over a time horizon, with an observation to shed/restore the loads at an interval of 15 minutes. Further, the next case assumed an unequal availability of DERs with major disruption, disconnecting lines 26-27, 13-18, 91-93,

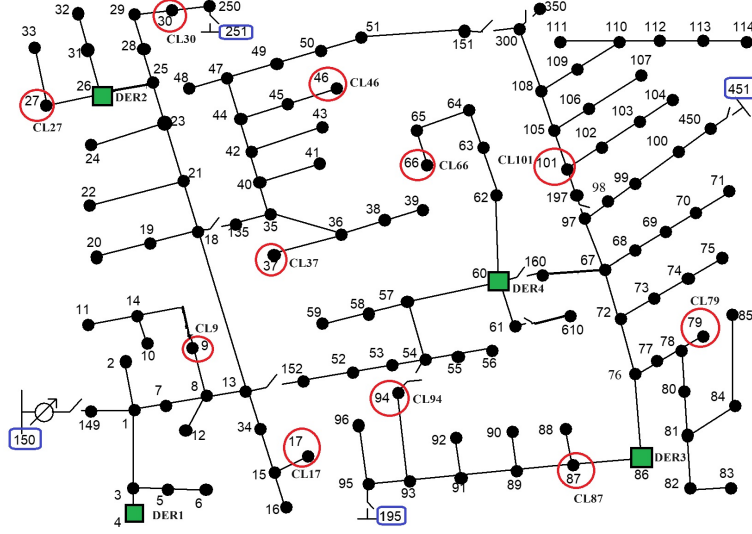


Figure 3.7: Modified IEEE 123 Bus Test Feeder.

Table 3.7: Strategy for Minor Damage with Grid Islanding

Active DERs	DER Availability	% P_{CL} at t_{dis}	CLs Served	T_k^{res} (hours)	U_{res}^{DER}
DER-1	0.95	18.18	9, 17	10.84	0.5
DER-2	0.95	36.36	27, 37, 30, 46	10.38	0.9
DER-3	0.95	18.18	101, 66	10.59	0.5
DER-4	0.95	27.27	79, 87, 94	19.6	0.55

54-57, and 67-97. It considers $\alpha_3 = 0.92$ and 0.95 for other DERs. Algorithm 1 suggested closing TLS 54-94 and operating DER2 and DER3 in GFR mode. The optimal measure served 81% of CLs and 88.6% of loads in the PDS.

Grid Islanding with Alternate Feed Available

This case assumed a disruption at the transmission side that disconnected the main supply to the distribution system. The event disconnected the substation at bus 150, resulting in grid-islanding. In such outages, the proposed PERA investigates an alternate feed to re-energize the PDS. This work considers the alternate feed available at bus 451 [64] to bounce back to the grid-connected mode. On implementing, the proposed PERA successfully restored the PDS with 100% load supplied at t_{st2}^5 .

Table 3.8: Strategy for Major Damage with Grid Islanding

Active DERs	DER Availability	% P_{CL} at t_{dis}	CLs Served	T_k^{res} (hours)	U_{res}^{DER}
DER-1	0.95	27.27	9, 17, 94	13	0.65
DER-2	0.95	27.27	30, 37, 46	10.24	0.65
DER-3	0.92	18.18	79, 87	10.59	0.64
DER-4	0.95	18.18	66	19.51	0.6

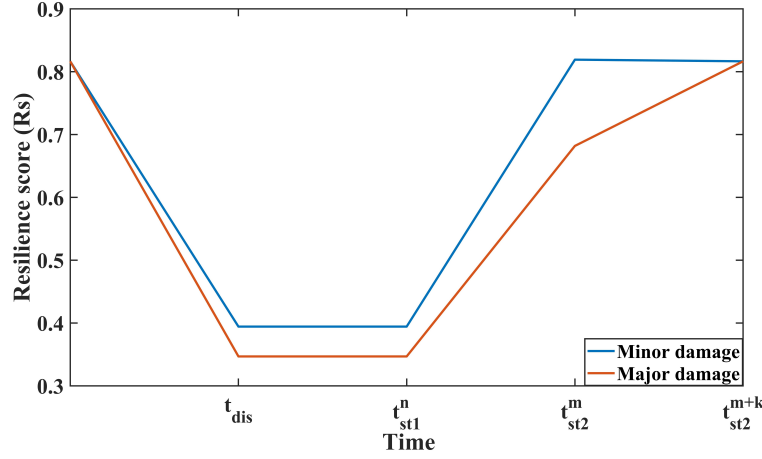


Figure 3.8: Resilience Score with PERA on DER-rich Unbalanced 123 Bus Feeder.

Event Resulting in Grid Islanding

This study also investigates the performance in the case of grid islanding with no alternate feed. This scenario disconnected 100% of the load and generated a similar case presented in [51]. The comparative results for optimal restoration are given in Table 3.7 and Table 3.8, with minor and major disruptions, respectively. This section considers the same outages as in grid-connected mode with the same DER availability as discussed above. The optimal results for minor damage in stage I suggest operating DER1, DER2, and DER3 as GFR-DERs in voltage control mode to deliver 100% restoration with all CLs and non-CLs supplied. The restoration time and the DER unavailability are computed in Table 3.7, which shows similar restoration results with the proposed approach even using fewer DERs than [51]. Similarly, Table 3.8 represents the results of the major damage. The algorithm suggested operating DER2 and DER3 in GFR-mode with TLS 54-94 closed to supply all the loads by the end of stage II, i.e., at t_{st2}^5 . In the next iteration, the PDS experienced

the unavailability issue with $\alpha_3 = 0.92$; however, there was no power mismatch, and 88.6% of the load was supplied with two unserved CLs. As the final outcome, a maximum of CLs was restored with the suggested restoration strategy in stage I, and many of the non-CLs were also supplied upon optimizing power and energy with fewer DERs as compared to [51]. Fig. 3.8 illustrates the evaluation of the resilience score in both damage scenarios and successfully replicates the bounce back of the PDS at t_{st2}^{m+k} .

3.5 Outcomes

This chapter proposed a novel power and energy restoration algorithm (PERA) for resilience-driven load restoration over the time horizon in DER-rich distribution systems. This work is submitted for publication [P5]. The proposed algorithm is implemented in two stages: maximizing power to critical loads (CLs) in stage I, and optimizing power and energy to all loads in stage II. PERA is developed to restore the events leading to (a) minor/major disruption causing partial feeder islanding, (b) main grid islanding, (c) island-within-island, and (d) island with alternate feed available. Developed penalty-based iterative optimization is used to obtain a unique switching reconfiguration vector while optimizing for (i) minimum of CLs supplied, (ii) maximum of loads restored, (iii) healthy voltage profile with minimum losses, and (iv) resilient restoration path. The generated (redundant) feasible paths supplying the loads enhance the operational resilience of a distribution system. The utilized resilience metric (which has been proposed in Chapter 2) correlates various operational attributes and quantifies an integrated resilience score, which is not adequately captured by existing metrics. The integrated score ensures the optimal resilient path, restoring maximum loads with DER intermittency over the time horizon. The time-step-based load restoration energizes the CL with an immediate effect and picks the essential/non-essential loads in stage II on optimizing at 15-minute intervals. The optimization continues until the repair time or till the system is again grid-connected. The developed algorithm is simulated on balanced and unbalanced DER-rich distribution systems. The comparative results show the advantage of the proposed algorithm over the present approaches. The proposed PERA is capable of reducing the

power consumption by implementing voltage-responsive loads for loss minimization and feeder voltage regulation to optimize the energy, considering (a) weather-dependent DER availability, (b) real-time MW capacity, (c) DER types (grid following, grid forming, or grid following with grid forming capability), and (d) resilience score. Results are validated for IEEE-33 and IEEE-123 node systems with inverter-based DER.

One of the key challenges of proposing a resilience metric has been addressed in Chapter 2, and Chapter 3 builds on this by ensuring dynamic restoration over the time horizon during extreme events. This naturally sets the stage for the next objective, examining the impact of cyber-physical vulnerabilities on the power distribution system.

Chapter 4

Resiliency-Driven Vulnerability Assessment for Cyber-Induced Physical Events

4.1 General

Frequent severe power outages in power systems underscore the system's inability to manage the high-impact, low-probability events effectively. The occurrence of such events might increase in the near future. This low probability event could be a (a) cyber, (b) physical, or (c) neither a cyber nor physical event, that may severely damage the power infrastructure and have a crucial impact on the system's ability. Thus, it is necessary to strategize for a power system that is both reliable and resilient. Some recent blackouts indicate that resilience is vital for a power system [65]. Even a slight disruption can convert into a massive blackout due to the lack of resilience. As a result, in recent years, several researchers have conducted studies to investigate the detrimental impact of such events and build a secure and resilient power system [66]. However, the challenge remains the same with a smart and advanced opponent bypassing the security tools to originate an erroneous event [67]. Hence, there is a need to estimate the risk in advance to estimate resilience. Thus, this work helps the operator focus on the same by the proposed tri-stage architecture- VulnAT- to monitor and quantify the system's resilience in different scenarios. It aids in developing a secure,

reliable, and resilient DER-rich cyber-physical PDS. Thus, key contributions of this study are:

1. Proposed severity-based vulnerability assessment tool (VulnAT) models a tri-stage architecture to monitor and analyze the impact of cyber-induced physical vulnerabilities in distribution systems. The methodology details the process of event classification, identification, and management, interfacing online and offline modes, utilizing historical and real-time exposures for resilient planning and operation of a DER-rich PDS.
2. Developed decision-making algorithm recommends the most effective remedial measure on estimating the severity-based impact for a quick and effective response. It utilizes centroid-based partition clustering to classify the event into clusters concerning CVSS-based severity scores and suggests optimal restorative measures for highly severe events. The supremacy of this approach is the consideration of events having medium severity. It utilizes the Jaccard index to reflect the similarity score of event pattern recognition and suggest relevant proactive measures.
3. Proposed comprehensive resilience quantification combines physical and topological attributes to compute the resiliency. The physical score ensures the operational flexibility of the PDS, delivering maximum power supply to CLs at the time of interruption. The topological attribute utilizes graph theory-based centrality indices to ensure the maximum connectivity between the nodes and delivers a weighted topological robustness score using the analytical hierarchical process to produce comparative pairwise criteria weights for resilience quantification.
4. Proposed tri-stage architecture and the metrics are validated through rigorous case studies with distinct scenarios on a modified DER-rich IEEE 33 bus distribution system. The technical implementation utilizes ETAP, MATLAB, and Cytoscape software to illustrate the application of the methodology in different vulnerable scenarios, showcasing the success rate of VulnAT and the proposed resilience metric.

Some of the prior works [40], [43], [45], [68], [69], [70], [71], as stated in Table 4.1, provides valuable contributions toward assessing cyber-physical resilience of power grids and micro-

Table 4.1: Survey Table: Comprehensively Comparing Prior Studies

Ref.	Objective	Methodology	Advantages	Limitations	Case Studies
[40]	Developed CP-TRAM to assess resiliency in transmission systems	Resiliency assessment metric integrating cyber vulnerabilities and physical impacts	Quantitative metrics for resilience; addresses both cyber and physical aspects	Limited focus on transmission systems; applicability to distribution systems is unclear	Simulation-based case studies
[43]	Enhanced microgrid resiliency against cyber threats	Integration of cybersecurity measures in microgrid operations	Provides a framework for improving microgrid resilience	Does not consider the severity of impacts or worst-case event scenarios	Implementation on specific microgrid scenarios
[45]	Developed CyPhyR, a tool for measuring microgrid resiliency	Cyber-physical analysis tool for resilience enhancement	Quantitative analysis of microgrid resilience; integrates cyber-physical considerations	Limited application to microgrids; assumes static threat models	Validation through simulated microgrid setups
[68]	Enhanced cybersecurity of power grid	Theoretical modeling and strategies for cyber-physical systems	Comprehensive overview of security challenges and strategies	Generalized approach with no specific metrics or validation	Conceptual case studies on grid systems
[69]	Analysed cyber event's impacts on power grids	Integrated methods to quantify the physical impact of cyber events	Method to connect cyber vulnerabilities to physical consequences	Lack of focus on recovery strategies; assumes predefined event scenarios	Real-world-inspired cyber event scenarios
[70]	Developed CP-SAM to monitor microgrid resilience	Security assessment metric for microgrids	Quantitative assessment of cyber-physical resilience	Assumed it is challenging for attackers to compromise control centers, which is unrealistic given advanced attack methods	Simulation-based case studies on microgrids
[71]	Cyber-physical anomaly location and classification in power systems	Integrated anomaly detection using cyber and physical data	Effective integration of cyber and physical data; practical anomaly classification method	Focused primarily on anomaly detection without recovery strategies	Case studies on distribution systems with simulated anomalies

grids through security strategies, resiliency metrics, and anomaly detection methods. But they are largely limited by a focus on transmission or microgrid-level systems, predefined/static event assumptions, and minimal emphasis on dynamic recovery strategies. This leaves a research gap for comprehensive resilience assessment in distribution systems under evolving cyber-physical threats.

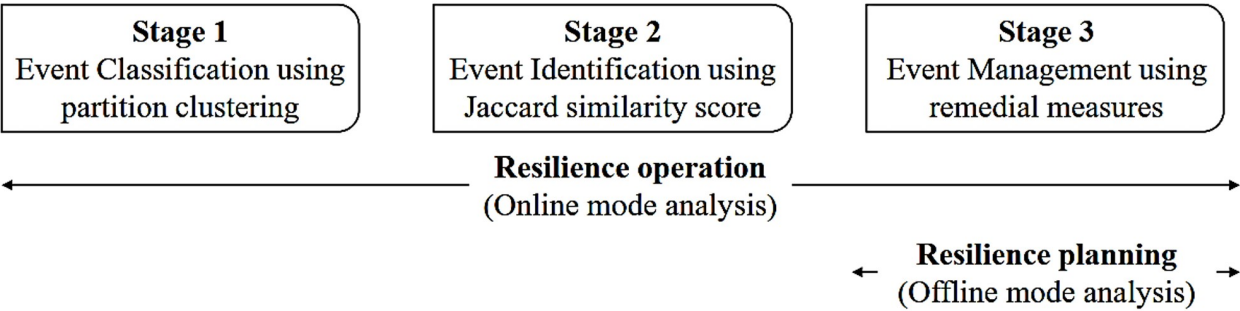


Figure 4.1: Overview of the Proposed Methodology.

Table 4.2: Severity Score Range- Depicting the Impact of the Event on the PDS

Severity Score	0.0	0.1-3.9	4.0-6.9	7.0-10.0
Rating	None	Low	Medium	High

4.2 Framework of the Proposed Tool

The developed VulnAT performs resilience monitoring in both real-time and offline mode, investigating the cyber-physical vulnerability and suggesting relevant measures, as illustrated in Fig. 4.1. It analyzes the associated risk in terms of severity and aids the system operator in suggesting appropriate measures concerning the intensity of the vulnerability. The proposed methodology not only warns of highly severe events but also considers the events with medium severity to establish a resilient PDS. Based on the severity ratings defined in Table 4.2, a threshold (τ) of 7 is determined that compels the tool to proceed with highly vulnerable scenarios in offline mode. The optimal restorative measures are the prime result of the offline analysis that aids the operator in taking immediate remedial actions on the field. In offline mode (planning phase), the methodology considers the events (i) from the historical dataset (i.e., CVE database) and (ii) by randomly assigning the parameters defining exploitability-impact metrics and obtaining a base or severity score ($\beta_{s,t}$). The decision-making algorithm is designed to minimize the sample space of the generated events and produce possible remedial actions based on the impact of the event. These measures ensure the full

availability of CLs by network reconfiguration and DER integration. The remedial measure having the maximum resilience score is prioritized and suggested as the post-event restorative measure. In online mode, it analyses the real-time event and classifies the vulnerability using centroid-based partition clustering, k-means, based on the evaluated $\beta_{s,t}$. Thus, initially, the algorithm is equipped with (a) offline-generated high-severity scenarios and their respective remedial actions and (b) a historical dataset with event characteristics, respective scores, cause of the event, and their individual measures. Once a vulnerability is detected in the real-time operational phase, the $\beta_{s,t}$ is computed. Then, based on the evaluated score, the cluster partitioning confirms the course of action to be taken. Immediate post-event action is required if $\beta_{s,t}$ of the vulnerability is above τ . On the contrary, if the evaluated $\beta_{s,t}$ observes a medium-severe vulnerability, then a warning to take a proactive measure is produced. Various factors for computing the $\beta_{s,t}$ are defined as follows.

4.2.1 Base Score Evaluation

A security measure is required to analyze the complexity and impact of vulnerability on a PDS. CVSS is utilized here to quantify the severity-based impact of an event. It generates a string vector and evaluates a numerical score based on device-level qualitative factors, such as low, medium, and high, considering the impact of the vulnerabilities. The computed score ranges from 0 to 10. This score is generated and categorized (in the CVE list) for all the known past vulnerabilities. However, there could be many more vulnerabilities that are not severe at the moment and thus not encountered under high severity, but can be worse in the future. The computed score is composed of two sub-scores: exploitability and impact. Both the scores are generated from respective metrics: base exploitability and base impact metrics [44]. The exploitability metrics depend on AV, AC, PR, and UI. The parameters such as Attack Vector (AV), Attack Complexity (AC), Privileges Required (PR), and User Interaction (UI) follow the standard CVSS framework and are retained in abbreviated form for consistency with established cybersecurity literature. AV resembles the context of exploiting the target (either network, adjacent, local, or physical access). It has the maximum value if the exploitation is via the network. AC provides the condition for

a successful attack (either low or high). Similarly, the authorization to attack is reflected by PR (either high, low, or none), and UI gives the user involvement (either none or required). Likewise, the impact score depends on Confidentiality (C), Integrity (I), and Availability (A), which describes the impact of the vulnerability (either none, low or high). The scope is one of the key elements to evaluate the base score. The base score changes with the scope. Scope (S) changes when the vulnerable component gets affected beyond its security level, i.e., a non-vulnerable component is affected after the exploitation of the vulnerable component. For example, suppose an attacker arranges an authentic source to send packets over the network, and the user trusts the poisoned cache with no impact on confidentiality and availability. In that case, the exploitability vector is AV:Network/AC:High/PR:None/UI:None/S:Change, and the impact string vector be C:None/I:High/A:None. These factors will evaluate the base score as follows. The following equations are derived from CVSS specification [44] and used to evaluate sub-scores.

$$\zeta_{tint} = 1 - [(1 - C) \times (1 - I) \times (1 - A)] \quad (4.1)$$

if (S is unchanged)

$$Impact = 6.42 \times \zeta_{tint} \quad (4.2)$$

else

$$Impact = 7.52 \times (\zeta_{tint} - 0.029) \quad (4.3)$$

$$Exploitability = 8.22 \times AV \times AC \times PR \times UI \quad (4.4)$$

if (S is unchanged)

$$\beta_{s,t} = \min(Impact + Exploitability, 10) \quad (4.5)$$

else

$$\beta_{s,t} = \min(1.08 \times (Impact + Exploitability), 10) \quad (4.6)$$

Equation (4.3) is modified by observing no significant difference between the actual and obtained values. Based on the calculated base score from (4.5) or (4.6), a qualitative severity rating is

generated via the modified CVSS score shown in Table 4.2. The numerical constants in (4.2)-(4.6) are derived from the CVSS document [44].

4.2.2 Factors Defining Resilience Metric

In this chapter, the resilience metric introduced in Chapter 2 is further adapted to suit the proposed architecture. Unlike the earlier formulation, which considered three attributes, only two are emphasized here: operational flexibility and topological robustness. These two dimensions are sufficient to capture the system's ability to withstand and recover from cyber-induced physical contingencies under the adopted framework. The third dimension (operational redundancy), while valuable in other contexts, is not explicitly incorporated here as the architecture and problem formulation primarily hinge on flexible operational adjustments and the robustness of the network topology. This selective consideration ensures the analysis remains both problem-specific and computationally efficient, without compromising the validity of the resilience evaluation.

The Resilience Metric

As the topological characteristics are not alone sufficient to determine a resilience score, this methodology also considers the physical properties of a PDS to capture the operational flexibility ($f_{sc,t}$). The evaluation of the physical score appraises the optimal remedial measure, restoring the maximum load with the most supply to CLs and minimum system losses. The criteria to scrutinize the optimal remedial measure out of the suggested remedial actions are based on the following constraints:

- Path (from source to CL) among the possible solutions that form any loop with the connected branches does not maintain the radiality and is straightaway rejected.
- Paths from (1), supplying maximum power to the distribution network (at t_{int}) with minimal system losses, are given priority and referred to as the feasible solution.
- Paths from (2), supplying at least a minimal number of the CLs, are chosen as the optimal unique solution to restore the PDS at the time of interruption.

Thus, the optimal solution is the unique solution generated from the possible feasible solutions. It stands on the criteria of supplying maximum electric power, meeting the CL power, and maintaining the radiality. Hence, the operational flexibility score ($f_{sc,t}$) is defined as the ratio of CL supplied at t_{int} to the available loads in time T . This physical attribute confirms the maximum availability of CLs and is utilized in evaluating the resilience score to observe the resilience of a distribution network with the optimal restoration measure. The resilience metric is defined as follows:

$$R_s = t_{sc,t} + \left\{ \frac{\sum_{i=1}^{N_t} \int_{t_{int}}^{t_{rec}} n_{i,t} dt}{\sum_{i=1}^{N_t} \int_0^{t_{rec}} n_{i,t} dt} \right\} \quad \forall t \in \mathcal{T} \quad (4.7)$$

The resilience score in (4.7) combines the topological and physical attributes, where the lower and upper bounds of the score lie in $(0, 2]$. By this, it is understood that the network is entirely resilient at $R_s = 2$ and vice versa. The range of the score is user-specific and decided based on the relative importance of the attributes with respect to the objective of the study. AHP can be further utilized to compute the respective weights (if required). In this study, the physical and topological attributes share equal importance, and thus, the resilience score lies in the range of $(0, 2]$.

4.3 The Tri-stage Architecture

The proposed methodology aims to analyze a vulnerability in three stages, i.e., event classification, identification, and management, as shown in Fig. 4.2. Stage 1 involves event classification by partitioning data into three clusters using the K-Means clustering algorithm. This partition-based method calculates centroids iteratively to minimize intra-cluster variance and improve clustering accuracy. The algorithm selects cluster centers (centroids) and assigns data points to the cluster with the nearest centroid based on Euclidean distance. In this study, the partitioning is based on the calculation of $\beta_{s,t}$. Cluster 1 consists of all the vulnerabilities having low severity with $\beta_{s,t}$ less than 5. Such events do not require any remedial action. Whereas the event that falls under cluster 3 has higher severity with $\beta_{s,t}$ greater than 7, and requires an immediate post-event measure to establish a

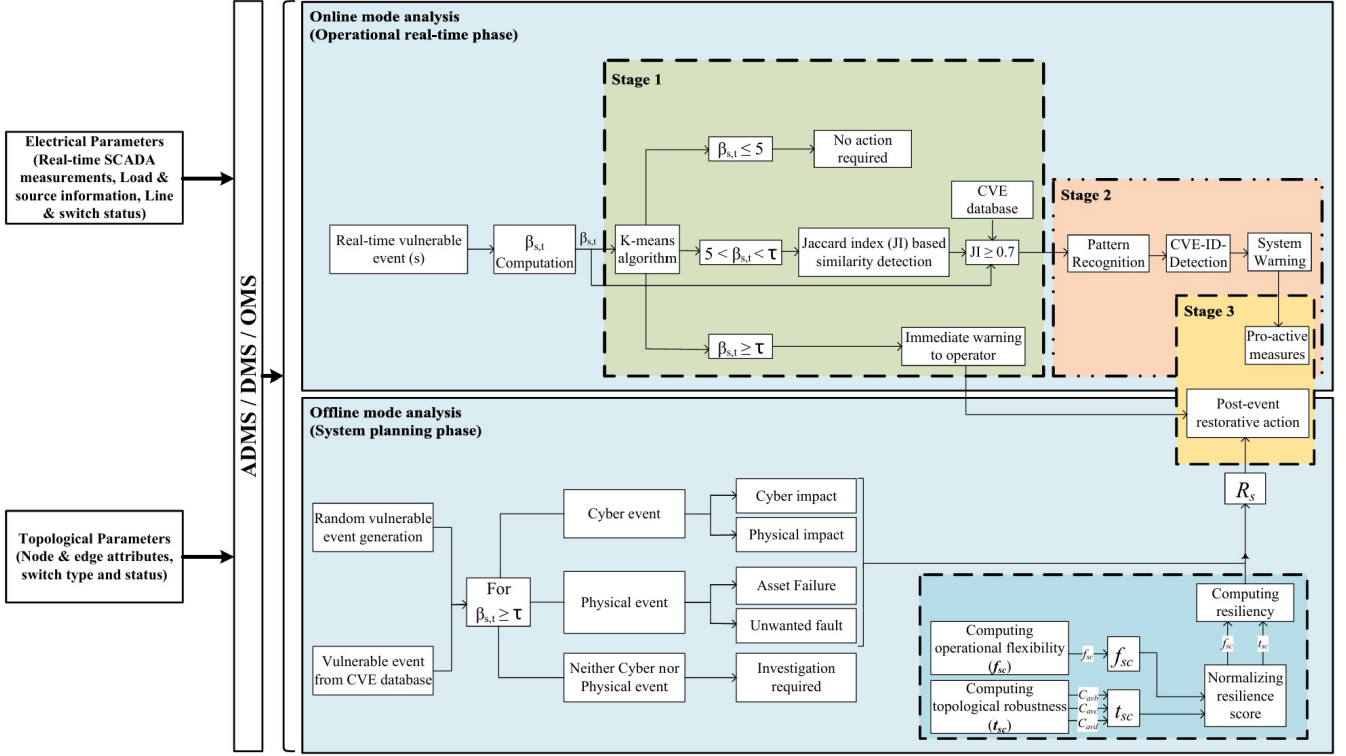


Figure 4.2: Detailed Representation of Vulnerability Assessment Tool (VulnAT).

resilient PDS. The vulnerabilities with $\beta_{s,t}$ between 5 and 7 have medium severity and lie in cluster 2. The proposed VulnAT holds the supremacy in considering these medium-severe vulnerabilities that can have a high impact in the future. Examples of such vulnerabilities are detailed in Table 4.3. Stage 2 performs a comparative analysis between the real-time (medium severe) vulnerability and the historically trained CVE dataset to identify similar patterns using the Jaccard similarity index. The developed algorithm thus suggests implementing a proactive measure for the vulnerability. A detailed explanation of each stage is given as follows.

4.3.1 Event classification using Partition Clustering

VulnAT utilizes unsupervised k-means to cluster the data into different classes. The tool extracts the event principal characteristics, numerical score, CVE-ID, severity level, and vulnerability sub-

Table 4.3: Examples of Similar Vulnerabilities from the CVE Database

Vulnerability (CVE)	$\beta_{s,t}$	Description	Similarity score	Observation
CVE-2006-3344	7.5	Use universal plug to modify protected files and bypass authentication via local user with a wireless router (in Siemens).	71%	Prevention from similar vulnerability with change in integrity and access level only.
CVE-2016-2846	6.4	Use unspecified vectors to bypass user program block via remote attackers using CPU devices (in Siemens).		
CVE-2017-6872	6.4	Alter the historical stored measurement data with access to port 21/TCP (in Siemens OZW672 and OZW772 all versions).	85%	Both vulnerabilities have six common characteristics (only change in complexity).
CVE-2017-6873	5.8	Corrupt the data with man-in-the-middle attack on web server on port 443/TCP (in Siemens OZW672 and OZW772 all versions).		
CVE-2018-4838	5.0	Manipulate the device firmware using web interface (TCP/80) of affected devices (in Ethernet module variants).	71%	With the change in impact factor, the low severe vulnerability becomes highly severe.
CVE-2018-11452	7.8	Denial-of-service (DoS) scenario using corrupt packets to port 102/TCP in communication module (in firmware variants).		
CVE-2019-10930	6.4	Allows attacker to modify the system file using corrupt communication packets to port 443/TCP (SIPROTEC 5 devices).	85%	Three almost similar vulnerabilities occurring in a different range can be cured with proactive measures.
CVE-2019-10931	5.0	Corrupt communication packets to port 443/TCP could cause a DoS scenario (in SIPROTEC 5 devices).		
CVE-2018-11451	7.8	Corrupt communication packets to port 102/TCP could affect products with DoS (in SIPROTEC 5 relays, firmware variants).		

scores from the CVE database and feeds the data to the k-means clustering algorithm [72]- [73]. This work implements the algorithm in the Python platform, where it partitions the data with n observations into k clusters. Each observation in a cluster has a cluster centroid and a relationship with the nearest neighbor. This assignment of data points into a cluster results from minimizing Euclidean distance [74]. The algorithm converges when the centroid in the last two iterations remains the same, i.e., by minimizing the objective function, in this case, Euclidean distance, given as follows:

$$\|P - Q\| = \sqrt{\sum_{i=1}^n (q_i - p_i)^2} \quad (4.8)$$

where $P = [p_1, p_2, \dots, p_n]$ and $Q = [q_1, q_2, \dots, q_n]$ are two sets of observations taken to minimize the within-cluster sum of squares, given as:

$$\arg \min \sum_{x=1}^n \sum_{c_i \in C} (c_i, x)^2 \quad (4.9)$$

where c_i is the centroid associated with each cluster c for each observation x . This work implements the algorithm using the Python platform with $k = 3$. Where the model assumes

three clusters based on the severity rating from CVSS [44]. For compelling resilience studies, the vulnerabilities with either high or critical ratings in [44] are marked as high-severity events. Thus, a model with three clusters is formed to minimize the distance and find a new centroid in each updated step by:

$$c_{i_{new}} = \frac{1}{x_{c_i}} \sum_{x_i \in x_{c_i}} x_i \quad (4.10)$$

where $c_{i_{new}}$ is the new centroid from clustered observations for all observation x_i that belongs to cluster c and is denoted by x_{c_i} . The main advantage of using Euclidean distance over the other methods is its non-affecting nature in altering the distance between two observations caused by outliers.

4.3.2 Event Identification using Jaccard Index

Stage 2 utilizes the Jaccard index to record the similarity between two vectors of vulnerable events. One string vector represents the real-time vulnerable event, and the other consists of the parameters from the CVE list. Once the model is trained, the algorithm identifies the input data with a similarity index greater than 70%. It has been empirically observed that if the new vectors pose more than 70% similarity, their severity jumps from cluster 2 to 3. Once the new data satisfies the Jaccard index criteria and matches the learned data, the algorithm displays the respective CVE-ID and its corresponding cause of failure with parameters. Based on the generated warnings from stages 1 and 2, a system operator or engineer aids in taking the desired remedial action for respective real-time vulnerabilities in stage 3. The methodology suggests proactive measures for the vulnerabilities with medium severity. The measures are further explained in the event management.

4.3.3 Event Management using Remedial Measures

It is evident that VulnAT performs resilience monitoring in both real-time and offline modes. Stage 3 is trained to suggest either proactive or post-event measures, depending on the responses from stages 1 and 2. The measures are suggested to maintain the radiality in the PDS, assuming enough

sectional switches in the network. Suppose a system experiences a high-severity event with $\beta_{s,t}$ in cluster 3. In that case, the algorithm immediately warns the operator to prevent the PDS by suggesting appropriate post-event measures in real-time. The suggested optimal action ensures the high availability of CLs. It increases the level of resilience by investigating the planning measures, such as hardening of critical components, optimal DER allocation, positioning redundant switches in PDS, and operational measures, such as network reconfiguration and DER integration [75]. The listed measures are chosen to restore the PDS and supply the maximum number of CLs under the event. Hardening of poles and lines requires deliberately high investment, i.e., up to \$4000-\$6000. Thus, the proposed methodology does a rigorous analysis and suggests the resilient remedial measure from network reconfiguration and DER integration based on the criteria to scrutinize the optimal measure. The planning measures can be opted for in extremely severe events, such as weather events or industry practices. The proposed offline analysis allows the operator to retaliate against cyber events, physical events, or any malfunction in real-time. The operator can directly take action from historical measures taken in the past, listed CVE, or from suggested offline measures.

For events with a medium severity, the algorithm generates a warning to take a proactive measure to prepare for the future. Table 4.3 gives a brief overview of some past vulnerabilities and the reoccurred similar vulnerabilities with their pattern similarity index. It illustrates that the low-severity case (in the past) can be of high severity with the only change in some factors. For example, CVE-2018 – 4838 was a vulnerability with $\beta_{s,t}$ of 5.0, which occurred by manipulating the device firmware. This entered a high severity category by compromising only two factors in the impact vector, i.e., integrity with high availability. The approach suggests respective proactive measures from the listed actions and cures the upcoming worst-case vulnerabilities for the future.

4.4 Demonstration of Proposed VulnAT and Resilience Metric

4.4.1 Case study: Impact-based Severity Assessment

This work focuses on three possible events: (a) cyber event, (b) physical event, and (c) neither cyber nor physical events. A disruption in PDS due to bad data or abnormal failure is counted neither as a cyber nor a physical event. In such events, this methodology suggests carrying out a further investigation as required. Identifying the cause and locating such events have already been explored in the past [71], [76]. In case of events having a cyber impact, the event can be reversed if it has no harsh effect on the system. However, in the case of events with a physical impact, the developed methodology suggests an optimal restorative measure (i.e., a post-event measure). The suggested restorative measures can immediately cure any event that leads to a physical impact, whereas a thorough analysis is needed to analyze the cyber impacts. This section provides a brief of cyber events that have a cyber impact and affect the confidentiality, integrity, and availability (CIA) of the control data in a distribution network. The integrity and availability-based attacks directly impact the severity of the power system [77]. At the same time, confidentiality plays a vital role in the case of critical restricted information and the security of a power system. Therefore, this chapter examines the impact of each parameter in the CIA triad individually to minimize the adverse influence on the PDS.

Integrity-based Impact

Attacks such as false data injection [78]- [79] or man-in-the-middle [80] directly corrupt the measurements or signals and are considered to have the worst impact on the integrity. Such cyber events allow attackers to modify the critical information of the involved components in a PDS. To implement such events, an attacker must have complete control over the outcomes led by the malicious modification that seriously impacts the distribution network.

Remark 1: In order to observe the worst integrity impact, this work assumes that the attacker has full prior knowledge of the critical components of a PDS.

To get proper exposure, let us consider a similar past vulnerability with string vector AV:Network/

AC:High/PR:None/UI:None/S:Change/C:None/I:High/A:None, having a high impact on integrity with $\beta_{s,t} = 6.8$, and no impact on C and A. This attack was framed on the server with no authorized user interaction. In a PDS, such an event is possible if the attacker aims to manipulate the sensor measurement via a supervisory control and data acquisition (SCADA) network, which can disrupt the system operation [81]. SCADA is the lifeline of an industrial power network that acts as a communication link between all devices. Any malicious modification in the SCADA network can easily disturb the system's stability by manipulating the voltage, power, and frequency. The introduction of false data in system measurements is generally detected via state estimation [78]. Such events with high integrity impacts can be avoided if the data is protected from any unauthorized access or users. However, it is hard to maintain consistency each time. So, according to **Remark 1**, let us consider that the attacker has prior knowledge of CLs and made the changes in the substation node voltage. The disconnection of the main grid from the downstream loads led to a high-power disruption. Case 3 in the simulation represents the working of the proposed methodology in such cases.

Confidentiality-based Impact

The effect of events with prior knowledge of critical information has already been explored, but not with the restricted system data. The complete loss of confidentiality is considered when the attacker can access the system-restricted data.

Remark 2: To discuss the worst confidentiality impact, it is worth assuming that the attacker has uncovered all the critical information from the attacked component.

To explore this case, let us consider that the attacker has gained access to the password-protected relay and can now execute false commands that may cause a significant loss of confidentiality. For example, a vulnerability 2016-CVE-5558 occurred in the past via executing a random erroneous code. The event impacted the confidentiality with $\beta_{s,t} = 8.6$, lying in the high severity range and having no impact on integrity and availability. Regarding Remarks 1 and 2, both C and I-based impacts are possible if there is a malicious modification or theft of critical information in a PDS.

Availability-based Impact

Denial-of-service attacks [82] are the perfect example of such attacks that disturb the operational security of a power system. For example, if a configuration file of a relay is tampered with by an unauthorized means and there is a change in file content, it may result in a high availability impact. As discussed in Remark 1, this same event can create a high-integrity impact if an attacker manipulates the parameters obtained by the relay.

To elaborate on this case, let us consider a past vulnerability, CVE-2014-6271, with high availability impact and $\beta_{s,t} = 9.8$. This occurred with an arbitrary code execution where the attacker gained complete access to the affected system. The impact reduced the system performance; however, it could have been rectified with an immediate failover plan. Thus, the developed methodology can deal with such events in real-time in a distribution system.

Confidentiality v/s Integrity v/s Availability-based Impacts

Remark 3: A perfect exploitability vector can be constructed as AV:Network/AC:Low/PR:None/UI:None/S:Change with the maximum exploitability score evaluated from (4). The impact may vary with respect to the access and modification of data or the operation of the resources.

An event remains in the medium severe range if either C, I, or A has a low impact with $\beta_{s,t} = 5.8$. For this, the K-means algorithm identifies similar vulnerable events to suggest a proactive measure for such scenarios. Indeed, this enhances resilience and indicates how aware the system is. However, if any impact parameter is high, the event enters the high severity rating, and an immediate post-event restorative measure is suggested. Although, as per the remarks mentioned above and exploring the CIA impacts individually, it can be said that confidentiality is the crucial element for a secure system. Confidentiality impact as None ensures a safe system with no unauthorized access to critical information. However, no system can ensure confidentiality without integrity. None in the integrity impact ensures a reliable system with no malicious data. Availability ensures easy accessibility of data with no tampering with resources. Thus, a methodology is required to train the PDS, suggesting both proactive and post-event measures to enhance resilience. In this

study, the Jaccard index identifies similar vulnerable events to train the algorithm to be effective in real-time scenarios. The following case studies demonstrate the significance of the proposed methodology.

4.4.2 Test Cases and Simulation Results

This work validates the effectiveness of the developed methodology with three typical scenarios of distinct vulnerabilities having a physical impact. The demonstration is carried out on the benchmark IEEE 33-bus radial distribution system operating at 12.65 kV, with active and reactive demands of 3.72 MW and 2.3 MVar, respectively. The same PDS, along with the DERs (assumed disconnected initially) and TLSs considered in the previous chapters, is adopted here as well to ensure continuity. This allows for a rigorous analysis and demonstrates the effectiveness of the proposed results under a consistent system framework. The distribution system has been modeled on ETAP with DER integration to analyze the load-demand profile, and the decision-making algorithm is designed on MATLAB 2021a. An open-source software, Cytoscape [83], has been used to establish full connectivity between the nodes given by the topological factors in the undirected graph. MATLAB/MATPOWER6.0 first generates possible switching reconfigurations for an outage scenario, where the optimization algorithm selects ‘gbest’ (the optimal switching configuration) among the generated solutions. The ETAP then simulates the power flow under the outage scenario with ‘gbest’ configuration. Here, Cytoscape has been used in parallel to model the topological aspects of the system and derive graph-theoretic insights, which were incorporated into MATLAB for calculating the integrated resilience score.

Since this work defines resiliency as the ability of a PDS to serve the CLs with or without utility; thus, CLs do not participate in load shedding. If the system enters load shedding due to the time and weather-dependent supply of DERs [84], then non-essential loads are shed first, followed by the essential loads. The essential loads start recovering only if all the CLs are supplied. If DER1 and DER2 fail to fulfill the supply to CLs, the backup DER (operating in grid-forming mode) provides the supplementary supply and improves the system’s adaptability. This generalized

methodology, i.e., the tool with the developed algorithm, is feasible for any larger distribution network with redundant sources and switches. The case study describes the working of the algorithm and the impact of vulnerabilities to establish a resilient distribution network in detail. According to the definition of resilience by the task force, “Resilience is the capacity to endure and mitigate the impact of disruptive events, encompassing the ability to anticipate, absorb, adapt to, and swiftly recover from them” [7]. Although the present literature still lacks a universal definition of resilience, this study implements the traits of a resilient PDS as follows:

- **Anticipate:** It foresees medium-severe events and suggests respective proactive actions to prepare for them in advance. This prepares a PDS to be aware of potential future threats and plan accordingly for high-severity events.
- **Absorb:** It has the capability to monitor and withstand the impact of both medium-severe and high-severe events without significant damage. It plans for high-severe events in offline analysis and thus minimizes its impact in real-time scenarios.
- **Adapt to:** The methodology effectively copes with the changing CVE database, ensuring that it adapts to all vulnerabilities and provides recovery in each situation.
- **Recover:** Stage 3 in tri-stage architecture provides a swift recovery by following either proactive or post-event measures. The optimal remedial measure helps to quickly bounce back to normal operating conditions following an event.

Thus, the proposed resilience metric clearly emphasizes and demonstrates each aspect of resilience as defined by the task force. The following case study validates the applicability of the proposed architecture, algorithm, and metric, ensuring the preparedness for a wide range of potential vulnerabilities in a distribution network.

Case 1) Loss of a Single Switch (Effectiveness for Medium-severe Events in Online Mode)

To analyze the performance of the proposed methodology in online mode, the testbed implements the scenarios with medium severity in the PDS. This can be achieved by closing or opening a random switch. If an attacker intentionally opens a normally closed sectional switch or closes an open

Table 4.4: Severity-based Optimal Pro-active and Post-event Measures

S.No.	Event	$\beta_{s,t}$	Best resilient remedial actions (*C = closed; O = open)																	Resilience Score (at t_{res})
			Sectional Switches (Normally Closed)														Tie-lines (Normally open)			
			SS4	SS5	SS6	SS9	SS10	SS11	SS12	SS20	SS25	SS22	SS29	12-22	9-15	25-29	18-33	8-21		
E-I	4-5	5.3 (<7)	O	C	C	O	C	C	C	C	C	C	C	C	O	C	O	O	1.85	
E-II	12-13	6.4 (<7)	C	C	C	C	C	C	O	C	C	C	C	O	C	O	O	O	1.98	
E-III	3-23	5.0 (<7)	C	C	C	C	C	C	C	C	C	O	C	O	O	C	O	O	1.88	
E-IV	5-6, 6-7, 6-26	7.3 (>7)	C	O	O	C	C	C	C	C	O	C	C	C	O	C	O	O	1.92	
E-V	9-10, 20-21, 29-30	8.6 (>7)	C	C	C	O	C	C	C	O	C	C	O	C	C	O	C	O	1.97	
E-VI	9-10, 10-11, 11-12	9.4 (>7)	C	C	C	O	O	O	C	C	C	C	C	C	O	O	O	O	1.91	

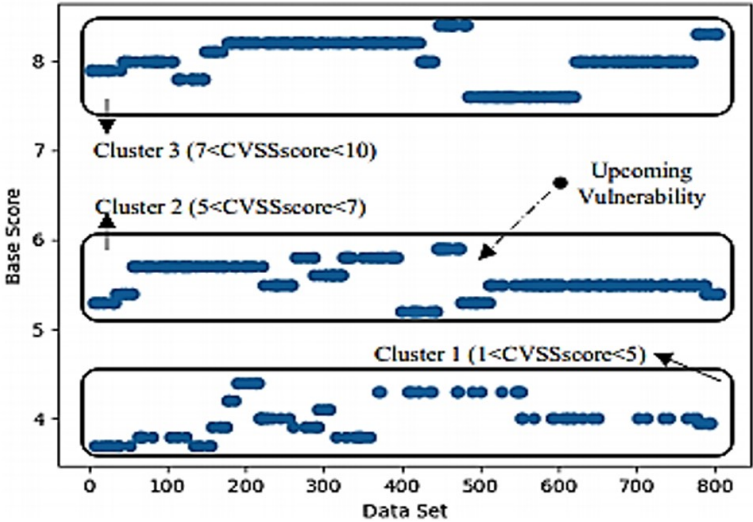


Figure 4.3: Scatter Plot for K-means with K=3 for Severity-based Cluster.

TLS, it may affect the regular operation of a radial PDS. The harsh effect can be prevented if the system operator has prior knowledge of the scenario. However, if the operator fails to resolve the issue via remedial action in time, it may badly affect the resiliency of the system. This is because the downstream loads remain unsupplied with the loss of a single switch in a radial PDS. Table 4.4 (E-I to E-III) represents different scenarios and their respective measures in case of a cyber or physical event. The algorithm primarily classifies the event’s severity, as shown in Fig. 4.3, representing cluster formation gleaned from base scores. Since the $\beta_{s,t}$ of the considered events (E-I – E-III) lies

in the range of 5-7, the exploitability enters stage 2. The algorithm specifies this upcoming event into a clustered group of points, cluster 2 in this case. Based on this, the pattern reorganization process is done within cluster 2. A similar implementation of the algorithm is carried out for all vulnerable scenarios. Here, E-I to E-III represent three events with N-1 vulnerability at 4-5, 12-13, and 3-23, having a physical impact. E-I assumed a low-complexity cyber-physical event that compromised the system's confidentiality with access to some prior knowledge of the PDS. This event has a string vector AV:Network/AC:High/PR:None/UI:None/ S:Change/C:Low/I:None/A:None. This case considered the effect of AV, AC, and C, with a $\beta_{s,t} = 5.3$. The algorithm enters stage 2 and exhibits the CVE-ID of the vulnerability, satisfying the Jaccard index by comparing the vector similarity with the CVE database. Thus, stage 2 generates a system warning to scrutinize the best proactive measure. The algorithm suggests an optimal remedial action with 100% load recovery on closing TLSs 1 and 3 with DER 3 active and SS9 open to maintain the radiality. This measure aids the operator in preparing the PDS for a similar vulnerability with high severity in the future. It can be a result of the historical dataset (i.e., from the CVE database) or suggested by post-event remedial measures. The restoration process for the CLs is shown in Fig. 4.4, representing the restoration of electrical power with interruption at 0.1 sec. It clearly imitates the resilience enhancement of the PDS in the vulnerable scenario. The suggested post-event measure instantly restored the power (with all CLs supplied) at 0.2 sec. Furthermore, the PDS attains full recovery at 0.4 sec on repairing SS4. Fig. 4.4 shows an increase in power consumption at certain buses (e.g., bus 24) because a sudden change in power generation is not feasible. The voltages of all energized buses, including bus 24, show a similar behavior due to the instant exploitation of branch 4-5. Initially, the energized loads consumed more than their rated power, but after implementing the suggested optimal measures, the loads returned to nominal levels. By 0.4 sec, the system had stabilized, and the bus voltages and load consumption returned to normal.

Similarly, events E-II and E-III are assumed to have a physical event leading to physical impact with $\beta_{s,t} < 7$. The optimal remedial measures given in Table 4.4 provide full recovery of the PDS with 100% CL restoration. The physical score represents operational flexibility for each measure to

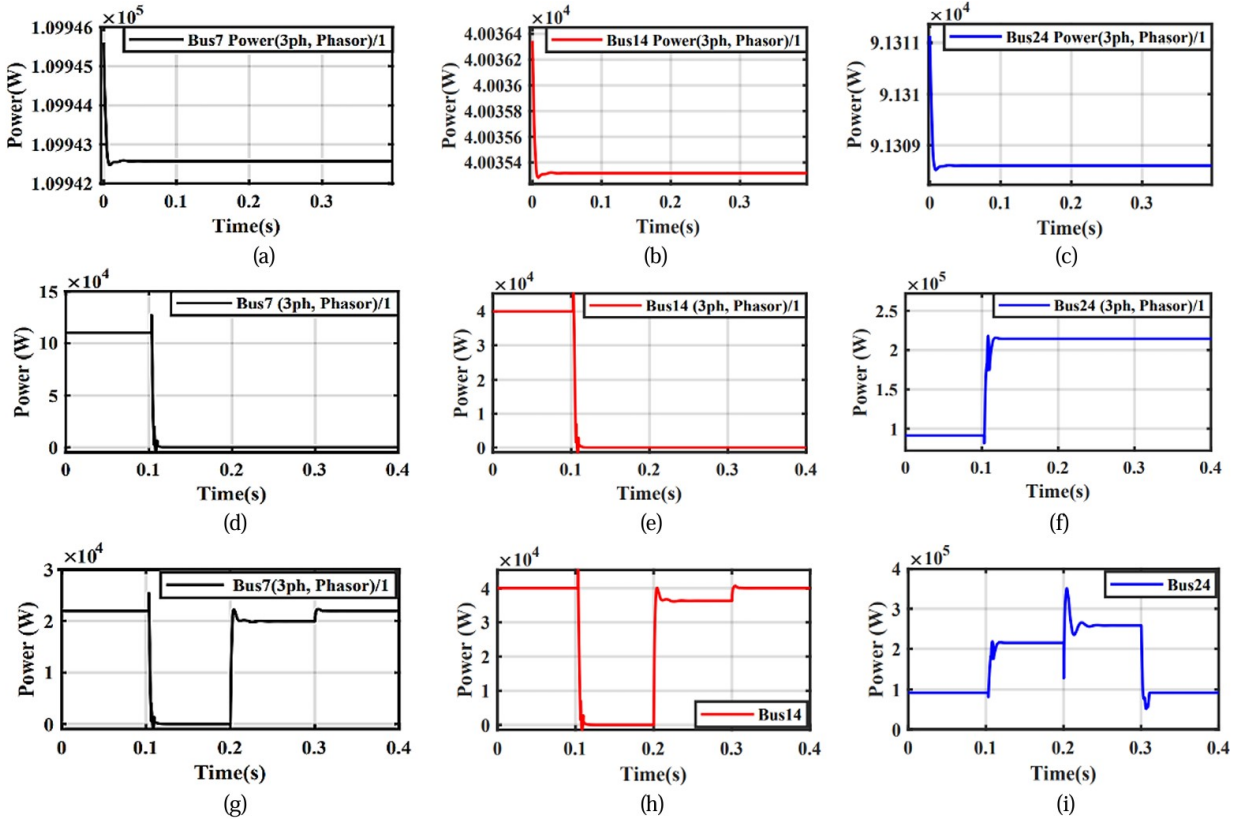


Figure 4.4: Performance Analysis of CLs at Bus 7, 14 and 24: (a), (b) & (c) Represent Normal Operation Before the Event; (d), (e) & (f) Illustrate the Impact of E-I on Loss of Single Switch 4-5 at 0.1 sec (t_{int}); (g), (h) & (i) demonstrate optimal restorative measure on closing tie-lines 12-22 and 25-29, opening SS9 and integrating DER-3 for 100% restoration.

assist in scrutinizing the optimal restorative measure out of the possible remedial solutions. These weights are individually multiplied by the centrality indices computed from the undirected graph and produce the topological robustness score t_{sc} to quantify the R_s as the combination of physical and topological factors.

Case 2) Loss of Multiple Switches (Effectiveness for Highly-severe Events in Offline Mode)

To evaluate the effectiveness of the methodology in case of events with high severity, this study considers a coordinated attack on the distribution system and computes the R_s in $N - K$ vul-

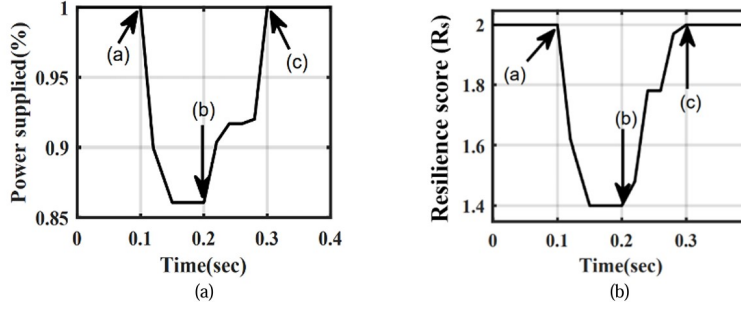


Figure 4.5: Post-event Measure for E-V with Multiple Switch Failure: (a) 100% Recovery with Suggested Optimal Strategy, (b) Resilience Enhancement.

Table 4.5: Resiliency Metric for Multiple Coordinated Events

Event	Operational TLSs	Resilience Score	
		t_{int}	t_{res}
E-IV	TLS1, TLS3	1.2	1.92
E-V	TLS1, TLS2, TLS4	1.62	1.97
E-VI	TLS1	1.56	1.91

nerability. The North American Electric Reliability Corporation states that these attacks have the highest impact on security and can affect a significant part of the system with cascading failures. To execute these kinds of attacks, an attacker must have complete knowledge of the network configurations. Hence, it is not easy to implement these, as the attacker needs to coordinate from multiple points. This work simulates multiple offline scenarios and encounters the events with multiple vulnerabilities listed in Table 4.4 (E-IV to E-VI). Event E-IV is considered an event exploiting multiple branches, i.e., 5-6, 6-7, and 6-26, leaving node 6 isolated. This vulnerability reduces the system's resilience with the disconnection of bus 6 and causes a high impact on the PDS, reducing its resilience from 2 to 1.2. Fig. 4.5 illustrates that the suggested resilient post-event action has the best topology and resilience among other possible measures. This optimal restorative measure improves the resilience to 1.92 with the network reconfiguration and DER integration. The resilience enhancement is shown in Table 4.5, which briefs the resilience metric in case of coordinated attacks. It records the resilience at t_{int} and enhancement in the score at t_{res} .

Similarly, E-V is considered a string vector having high integrity impact AV:Network/AC:High/PR:None/UI:None/S:Unchange/C:Low/I:None/A:None. It has been considered that the attacker modified the network load data with a random disruption on 9-10, 20-21, and 29-30. Such a scenario may produce an adverse effect on the protection of the system in real-time. Thus, a PDS must be prepared with the post-event remedial measures for short-term resilience enhancement at any instant. Hence, this algorithm suggests the best resilient solution that attains full recovery with three TLSs and one active DER. A detailed explanation of stepwise load recovery with resilience enhancement is shown in Fig. 4.5, where pt. (a) resembles tint (the point of interruption) at 0.1 sec; pt. (b) shows t_{rec} (the moment recovery starts) with switch and DERs at 0.2 sec; and pt. (c) depicts tres (when the system gets fully recovered) at 0.4 sec. The event E-VI formulates a rare and highly vulnerable scenario with simultaneous attacks on 9-10, 10-11, and 11-12. This case observed the worst resilience score among the three multiple-event scenarios, with a high impact on integrity and availability. The event disrupted half of the system, with buses 10 and 11 isolated. However, the suggested measure attained a recovery of 95% and increased the resilience from 1.56 to 1.91. Hence, the event worsens with the increase in impact factors. Fig. 4.6 represents the exploitability and impact scores for all the events that clearly show the effect of the impact subscore on $\beta_{s,t}$. Since these vulnerabilities are generated in offline analysis, this can help an operator to suggest the most resilient defensive measure in the future in real-time. The results demonstrate that the proposed VulnAT provides an edge for the operator to assess the risk of the event in $N - 1$ and $N - K$ vulnerabilities and choose the best resilient measure at t_{int} . However, besides partial islanding, a vulnerable event could cause a worse event with grid islanding. The following case demonstrates the performance of the proposed VulnAT in improving resilience.

Case 3) Attack on Substation node (Effectiveness of Online Mode with Severity more than 7)

On implementing this case, the algorithm first computes the $\beta_{s,t}$ and finds it to be in the high severity range. Upon classification, it immediately warns the operator to suggest a post-event measure with acute consideration of the resilience score. This subsection evaluates the effectiveness of the methodology in dealing with such integrity-based impacts on a DER-rich PDS. The operator

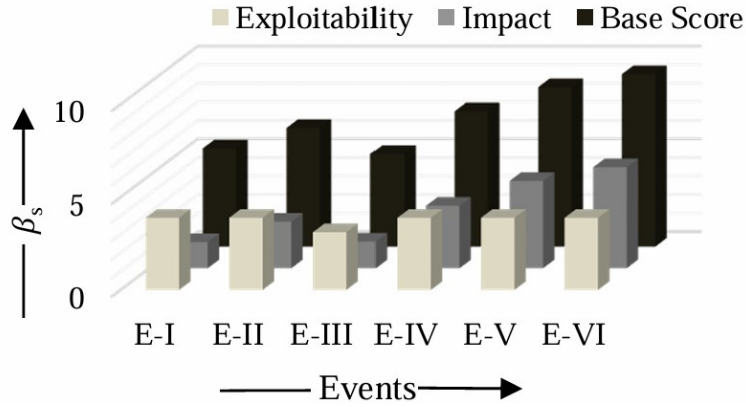


Figure 4.6: Exploitability and Impact Subscores for all Events.

Table 4.6: Possible Remedial Action with DERs in PDS

Possible solution with DERs			Average centrality indices for topological robustness score			R_s
SW1	SW2	SW3	C_{avb}	C_{avc}	C_{avd}	
O	O	O	0.2126	0.1149	1.7222	0.63
C	O	O	0.2213	0.1141	1.7777	1.91
C	C	O	0.2172	0.1197	1.8333	1.94
C	C	C	0.2188	0.1221	1.8888	1.95

scrutinizes all possible offline-generated measures in the database to deliver the optimal remedial measure. Stage 3 computes the resilience score for each remedial action and suggests the most resilient in case of vulnerability. There are three DERs in the system that operate independently in this situation. This event utilizes the backup DER to maintain the surplus supply and serve CLs for the maximum time. Table 4.6 records the resilience enhancement of the system with the interaction of DERs. At the time of the event, with SS1 open and no DERs connected, the system’s resilience was observed to be the worst at 0.6319 with no load unsupplied. The operation of switch SW1 integrates the DER1 at node 18, which improves the resilience to 1.91. Then, the score improves gradually with the integration of DERs. With an attack on the substation node and suspended SS1, the score reaches the maximum of 1.9549 with all DERs connected. Hence, this methodology allows the operator to take the most resilient post-event measure in real-time with no delay.

4.5 Superiority of the Proposed Tool: Comparative Analysis

Most of the listed studies have presented various approaches exhibiting the defense mechanism against cyber-physical vulnerabilities in a PDS. CVSS is a standard tool to quantify a vulnerability based on qualitative parameters such as low, medium, and high. It derives the score, constituting exploitability and impact subscores. The extent of the exploitability and the implicated impact are prime observations in CVSS. Various researchers have already explored computing and enhancing resilience, but have neglected to address the impact due to the severity of vulnerable events in DER-rich PDS. Recent work in [70] considered various factors to study the cyber-physical resilience of a PDS. However, the metric evaluation assumes that it is challenging for an attacker to attack a control center, which is inaccurate due to the advanced technologies, intelligent devices, and smart attackers. Thus, a methodology must prepare a PDS for the worst case, considering each possible event. The proposed VulnAT considers the real-time events in tri-stage online mode and the historical or randomly generated events in offline mode to prepare the system for each possible cyber-physical event in a PDS. To establish the supremacy of the proposed approach, let us explore it from the impact point of view. [43] proposed a metric and delivered a defense mechanism that aids the operator in assessing the impact at each instant. The impact-based analysis suggests remedial measures but does not consider the severity of the impact. The proposed methodology delivers a resilient PDS by suggesting proactive and post-event measures, considering severity-based impact analysis for each vulnerability. Similarly, most of the recent works of literature establish a resilient network utilizing a similar scoring system, CVSS, but the generalized approach in this thesis increases the flexibility to tackle the cyber-physical vulnerable events with resilience enhancement.

4.6 Outcomes

This chapter aspires to scrutinize the impact of cyber-physical vulnerabilities on the resilience of a DER-rich PDS. The work is based on the publications [P2] and relates to the increasing

threats in the PDS. This chapter presents the vulnerability analysis tool (VulnAT) that models a tri-stage architecture, interfacing online and offline modes to classify, identify, and manage a cyber, physical, or any real-time exploitability. The proposed methodology utilizes partition clustering to classify the event data into severity-based clusters. Different actions are taken based on the impact of the event. The developed algorithm analyzes the real-time event and suggests a severity-based operational measure to restore the PDS promptly. An immediate warning is generated in case of highly severe events, and the algorithm quantifies the resilience score to suggest an optimal restorative measure to supply the CLs. The supremacy of the algorithm is the utilization of the Jaccard index to evaluate the similarity score for the events and suggest a proactive measure for the events with medium severity. The offline mode intensifies the system restoration by scrutinizing the most resilient measures for highly severe vulnerabilities and suggesting them in real-time. Evaluation of the resilience score combines the physical and topological attributes. Topological robustness utilizes priority-based pairwise criteria weights to evaluate the weighted score using graph theory-based centrality indices. The computed resilience score for each remedial measure provides a privilege to the methodology of ensuring the maximum power supplied to the CLs. The effectiveness of the proposed VulnAT is validated through case studies, where the resilience score reflects the system's ability to adapt under varying severity levels of cyber-physical events. The results demonstrate improved CL supply and the timely identification of high- and medium-severity events, enabling faster, more informed restoration decisions.

The proposed tool and the decision-making algorithm enhance resilience and topological robustness against vulnerable events. Moreover, the impact-based analysis of highly impactful and similar cyber vulnerabilities has a crucial role in building a resilient distribution network. Future work could improve the tool by utilizing weather-dependent data to enhance real-time vulnerability analysis for real-world and large-scale validations. This forms the foundation of the final objective of this thesis.

Chapter 5

Restoration Framework for a Resilient System Against Extreme Events

5.1 General

Most of the meteorological events, including storms, precipitation, and hurricanes, carry a very high wind speed, sufficient to destroy a colossal number of overhead lines and poles. Such events require an acute weather-dependent analysis to integrate the weather data and understand its impact on the system [85]- [86]. This demands event modeling to observe the failure probability and determine a methodology to build a resilient network, restricting the inordinate maintenance cost against wind events. The maximum sustained wind may cause short circuits or faults due to swinging power lines, interrupting the supply. Also, the gust can make a tree fall on a line or pole, resulting in single or multiple outages. The probability of failure at the component level is analyzed by the fragility curve. Some of the existing literature utilized fragility curves, focusing on weather-dependent resilience to describe the withstand capability of a system [1], [36], [87], [88]. However, the research gap is the limited real-time damage-based analysis. A detailed formulation must model the impact, analyze damage, and suggest remedial actions for a resilient PDS. This study statistically models a hybrid fragility curve for vulnerable components by developing a hy-

brid dataset. It visualizes the dynamic wind effect and determines the maximum and critical wind speed to carry out the damage analysis for a realistic weather-dependent analysis. The damage not only depends on the intensity of an event but also the infrastructural and environmental factors, such as the type and age of components. This approach investigates comprehensive damage and suggests a corresponding cost-effective measure. The damage-based resilience assessment maximizes the CL availability and minimizes the cost by suggesting the retrofit or replacement of damaged components. Most of the past methodologies optimized the operation by considering a static system under failure conditions. However, extreme events are highly uncertain, and the action should be optimized based on the current state. This study formulates an approach by considering uncertainty with 95% confidence intervals. To model these uncertainties, stochastic programming is one of the best ways to handle them efficiently [89]. Techniques such as Monte Carlo and MDP [90] are also used to model extreme events. MDP is a tuple in reinforcement learning defined by its states, actions, and immediate reward, where the problem is represented by a transition matrix depicting the transition of states [91]. The proposed approach captures the state-based action by framing an optimal policy on utilizing dynamic programming. Further, in extreme events, there could be multiple outages, and DGs, microgrids, and DERs [92] are required to enhance resilience. Even IEEE standard 1547 [93] encourages load restoration using DGs with intentional islanding. Most of the studies introduced hardening measures with DG integration [94], deploying backup DGs and TLS [95], uncertainty modeling [96], and multi-level feeder restoration by DERs [97] for resilience enhancement. However, there has been a limited study suggesting the restoration based on the damage level of the PDS. The proposed approach quantifies the damage and then suggests a respective restoration measure to improve the resilience. It encourages the system operator and engineers to deliver a cost-effective and optimal resilient strategy by analyzing the real-time damage intensity at dynamic wind speeds.

The major points covered in this work are:

1. Developed restoration approach utilizes a DTMC to deliver a remedial action for each state over time. The state transition exhibits five stages: normal, failure, retrofit, replace, and

restore, and optimizes the cost as a reward for each state-based action. The supremacy of the approach is in delivering the optimal load restoration results while suggesting the remedial measures concerning the DLAM.

2. Constructed hybrid dataset models the fragility curves for vulnerable overhead components and delivers a more realistic weather-dependent resilient framework.
3. Developed a look-ahead damage matrix to examine the real-time component status. It evaluates a unique damage-level assessment matrix to capture the damage intensity and adopt the mitigating and hardening measures accordingly.
4. Proposed event-driven dynamic algorithm devises a deterministic policy expressing the cost function, suggesting an optimal action for each state, and simultaneously optimizing the cost and restoration against uncertain wind-induced events.

5.2 Fragility Modeling for a Resilient PDS

5.2.1 Data Requirement and Assumptions

Modeling the intensity of an event is a complex exercise and requires environmental and topological statistics. Probabilistic assessment is challenging in terms of mathematical formulation and depicting results. The developed approach frames all the challenges with given assumptions to achieve smooth results:

- Since a PDS is not expanded over regions, it is assumed to have uniform weather conditions. All poles/lines experience the same wind speed and share the same fragility curve.
- The existing algorithm can incorporate varying weather conditions in different geographical regions as needed.
- Since each pole and line's condition is not known initially, all components are considered to be the same. The developed formulation can incorporate the known initial conditions.
- The cost of preventive maintenance, retrofitting, replacing, and hardening of components is subjective and may vary based on the available information.

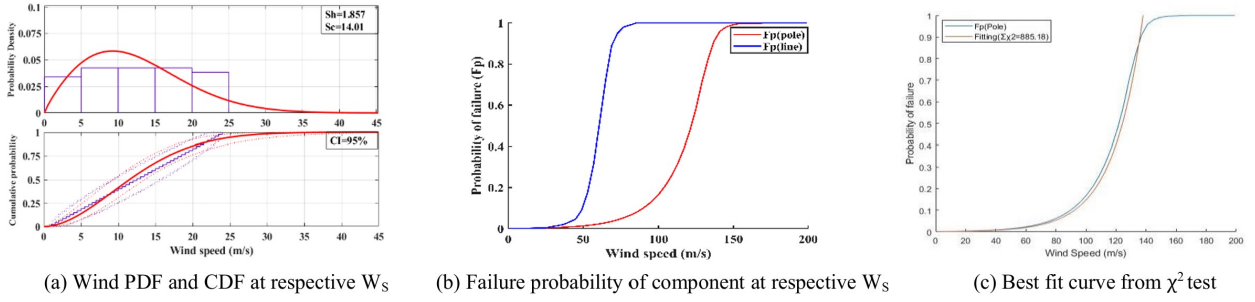


Figure 5.1: Wind Profile and Fragility Curve Modeling.

- Since the probability of failure is subject to uncertainty due to age, type, and environmental factors, the modeling of each curve is done with 95% confidence intervals.
- The real-time wind speed is known for the damage analysis.

5.2.2 Wind-event Modeling

It is required to model the events to access and enhance the network resilience. Past literature highlights that high winds engender massive damage to a PDS than to a substation or transmission system. This study captures the wind effect and records wind speed as a global parameter for event modeling. To acknowledge the probabilistic nature of a wind event, it is required to analyze the statistical dataset using a PDF that best fits the data. This study uses a hybrid dataset that constitutes empirical and historical data. Using only empirical data makes an approach highly situation-specific, which only captures the event-specific data. To strengthen the analysis for a realistic weather-dependent framework, this approach develops a hybrid dataset with historical wind data acquired by [98]. This study investigates normal, exponential, gamma [99], generalized Pareto, Rayleigh, and Weibull [38] distributions to analyze the best-fit PDF. The results yield that the Weibull distribution has the best fit to represent the wind profile. The PDF, CDF, and fragility curve for probabilistic wind assessment are shown in Fig. 5.1, consisting of 500 wind samples. The best-fit wind speed profile has been evaluated using the two-parameter Weibull distribution function given as,

$$F(W_s) = \begin{cases} \frac{S_h}{S_c} \left(\frac{W_s}{S_c}\right)^{S_h-1} e^{-\left(\frac{W_s}{S_c}\right)^{S_h}}, & W_s \geq 0 \\ 0, & W_s < 0 \end{cases} \quad (5.1)$$

$$F(W_s) = \begin{cases} 1 - e^{-\left(\frac{W_s}{S_c}\right)^{S_h}}, & W_s \geq 0 \\ 0, & W_s < 0 \end{cases} \quad (5.2)$$

where the value of S_h less than 1 indicates a decreasing failure rate, and vice versa. The failure rate is constant at S_h equals 1. This model considers an increasing failure rate owing to uncertainty. Due to the aging of poles, the strength of lines, and environmental factors, the failure rate increases with time. This uncertainty is symbolized by a confidence interval in statistical analysis and shown by the deviation in the slope of the curve. The observations are made with an assumption of 95% confidence limits that imply 95% confidence of the true fragility function for component [100]. Among various possible measures [101], MLE has been used to estimate the parameters because of its efficiency in handling large datasets with minor variance. The S_h and S_c parameters are derived by MLE and evaluated as,

$$\theta_{MLE} = \arg \max \{ \ln[L(W_s; S_h, S_c)] \} \quad (5.3)$$

where,

$$L(W_s; S_h, S_c) = \prod_{i=1}^n F(W_{s_i}) \quad (5.4)$$

$$L(W_s; S_h, S_c) = S_h^n S_c^{-n} \left(\prod_{i=1}^n W_{s_i} \right)^{S_h-1} \exp \left(-\frac{1}{S_h} \left(\sum_{i=1}^n W_{s_i} \right)^{S_h} \right) \quad (5.5)$$

$$\ln[L(W_s; S_h, S_c)] = n \ln(S_h) - n \ln(S_c) + (S_h - 1) \sum_{i=1}^n \ln(W_{s_i}) - S_c \sum_{i=1}^n W_{s_i}^{S_h} \quad (5.6)$$

Equation 5.3 represents the compact form of the likelihood function, and (5.6) takes the natural logarithm to find the maximum likelihood estimates of (S_h, S_c) numerically. The detailed MLE process can be learned from [102].

5.2.3 Fragility Modeling of Distribution Pole and Line

The damage estimation is indicated by fragility curves, representing a probabilistic relationship of component failure concerning the event intensity. Some studies develop empirical curves [103], and some produce analytical curves [104]. This study creates a hybrid dataset, as it is highly uncertain to consider only observational, experimental, judgmental, or historical data. The fragility curve for poles describes their strength against strong winds. PDSs can have different specifications for concrete and steel pole types. This research is not pole-specific, and all poles are considered new initially. To construct a fragility curve and approximate the failure, it is necessary to define the relation as a function of W_s . Such an observation has already been approximated by [105], [106]. The mathematical model given below relates the failure rate exponentially to the wind speed,

$$F_p = A_p e^{B_p \cdot W_s} \quad (5.7)$$

where coefficients A_p and B_p represent the uncertainty that varies with topological and environmental factors. A statistical analysis has been done to compare the observed and required results using the chi-square test to determine the best fit curve. A non-linear programming solver is used to minimize errors concerning parameters. The obtained values of A_p and B_p are 0.009382 and 0.0505, respectively. The fragility curve for the pole is given in Fig. 5.1(b), and the fitting of the data is shown in Fig. 5.1(c). The detailed explanation of Fig. 5.1(b) is given as,

$$P(F_{p_i}) = \begin{cases} 0, & W_s < W_{max} \\ F_p(pole), & W_{max} \leq W_s < W_{critical} \\ 1, & W_s \geq W_{critical} \end{cases} \quad (5.8)$$

Equation 5.8 describes the impact of wind speed on distribution poles with W_{max} and $W_{critical}$ as 50 and 150 m/s, respectively. If W_s crosses the critical value, the pole may immediately collapse and need replacement. For distribution lines, resilience depends on several measures, such as environmental factors, weather conditions, or simultaneous pole outages. The fragility curve of a line is different from that of a pole, but the failure of a line is much dependent on a pole. Fig. 5.1(b)

relates the F_p of a line at respective wind speeds and can be expressed as,

$$P(F_{l_i}) = \begin{cases} 0, & W_s < W_{max} \\ F_p(line), & W_{max} \leq W_s < W_{critical} \\ 1, & W_s \geq W_{critical} \end{cases} \quad (5.9)$$

W_{max} for a distribution line is 30 m/s, and $W_{critical}$ is 80 m/s.

5.3 Mathematical Formulation

The proposed approach utilizes reinforcement learning to formulate the problem mathematically. The problem has been defined using MDP, reflecting each time step as a state vector where the future state is dependent on the set of actions taken in the present state. Each state receives a reward for the associated action that is defined in terms of operational cost. The parameters involved in MDP formulation are defined below.

5.3.1 Parameters Formulating MDP

State: The state vector X_n is a controlled Markov chain representing various states. Fig. 5.2 represents a directed graph or a transition diagram describing all involved states to analyze the impact of an event at each step. The graph shows five different states that observe the generalized causality principle in which the probability of the future state is only dependent on the present state. Mathematically, X_n is said to be a DTMC such that,

$$P\{X_{n+1} = j \mid X_0 = i_0, X_1 = i_1, \dots, X_n = i\} = P\{X_{n+1} = j \mid X_n = i\}, \quad \forall n > 0, \forall i_0, \dots, i, j \quad (5.10)$$

Let there be an action X_n for each state, such that X_{n+1} depends on the action taken in the current state given as $f_n(X_n, U_n, W_n)$, where W_n is the associated random disturbance in the present state.

Action and Reward Associated: These actions result from the event's intensity and damage

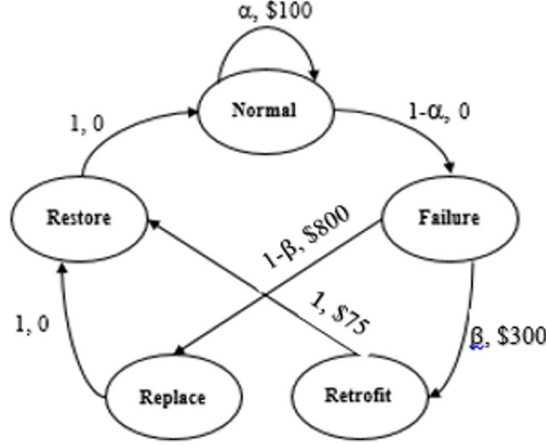


Figure 5.2: State Transition Diagram with $X_n = 5$.

caused by the event. At each time n , an action U_n is taken, where $U_n \in U(X_n) \subset C_n$ and $U(X_n)$ is the set of possible actions taken by observing state X_n , and C_n is the action space at time n . The reward function of MDP is the best tool to estimate the operational cost, and a reward of $\mu_n(X_n)$ is awarded for a particular state action, given as,

$$U = \{\mu_1(X_1), \mu_2(X_2), \dots, \mu_n(X_n)\} \quad (5.11)$$

State Transition matrix: The following matrix λ_p shows the probability of transition from one state to the next state. The set of system states is defined as $X = \{\text{normal, failure, retrofit, replace, restore}\}$. The transition probability matrix λ_p represents the probability of transition between these states, where each element λ_{ij} denotes the probability of transitioning from state i to state j . The parameters α and β represent transition probabilities between specific states.

$$\lambda_p = \begin{bmatrix} & \lambda_{nor} & \lambda_{fail} & \lambda_{ret} & \lambda_{rep} & \lambda_{res} \\ \lambda_{nor} & \alpha & 1 - \alpha & 0 & 0 & 0 \\ \lambda_{fail} & 0 & 0 & \beta & 1 - \beta & 0 \\ \lambda_{ret} & 0 & 0 & 0 & 1 & 0 \\ \lambda_{rep} & 0 & 0 & 0 & 0 & 1 \\ \lambda_{res} & 1 & 0 & 0 & 0 & 0 \end{bmatrix}$$

λ_p matrix follows two axioms:

1. $\lambda_{ij} \geq 0 \quad \forall i, j \in S$
2. $\sum \lambda_i^{row} = 1 \quad \forall i \in S$

5.3.2 Dynamic Programming and Optimal Policy Formulation

This work formulates an optimization model to make an optimal decision at each stage. Let us consider the above five states as five different stages. For the purpose of dynamic programming formulation, these system states are further abstracted into two representative conditions, namely healthy (X_1) and damaged (X_2), to simplify the decision-making process while preserving the overall system behavior. Thus, at each stage, two conditions, X_1 and X_2 , are defined with respective actions. X vector recognizes the condition as a state; X_1 signifies healthy, and X_2 represents the broken state. U is the action-value function for each state with two policies: either maintain/don't maintain or replace/retrofit the component. The dynamic algorithm expresses an additive cost function that accumulates the cost at each updated state, starting from X_n . The deterministic policy expressing the expected cost function is,

$$X = \{X_1, X_2\} \quad (5.12)$$

$$U = \{u_1, u_2\} \quad (5.13)$$

$$u_1 = \{\mu_1(X_1), \mu_2(X_2)\} = \{\text{maintenance, no maintenance}\} \quad (5.14)$$

$$u_2 = \{\mu_3(X_3), \mu_4(X_4)\} = \{\text{retrofit, replace}\} \quad (5.15)$$

Objective:

$$\arg \min_{\Pi} J_{\Pi}(X_0) \quad (5.16)$$

$$J_{\Pi}(X_0) = \min_{\Pi} \mathbb{E} \left\{ \sum_{n=0}^{N-1} g_n(X_n, \mu_n(X_n), w_n) + g_N(X_N) \right\} \quad (5.17)$$

Table 5.1: Investment Cost Description

Cost (USD)	Description	Associated action	Reference
75	C_{maint}	Preventive maintenance	Assumed
300	C_{ret}	Repairing component	[17]
800	C_{rep}	Replacing component	[17]
4000	$C_{\text{hard,pole}}$	Adding transverse guys	[36]
5924	$C_{\text{hard,line}}$	Hardening of line	[15]

$$J_N(X_N) = J_4(X_4) = 0 \quad (5.18)$$

$$J_{n-1}(X_{n-1} = \text{working}) = \min \begin{cases} C_{\text{maint}} - C_{\text{profit}}(1 - F_{p(m)}) + \mathbb{E}[J_n(X_n)], \\ -C_{\text{profit}}(1 - F_{p(n)}) + \mathbb{E}[J_n(X_n)] \end{cases} \quad (5.19)$$

$$J_{n-1}(X_{n-1} = \text{damage}) = \min \begin{cases} C_{\text{ret}} - C_{\text{profit}}(1 - F_p) + \mathbb{E}[J_n(X_n)], \\ C_{\text{rep}} - C_{\text{profit}} + \mathbb{E}[J_n(X_n)] \end{cases} \quad (5.20)$$

Equation (5.16) defines the policy in a compact form where $J_\pi(X_0)$ is the expected cost starting from state X_0 under policy π , and intends to minimize the cost having a deterministic single-stage cost function $g_n(X_n, \mu_n(x_n), w_n)$ and terminal cost $g_n(X_n)$. The policy to determine the optimal action is abstracted in (5.19)–(5.20), where $F_{p(n)}$ is the failure probability at no maintenance, and $F_{p(m)}$ is the failure probability after the component has undergone maintenance. C_{maint} , C_{ret} , C_{rep} , and C_{hard} are the costs to maintain, retrofit, replace, and harden a component, respectively, and C_{profit} is the cost if the component continues to be in a healthy state after an event. The approach assumes a fixed investment cost, implying each state-based action, as shown in Table 5.1. *The cost data in this study are presented in USD to maintain consistency with existing literature. However, the proposed methodology is scalable, and the cost models can be readily adapted to Indian currency and region-specific cost data for practical implementation.* Here, the total operating cost is the accumulation of mitigating and hardening costs. The mitigating cost deals with network reconfiguration, DER integration (\$8kW/h) [107], or retrofitting, whereas hardening costs include redundant sources and switches, or planning costs such as precautionary undergrounding of lines

or pole guying. Equation (5.19) minimizes the expected cost by comparing two optimal actions $\mu_1(X_1)$ and $\mu_2(X_2)$, and suggests maintenance as the optimal action for $\mu^*(x_{n-1} = \text{working})$. However, for a damaged line or pole ($\mu^*(x_{n-1} = \text{broken})$) it suggests retrofitting as the optimal solution.

The above dynamic programming formulation is integrated with the simulation framework by mapping system states to component conditions (e.g., working and damaged states) and control actions to remedial measures such as maintenance, retrofit, replacement, and restoration. At each stage, the optimal decision is selected based on the minimum expected cost, and the resulting policy is implemented within the simulation to evaluate system performance under different damage scenarios.

5.3.3 Problem Statement

This work formulates a two-stage stochastic problem, where the earlier section presents the formulation of the first stage, followed by the mathematical modeling using MDP and dynamic programming. The proposed formulation is integrated with the simulation framework to evaluate system behavior under different damage and restoration scenarios. This section presents the constraints involved in system modeling and simulation.

$$\text{Variables: } \theta_{ij,t}^\varphi \in \{0, 1\}, \quad \theta_{i,t}^{DER} \in \{0, 1\}, \quad S_{ij,t}^c \in \{0, 1\} \quad (5.21)$$

$$0.95 \times \theta_{i,t}^\varphi \leq V_{i,t} \leq 1.05 \times \theta_{i,t}^\varphi, \quad \forall i \in \Omega_B, \forall t \in T \quad (5.22)$$

$$0.95 \times \theta_{i,t}^{DER} \leq V_{i,t}^{DER} \leq 1.05 \times \theta_{i,t}^{DER}, \quad \forall i \in \Omega_B, \forall t \in T \quad (5.23)$$

$$\theta_{i,t}^\varphi P_i \leq P_i^{DER} \quad \text{and} \quad \theta_{i,t}^\varphi Q_i \leq Q_i^{DER}, \quad \forall i \in \Omega_B, \forall t \in T \quad (5.24)$$

$$-S_{ij}^{\max} \leq S_{ij}^\varphi \leq S_{ij}^{\max}, \quad \forall (i, j) \in \Omega_L \quad (5.25)$$

$$S_{ij} = P_{ij} + jQ_{ij} \quad (5.26)$$

$$-S_{ij,t}^c P_{ij}^{\max} \leq P_{ij,t}^\varphi \leq S_{ij,t}^c P_{ij}^{\max} \quad (5.27)$$

$$-S_{ij,t}^c Q_{ij}^{\max} \leq Q_{ij,t}^\varphi \leq S_{ij,t}^c Q_{ij}^{\max} \quad (5.28)$$

$$l_{ij} = \xi_{i,j,t}^\varphi, \quad \forall (i,j) \in \Omega_L, \quad \forall t \in T \quad (5.29)$$

$$T_{rep,t,int}^{pole,\xi} = rand(3, 5) \quad \text{and} \quad T_{rep,t,int}^{line,\xi} = rand(1, 2) \quad (5.30)$$

$$T_{rep}^{max} = n_p \cdot T_{rep,t,int}^{pole,\xi} + n_l \cdot T_{rep,t,int}^{line,\xi} \quad (5.31)$$

$$T_{res}^{DER} = \frac{P^{DER}}{\sum_{i=1}^N P_i^{CL}} \quad (5.32)$$

$$T_{rep}^{max} < T_{net}^{res} \quad (5.33)$$

The constraints involved in restoring CLs are described in (5.22)-(5.33). $\theta_{i,t}^\varphi$, $\theta_{i,t}^{DER}$, and $S_{ij,t}^c$ are binary variables introduced to limit the voltage magnitude, DER operational capacity, and TLS action, respectively. Constraint (5.22) restricts the voltage limit within a specified range. It remains in a safe range if the value of $\theta_{i,t}^\varphi$ is 1 at time t with damage φ . However, the voltage for a damaged line (i, j) is forced to be 0. Constraints (5.23)-(5.24) impose the DER limits, where each DER is designed with fixed reserve energy to supply the CLs. These DERs form a networked microgrid for an effective restoration with $\theta_{i,t}^{DER}$ that varies same as $\theta_{i,t}^\varphi$. Constraints (5.25)-(5.28) show the maximum active and reactive power, which should be less than or equal to the power served to CLs via DER. Constraint (5.27)-(5.28) ensures the network connectivity and approximates the power flow limits. Here $S_{ij,t}^{c,\varphi}$ represents the switching scenario for damage φ . It depends on the TLS that if a line (i, j) contains a tie-switch and is closed at time t , then $S_{ij,t}^{c,\varphi}$ is 1, else 0. If a TLS exists but is open, it will force the line flows to be zero. Constraint (5.30)-(5.31) has been adopted from [21] to evaluate the repair time of the damaged component. It calculates the maximum time to repair by accumulating the individual repair times of the pole and line in (5.30), with n_p and n_l being the number of poles and lines, respectively. Equation (5.32) has been acquired from reference [51] to determine and compare the maximum supply duration to CLs, where p^{DER} is the energy of a particular DER and P_i is the power served to i^{th} CL by a particular DER. This work also compares the restoration unavailability (U_{res}) from [51] to validate the effectiveness of the

proposed approach. Constraint (5.33) verifies that the repair time taken by this methodology must be less than the restoration time of CLs. In addition to these constraints, the radiality of PDS must be maintained such that there is no loop formation and each load is fed by at least one source. For this, the network is assumed to have enough sectional switches.

5.3.4 Resilience Assessment and Enhancement

Resilience Assessment with Look Ahead Damage Policy

The system operator is assigned to inspect the damage and suggest the remedial measures after an event. Typically, the actions are limited in options due to restricted TLSs and DERs that participate in the remedial operation. This validates the necessity to discover the event criticality before and during the event. This approach allows the operator to predict the failure probability and damage intensity for individual events. It confirms the existence of each critical component and thus provides an optimal action to optimize the restoration and cost simultaneously. The proposed methodology examines the system at each interval via observing the component's status ξ .

$$\xi = \begin{cases} 1, & \text{normal} \\ 0, & \text{damaged} \\ -1, & \text{broken} \end{cases} \quad (5.34)$$

At any moment, if ξ is found to be 0, then the intensity of the event is estimated from DLAM, denoted by $\{\phi\}$, and ‘% failure’ is computed from Table 5.2.

$$\phi = \{\phi_n, \phi_l, \phi_m, \phi_r\} \quad (5.35)$$

DLAM describes four levels, where φ_n represents the *no damage state*. The state φ_l corresponds to a scenario with wind speed less than $W_{\max}$. In this case, the system may experience minor damage with at most two lines, poles, or switches affected. If the wind speed exceeds $W_{\max}$, it may lead to either minor or major disruptions depending on the severity level φ_m . The system

Table 5.2: Damage Level Assessment Matrix (DLAM)

Damage Level (φ)	% Failure	Damage description	Component Status
None	No damage	No pole, No line damage	Remains same
Low	At least 5% failure of poles, 5% of switches, 5% of lines	Failure of at most 2 lines, 2 poles	Preventive maintenance /Repair
Moderate	At least 40% failure of poles, 40% of switches, 40% of lines	Failure of at most 13 lines, 13 poles	Repair/ Replace
High	More than 40% failure of all components, or the network leads to collapse	Failure of at most 23 lines, 23 poles	Replacement

requires immediate recovery in this scenario through mitigating measures, and the damaged components must be repaired. A complete collapse of the PDS is indicated by φ_h , where $W_s > W_{critical}$, resulting in more than 40% disruption. Such extreme wind conditions may cause line or pole break-ages; hence, the policy recommends replacing broken components to ensure long-term resilience enhancement.

Resilience Enhancement Measures

The developed algorithm demonstrates the decision-making capability of the approach for re-silience enhancement. It proposes a novel methodology that detects the real-time component status and evaluates the severity and damage level to compute the resilience. The optimal action further enhances the resilience via suggested mitigating and hardening measures.

- 1. **Mitigating Measures:** The developed framework captures the event characteristics and adopts mitigating measures as required. Usually, the existing literature directly replaces the component [19], suggests vegetation management [108], or allocates repair crews [109] without inspecting the intensity of the damage. This work used the HAZUS model developed by the Department of Homeland Security and the Federal Emergency Management Agency,

Algorithm: Damage-based optimal decision making

Initialize: $W_{\max}$, W_{critical} , DLAM, Set of Actions $\{U_n\}$,
Set of Rewards, Location of CLs, ELs, Non-ELs
Input: W_s , State $\{X_n\}$, $F_p(\text{Pole})$, $F_p(\text{Line})$, ξ
Output: Optimal Action $\{\mu_n(X_n)\}$, Expected cost $J_\pi(X_n)$

- 1: Run Optimal Power Flow $\ni t = t_{\text{int}}$
- 2: **for** each component
- 3: Generate all possible states $\{X_n\}$
- 4: Update component status (ξ')
- 5: **if** ($\xi' = 0$) $\subset \xi$
- 6: Evaluate ' φ ' from DLAM
- 7: Select the optimal action $\mu_n(X_n) \in U(X_n)$
- 8: Suggest mitigating strategy
- 9: **for** all combination of actions
- 10: $\triangleright$ Evaluate EPS
- 11: $\triangleright$ Calculate system loss
- 12: $\triangleright$ Compute R_s
- 13: **end for**
- 14: **else if** ($\xi' = -1$) $\subset \xi$
- 15: $\varphi = \varphi_h$
- 16: $\mu_n(X_n) = \text{replace}$
- 17: **end else if**
- 18: **end if**
- 19: **end for**
- 20: **Record** Resilience Enhancement
- 21: **Display** $\mu_n(X_n)$, $J_\pi(X_n)$

focusing on defining damage intensity. This approach examines the real-time component status ξ and computes the intensity of the damage by DLAM. The DLAM has been developed after a rigorous analysis based on a well-defined standardized tool. It states that for ϕ_l , the mitigating measures could be the preventive maintenance or retrofitting while attaining restoration via network reconfiguration using TLSs and DER integration. It is evident that the operational cost increases with the DER integration. Thus, the methodology suggests restoration via the network reconfiguration followed by DER integration (if required) to minimize the cost. For high-level damage, it suggests direct replacement of the com-

ponent with a higher class or the same [38]. However, for moderate damage, the policy suggests replacing completely damaged components and retrofitting the partially damaged components. These immediate remedial actions reduce the outage duration and the expected cost associated with the wind-related event. Unlike the previous studies, this work does not encourage the component's direct replacement. This chapter employs a different resilience metric in accordance with the requirements. It recognizes the damage caused by a sustained outage and then evaluates the network resilience, estimated by,

$$R_s = (1 - \xi) \cdot \text{EPS} - \text{CCL} \quad (5.36)$$

where,

$$\text{EPS} = \left\{ \frac{\sum_{i=1}^n \int_{t_{\text{int}}}^{t_{\text{res}}} P_{i,t} dt}{\sum_{i=1}^N \int_0^{t_{\text{res}}} P_{i,t} dt} \right\} \quad \forall t \in T \quad (5.37)$$

EPS is the fraction of energized loads, and CCL is the CL supplied at instant t .

The R_s frames the success rate of the network, with $(1 - \phi)$ being the pre-event probability of damage. (5.37) describes the in-event system availability with n and N being the total loads and sources in the PDS. The post-event absorbing capacity is given by the CCL, which represents the fraction of CLs supplied after the event. For CL disintegration, the optimum policy suggests an immediate implementation of mitigating strategies to reduce the system downtime and enhance the PDS resilience.

2. **Hardening Measures:** The planning stage includes undergrounding of cables, substation elevation, and tree-trimming to reduce the impact of an event. Some integrated solutions, such as enhancing situational awareness and utilizing local DGs, are already in use as proactive measures. At first, the proposed approach suggests analyzing the damage intensity and restoring the network via mitigating measures to minimize the expected cost. Otherwise, precautionary undergrounding, strengthening the critical components (adding transverse guys) [110], or upgrading pole class [38] are advised for system hardening [111]. If

the W_s crosses the critical speed, either a tree or any element can destroy a pole or line. In that case, an immediate replacement of the component is suggested. However, DERs, TLSs, and sectional switches operate as needed to fulfill the EPS along with the desired replacement.

In addition to structural reinforcement and component replacement, improving system observability plays a critical role in enhancing resilience. Optimal placement of PMUs ensures that the network can be effectively monitored and faults can be detected early, enabling faster restoration actions. The PMU placement strategy proposed in [112] utilizes the BOI and SORI as key metrics. BOI identifies critical buses whose observability is essential for maintaining system monitoring, while SORI evaluates the redundancy of observability paths, ensuring that measurement coverage is maintained even under component outages.

The method optimizes PMU allocation by minimizing the total number of units required while guaranteeing full observability across the system. Special attention is given to ZIBs, which help in inferring system states without direct measurement, and critical load prioritization, ensuring that essential areas of the network receive monitoring coverage first. This observability-driven hardening measure complements the restoration framework by providing operators with the data and insights needed for informed decision-making during extreme events, thus reducing downtime and enhancing the system's ability to recover.

5.4 Case Study and Result Discussion

A rigorous case study has been carried out to validate the effectiveness of the approach on the IEEE 33 bus radial PDS shown in Fig. 5.3. The real-time simulation and modeling have been done on ETAP, and the algorithm is designed on MATLAB to generate desired state-based actions. The loads are divided into three categories: CLs (highest priority), essential, and others.

The proposed technique assesses the impact of wind-induced events on the modified distribution systems and suggests mitigating and hardening measures. A system may undergo various

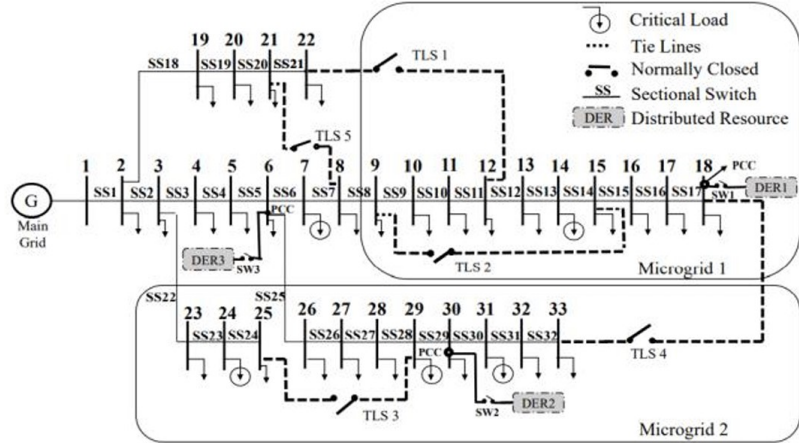


Figure 5.3: IEEE 33 Bus Modified Distribution System with DERs and CLs.

Table 5.3: Post-event Inspection at Various W_s

W_s (m/s)	Affected Component (Line / Pole)	F_p (%)	ξ	Reinforced outages		ϕ (%)	CCL (%)	EPS (%)	T_{rep}^{max} (hours)	T_{net}^{res} (hours)
				Poles	Lines					
40	Line 10-11	2.37	1	11-12-...-18	11-12, 12-13, ... , 17-18	25	80	85.81	1.9	2
80	Line 26-27	17.52	0	27-28-...-33	27-28, 28-29, ... , 32-33	22	60	77.5	1.6	2
120	Pole 6	39	0	7-8-...-18, 26-27-...-33	6-7, 7-8, ... , 17-18, 6-26, 26-27, ..., 32-33	64	20	45.65	4.5	5
150	Pole 3	99	-1	4-5-...-18, 23-24-...-33	3-4, 4-5, ... , 17-18, 3-23, 23-24, ..., 32-33	82	0	12.68	4.8	6.2

states following an extreme event (as explained in Fig. 5.2). This work designs the problem considering all five states to model the stochastic framework for HILP events. Initially, both the critical components, the distribution line and the pole, are considered healthy.

5.4.1 Probabilistic Assessment of Wind-Induced Events

The case study estimates the probability of damage and investigates the optimal policy to suggest the remedial measures at a lower expected cost.

Case 1: Implementing outages on IEEE 33-bus system: To validate the effectiveness of the formulated methodology, Table 5.3 demonstrates four distinct scenarios exhibiting the eventual impact of the disintegration of a line or a pole owing to dynamic wind speeds on the PDS shown

in Fig. 5.3. This case restores the system considering equal availability of each DER.

The first case assumed that line 10-11 is damaged with exposure to W_s of 40 m/s. This loss subsequently affected 8 poles and 8 lines, leading to 25% damage and disconnected 1 CL at node 14. Fig. 5.1(b) illustrates that this does not have a significant impact due to low F_p , and thus the DLAM suggests retrofitting as the optimal action for 100% restoration at minimum cost. As obtained from (5.31), the maximum possible time to repair the line is 1.9 hours. Meanwhile, the approach suggests the best mitigating measure along with the repair of the component. The remedial measure with maximum EPS and minimum system losses has been given the topmost priority. Fig. 5.4(a) shows that the best resilient and cost-effective measure is to restore with TLS 9-15 and 12-22, and no DERs are active. As calculated from (5.32), the restoration time to supply CLs is 2 hours, and both the TLSs remain active for that time. The next case assumed that line 26-27 get affected by a short circuit at a wind speed of 80 m/s that disconnected 22.5% of the load with 40% CLs. The algorithm suggests an immediate retrofitting of the line as the optimal action. Since the repair time is 1.8 hours, TLS 25-29 was brought into operation, which supplied the network for 2 hours, and the resilience enhancement via the suggested mitigating measures is displayed in Fig. 5.4(b).

The third scenario considered a fall of a tree limb on pole 6 owing to a wind speed of 120 m/s. This disconnected 50% of the network from the primary source, out of which 80% of the CLs remain unserved. The algorithm immediately suggests closing TLS 8-21 and 25-29 to recover the CLs. This set of combinations yields 97.5% of load recovery with all CLs and ELs supplied. The DLAM investigates this case with moderate damage, having 39% F_p , and thus the pole can either be repaired or replaced. However, the optimal policy suggests retrofitting as the cost-effective and feasible action, but the decision lies in the age of the pole. To exemplify, the fourth case assumed a worst and rare event where W_s crosses the critical value with 99% F_p of pole. The reinforced outage led to significant destruction with the disintegration of 87.3% of the load and all CLs. Since

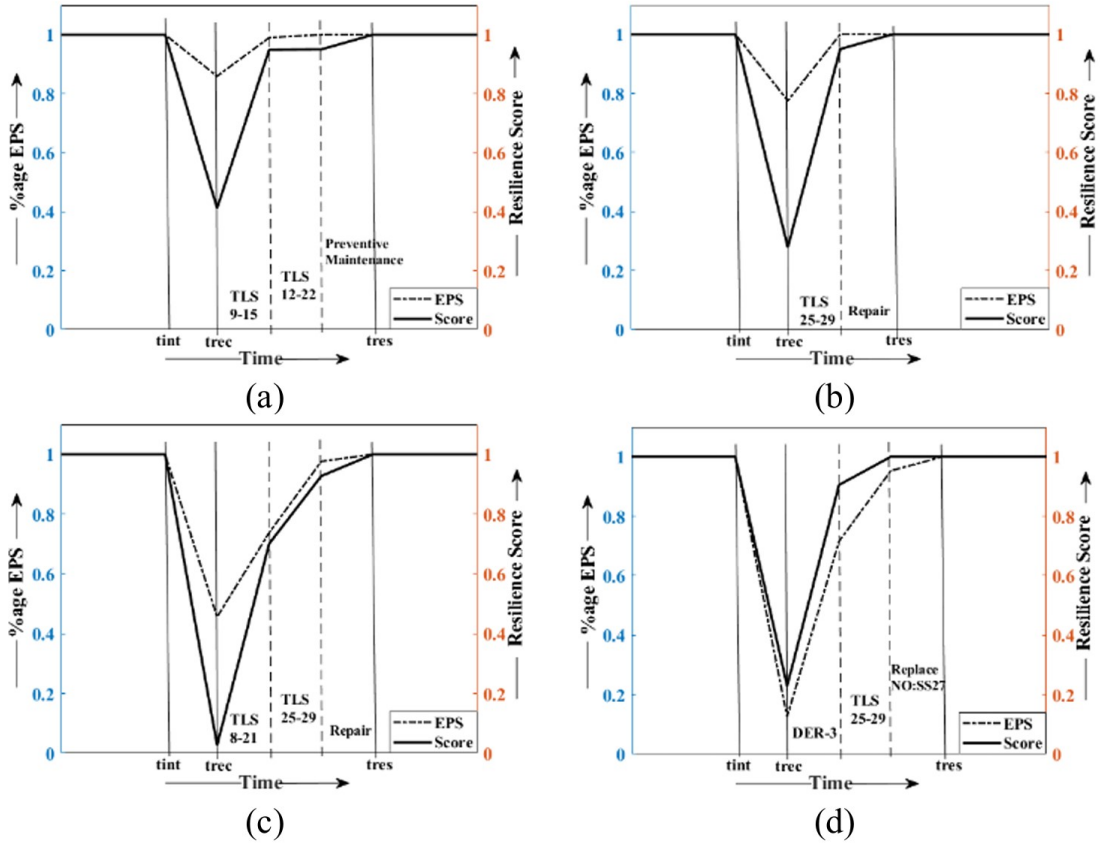


Figure 5.4: Resilience Enhancement with Maximum Restoration by Suggested Policy.

all the DERs have the same availability, the restoration strategy suggests integrating DER-3 and TLS 25-29 for recovery, as illustrated in Fig. 5.4(d) and Table 5.4. As calculated from (5.32), the DER and TLS successfully serve the load for 6.2 hours, which exceeds the time to repair. Thus, the suggested strategy meets the objective to restore the maximum possible load for a longer duration. To deliver a cost-effective, resilient operation, the policy evaluated the gross system damage via DLAM and suggested immediate replacement of the pole due to collapse at such high winds.

In a radial distribution system, these $N - 1$ outages result in $N - 2$ or 3 and requisite immediate mitigating action for a resilient PDS. Henceforth, our methodology suggests a mitigating plan for an immediate bounce back and a policy-based, cost-effective hardening strategy for long-term

Table 5.4: Suggested Mitigating and Hardening Strategy at 150 m/s

Suggested measures	CCL (%)	EPS (%)	Resilience score (R _s)	Recovery cost (\$)
DER3	80	71.55	0.2289	50
TLS 25-29	100	95	0.9052	-
Replace	100	100	1.0000	800

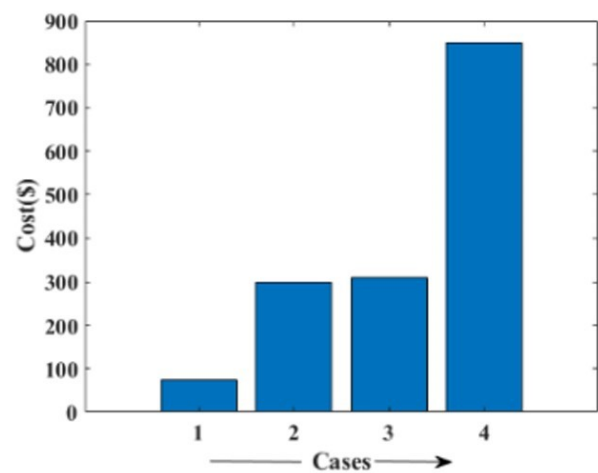


Figure 5.5: Expected Restoration Cost for all the Events.

resilience enhancement.

Fig. 5.5 presents the comparison of restoration cost for the four considered cases under different disturbance and mitigation scenarios. The proposed methodology analyzes the probability of component failure and associated damage intensity to identify cost-effective restoration strategies while ensuring system resilience.

In the first scenario, the restoration is achieved using two TLSs and preventive maintenance, resulting in the lowest restoration cost due to minimal intervention and effective use of existing network redundancy. In the second scenario, the restoration involves a single TLS operation combined with repair actions, resulting in a moderate increase in cost due to the inclusion of repair steps. The third scenario further incorporates two TLS operations along with repair, which increases the restoration cost compared to Case 2, as additional switching and repair efforts are

required to restore system functionality.

In contrast, scenario four exhibits the highest restoration cost, as it involves DER integration, TLS operation, and eventual component replacement. While this approach ensures system recovery under severe damage conditions, the inclusion of DER deployment and infrastructure replacement significantly increases the overall cost.

The results demonstrate that the proposed framework not only suggests appropriate remedial actions based on system conditions but also enables cost-effective restoration by optimally utilizing available resources such as TLS operations and selective DER integration. Compared with approaches that rely solely on extensive DER deployment, the proposed methodology achieves comparable or improved restoration performance at reduced operational and retrofitting costs. This highlights the capability of the framework to deliver a resilient and economically efficient power distribution system.

Case 2: Effect of Simultaneous Outages on Components The probability of survival of a component is an event-specific function. Mitigating and restoring measures are adequate in case of predictable outages. However, these strategies are restricted to $N - k$ or simultaneous uncertain events. It is thus required to study the dependence of components to serve timely preventive actions. In a radial distribution system, a single outage is forced to disconnect the downstream-connected loads. A pole is generally connected with two or more distribution lines, and a line connects two simultaneous poles. Hence, if a tree falls on a distribution line, the subnetwork connected to the source will get the supply, and the other section will get the supply via the suggested restorative measure. Thus, a pole failure is possible if only a pole is damaged or both the connected lines are broken. This can be expressed as:

$$P(F_P) = P(F_{L_i} \cap F_{L_j}), \quad \forall (L_i, L_j) \in \Omega_L, P \in \Omega_B \quad (5.38)$$

$$P(F_{P_i}) = \sum_{i,j=1}^{\Omega_L} P(F_{L_i}) \times P(F_{L_j}) \quad (5.39)$$

Equation 5.38 describes the dependency of a pole, i.e., a situation with simultaneous line outages resulting in an isolated pole or pole collapse. Whereas a line failure could be direct or indirect

(if any of the connected poles fail) and can be expressed as:

$$P(F_L) = P(F_{P_i} \cup F_{P_j}), \quad \forall (P_i, P_j) \in \Omega_B, L \in \Omega_L \quad (5.40)$$

$$P(F_{L_i}) = \sum_{i,j=1}^{\Omega_B} P(F_{P_i}) \times P(F_{P_j}) \quad (5.41)$$

Equation 5.40 expresses that the failure of a single pole can disconnect two simultaneous lines and is sufficient to collapse the downstream PDS if no immediate remedial action is taken. Thus, a pole outage is more severe than a line outage and should be prioritized. The following case demonstrates the dependence of component failure and the simultaneous effect on the PDS. Let us consider a worst-case scenario of a 33 bus system where a tree limb hits PDS with W_s of 150 m/s, causing multiple failures with the collapse of pole 13 and line 13-14 (which disconnected a CL at node 14). Thus, for an immediate bounce back, the policy suggested restoration via mitigating measures with a priority to restore the pole. Hence, TLS 9-15 operated and restored 97% load. The optimal policy suggests the replacement of pole 13 and line 13-14 due to complete damage. The PDS successfully attains 100% recovery at tres via the suggested measures.

5.4.2 Comparative Analysis and Algorithm Effectiveness

A real-time weather event is subjected to various estimates, such as environmental factors and topological measures. These events are highly uncertain, and the optimization is based on the current system state. Most of the previous studies consider a static PDS under failure and do not optimize or capture the state-based actions. To evaluate the approach considering uncertainties, we have utilized a state-based optimal action policy framed by dynamic programming, where the uncertainty is modeled with a 95% confidence interval. This study does not provide random remedial measures, but it evaluates the failure probability, real-time component status, and damage level intensity at dynamic wind speeds. It also ensures that the maximum repair time must be less than the restoration time to serve CLs. The resilience enhancement has been shown in Fig. ??, where the EPS is fully recovered at a lower expected cost suggested via mitigating and hardening measures, which are appropriate for long-term planning and operation of PDS.

5.5 Outcomes

This work develops a comprehensive resilience enhancement framework for distribution systems by integrating two key strategies: mitigating and hardening measures to address the impact of uncertain wind events and improve system robustness. The mitigation strategy presented in publication [P3] is realized through a novel two-stage stochastic restoration approach, where the first stage statistically determines the fragility curves of vulnerable components and derives mathematical models expressing their failure probabilities at respective wind speeds. The second stage formulates the restoration problem using a DTMC to deliver a cost-effective and resilient solution. The developed state-transition matrix, which includes the states normal, failure, retrofit, replace, and restore, is represented through a directed graph, and an event-driven dynamic algorithm defines deterministic policies that minimize expected costs based on state-dependent actions. The DLAM is used to recommend remedial measures depending on the severity of damage, while the resilience score is evaluated by considering pre-event damage probabilities, system availability during events, and post-event absorbing capacity under dynamic conditions.

Complementing these mitigation strategies, hardening measures focus on improving system observability through optimal placement of PMUs, as detailed in [P4]. By leveraging observability indices and redundancy metrics, the approach ensures that the system can be monitored effectively with a minimal number of measurement units, supporting proactive fault detection and control.

Together, these strategies provide a holistic framework that not only helps in minimizing operational costs and outage durations but also strengthens the ability of distribution systems to withstand and recover from extreme events. The effectiveness of the proposed approach is validated through case studies, where distinct variations in restoration cost are observed across different damage scenarios, reflecting the impact of mitigation and hardening measures. Lower-cost solutions are achieved through selective switching and DER utilization, whereas higher costs are associated with severe damage requiring component replacement. The combined approach enhances both immediate restoration capabilities and long-term system robustness, contributing significantly to resilient operation under uncertain environmental conditions.

Chapter 6

Conclusion and Prospects

6.1 General

The increasing penetration of DERs into modern distribution networks has transformed the operational paradigm from conventional, centrally-controlled systems to decentralized, dynamic, and uncertainty-driven networks. While DERs enhance sustainability and flexibility, their integration also introduces variability, cyber-physical vulnerabilities, and operational complexity. Ensuring resilience, defined as the system's ability to anticipate, withstand, adapt to, and recover from disruptive events, has therefore become a central requirement in the planning and operation of distribution systems.

This thesis explored the resilience dimension of DER-rich power distribution systems through a series of frameworks addressing operational, cyber-induced, and extreme event scenarios. The contributions span the development of a multi-stage resilience metric, its application in DER-centric restoration, a cyber-physical vulnerability assessment tool, and a damage-based stochastic restoration framework under wind-induced failures. Collectively, these works establish a structured methodology for quantifying and enhancing resilience across different disruption scales and event types.

6.2 Concluding Remarks

This thesis, as stated in the introduction, focused on defining, quantifying, and enabling resilience in modern DER-rich power distribution systems. The five chapters collectively addressed this central research question from different perspectives, ranging from metric development, DER-centric restoration, cyber-physical vulnerability analysis, to damage-based stochastic restoration under extreme events. The proposed strategies were validated through rigorous case studies on balanced and unbalanced distribution systems, ensuring consistency between the theoretical framework and simulation results. This section summarizes each chapter's contribution toward fulfilling the overall objective of resilience enhancement.

1. *Chapter 1: Introduction*

The first chapter of the thesis comprehensively examines key elements, including motivation, literature review, identified research gaps, scopes, assumptions, basic definitions, research objectives, and overall outline. This chapter discusses each aspect in detail to lay a strong conceptual foundation and sets the contextual base for the propositions in the subsequent chapters.

2. *Chapter 2: Proposed Multi-Stage Operational Resilience Metric*

This chapter proposes a novel integrated resilience assessment metric (IRAM) to support real-time operations in DER-rich distribution systems. This multi-stage metric significantly contributes to developing a formal resilience-driven solution in evolving distribution grids. The proposed metric utilizes pairwise criteria weights for resilience computation based on comprehensive attributes- operational redundancy, operational flexibility, and topological robustness. It plans for DER services by considering their operation and control modes, and real-time weather-dependent availability. The developed algorithm uses iterative meta-heuristic optimization to scan the system at different intervals and yield the optimal resilience-driven post-event restorative measure on observing the path redundancy. This study also

utilized weighted graph theory to compute the centrality indices, maintaining an efficacious level of robustness. The effectiveness of the proposed approach is validated through rigorous case studies, and detailed results demonstrate that the developed approach maximizes the distribution system's resilience amid extreme events.

3. *Chapter 3: A DER-Centric Approach Considering Metric-Driven Assessment*

This chapter proposes a two-stage optimization algorithm for resilience-driven system restoration, considering load prioritization based on event duration, impacts, and resource management. The first stage utilizes penalty-based constraint handling to solve the non-linear optimization and restore maximum CLs with suggested network reconfiguration. Moreover, it considers the operation and control modes of DER to deliver the optimal solution. The second stage optimizes power and energy beyond CLs, considering DER connectivity and resource management at different time steps. It looks ahead and restores by optimizing DER's real-time availability, capacity, and repair time for sustainable restoration. Voltage-responsive loads are modeled, addressing the non-linear multi-constraint power flow optimization. Results are satisfactory for a resilience metric-driven restorative approach while considering the challenges in DER-rich distribution systems.

4. *Chapter 4: Resiliency-Driven Vulnerability Assessment for Cyber-Induced Physical Events*

In this chapter, a comprehensive tri-stage architecture for vulnerability assessment, involving event classification, identification, and management, has been proposed, supporting robust data analysis on interfacing online and offline modes. The vulnerability assessment tool inspects and analyzes the impact of events for resilient planning and operation of a renewable-rich distribution system. The contribution of this work is significant concerning the previous efforts, where the common vulnerability scoring system has only been used to analyze the performance with no motive to suggest event-specific remedial actions. Also, the ability to handle both medium and high-severity events by a decision-making algorithm intensifies the scope of the proposed methodology in improving resilience. The combination of theoretic-

cal modeling, statistical analysis, and various case studies validates the success rate of the vulnerability assessment tool and the proposed resilience metric.

5. *Chapter 5: Restoration Framework for a Resilient System Against Extreme Events*

This chapter develops a stochastic framework that formulates the problem as a two-stage approach against wind-induced extreme events. The first stage investigates the dynamic wind impact on the vulnerable overhead components and models the component-level fragility curves. This approach overpowers the past fragility modeling by framing a hybrid dataset to strengthen the damage analysis for a realistic weather-dependent framework. The second stage formulates the problem mathematically using a Markov decision process, where the state transition is illustrated via a directed graph depicting the statistically estimated action and reward. A novel event-driven dynamic programming algorithm is devised to minimize the expected cost function by deriving an optimal policy for each state. The damage-level assessment matrix evaluates the real-time system damage status that aids the system operator in suggesting relevant mitigating and hardening measures. The proposed framework successfully delivers a resilient power distribution system at minimum cost.

6.3 Future Work

The integration of DERs into power distribution systems presents evolving challenges, both in operational planning and resilience enhancement. While this thesis establishes a foundation for resilience quantification, DER-centric restoration, cyber-physical vulnerability analysis, and stochastic restoration under extreme events, several directions remain open for future exploration:

6.3.1 Adaptive and Real-Time Resilience Assessment

The proposed resilience metric can be extended with adaptive capabilities that continuously update weight factors based on real-time data, operator feedback, or evolving grid conditions. Incorporat-

ing machine learning for dynamic adjustment may enhance decision-making under fast-changing event profiles.

6.3.2 Advanced Cyber-Physical Security Integration

While this thesis introduced a cyber-induced vulnerability framework, future work may investigate the integration of intrusion detection systems, blockchain-based transaction security, or artificial intelligence-driven anomaly detection to enhance resilience under sophisticated cyber-physical threats.

6.3.3 High-Fidelity Weather and Climate Event Modeling

The damage-based stochastic restoration model can be extended by coupling fragility analysis with high-resolution weather forecasting. Using climate projections and geographic information systems (GIS) will allow proactive restoration planning under compound extreme events such as concurrent storms, floods, or heatwaves.

6.3.4 Applicability to Indian Distribution Systems and Practical Extension

The IEEE distribution test systems used in this thesis are widely used benchmark networks in power system research for testing and comparison of new methods. Although originally based on typical U.S. distribution systems, their structure is general and represents key features such as radial topology, load distribution, and operational constraints found in practical distribution networks.

The developed framework is independent of geographical location and can be applied to any distribution system by updating system parameters according to local utility data. For Indian distribution systems, this includes adjustment of feeder loading, network configuration, protection settings, reliability indices, and cost data. The cost values used in this work are presented in USD

for consistency with existing literature but can be converted to Indian currency without affecting the proposed methodology.

Application of the proposed methods on actual Indian utility networks is identified as a future extension to further enhance practical relevance. While the methods are validated using IEEE test systems, real-world application on large, unbalanced, and heterogeneous distribution networks remains an important extension. In this direction, collaboration with utilities and implementation through hardware-in-the-loop (HIL) testing and field demonstrations can further establish the practical feasibility and industrial relevance of the proposed work.

6.3.5 Policy-Based and Market-Driven Restoration Strategies

Future work may also integrate regulatory frameworks and resilience incentive mechanisms, considering both technical and economic perspectives. Policy-based restoration can bridge the gap between resilience planning and stakeholder-driven market operations, ensuring wider adoption in practical systems.

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List of Publications

- [P1] [S. Sajwan](#), B. K. Panigrahi and A. K. Srivastava, "Multi-Stage Operational Resilience Metric-Driven Optimal Service Restoration in DER-Rich Power Distribution Systems," *IEEE Access*, vol. 13, pp. 95275-95287, 2025, doi: 10.1109/ACCESS.2025.3574480.
- [P2] [S. Sajwan](#), B. K. Panigrahi, and A. K. Srivastava, "A resiliency-driven vulnerability assessment tool for cyber-induced physical events in renewable-rich distribution systems," *Electric Power Systems Research*, vol. 246, no. 111709, Sep. 2025, doi: 10.1016/j.epsr.2025.111709.
- [P3] [S. Sajwan](#), B. K. Panigrahi and A. K. Srivastava, "Damage-Based Stochastic Restoration Against Wind-Induced Events for a Resilient Distribution System," *2024 IEEE PES Innovative Smart Grid Technologies - Asia (ISGT Asia)*, Bengaluru, India, 2024, pp. 1-6, doi: 10.1109/ISGTAsia61245.2024.10876322.
- [P4] [S. Sajwan](#), "Quantifying Resilience for Power Systems with Optimal Placement of PMUs to Establish a Resilient Smart Grid," *2022 IEEE IAS Global Conference on Emerging Technologies (GlobConET)*, Arad, Romania, 2022, pp. 1049-1055, doi: 10.1109/GlobConET53749.2022.9872389.
- [P5] [S. Sajwan](#), B. K. Panigrahi, and A. K. Srivastava, "DER-Centric Power and Energy Restoration to Enhance Resilience of Power Distribution Systems: A Metric-Driven Approach", *Journal of Modern Power Systems and Clean Energy*. (Revised- R1 submitted)

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Academic Qualification

Ph.D. - Indian Institute of Technology, Delhi Electrical Engineering <i>Thesis title: Quantifying and Enabling Resilience for DER-Rich Power Distribution Systems CGPA 8.0</i>	2018 – Present New Delhi, India
M.Tech. - Gautam Buddha University, Greater Noida Power Systems <i>Thesis title: Optimal Placement of PMUs with and without ZIBs using Metaheuristic Algorithm CGPA 8.88</i>	2017 – 2018 Greater Noida, India
Int. B.Tech. - Gautam Buddha University, Greater Noida Electrical Engineering <i>Project title: Unauthorized Object and Living Entity Detector with PROTEUS & Arduino Uno devices CGPA 8.88</i>	2013 – 2017 Greater Noida, India

Work Experience

Visiting Research Scholar West Virginia University, USA - Grid-integration studies, power flow solutions, modeling, and control of renewable-integrated power systems. - Developed and implemented resilience-driven service restoration strategies for DER-rich distribution networks. - Conducted grid-following/grid-forming (GFL/GFM) integrated distribution system studies. - Implemented integrated studies with challenges (operation and control modes) and impact (uncertain weather availability) of DERs. - Simulated balanced IEEE-33 and unbalanced IEEE-123 bus systems for contingency-based operational decision-making. - Analyzed single and multiple outage impacts on bus voltage profiles using ETAP/PSCAD.	Sept 2023 - Mar 2024
Research Assistant Indian Institute of Technology, Delhi - Performed grid integration and power flow analysis of renewable-integrated power systems under steady-state and contingency conditions. - Modeled and simulated balanced/unbalanced three-phase and single-phase feeders using ETAP/PSCAD. - Performed laboratory testing of electrical machines, including synchronous and asynchronous motors. - Conducted transformer testing (open-circuit, short-circuit, direct loading) to derive equivalent circuit parameters, voltage regulation, and efficiency. - Applied distributed control methodologies for coordinated microgrid operation. - Conducted fault studies, voltage profile analysis, and load variation impact assessment. - Prepared detailed technical documentation, experimental procedures, and engineering reports for academic deliverables.	Aug 2018 - Dec 2021
Electrical Maintenance Intern NTPC - Badarpur Thermal Power Station, New Delhi, India - Assisted in electrical equipment operation, inspection, and preventive maintenance planning. - Conducted field inspections and performance checks of generators, transformers, and switchgear. - Supported fault diagnosis, outage rectification, and operational restoration of plant systems inspections. - Prepared technical reports, maintenance records, and test documentation.	May 2017 - June 2017
Operation and Maintenance Intern BSES Rajdhani Power Ltd (BRPL), New Delhi, India - Distribution network operation and preventive maintenance planning. - 11 kV/33 kV substation equipment inspection, testing, and calibration. - Distribution transformer, VCB/OCB, and protection relay maintenance. - Fault location, isolation, feeder reconfiguration, and service restoration. - Feeder load profiling, voltage regulation, and loss analysis using SCADA. - Preparation of technical logs, outage reports, and switching schedules.	May 2016 - June 2016

Academic Projects

Quantifying and Enabling Resilience for DER-Rich Power Distribution Systems (Ph.D.) - Developed resilience metric-driven frameworks for optimal service restoration in DER-integrated power distribution systems under extreme events and cyber-physical contingencies. - Designed and implemented optimization models (PSO-based and stochastic approaches) for switch reconfiguration, DER dispatch, load management, and voltage regulation. - Modeled voltage-dependent loads and Conservation Voltage Reduction (CVR) for operational efficiency improvement. - Major software tools: ETAP, Cytoscape, MATLAB/Simulink, PSS/E, Python; applied advanced power flow algorithms and optimization techniques.
Wide area backup protection utilizing Phasor Measurement Unit (PMUs) (M.Tech. thesis) - Project focused on PMU-based monitoring and protection of power systems, addressing load encroachment issues, dynamic state estimation, and advanced fault detection to improve system reliability and security under diverse operating and contingency scenarios.
Unauthorized Object and Living Entity Detector with PROTEUS & Arduino Uno (M.Tech. minor project) - Development of an alert system to detect the target and display the distance on measurement. - System designed in Proteus with hardware implementation utilizing Arduino Uno.

Modeling of home automation module in PROTEUS software (B.Tech. major project)

- Controlled home appliances with only one tap on a mobile phone.
- Designed a password-protected system in Proteus with hardware implementation.

Skills

-  **Software Applications**
 - MATLAB/Simulink, ETAP, Power World, Cytoscape, Open-DSS.
-  **Real-time Simulation Platforms**
 - Hands-on experience with ETAP Real-time, RTDS, PSS/E, OPAL-RT, SCADA, Relays.
-  **Programming Languages**
 - MATLAB, Basic C, C++, Python, JAVA.
-  **Miscellaneous**
 - Windows Operating System, Microsoft Office, Overleaf, Literature reading, Analytical and problem solving, Teaching, Public Speaking, Paper Publishing, Research Writing.

Leadership Skills

Coordinated the following events

- Organized “IEEMA Engineer Infinite Conference” sponsored by IEEE Delhi & UP Section, 2018.
- Organized “IEEE Teacher In-Service Program (TISP)” at Jamia Millia Islamia, by IEEE Delhi Section.
- Organized “IEEE International Conference NANOIM 2017” at Gautam Buddha University, Nov. 2017.
- IEEE treasurer, IEEE-Student Branch (GBU-SB), 2016-2018.
- Represented the school at the “Regional level” in the children’s science congress, 2011.

Publications

- * S. Sajwan, B. K. Panigrahi and A. K. Srivastava, “Multi-Stage Operational Resilience Metric-Driven Optimal Service Restoration in DER-Rich Power Distribution Systems,” in *IEEE Access*, vol. 13, pp. 95275-95287, 2025, doi: 10.1109/ACCESS.2025.3574480.
- * S. Sajwan, B. K. Panigrahi, and A. K. Srivastava, “A resiliency-driven vulnerability assessment tool for cyber-induced physical events in renewable-rich distribution systems,” in *Electric Power Systems Research*, vol. 246, no. 111709, Sep. 2025, <https://doi.org/10.1016/j.epsr.2025.111709>.
- * S. Sajwan, B. K. Panigrahi and A. K. Srivastava, “Damage-Based Stochastic Restoration Against Wind-Induced Events for a Resilient Distribution System,” 2024 IEEE PES Innovative Smart Grid Technologies - Asia (ISGT Asia), Bengaluru, India, 2024, pp. 1-6, doi: 10.1109/ISGTAsia61245.2024.10876322.
- * S. Sajwan, “Quantifying Resilience for Power Systems with Optimal Placement of PMUs to Establish a Resilient Smart Grid.” 2022 IEEE IAS Global Conference on Emerging Technologies (GlobConET), Arad, Romania, 2022, pp. 1049-1055, doi: 10.1109/GlobConET53749.2022.9872389.
- * S. Sajwan, M. K. Singh and S. Urooj, “Physical relocation of PV panel for optimization of power under PSC in PV array,” 2018 IEEMA Engineer Infinite Conference (eTechNxT), New Delhi, India, 2018, pp. 1-6, doi: 10.1109/ETECHNXT.2018.8385322.
- * S. Sajwan, S. Urooj and M. K. Singh, “Design and Implementation of Unauthorized Object and Living Entity Detector with PROTEUS and Arduino Uno,” Information Systems Design and Intelligent Applications, Advances in Intelligent Systems and Computing, vol. 672, Springer, Singapore, 2018, doi: 10.1007/978-981-10-7512-4_55.
- * M. K. Singh, S. Sajwan and N. S. Pal, “Solar assisted advance smart home automation,” 2017 International Conference on Information, Communication, Instrumentation and Control (ICICIC), Indore, India, 2017, pp. 1-6, doi: 10.1109/ICOMICON.2017.8279092.
- * S. Sajwan and S. Urooj, “PMU - A Flexible Technology for Measurement of Real-Time Data: Review,” Proc. NANOIM 2017 (3rd Nanotechnology for Instrumentation and Measurement Workshop), Gautam Buddha University, Greater Noida, India, Nov. 2017.
- * S. Sajwan, B. K. Panigrahi, and A. K. Srivastava, “DER-Centric Power and Energy Restoration to Enhance Resilience of Power Distribution Systems: A Metric-Driven Approach,” [Revised – R1 Submitted].

Personal Details

- **Languages Known:** Hindi, English.
- **Nationality:** Indian.
- **Passport No.:** X6618088.
- **Permanent Address:** B-21, 1st floor, Freedom Fighter Enclave, Gate no. 3, Neb Sarai, New Delhi, India- 110068.
- **Strengths:** Adaptable, Calm mindset, Innovative, Leadership, Organizing large-scale events, Teamwork and Collaboration.
- **Hobbies:** Cooking, Travelling, Reading.
- **Area of Interest:** Power system protection, Contingency analysis, Network Restoration, DER-integrated power distribution systems, Distribution system Planning and operations, Wide area measurements, Reliability and resiliency.

References

- **Prof. B. K. Panigrahi** (Ph.D. Supervisor)
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Declaration

I hereby declare that the information furnished above is true to the best of my knowledge.