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PROBABILISTIC MODELING OF SIMULTANEOUS FAILURES FOR POWER SYSTEM RESILIENCE AND NETWORK EXPANSION PLANNING

TESIS PARA OPTAR AL GRADO DE DOCTOR EN
INGENIERÍA ELÉCTRICA

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RESUMEN DE LA TESIS PARA OPTAR AL GRADO DE
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PROBABILISTIC MODELING OF SIMULTANEOUS FAILURES FOR POWER SYSTEM RESILIENCE AND NETWORK EXPANSION PLANNING

This thesis addresses the modeling of simultaneous failures in power systems under extreme events. In the first part, it proposes a novel substation-level representation for seismic resilience assessment, introducing a bay-based framework that captures partial and conditional outages. Unlike traditional models that treat substations as monolithic units, the proposed method considers internal configurations and connectivity, allowing more granular simulation of outage scenarios. The methodology is applied to a modified IEEE 24-bus network and the Chilean transmission system to evaluate the impact of earthquakes, showing improvements in estimating expected energy not supplied and identifying vulnerabilities not captured by traditional models.

In the second part, the thesis presents a simulation-based planning framework that integrates cascading failure dynamics into network expansion and battery storage investment decisions. It employs an Optimization via Simulation (OvS) approach with detailed system failure simulations to evaluate the effectiveness of network enhancements. AC power flow models simulate the evolution of outages within the planning loop, enabling assessment of infrastructure portfolios based on their ability to reduce blackout severity. The framework is applied to two test systems: a modified IEEE 24-bus network and the German transmission network, supporting the identification of cost-effective solutions to mitigate cascading outages.

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MODELADO PROBABILÍSTICO DE FALLAS SIMULTÁNEAS PARA LA RESILIENCIA DEL SISTEMA ELÉCTRICO Y LA PLANIFICACIÓN DE LA EXPANSIÓN DE LA RED

Esta tesis aborda la modelación de fallas simultáneas en sistemas eléctricos bajo eventos extremos. En la primera parte, se propone una representación a nivel de subestación para evaluar la resiliencia sísmica, mediante un esquema basado en bahías (paños) que captura desconexiones parciales y condicionales. A diferencia de modelos que tratan subestaciones como unidades monolíticas, el enfoque propuesto considera configuraciones internas y conectividad, permitiendo simulaciones más detalladas. La metodología se aplica a una versión modificada del sistema IEEE de 24 barras y al sistema de transmisión chileno para evaluar el impacto de terremotos, mostrando mejoras en la estimación de energía no suministrada esperada e identificación de vulnerabilidades no detectadas por modelos convencionales.

En la segunda parte, se presenta un marco de planificación basado en simulación que incorpora la dinámica de fallas en cascada en decisiones de expansión de red e inversión en almacenamiento. Se utiliza un enfoque de Optimización mediante Simulación con simulaciones detalladas para evaluar la efectividad de las mejoras. Modelos de flujo de potencia AC simulan la evolución de fallas dentro del proceso de planificación. El marco se aplica en el sistema IEEE de 24 barras y al sistema de transmisión alemán, permitiendo identificar soluciones costo-efectivas para mitigar apagones en cascada.

Para Evelyn, por su amor, paciencia y apoyo incondicional ♡.

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1. Introduction

This chapter presents the motivation behind this research, focusing on three key aspects: the increasing vulnerability of modern power systems to complex and simultaneous outages, including failures within substation components and cascading failures; the limitations of traditional network expansion planning practices in addressing such events; and the emerging role of new technologies in supporting more effective investment strategies. Furthermore, this chapter outlines the main hypothesis and defines both the general and specific objectives that guide the development of this thesis.

1.1. Motivation

This thesis is motivated by the need to improve power network planning through detailed system failure modeling, addressing cascading outages and guiding investment strategies beyond traditional approaches.

This section is structured as follows. Initially, the discussion focuses on how modern power systems are increasingly exposed to high-impact, low-probability events, including both natural hazards and technical disturbances, which can trigger cascading outages with widespread consequences due to the interaction of these events with existing operational and structural vulnerabilities.

Next, the discussion moves to the limitations of traditional network expansion planning practices, which are typically based on deterministic criteria such as the $N-1$ rule. While these criteria are designed to ensure security against isolated contingencies, they do not account for the evolving complexity of modern power systems, including the possibility of multiple simultaneous failures or the dynamic propagation of outages through protection systems and network dependencies. As a result, conventional planning models may overlook critical vulnerabilities and underestimate the scale of potential disruptions.

The final topic addresses the role of emerging technologies, such as battery energy storage systems, adaptive protection schemes, and smart grid automation, in enhancing the flexibility and responsiveness of power systems. These technologies offer new capabilities for managing uncertain and disruptive conditions, particularly when facing events that fall outside the assumptions of traditional planning frameworks. Their integration into investment planning processes is essential for identifying cost-effective strategies that improve system performance and minimize the impact of large-scale disturbances.

1.1.1. The vulnerability of modern power systems to HILP events

Modern electric power systems are increasingly exposed to high-impact, low-probability (HILP) events, which pose complex challenges due to their rare occurrence and catastrophic impacts. These events include both natural hazards, such as earthquakes, hurricanes, and wildfires, and endogenous technical disruptions, such as protection misoperations, equipment failures, or software faults. Their consequences are often severe, not because the initiating events are always extreme in magnitude, but because they interact with structural and operational vulnerabilities of the system, triggering disproportionate effects such as wide-area blackouts.

One of the most well-known critical threats is the cascading failure, which the North American Electric Reliability Corporation (NERC) defines as "the uncontrolled successive loss of system elements triggered by an incident at any location" [1]. A cascading outage may be initiated by a routine disturbance, such as the tripping of a transmission line or the malfunction of protection equipment [2], that causes a redistribution of power flows, potentially overloading nearby components. As those elements disconnect in turn, a chain reaction may unfold, impacting progressively larger portions of the network and ultimately resulting in system fragmentation or collapse [3].

Although cascading failures are typically associated with technical disturbances under normal weather conditions, they may also be initiated or exacerbated by HILP events of natural origin. Earthquakes, for instance, can damage substation equipment, simultaneously trip multiple transmission lines, and disable local protection systems. Similarly, hurricanes and wildfires can trigger correlated line outages, tower failures, or insulation faults, which may not be independently severe but collectively initiate complex and difficult-to-contain cascading sequences. In these cases, the initial set of failures is not random, but correlated through space or time, violating the assumptions underpinning standard contingency analysis frameworks such as $N-1$.

Several major blackouts in recent decades exemplify the range of initiating events that can precipitate widespread failures, as presented in Table 1.1 highlights several of the most notable blackouts. The 2003 Northeast blackout in North America began with vegetation contact and a software error, but evolved into a major outage due to insufficient situational awareness and the absence of containment mechanisms [4]. In contrast, the 2016 South Australia blackout was triggered by extreme weather that physically damaged transmission infrastructure and activated frequency protection mechanisms in wind generation units, leading to generation loss and frequency collapse. More recently, the 2021 Texas blackout combined a rare cold snap with gas supply failures and demand surges, exposing how operational limits can be breached when stress accumulates from multiple domains [5].

While these events differ in origin and evolution, they reveal a common theme: the power system's vulnerability is not solely determined by the scale of the initiating event, but by how the event interacts with system topology, control mechanisms, and protection logic. A

Table 1.1: Some major power grid blackouts caused by cascading failures.

Reference	Date	Country / Region	People affected (million)	Causes
[6]	January 2023	Pakistan	220	Voltage fluctuation
[6]	October 2022	Bangladesh	140	A transmission line tripping
[5]	February 2021	U.S., Texas	10	Bad weather conditions
[7]	August 2020	Sri Lanka	11	Failure in a power plant
[8]	August 2019	United Kingdom	1	Lightning strike
[9]	January 2018	Sudan	41.5	Cascading failure
[10]	September 2017	U.S., Southeast	7.6	Line cascading failures
[10]	March 2017	U.S., New York	21	Line cascading failures
[11]	September 2016	South Australia	1.7	Extreme weather conditions
[12]	June 2016	Kenya	10	Power transformer tripping
[13]	November 2014	Bangladesh	150	HVDC lines outage
[14]	July 2012	India	620	Transmission line overloaded
[15]	September 2011	Mexico, U.S.	2.7	Transmission line tripping
[16]	September 2003	Italy	57	Tree flashover
[17]	August 2003	Eastern U.S., Canada	50	Generator tripping
[18]	January 2001	India	230	Substation outage

minor equipment failure in a heavily loaded area can escalate into a major disruption if it triggers unexpected protection actions or isolates critical nodes. Similarly, infrastructure that appears robust under $N-1$ conditions may prove vulnerable when subjected to spatially correlated disturbances from a natural hazard. These interactions are often poorly captured by conventional planning and operation tools.

In this context, HILP events must be understood not only as extreme exogenous threats, but also as triggers of systemic instabilities due to their ability to initiate multiple simultaneous or dependent failures. For example, an earthquake may simultaneously affect multiple substations and lines across a region, disabling primary and backup protections, while also impairing communication and control capabilities. This creates a fundamentally different problem from traditional reliability studies, which typically assume independent, single-component failures and controllable post-contingency responses. In the presence of HILP events, these assumptions break down, and the system's response may depend on

Table 1.2: Frequency and impact of blackouts.

Cause	**Frequency**	**Average number of customers affected**	**Average size of blackout in MW**
Earthquake	0.8	375,900	1,408
Hurricane/tropical storm	4.2	782,695	1,309
Ice storm	5.0	343,448	1,152
Wind/rain	14.8	185,199	793
Other external cause	4.8	246,071	710
Other cold weather	5.5	150,255	542
Fire	5.2	111,244	431
Tornado	2.8	115,439	367
Intentional attack	1.6	24,572	340
Lightning	11.3	70,944	270

nonlinear and compounding failure dynamics.

Table 1.2 shows a summary of the frequency of blackouts in the US between 1984 and 2006, and their causes. These events have caused not only structural damage, but also operational instability due to their sudden and widespread nature. The table highlights the range of consequences, from component failures and substation collapse to large-scale load curtailment and long-term service disruption.

In summary, modern power systems are structurally and operationally vulnerable to a wide range of initiating events, including both internal failures and externally driven HILP scenarios. Their effects are amplified by increased interconnectivity, dependence on automated protections, and complex load-generation dynamics. As recent events have demonstrated, failures do not have to be extreme to become consequential—they simply have to interact with existing vulnerabilities in ways that amplify their reach. Understanding this requires moving beyond traditional security assumptions and embracing a broader view of systemic risk, in which the type, timing, and correlation of initiating events play a critical role in determining system behavior under stress.

1.1.2. Limitations of traditional network expansion planning practices

Traditional network expansion planning has historically relied on deterministic reliability standards [19], particularly the $N-1$ security criterion. This principle ensures that the power system can withstand the failure of a single component without service interruption. Under this paradigm, planning efforts prioritize reinforcement measures such as constructing new transmission lines, upgrading existing infrastructure, adding redundancy, and implementing reactive power compensation devices [20]. These measures are designed to maintain power flow feasibility and voltage stability under single-contingency scenarios, providing a baseline of operational security.

While these strategies are effective for addressing credible contingencies, they are not designed to handle the complex dynamics involved in cascading failures. In highly interconnected power systems, a single initial fault, if not properly managed, can propagate rapidly through the network, causing multiple subsequent failures and ultimately leading to large-scale blackouts. These chain reactions often involve operational dependencies, protection miscoordination, and load-generation imbalances that are not adequately captured by traditional $N-1$-based models [21].

Recent large-scale blackouts, such as the events in India (2012) and South Australia (2016), have underscored the limitations of current planning practices and the urgent need to rethink the scope of system adequacy assessments. In these cases, compliance with $N-1$ criteria was not sufficient to prevent system-wide failures, revealing critical gaps in the ability of existing models to anticipate and mitigate HILP-type events [22].

Across international power systems, deterministic criteria like $N-1$ continue to form the foundation of expansion planning. However, their implementation varies and is evolving in response to growing system complexity and risk. For instance, Germany, Japan, and Great Britain apply extended variants such as $N-1-1$ or $N-2$ under specific operating conditions or for critical infrastructure. Meanwhile, countries like New Zealand and the United States are beginning to integrate probabilistic approaches or cost-benefit analyses for selected segments of the network. Nevertheless, in most cases, regulatory frameworks remain fundamentally deterministic, and formal adoption of probabilistic planning remains limited or under development. A comparative summary of current international practices is provided in Table 1.3, which highlights the diversity of planning security criteria and the varying degrees of adaptation to modern risks.

Despite these adaptations, traditional expansion models still face structural limitations. Most conventional approaches focus on meeting future demand at minimum investment cost, using simplified assumptions to maintain tractability, such as representative operating hours or aggregated system representations. While practical, this simplification omits the temporal and spatial complexity of real system operations, especially under stress conditions. Moreover, the prevailing use of $N-1$ deterministic rules fails to address the probabilities and consequences of multiple contingencies, which can result in either overbuilt infrastructure or unaddressed vulnerabilities in the network. These oversights may be particularly critical when considering the risk of cascading failures, whose complex and sequential nature cannot be adequately captured by simplified, deterministic models.

This widespread reliance on deterministic approaches creates a methodological gap when it comes to quantifying and mitigating the risk of cascading outages. Deterministic criteria focus on specific, predefined contingencies and fail to account for the interactions and propagation mechanisms that characterize cascading failures. As a result, system planners may overlook network configurations that appear secure under $N-1$ but are actually vulnerable to domino effects under realistic operating conditions.

Furthermore, traditional models often exclude cascading failure dynamics from the planning objective itself. They verify that a proposed network meets contingency requirements, but they rarely optimize investment decisions based on expected outage costs or probabilities of failure propagation. This simplification risks underestimating the true value of investments

Table 1.3: International experience in planning security criterion.

Country	**Planning Security Criterion**	**Main Characteristics / Observations**
Chile	$N-1$ with probabilistic relaxation	Based on 2014 standard; allows limited probabilistic relaxation (e.g., via EDAC schemes)
Germany	$N-1$ minimum; $N-1-1$ and some $N-2$	Extended $N-1$ planning adopted for maintenance; evaluates critical multiple contingencies
Great Britain (National Grid)	$N-2$	SQSS standard; 2018 update clarified $N-1-1$ use geographically
USA (NERC)	$N-1-1$ (considering one planned outage)	Contingency-based deterministic framework; 2019 revision reinforced sequential event assessment
New Zealand	$N-1$ in the core network; $N-k$ in the economic network, with k derived by a CBA	Applies cost-benefit analysis (CBA); hybrid deterministic-probabilistic approach
Japan	$N-1$ and some $N-2$	Post-2021 use of non-firm connections with protection; dynamic compliance with $N-1$
Brazil	$N-1$	Transitioning toward risk-based segmentation; currently deterministic

in system flexibility, redundancy, or control strategies that could effectively contain or prevent cascading events.

In summary, while deterministic criteria such as $N-1$ have long served as the foundation for transmission expansion planning, their underlying assumptions are increasingly misaligned with the operational realities of modern power systems. These approaches are ill-suited to address the propagation mechanisms inherent in cascading failures and are incapable of modeling the simultaneous, spatially correlated disruptions triggered by HILP events. The continued reliance on simplified, contingency-based planning frameworks limits the ability to anticipate systemic risks and undervalues investments in technologies and strategies that can mitigate their impact. Addressing these gaps requires a paradigm shift toward planning methodologies that incorporate failure dynamics, uncertainty, and cross-domain interdependencies as central elements in the decision-making process.

1.1.3. The role of new technologies for investment planning

As modern power systems face increasing exposure to HILP-type events, the limitations of conventional planning approaches become more evident [23]. In this context, emerging technologies are playing a fundamental role in reshaping how network investments are conceived, prioritized, and evaluated. Technologies that offer dynamic control, fast response, and system-wide visibility provide new capabilities for managing systemic risk and adapting to disruptions that fall outside the bounds of traditional $N-1$ planning.

Among these technologies, battery energy storage systems (BESS) have gained prominence as a critical asset to support power system reliability [24]. Their ability to provide services such as frequency regulation, voltage support, and fast ramping during both normal and contingency conditions makes them an essential element in modern grid operation. Unlike conventional generation, batteries can switch between charge and discharge states within milliseconds, stabilizing the system in moments of stress. This rapid response is particularly valuable in scenarios involving cascading outages, where the timing and sequence of protective actions can determine whether a failure is contained or escalates.

Evidence from real-world applications further demonstrates the value of BESS in improving operational resilience. For instance, a pioneering battery system installed in Alaska has, over a period of 16 years, prevented approximately 30,000 power outages, reducing local interruption rates by 90 % through its rapid response capability during grid disturbances [25]. These results illustrate how energy storage can not only support daily system operations, but also play a strategic role in mitigating the impacts of system failures, particularly under stress scenarios such as cascading outages.

In parallel, the development of smart grid technologies, including advanced metering infrastructure, adaptive protection, real-time monitoring, and automated grid reconfiguration, has enabled a more responsive and observant network [26]. These technologies enhance situational awareness and shorten response times to evolving threats, particularly when dealing with fast-developing cascades. For instance, automated protection systems can dynamically isolate faulted sections, re-route power flows, and prioritize critical loads, thus mitigating the system-wide impact of initial failures. Nevertheless, their full potential is often overlooked in planning tools that treat operational flexibility as external to investment analysis.

To navigate these growing challenges, recent studies have emphasized the importance of adopting integrated planning frameworks that explicitly consider the trade-offs between cost, complexity, and system-wide performance under stress. One conceptual structure for addressing these trade-offs is the resilience trilemma, shown in Figure 1.1, which articulates the three core dimensions of investment strategies: robustness, redundancy, and flexibility and responsiveness. Robustness refers to hardening assets to withstand stress (e.g., substation fortification); redundancy to building alternate paths and capacities; and flexibility to deploying fast, intelligent control solutions that adapt under changing system states.

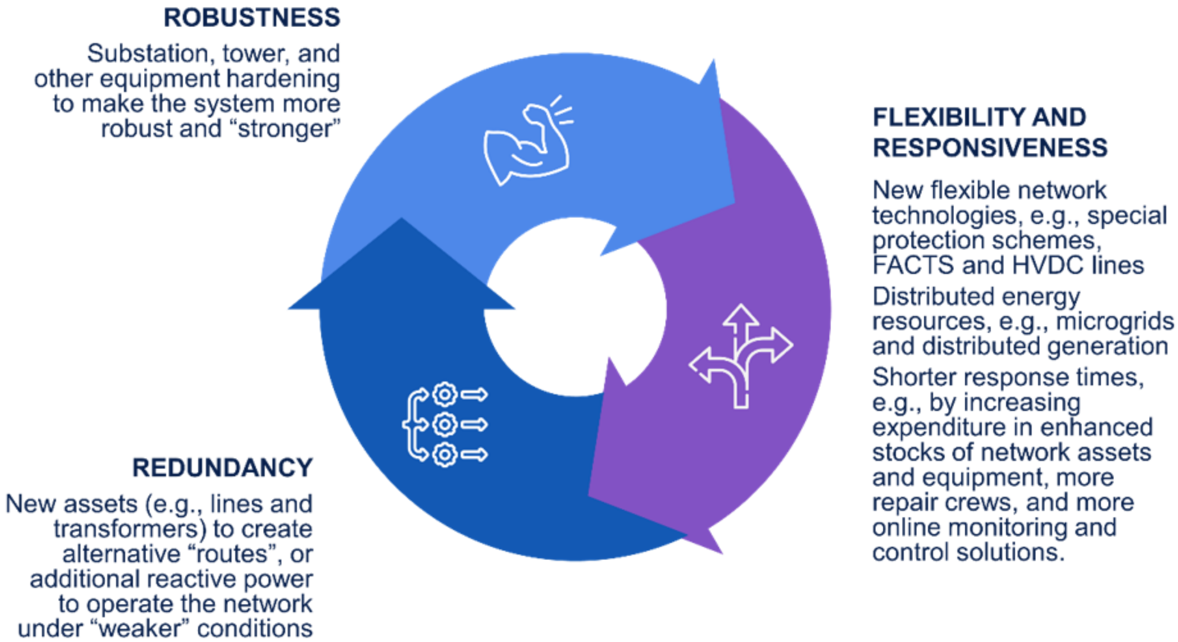

Figure 1.1: The resilience trilemma of investment portfolios. Adapted from [27].

Given these benefits, recent literature and industry assessments have increasingly called for a shift toward integrated planning frameworks that account for the role of these technologies in system resilience and flexibility [27], [28]. Traditional expansion planning approaches often overlook the multi-functional value of storage and automation, treating them as operational tools rather than investment options. However, incorporating these technologies early in the planning process, alongside transmission expansion, can reduce long-term costs, increase the efficiency of infrastructure deployment, and significantly strengthen the grid's ability to withstand rare but high-impact events, such as cascading failures [29].

In this light, the integration of battery storage and smart grid technologies is not only an operational enhancement but a strategic investment decision. As such, their modeling must be embedded into modern planning frameworks capable of capturing the interactions between infrastructure design, operational flexibility, and systemic risk.

In summary, despite significant advancements in modeling cascading failures, expanding grid infrastructure, and deploying new technologies, a critical methodological gap remains in how modern power systems are planned and reinforced to withstand large-scale disruptions. Current planning tools typically rely on deterministic security criteria and linearized representations of the network that do not fully capture the dynamic and sequential nature of cascading outages. These tools often exclude such phenomena from the core optimization process, addressing them only through separate post-contingency analyses or simplified approximations.

1.1.4. Motivation summary

The motivations and relevance of this research topic can be summarized according to the following points:

- Modern power systems are increasingly exposed to high-impact, low-probability (HILP) events, including both natural hazards and technical disturbances. These events can trigger cascading failures that propagate through operational dependencies and protection systems, causing widespread service interruptions. Their impacts are not necessarily tied to the severity of the initiating event, but rather to how the event interacts with existing vulnerabilities in the power network.

- Traditional transmission expansion planning practices are mostly based on deterministic criteria such as the $N-1$ rule, which are insufficient to address the dynamic nature of cascading outages or multiple simultaneous failures. Real-world events, such as those triggered by extreme weather or natural hazards, have even led to chaotic societal conditions—exposing failure scenarios that go far beyond $N-1$ or $N-2$ events. These observations clearly highlight the need to rethink current planning practices and to modify existing standards to account for HILP events within network design and expansion decision-making frameworks.

- Emerging technologies such as battery energy storage systems (BESS), advanced protection schemes, and smart grid infrastructure offer new capabilities to support grid operation under stress. These technologies enhance the system's responsiveness and can play a strategic role in mitigating the impacts of disruptions. However, they are often not considered as part of long-term investment strategies due to limitations in current planning frameworks.

- A conceptual foundation to guide future investment strategies is provided by the resilience trilemma, which highlights the trade-offs among robustness, redundancy, and flexibility. Each of these dimensions offers different advantages in the face of disruptive events, and effective planning must consider balanced portfolios that combine them.

- Despite progress in simulation tools and technology deployment, a methodological gap persists between failure modeling and investment decision-making. In particular, detailed failure simulations—such as those involving cascading outage mechanisms and substation-level modeling—are rarely integrated into the optimization process. Conventional tools often rely on linear approximations that do not capture the sequential and nonlinear nature of failures, limiting their ability to support planning under realistic risk scenarios.

1.2. General description of the research

This research addresses the planning and evaluation of electric power systems under the threat of large-scale disturbances, with a particular focus on cascading failures and hazard-induced disruptions. The work is structured around two core lines of analysis: the assessment of network vulnerability using detailed failure simulations, and the optimization of transmission and storage investments to reduce the impacts of cascading outages.

The first part of the research focuses on the development of a detailed modeling framework to evaluate the effects of natural hazards on power system infrastructure. Specifically, it introduces a bay-level substation outage model to capture the internal structure and conditional availability of substations under seismic events. This model improves upon conventional representations by considering partial outages, enabling a more accurate estimation of the impact of earthquakes on system operability. The proposed methodology includes hazard characterization, fragility modeling, and quantification of resilience metrics. It will support the analysis of how the system responds to severe but realistic disruptions caused by external events.

The second part of the research develops a simulation-based optimization framework to identify cost-effective investment strategies in network expansion and battery storage under cascading failure risk. This framework combines sampling of initial contingencies, investment decision variables, and the simulation of detailed system failure propagation using AC-based models. Unlike traditional approaches that rely solely on contingency analysis, this method captures the sequential disconnection of components, overloads, islanding, and underfrequency protection mechanisms. As a result, it allows for the evaluation of investment portfolios based on their ability to reduce both the probability and the severity of cascading events.

A central contribution of this work is the integration of detailed failure simulations into network investment planning methodologies. This integration will allow planners to evaluate trade-offs between robustness, redundancy, and flexibility when designing infrastructure capable of operating under uncertain and complex failure scenarios. The proposed methods will go beyond static contingency criteria by incorporating nonlinear system responses and dynamic protection interactions.

In summary, this research contributes to the development of power system planning methodologies that go beyond deterministic assumptions and incorporate the complexity of modern networks exposed to disruptive events. By combining vulnerability assessment and investment optimization under failure propagation, this thesis aims to support the design of more secure and cost-effective infrastructure solutions for future power systems.

1.3. Hypothesis

The hypotheses of this research are:

- The representation of initial outages using detailed system failure models, such as substation-level seismic modeling and protection-driven cascading simulations, significantly alters the estimated impact of disruptive events compared to conventional contingency analysis.

- The network expansion and storage planning framework based on Optimization via Simulation (OvS) can effectively support investment decisions in power systems by identifying optimal infrastructure solutions that mitigate cascading outages, leveraging detailed system failure simulations with a full AC power flow representation.

- Explicitly incorporating cascading outages into the investment planning process leads to substantially different and more effective decisions compared to conventional models, by identifying the optimal mix of network assets—such as transmission lines, transformers, battery storage systems, and reactive power compensators—that minimize the risk and impact of large-scale system failures.

1.4. Objectives

1.4.1. General objective

The main objective of this research project is to develop a planning approach that integrates detailed failure simulations such as cascading outage modeling and substation-level seismic analysis into network investment decision-making to improve the assessment of power system vulnerability and support the identification of infrastructure strategies that minimize the impact of high-impact, low-probability events.

1.4.2. Specific objectives

The specific objectives are:

1. To review the state-of-the-art methods for modeling hazard-induced failures and cascading outages in power systems, and to identify the main limitations of conventional network planning practices under high-impact, low-probability events.

2. To develop and implement a detailed substation-level modeling framework for simulating the effects of seismic events on system components, including the conditional availability of electrical bays and the quantification of outage impacts.

3. To propose a novel methodological framework for optimizing network expansion and battery storage investments using an Optimization via Simulation (OvS) approach, with the purpose of reducing the risk and severity of cascading outages in power systems.

4. To integrate a detailed system failure simulation model that captures dynamic phenomena, such as voltage and frequency protection mechanisms, and provides a comprehensive analysis of cascading outages and the effectiveness of mitigation strategies.

5. To strategically combines network expansion, including the addition of transmission assets, and the use of battery storage and reactive power compensation devices to identify the optimal mix of solutions to reduce the impact of cascading outages.

6. To demonstrate the scalability and applicability of the proposed framework to large-scale power systems, validating its performance through case studies that reflect realistic system conditions and investment scenarios.

1.5. Contribution of this research

The first contribution is related to the literature review, which accomplishes specific objective 1, and is stated as follows:

A. A comprehensive review of the literature on hazard-induced failures and cascading outages in power systems, as well as their implications for network planning. This review consolidates methodologies used to represent failure propagation, discusses the limitations of traditional $N{-}1$-based planning under high-impact, low-probability conditions, and identifies the gap in integrating detailed failure models into long-term investment frameworks.

The remaining set of contributions is structured into three parts: the first relates to modeling substation-level failures due to seismic events, the second to assessing system response under cascading outages and investment decision-making, and the third to the development of an optimization framework for planning under cascading risks. These contributions correspond to specific objectives 2 to 6, as follows:

The first part addresses the evaluation of hazard-induced failures and includes the following contribution:

B. A substation-level outage model based on the bay structure of electrical substations is proposed to assess the impact of seismic events on system components. This model enables the quantification of partial outages and the estimation of expected energy not supplied, providing a more accurate and scalable representation of failure impacts in transmission networks.

The second part focuses on cascading outages and their impact on investment decisions:

C. A detailed comparative analysis between traditional contingency-based planning and investment planning that explicitly incorporates cascading failures. This study demonstrates how failure propagation affects system response, and shows that investment decisions differ significantly when cascading outages are considered.

The third part presents a methodological contribution that supports planning under cascading outages:

D. The development of a a novel methodological framework for optimizing network expansion and battery storage investments using an OvS approach, which aims to effectively mitigate the risks posed by cascading outages in power systems.

E. The framework integrates a detailed system failure simulation model that captures dynamic phenomena, such as voltage and frequency protection mechanisms, and provides a comprehensive analysis of cascading outages and the effectiveness of network enhancements.

F. The framework strategically combines network expansion, including the addition of transmission assets, and the use of battery storage and reactive power compensation devices to identify the optimal mix of solutions to reduce the impact of cascading outages.

1.6. Publications

The following peer-reviewed journal and conference papers are directly related to the topics addressed in this thesis:

[J1] **A. Villamarín-Jácome**, R. Moreno, M. Panteli, M. Noebels, E. Martínez Ceseña, and R. Preece, “Optimizing Network Expansion and Battery Storage to Mitigate Cascading Outages via Detailed System Failures Simulations,” in *IEEE Access*, vol. 13, pp. 81462-81473, 2025.

[C1] **A. Villamarín-Jácome** and R. Moreno, “Seismic Resilience Assessment of Electric Power Systems Using a Substation Bay-level Model,” *2022 17th International Conference on Probabilistic Methods Applied to Power Systems (PMAPS)*, Manchester, United Kingdom, 2022, pp. 1-6.

[C2] **A. Villamarín-Jácome**, A. Velásquez-Lozano and M. Saltos-Rodríguez, “Resilient Transmission Planning of the Ecuadorian Power System Against Earthquakes,” *2022 IEEE Sixth Ecuador Technical Chapters Meeting (ETCM)*, Quito, Ecuador, 2022, pp. 1-6.

[C3] M. Saltos-Rodríguez, M. Aguirre-Velasco, A. Velasquez-Lozano, D. Ortiz-Villalba, **A. Villamarín-Jácome** and J. R. Haro, “Resilience Assessment in Electric Power Systems Against Volcanic Ash,” *2022 IEEE Power & Energy Society General Meeting (PESGM)*, Denver, CO, USA, 2022, pp. 1-5.

[C4] M. Saltos-Rodríguez, M. Aguirre-Velasco, A. Velásquez-Lozano, **A. Villamarín-Jácome**, J. R. Haro and D. Ortiz-Villalba, "Resilience Assessment in Electric Power Systems Against Volcanic Eruptions: Case on Lahars Occurrence," *2021 IEEE Green Technologies Conference (GreenTech)*, Denver, CO, USA, 2021, pp. 305-311.

[C5] M. Saltos-Rodríguez, M. Aguirre-Velasco, A. Velásquez-Lozano, D. Ortiz-Villalba and **A. Villamarín-Jácome**, "Distributed Generation for Resilience Enhancement on Power Distribution System Against Lahars Occurrence After a Volcanic Eruption," *2021 IEEE PES Innovative Smart Grid Technologies Conference - Latin America (ISGT Latin America)*, Lima, Peru, 2021, pp. 1-5.

[C6] M. Aguirre-Velasco, M. Saltos-Rodríguez, A. Velásquez-Lozano, D. Ortiz-Villalba and **A. Villamarín-Jácome**, "Network Allocation and Optimal Sizing of BESS for Resilience Enhancement on Power Distribution Systems Against Volcanic Eruption," *2021 IEEE Power & Energy Society General Meeting (PESGM)*, Washington, DC, USA, 2021, pp. 01-05.

[C7] A. Velásquez-Lozano, M. Aguirre-Velasco, M. Saltos-Rodríguez, D. Ortiz-Villalba and **A. Villamarín-Jácome**, "Optimal Planning of VAR Compensator for Voltage Regulation Enhancement on Power Distribution Systems Against Volcanic Eruptions Events," *2021 IEEE Green Technologies Conference (GreenTech)*, Denver, CO, USA, 2021, pp. 298-304.

1.7. Thesis overview

The remainder of this thesis is structured into five additional chapters, briefly described as follows:

Chapter 2 presents a comprehensive literature review on transmission network expansion planning under risk. It highlights the limitations of traditional planning practices based on $N-1$ security criteria and reviews recent methodological advances to incorporate cascading outages into investment models. The chapter concludes with a gap identification regarding the integration of cascading risk and emerging technologies in large-scale planning models.

Chapter 3 focuses on the resilience assessment of power systems under seismic hazards, introducing a novel substation outage modeling approach based on bay-level representation. It describes the methodological framework, outlines the probabilistic modeling stages, and applies the approach to the IEEE RTS 24-bus system and the Chilean transmission network. The results demonstrate how the proposed modeling improves the granularity and realism of seismic resilience assessments.

Chapter 4 explores the impact of cascading outages on system response and investment decisions using an illustrative three-bus network. The chapter compares the system behavior and network expansion decisions under traditional contingency analysis and under detailed cascading failure simulations, highlighting the importance of explicitly modeling cascading phenomena in investment planning.

Chapter 5 introduces a simulation-based optimization framework for network planning under cascading outages. The framework integrates sampling of initial outage scenarios, investment optimization using Optimization via Simulation (OvS) approach, and detailed AC cascading failure simulations. The framework is validated and applied to the IEEE 24-bus system and the German transmission network to demonstrate its scalability and effectiveness in identifying cost-effective and resilient investment portfolios.

Chapter 6 concludes this thesis by summarising the main findings of the research and suggesting potential areas for future work.

2. Literature review

This chapter introduces the context and motivation of the research, focusing on three key aspects: the increasing exposure of power systems to HILP-type events, the limitations of conventional network planning practices in capturing failure propagation mechanisms, and the potential of emerging technologies to improve investment decisions under uncertainty. Additionally, the chapter presents the main research hypothesis and establishes the general and specific objectives of the study. It concludes by outlining the original contributions, related publications, and the structure of the thesis.

2.1. HILP-type event modeling in power systems

HILP-type events, including natural hazards, extreme weather events, and coordinated cyberattacks, represent a growing threat to the continuity of electric power systems. These events are characterized by their infrequency and potentially catastrophic consequences [30]. Unlike conventional contingency events assumed under $N-1$ or $N-2$ security criteria, HILP events may simultaneously affect multiple elements across wide geographical areas, often initiating failure sequences that evolve into large-scale cascading outages. Their complex nature and systemic impact expose the limitations of conventional planning frameworks and have driven a growing body of research focused on their modeling and assessment [31].

A key challenge in modeling HILP-type events lies in accurately representing how external threats affect power system components, especially in critical infrastructure such as substations and transmission corridors. Early efforts in this area have relied on simplified representations of substations, where each substation is modeled as a monolithic node whose total capacity is reduced using a derating factor to reflect partial damage. In this approach, all lines, transformers, and loads connected to the substation experience the same reduction in functionality [32]. While computationally tractable, such simplified models cannot distinguish between partial and full outages, nor do they capture selective failures affecting only specific breakers, busbars, or transformers. As highlighted in several works, these limitations often lead to unrealistic outage patterns and an overestimation of blackout propagation [33, 34].

To increase modeling realism, some studies have moved toward representing substations at the level of individual components such as transformers, circuit breakers, and disconnectors. In this configuration, each piece of equipment can be assigned a unique fragility curve, allowing for differentiated failure probabilities under hazard exposure [35]. This equipment-level representation captures a wider range of failure patterns and yields more accurate simulations of system behavior following HILP events. However, its main drawback is limited scalability: for large networks with hundreds of substations and thousands of components, building and simulating such detailed models imposes heavy data and computational burdens. Several authors explicitly note that these practical challenges have restricted widespread adoption of equipment-level modeling in real system studies [36].

To balance realism and computational feasibility, intermediate strategies have emerged. These include the use of simplified internal substation topologies or structural templates reflecting common real-world designs. For example, augmented bus-branch models incorporate dummy branches or auxiliary nodes into standard power flow models to emulate breaker configurations and internal layouts [37]. These enhancements allow the selective disconnection of internal components while preserving compatibility with existing power flow solvers.

Other efforts employ graph-theoretic techniques to generate extended bus-branch models in which each substation is expanded into a subgraph representing its internal wiring. By assigning substation types (e.g., ring bus, breaker-and-a-half, double bus), researchers can automatically build system-wide models that preserve normal-condition electrical characteristics while enabling more granular fault simulation [38]. These approaches have made it possible to simulate thousands of HILP-induced scenarios in large systems, including regional earthquakes and severe storms.

Parallel to improvements in network topology modeling, substantial progress has been made in the development of probabilistic frameworks for HILP analysis. These frameworks rely on component-level fragility curves, which relate the intensity of the hazard (e.g., peak ground acceleration, wind speed) to the probability of failure for each asset. Using Monte Carlo simulations, thousands of hazard realizations can be sampled to generate plausible combinations of outages, which are then evaluated using power flow tools to compute performance indicators such as expected energy not supplied, unserved load, or total blackout area [39–42]. Incorporating performance-based engineering principles, such as those developed in the field of seismic risk analysis, some researchers have adapted the performance-based earthquake engineering framework to power systems. In these applications, each transmission bus or substation is modeled with its own fragility function and internal configuration, enabling more realistic and spatially distributed representation of failures [37]. These methods can account for differences in substation type, construction standards, and exposure to ground motion or other hazards, improving the accuracy of risk estimates and identifying vulnerabilities that would be masked in aggregated models.

Beyond the representation of initial hazard-induced outages, another critical dimension in HILP event modeling is the simulation of failure propagation [2]. This is particularly important in cascading failure studies, where the failure of one component can overload others, disrupt system balance, or activate protection schemes, leading to sequences of failures that evolve over time. To simulate these mechanisms, various cascading failure models have been developed, ranging from simplified DC-based models to more detailed AC-based recursive simulation frameworks.

DC-based models, such as the DC cascading failure model, solve linearized power flow equations and apply threshold rules for thermal overload, voltage deviation, or islanding.

They are computationally efficient and can be used for large-scale probabilistic simulations. However, they neglect important system dynamics such as voltage stability and reactive power, which limits their accuracy under extreme conditions [43]. In contrast, AC-based models incorporate full reactive power modeling and protection logic, such as undervoltage disconnection, underfrequency load shedding, and generator tripping. These models recursively simulate failure sequences, updating network topology and operational status after each event. While more computationally intensive, AC-based models provide significantly more accurate insights into the mechanisms and severity of cascading failures triggered by HILP events [44].

Alternative modeling paradigms, such as topological and stochastic models, have also been used to analyze the structure and behavior of power systems under stress. Topological models represent the grid as a network of nodes and edges and use graph-theoretical metrics (e.g., betweenness centrality, path redundancy) to estimate system vulnerability [45]. Though useful for qualitative assessments and initial screening, these models ignore physical laws and cannot simulate power flows or protection actions. Stochastic models, including Markov chains and branching processes, probabilistically represent the evolution of cascading failures but similarly lack integration with electrical behavior [46]. Recent literature has also explored interdependent infrastructure modeling, where cascading failures are simulated not only within the power grid but across interconnected systems, such as communications or water supply. These models are particularly relevant in modern infrastructure environments where outages in one system can propagate and amplify effects in another [47].

Despite the diversity of approaches and growing sophistication of modeling tools, a clear gap remains in the integration of detailed failure modeling for HILP events into planning frameworks. Many existing studies either oversimplify component-level impacts or fail to capture operational dynamics, such as protection interactions and time-varying system reconfiguration, that govern cascade evolution. Bridging this gap requires modeling frameworks capable of representing partial substation outages, differentiated equipment fragilities, and dynamic propagation mechanisms, all while remaining computationally tractable for large-scale probabilistic studies.

In summary, HILP-type event modeling in power systems requires combining probabilistic risk estimation, improved network topology representation, and dynamic failure simulation. While the literature has advanced considerably in each of these areas, bridging them in a way that is both computationally tractable and operationally meaningful remains a key research challenge. Addressing this need through detailed failure modeling constitutes a relevant and timely direction for future work in the planning and resilience analysis of power systems.

2.2. Electricity network expansion planning

Electricity network expansion planning[1] plays a critical role in ensuring the long-term adequacy, reliability, and economic efficiency of power systems. It consists of determining

[1]Network planning here refers to high voltage power networks. It excludes distribution and substation planning.

the optimal time, location, and number of new transmission lines or reinforcements to be installed, while satisfying a variety of technical, economic, and environmental constraints. The primary objectives of a typical expansion plan may include minimizing investment and operational costs, reducing network losses, meeting environmental regulations, alleviating congestion, ensuring supply adequacy, and maximizing social welfare [48].

Transmission Network Expansion Planning (TNEP) is the specific process by which expansion strategies for the high-voltage transmission system are evaluated over a long-term planning horizon. These strategies aim to meet forecasted demand growth, integrate new generation sources (particularly from renewable energy), and comply with technical and regulatory requirements [49].

Over the last decades, extensive research has been dedicated to developing mathematical models to solve the TNEP problem efficiently. Traditional approaches have focused primarily on cost minimization and can be broadly classified into classical optimization-based methods, such as linear programming [50,51], dynamic programming [52], nonlinear programming [53], and mixed-integer linear programming (MILP) [54,55]. Additionally, advanced decomposition techniques, such as Benders decomposition [56] and hierarchical decomposition [57], have been widely applied to break down the large-scale problem into more tractable subproblems. In some cases, these methods are combined with branch-and-bound algorithms [58] to efficiently explore the discrete solution space associated with investment decisions. In this context, the main works published so far on this topic are summarized in Table 2.1.

Beyond exact methods, heuristic and metaheuristic techniques, including genetic algorithms, simulated annealing, and particle swarm optimization, have been proposed to address the complexity and non-convexity of realistic formulations, particularly when integrating multiple constraints or nonlinearities [59]. More recent formulations have also considered hybrid approaches, which combine classical optimization with heuristic strategies to improve convergence and computational performance [60].

The TNEP problem is inherently challenging from a computational standpoint. It is widely recognized as a large-scale, nonlinear, non-convex, and mixed-integer optimization problem [61]. These characteristics stem from the discrete nature of investment decisions (e.g., whether or not to build a line), the nonlinearities associated with power flow equations, and the multiple layers of constraints, economic, regulatory, and operational, that must be satisfied. As a result, solving the TNEP problem for realistic systems often requires trade-offs between model accuracy, tractability, and computational efficiency [48].

Table 2.1: A comparison of selected features of selected references in network investment planning considering cascading outages.

Reference	Year	Candidate investments	Model	Protection mechanisms	Programming	Optimization method	S/D	Decision criteria
[62]	2023	Lines, generators	AC	Voltage, overload	MINLP	Two-stage OvS with Generalized Pattern Search	S	T+O+X
[63]	2022	Lines, transformers	AC	Voltage, overload	MINLP	Genetic algorithm	S	T+X
[64]	2022	Fault current limiters, BESS	AC	Voltage, overload	NLP	Hybrid Snake-Sine Cosine algorithm	D	T+O
[65]	2020	Lines	AC	Voltage, overload	MINLP	Forward pseudo-dynamic planning strategy	D	T+O+X
[66]	2020	Lines, generators	SOCP for AC	Not specified	MISOCP	CPLEX	D	T+O+X
[67]	2022	Lines, generators	DC	Overload	MINLP	Knapsack-based heuristic	S	O+X
[68]	2021	Lines	DC	Overload	MIP	Benders decomposition algorithm	D	T+O+X
[69]	2021	Lines	DC	Overload	NLP	Industrial Strength COMPASS (ISC) algorithm	S	X
[70]	2016	Lines	DC	Overload	LP	Not specified	D	X
[71]	2015	Lines	DC	Overload	LP	Branch-and-bound algorithm	D	T+X
[72]	2015	Lines	DC	Overload	MINLP	Multi-objective particle swarm optimization	S	T+O+X
[73]	2014	Lines	DC	Overload	MINLP	OptQuest Engine	S	T+X

Transmission expansion decisions are also made under uncertainty. However, in practice, the most common planning approach relies on deterministic criteria based on worst-case assumptions. For example, transmission infrastructure is typically designed to operate correctly under the most severe plausible operating conditions, such as peak demand or extreme weather events [19]. This conservative design philosophy ensures operational robustness but may lead to overinvestment if the worst-case scenarios are unlikely. Conversely, underestimating risks can result in system inadequacy, congestion, or even operational failure. Therefore, accurately characterizing uncertainty remains a central challenge in transmission planning [74].

Another key aspect of network expansion planning is its association with system reliability. Reliability-oriented TNEP methods evaluate the capacity of the grid to supply load while meeting predefined adequacy and security standards. These evaluations may include probabilistic indices such as Loss of Load Expectation (LOLE), Expected Energy Not Supplied (EENS), and Hierarchical Reliability Assessment (HRA) [75]. At the distribution level, customer-oriented reliability metrics such as Customer Interruptions (CI) and Customer Minutes Lost (CML) are commonly used to quantify the expected impact of equipment failures on service continuity. Although these probabilistic measures provide a richer representation of uncertainty than deterministic criteria, they remain largely focused on credible or historically frequent contingencies.

On the other hand, security assessments typically incorporate deterministic $N-1$ criteria, which ensure that the system can withstand the failure of any single component without violating operational limits. In some cases, extended criteria like $N-1-1$ or $N-2$ are also considered to address multiple contingencies, particularly in critical infrastructures [48].

While these models provide a robust foundation for decision-making, their scope is often limited to predefined sets of contingencies and simplified system behaviors. As a result, both deterministic and probabilistic approaches tend to overlook the correlated, cascading, and large-scale failures characteristic of HILP events. Therefore, appropriate extensions to traditional network planning approaches are essential to incorporate realistic hazard impacts and reflect the increasing complexity and dynamic nature of modern power systems.

A further challenge in incorporating HILP events into investment planning arises from the inherent probabilistic characteristics of such events. Because HILP scenarios exhibit extremely low occurrence probabilities, their expected impact—when computed through conventional probabilistic metrics—tends to approach zero. As a result, resilience-oriented investments that would significantly mitigate damage under these rare but catastrophic conditions appear economically unjustified when assessed purely through expected-value formulations. This creates a methodological and practical gap: while utilities and system operators recognize the potentially severe consequences of HILP events, traditional planning frameworks are not well-suited to capture their tail risks, correlated failures, or cascading effects. Addressing this challenge requires alternative decision-making tools that move beyond expected-value optimisation, incorporating risk-aversion, scenario-based assessments, or worst-case performance metrics that better reflect the societal and operational importance of safeguarding the grid against low-probability, high-impact disruptions.

2.3. Incorporating cascading outage risk into network planning

Cascading outages represent one of the most critical and least predictable threats to power system security and reliability. Triggered by either single events or multiple coinciding incidents, these failures propagate through complex chains of component disconnections and protective device activations, often culminating in large-scale blackouts. Major historical events, such as the 2003 Northeast blackout in the US and Canada, the 2015 Turkey blackout, and the 2019 UK blackout, underscore how these phenomena can emerge unexpectedly and spread rapidly across highly interconnected systems, impacting millions of users and critical infrastructures [18]. These cases highlight that cascading failures do not follow deterministic paths and are deeply influenced by operational stress levels, control responses, and sometimes unanticipated protection misoperations [76].

Traditionally, long-term transmission expansion planning has relied on deterministic reliability standards such as the $N-1$ criterion, which evaluates the ability of the system to withstand a single component outage. Although useful for ensuring security under common contingencies, these standards fail to capture the sequential and interdependent nature of cascading failures. Advanced models have since emerged to overcome these limitations, incorporating multi-contingency ($N-k$) scenarios or probabilistic risk evaluation frameworks, but many still neglect the actual propagation mechanisms and dynamic responses involved in cascading events [48].

To bridge this gap, researchers have proposed a wide range of cascading failure models that aim to replicate the behavior and spread of failures in complex power networks [77]. These models vary widely in fidelity, from topological and stochastic representations to physics-based simulations. Topological models abstract the network into nodes and edges, allowing for computationally fast vulnerability assessments using metrics like betweenness centrality or maximum flow. However, they lack the ability to reflect electrical laws such as Kirchhoff's laws, limiting their usefulness for resilience-oriented planning [29]. Stochastic models introduce probabilistic elements, often via Markov chains or branching processes, to estimate the probability of different failure paths. While efficient for large simulations, they do not capture the underlying physical mechanisms that drive cascade propagation [78].

More detailed simulations have focused on quasi-steady-state and quasi-dynamic models [79], typically based on iterative power flow solutions. Within this class, DC-based cascading failure models are widely used due to their simplicity and fast convergence. They provide insight into overload propagation and topology-dependent vulnerabilities. However, these models assume constant voltage magnitudes and neglect reactive power, rendering them insufficient for representing dynamic instability mechanisms such as voltage collapse or frequency deviations [80]. In contrast, AC-based cascading failure models incorporate both active and reactive power flows and allow for the inclusion of voltage and frequency protection schemes. This results in more realistic simulations of grid behavior under stress, including critical phenomena like unintentional islanding, undervoltage disconnections, and frequency collapse [81].

The complexity of AC power flow introduces computational challenges, especially under stressed or degraded network conditions where convergence may fail. However, recent developments have led to more robust and computationally efficient AC-based models, suitable for resilience studies. These models use iterative cascades where static AC power flow calculations are recalculated after each contingency, allowing for the simulation of cascading propagation across multiple "generations" of failures. Their validation, including cross-comparison with historical data and statistical benchmarking, has been supported by the IEEE Task Force on Understanding, Prediction, Mitigation, and Restoration of Cascading Failures [3].

Despite growing awareness of the severe impacts of cascading outages, their incorporation into network investment planning remains limited. Many existing planning tools treat cascading failures either as an external risk to be analyzed separately or simplify their dynamics using static contingency approximations. This creates a methodological gap: while infrastructure vulnerabilities may be identified through simulation studies, these insights are not systematically integrated into expansion decisions. Consequently, the ability to proactively design infrastructure that mitigates such risks is significantly reduced. Although the literature on cascading failures has expanded in recent years, providing detailed reviews and analysis techniques [2,3,6], most contributions focus on the characterization and modeling of cascade propagation itself, rather than on embedding this understanding into planning frameworks. Addressing this disconnect is essential for ensuring that future network investments not only meet demand and reliability standards but also enhance systemic resilience against complex, high-impact failure scenarios.

Early network investment planning models predominantly used reliability standards, such as the N-1 criterion [19], [82–84]. With the development of computational capabilities, more sophisticated models have emerged that allow the simultaneous consideration of multiple failures (i.e., N-k contingencies) [85–88]. While these approaches improve the understanding of blackout risks, they still fall short of addressing the cascading nature of failures.

Recent studies have made progress in addressing cascading outage risks in network investment planning [62–66, 89–98]. These works use various optimization models and simulation tools to provide insights into the mitigation of cascading outages. For example, probabilistic optimization models [63, 66, 95–97] evaluate investments by assessing the probability distribution of failures in different system configurations. Risk-based optimization frameworks [89, 91, 94] adopt metrics such as Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR). While adaptive optimization models [65, 90, 92] have been explored to sequentially optimize network investments while adapting to changing network conditions. These approaches add flexibility in responding to cascading outages as risks evolve. In addition, hybrid and heuristic optimization models [64] have been introduced to improve computational efficiency for large-scale systems. Simulation-based optimization models have been used to simulate cascading risks and guide network investment decisions [62, 93, 98], integrating cascading failure simulations directly into the optimization process.

In terms of strategies, several studies focus on the traditional expansion of the transmission network, advocating for the construction of new transmission lines, substations, and transformers to strengthen the resilience of the network and prevent cascading failures [63,65,89,92,95,96,98]. Others [62,91,93,94] emphasize reinforcing existing infrastructure to better withstand specific risks, such as extreme weather or seismic events. Finally, advanced technologies are being integrated into network planning models to improve resilience. Studies such as [64, 66, 90] explore the integration of Energy Storage Systems (ESS), but assess their individual potential to provide greater operational flexibility and responsiveness to cascading risks.

While significant progress has been made in addressing cascading outages through various models and approaches, there remains a need for further integration of detailed failure simulations and advanced technologies, such as battery storage and reactive power compensation, into network investment models. Approaches that combine network expansion with these advanced solutions, while efficiently handling cascading risks and balancing investment strategies, remain underexplored in the current literature. Our work contributes to this gap by presenting a comprehensive framework that not only integrates network expansion and battery storage but also uses detailed system failure simulations to capture dynamic phenomena, such as voltage and frequency protection mechanisms. This provides a more realistic representation of cascading outages and complements previous research by exploring computational challenges through a scalable optimization methodology applicable to large-scale networks. This framework allows for the exploration of different combinations of enhancements, providing valuable insights into effective strategies for reducing the risk of cascading failures while managing investment trade-offs.

2.4. Network enhancements to mitigate cascading outages

Traditional transmission expansion planning has long relied on the principle of redundancy to ensure system reliability under credible contingencies. By constructing new lines, substations, or transformers, planners aim to reduce congestion, distribute load flows more evenly, and ensure that the system can withstand single $(N-1)$ or, in some cases, multiple $(N-k)$ outages. This strategy has proven effective for enhancing robustness under isolated disturbances and is still widely applied in practical planning environments. However, these structural reinforcements, while important, may be insufficient when the system is exposed to rare but high-impact cascading failures, where dynamic instability, protection miscoordination, and voltage/frequency collapse become dominant mechanisms of propagation. In such events, redundancy alone does not guarantee containment or fast recovery, particularly if new lines fail to address dynamic support needs.

To complement physical expansion, recent studies have explored more flexible and dynamic strategies aimed at mitigating the risk of cascading outages. One such approach involves reinforcing existing infrastructure—for example, uprating or reconductoring lines, and installing protection schemes—to improve performance under stress or specific environmental threats such as wildfires, earthquakes, or extreme storms [28], [30], [34], [37]. These measures can delay or reduce the need for new transmission corridors while enhancing robustness to known localized risks.

A growing body of research has also focused on integrating advanced technologies into transmission planning frameworks. Among these, Battery Energy Storage Systems (BESS) have received increasing attention for their potential to enhance system resilience through fast-response capabilities. Batteries can inject or absorb real power within milliseconds, providing critical support during both normal operations and contingency events. In daily operation, they smooth renewable variability and manage peak demand, complementing transmission infrastructure and reducing stress on critical corridors. During outages, they act as virtual spinning reserves, able to arrest power imbalances, prevent overloads on healthy lines, and deliver reactive support to stabilize voltage profiles. As demonstrated by Gacitúa et al. (2023), co-planning transmission assets with strategically located BESS in the Chilean grid allowed the system to operate closer to its limits under N-0 conditions, reducing the need for certain transmission reinforcements and cutting overall expansion costs by 18 % [54]. In effect, BESS can enable a form of "corrective N-1" planning, wherein batteries are deployed to actively compensate for outages in real time—enhancing reliability and resilience without excessive overbuilding.

Beyond real power support, batteries interfaced through power electronics can also offer reactive power compensation, which is critical for maintaining voltage stability during disturbances. Voltage collapse is a common mode of cascading failure and often results from insufficient reactive power following a fault. In this context, traditional devices such as Static VAr Compensators (SVCs) and STATCOMs play a vital role in securing the voltage profile. Their placement prevents local undervoltage conditions from triggering wider system instabilities. Reactive resources are also fundamental for supporting undervoltage load-shedding schemes and generator recovery post-contingency. Several major blackouts have identified reactive support deficiencies as core drivers of instability [55].

In summary, modern planning frameworks that strategically combine network expansion with energy storage and reactive compensation offer a more holistic and cost-effective pathway to improve grid resilience. This co-optimization approach allows planners to identify the optimal mix of transmission and technological reinforcements, enhancing system stability not only under common contingencies, but also under severe, low-probability cascading events. The framework proposed in this thesis builds upon this direction, aiming to integrate detailed system failure simulations with coordinated investment decisions across lines, BESS, and reactive devices—thereby filling a critical gap in current planning methodologies.

In light of the limitations identified and the opportunities offered by modern technologies, the following chapter presents the methodological framework developed in this thesis. This framework combines detailed system failure simulations with investment planning decisions to more effectively mitigate cascading outages.

2.5. Summary and gap identification

This section summarizes the literature review and identifies the research gaps that this thesis aims to address.

2.5.1. HILP-type event modeling in power systems

The literature shows increasing efforts to understand the impacts of HILP-type events on power systems, particularly in terms of the initiation of large-scale outages and their cascading propagation. Recent studies have explored probabilistic frameworks, fragility-based models, and extended power flow representations to evaluate system vulnerability under extreme hazards. While some contributions incorporate enhanced substation configurations and AC-based recursive simulations, most works remain limited in their ability to integrate detailed failure modeling into investment planning tools. In particular, existing models often treat hazard-induced outages as uniform or binary events, oversimplifying the diverse physical behaviors and protection mechanisms that govern failure propagation. Furthermore, while simulation tools have become more sophisticated, they are frequently used for post-hoc analysis rather than informing long-term infrastructure decisions. As a result, there is a clear gap in the development of planning frameworks that explicitly integrate detailed outage simulations triggered by HILP-type events to guide network investment strategies.

2.5.2. Electricity network expansion planning under cascading outages

Transmission network expansion continues to be formulated primarily through deterministic planning approaches that rely on predefined contingencies, particularly the $N!-!1$ criterion. Although such models ensure operability under single failures, they do not capture the systemic nature of cascading outages or the nonlinear interactions that arise during extreme stress conditions. Recent works have highlighted the need to move beyond static contingency sets by embedding cascading failure analysis into the planning stage. However, very few methods successfully incorporate cascading outage propagation into the optimization loop. The failure dynamics are often treated as exogenous risks or approximated through scenario-based stress testing. As a result, current investment models lack the capacity to prioritize transmission upgrades and flexible assets based on their ability to reduce the likelihood or severity of cascading failures. This disconnect presents a methodological gap in designing infrastructure capable of withstanding multi-component disturbances in a cost-effective manner.

2.5.3. Integration of cascading failure models into planning

Despite advancements in cascading failure modeling—from DC-based propagation mechanisms to AC-based dynamic simulation—the integration of these models into long-term planning frameworks is still limited. In many cases, cascading simulations are performed separately from investment models, used only for ex-post validation or stress testing. This siloed approach fails to capture how the structure of investments influences, and is influenced by, the dynamic behavior of the grid under failure scenarios. Additionally, while some probabilistic optimization methods incorporate contingency sampling, they rarely include sequential failure dependencies or protection-driven disconnections. As such, a methodological gap persists in the unification of cascading failure models with infrastructure decision-making, especially under uncertainty. Closing this gap would enable planners to identify investment strategies that not only minimize operational costs but also reduce the risk and systemic impact of widespread outages.

2.5.4. Role of flexible technologies for cascade mitigation

Modern power systems increasingly rely on distributed technologies such as battery energy storage systems (BESS), reactive power compensation, and advanced control schemes to provide operational flexibility and enhance stability. These resources are especially important in mitigating the spread of cascading failures during high-stress conditions. However, the literature reveals that their role in expansion planning is often evaluated in isolation from failure propagation models. Most planning frameworks optimize their location or capacity based on operational cost or energy balancing, rather than on resilience metrics. Moreover, reactive power devices, despite their established role in maintaining voltage profiles, are commonly excluded from investment planning models. There is thus a need to integrate these technologies within holistic planning frameworks that explicitly account for their impact on system resilience, particularly in scenarios involving multi-stage disturbances. The lack of co-optimization between network reinforcements and flexibility assets under cascading risks remains a critical research gap.

3. Resilience assessment of power systems using bay-level substation modeling

3.1. Overview

This chapter introduces a resilience assessment framework for power systems subject to seismic hazards, with a particular focus on the modeling of substation outages. Substations have been widely recognized as among the most vulnerable components of the electrical grid during earthquakes, often accounting for a significant portion of the disruptions observed in past extreme events. Traditional resilience assessment models frequently rely on a monolithic representation of substations, assuming either full availability or total failure of the substation as a whole. While computationally efficient, this assumption neglects the internal structure of substations and the heterogeneous nature of damage under seismic stress, which can lead to substantial underestimation of the system's actual vulnerability.

To address this gap, this chapter proposes a substation modeling approach based on electrical bays, which are logical groupings of equipment within substations (e.g., breakers, disconnectors, busbars, and transformers). The proposed bay-level model assumes that if one critical component within a bay fails, the entire bay becomes unavailable. Consequently, the performance of the substation—and thus the power network—depends on the specific pattern of bay outages triggered by the seismic event. The outage probabilities are determined using fragility curves specific to medium-voltage substations, and damage states are assigned through Monte Carlo simulation. Compared to the monolithic approach, the bay-level representation offers a better balance between modeling realism and computational feasibility, especially for large-scale systems.

The bay-level substation model is embedded into a four-stage probabilistic resilience assessment methodology, which consists of: (i) hazard modeling using peak ground acceleration (PGA) as the seismic intensity measure; (ii) vulnerability assessment of each component through fragility functions; (iii) system response simulation using a pre- and post-contingency optimal power flow formulation; and (iv) quantification of resilience using both Expected Energy Not Supplied (EENS) and E-based metrics, which capture operational and infrastructure-level impacts.

To demonstrate the applicability and performance of the proposed methodology, two case studies are conducted. The first is based on the IEEE RTS 24-bus system, a benchmark test case commonly used for power system reliability analysis. The second case study examines the Chilean transmission network, which has real-world relevance given the country's exposure to high seismic activity. For both systems, multiple earthquake scenarios are simulated, and the system's ability to maintain service is quantified under both the monolithic and bay-level outage models.

The results show that the bay-level modeling leads to significantly higher estimates of EENS and more severe degradation of infrastructure and operational resilience indicators. In particular, for the Chilean transmission network, the proportion of damaged substations estimated with the bay-level model closely aligns with empirical evidence from the 2010 Maule earthquake. This confirms the practical relevance and improved accuracy of the approach. Moreover, the comparison with the monolithic model highlights how overly simplified representations can obscure the true extent of system vulnerabilities.

In summary, this chapter provides a technically robust and scalable modeling approach for substation outages in seismic resilience analysis. The proposed methodology contributes to improving the accuracy of resilience assessments, thereby supporting more informed and effective planning and investment decisions to enhance the robustness of power networks under natural hazards.

3.2. Introduction and motivation

In recent years, the increasing frequency and intensity of natural hazards have posed significant challenges to the resilience of electric power systems worldwide. Among these hazards, seismic events stand out due to their abrupt onset and potential to simultaneously disrupt multiple components across the transmission infrastructure. Substations, in particular, have been repeatedly identified as critical and highly vulnerable nodes, whose failure can trigger widespread outages and severely compromise system operability. Under such conditions, traditional risk assessment models, often based on coarse assumptions such as $N-1$ security criteria or monolithic substation representations, are insufficient to capture the full extent of damage propagation and service disruption.

To improve the accuracy and realism of resilience assessments, this chapter introduces a modeling framework that incorporates detailed substation outage representations based on electrical bays. This level of granularity enables the simulation of partial substation failures by recognizing that damage within a substation is often localized, affecting specific bays rather than the entire facility. Each bay is treated as a functional unit composed of interconnected elements such as circuit breakers, disconnectors, and transformers, whose failure—individually or in combination—can result in the unavailability of associated transmission paths. This detailed modeling approach allows for a more nuanced representation of substation behavior under seismic stress and enhances the ability to identify cascading impacts on the overall power network.

This chapter is motivated by the need to shift from oversimplified resilience assessments toward simulation-based methods that reflect the dynamic and nonlinear nature of infrastructure response under natural hazards. In line with emerging research trends in power system resilience [99], the proposed approach is integrated within a probabilistic framework that includes hazard modeling, vulnerability assessment via fragility functions, system response through optimal power flow analysis, and resilience quantification using resilience metrics. Such a framework ensures that resilience assessments are technically robust, offering actionable insights for investment and operational decision-making.

Furthermore, the inclusion of detailed substation modeling complements broader simulation-based methodologies that incorporate cascading failure dynamics. Just as detailed cascading outage simulations have proven essential in investment planning under systemic risk, bay-level substation modeling is key for realistic resilience assessments under natural hazard scenarios. Together, these approaches advance the field toward a unified framework for planning and assessing resilient electric power systems under both internal and external threats.

According to the IEEE PES Task Force, power system resilience is the ability to limit the extent, system impact, and duration of degradation in order to sustain critical services following an extraordinary event. Key enablers for a resilient response include the capacity to anticipate, absorb, rapidly recover from, adapt to, and learn from such an event. Extraordinary events for the power system may be caused by natural threats, accidents, equipment failures, and deliberate physical or cyber-attacks. [100]. Unlike traditional reliability (which deals with day-to-day outages and $N-1$ contingencies), resilience focuses on rare but extreme incidents, e.g. natural catastrophes, extreme weather, cyber/physical attacks, or widespread equipment failures, and how the grid survives and rebounds from them. Ensuring resilience has become a critical concern as modern societies grow more dependent on continuous electricity supply. In fact, despite extensive preparedness efforts, major power interruptions due to extreme events have grown more severe in recent years. This trend is evident in disasters such as hurricanes, wildfires, and earthquakes that have caused multi-day regional outages. Consequently, industry standards have started to address such scenarios: for example, NERC's planning criteria require studying "extreme event" contingencies (like loss of an entire substation or multiple co-located elements), although mitigating these high-impact events is not mandatory due to their rarity. In this context, detailed modeling of the grid's infrastructure is receiving increased attention as a means to better evaluate and improve system resilience. One important aspect is the modeling of substations at the bay level (node-breaker detail). A substation is a hub where multiple circuits interconnect through buses, circuit breakers, disconnect switches, transformers, and other devices. Traditional power flow models use a simplified bus-branch representation that collapses each substation to a single bus. This simplification cannot capture failure modes internal to the substation – for instance, a bus fault or breaker failure that knocks out several connections at once. During extreme events, such coupled failures become plausible (e.g. a substation flood or earthquake could disable numerous components simultaneously). Therefore, researchers have argued for using node-breaker or bay-level models in resilience studies, wherein each switch, bus, and bay is explicitly represented. This granular modeling allows simulation of complex outage scenarios that would be invisible in a bus-branch model. The past decade has seen significant efforts in academia and industry to incorporate detailed substation representations in resilience assessment, especially for scenarios involving natural hazards and cascading failures.

Substations are often identified as critical-vulnerability points in power networks. They concentrate key equipment in a single location, so a disaster impacting a substation can cause a disproportionate loss of functionality. Studies have noted that substations are among the most vulnerable components during events like earthquakes. For example, a strong earthquake might damage multiple breakers, bus structures, or transformers within a single yard. If the network is modeled coarsely (each substation as one node), it is difficult to represent the myriad ways such damage can unfold. In reality, substation outages can take many forms depending on which bays (i.e. the sets of breakers and switches connecting a line or transformer) are lost. A "partial" substation outage (losing some bays) will have a different network impact than a complete substation blackout. This granularity is crucial for resilience analysis: it determines whether power can reroute and which customers are cut off when a substation is hit by a disturbance. Another motivation for bay-level modeling is capturing cascading failure mechanisms. Many large blackouts have originated from sequences of failures that include substation-related events (such as protection system misoperations or bus faults). A breaker that fails to open on time can lead to a bus bar fault, which in turn trips multiple adjacent lines – a cascade initiation that a simple N-1 analysis would miss. Indeed, analysts have shown that even a single breaker operation (or mis-operation) can drastically change network topology and potentially destabilize the system. Representing every breaker and disconnect in the model allows simulation of "hidden" $N-2$ or $N-3$ contingencies caused by substation configurations or failure of protection devices. Without a node-breaker model, there is "no good way to translate individual component fragilities to the whole substation" behavior. This limitation motivates the adoption of detailed substation models so that the direct impact of component failures (and their combinations) on system topology and performance can be evaluated with fidelity. Finally, the push for renewable integration and smarter grids also ties into resilience at the substation level. As more automation and distributed resources are deployed, substations become an even more complex cyber-physical nexus. Evaluating resilience requires not only knowing that a line failed, but also which breaker opened, how the substation reconfiguration isolated the fault, and how quickly the station can be brought back. These considerations strengthen the case for detailed modeling. In summary, the motivation for bay-level substation modeling in resilience assessment is to capture the realistic outcomes of extreme events or cascading processes – outcomes that hinge on substation topology, equipment reliability, and operational configurations that simpler models would overlook.

3.2.1. Frameworks for substation outage modeling

Substation outage modeling is key to assessing the power system resilience against natural hazards. In this sense, we compare two frameworks to model substation outages after earthquakes. The first is the monolithic approach, the most used practice to model substations outages in resilience analysis. This model considers that all substation components behave as a single monolithic block. The second one is the proposed bay-level approach. This modeling approach includes the risk of bays outages within substations, considering that bay outages may affect the overall performance of the substation depending on its internal connections among bays and the external connections with other components (e.g., lines, generating units). Fig. 3.1 illustrates the differences between these two substation outage modeling approaches.

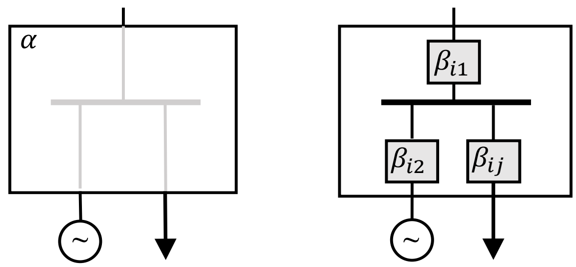

Figure 3.1: Modeling substation outage, (a) Monolithic approach, (b) Bay-level approach.

Monolithic approach

The monolithic approach is a simplistic model that considers the entire substation as a single monolithic block. The representation of this substation model is depicted in Fig. 3.1(a). In this case, the impact of hazard events is usually represented by a derating factor (α). This derating factor (between 0 and 1) is applied to the capacity of every component connected to the substation to model different degrees of impacts after an earthquake occurs. This factor equally derates the capacity of all lines, generation, and demand components connected to the substation (and transformers that are part of the substation). Considering a seismic hazard, the derating factor can be obtained through fragility curves and Hazus criteria [101]. The fragility curves express the probability of system components reaching different damage states, conditioned to the occurrence of a natural hazard. Hazus criteria define five damage states for fragility curves, expressed in terms of the derating factors of component functionality. These are (i) none (fully functioning), (ii) slight, (iii) moderate, (iv) extensive, and (v) complete damage. The power available capacities associated with the (i)–(v) states are 100 %, 95 %, 60 %, 30 %, and 0 %, respectively. The use of these specific derating levels is grounded in the Hazus–MH technical manual, which maps each damage state to an empirically supported estimate of remaining operational capacity. These values are based on historical observations of substation and equipment performance during earthquakes, complemented by engineering judgement on acceptable degradation thresholds. For instance, slight damage reflects minor misalignments or a small percentage of failed disconnect switches or breakers—conditions under which the substation can still operate almost normally, justifying the 95 % functionality level. Moderate and extensive damage involve increasing proportions of failed switching and transformer equipment, substantially limiting the substation's ability to transfer power; these are therefore modeled with 60 % and 30 % functionality, respectively. Complete damage represents the failure of all key components, resulting in a fully non-operational state (0 %).

The assignment of the damage states to the vulnerable components is done through a probabilistic method (e.g., Monte Carlo Simulation), as explained in Section 3.3.3.

Bay-level approach

In order to incorporate the risk of bays outages of substations in resilience assessment against earthquakes, it is necessary to develop a model to determine the unavailability of the bays after an earthquake strikes. In Fig. 3.1(b), the bay-level representation of the substation is presented. The network components are connected to the bays and the same type of bays are independent of each other.

The bay-level outage approach relates to the unavailability of the bays and the available capacity of each network component connected to the substation. $\beta_{\mathrm{i}j}$ represents the availability of the bays in scenario i, that is, if $\beta_{\mathrm{i}j} = 0$, the bay j is unavailable and if $\beta_{\mathrm{i}j} = 1$ indicates that bay j is available. The available capacity (AC_{i}) of the substation in the scenario i is determined by summation of the product of the power capacity of each network component connected to the bay (P_j) with its availability parameter $\beta \mathrm{i} j$. Table 3.1 shows the substation capacity outage based on electrical bays. The first column of the table indicates the scenarios of possible combinations of unavailability of the bays. The second column contains the combination of all possible bay unavailability states, and the third column contains the corresponding AC_{i} for each scenario i.

Table 3.1: Substation capacity outage based on electrical bays.

Scenario	$\mathrm{i} = 1, ..., 2^{N_{Bays}}; j = 1, ..., N_{Bays}$				AC_{i}
S_1	β_{11}	β_{12}	$\cdots$	β_{1j}	$\sum_{j=1}^{N_{Bays}} P_j \cdot \beta_{1j}$
S_2	β_{21}	β_{22}	$\cdots$	β_{2j}	$\vdots$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
S_{i}	$\beta_{\mathrm{i}1}$	$\beta_{j\mathrm{i}}$	$\cdots$	$\beta_{\mathrm{i}j}$	$\sum_{j=1}^{N_{Bays}} P_j \cdot \beta_{\mathrm{i}j}$

Once all possible scenarios of bay outage states in the substation and their respective AC_{i} are identified, they are classified considering the power available capacity as seen in Table 3.2. The five damage states considered this way are none, slight, moderate, extensive, and complete. The available capacity is divided according to Hazus criteria. If the AC_{i} of the substation is greater than 95 % and less than or equal to 100 %, the substation is considered undamaged. Likewise, if the AC_{i} is greater than 60 % and less than or equal to 95 %, the substation is considered slightly damaged. If the AC_{i} is greater than 30 % and less than or equal to 60 %, the substation is considered moderately damaged. If the AC_{i} is greater than 0 % and less than or equal to 30 %, the substation is considered extensively damaged. If the AC_{i} is equal to zero, the entire substation is considered completely damaged. Finally, the bay outage states are classified in a set of outage scenarios depending on the substation damage states. The sets of outage scenarios obtained are none (Ω_N), slight (Ω_S), moderate (Ω_M), extensive (Ω_E) and complete (Ω_C). In order to obtain the bay outage scenario (S_{i}) within the set of outage scenarios, we generate a uniformly distributed random integer number that returns a random scalar integer between 1 and the maximum size of the set of outage scenarios. Thus, we assign the bays outage scenario based on the chosen random scalar integer. If the status of a bay is one, the component connected to it is available. Conversely, if the status of a bay is zero, the component connected to it is unavailable.

Table 3.2: Classification of outage scenarios by damage states.

Damage state	**Hazus criteria**	**Classification by available capacity**
None	100 %	$\forall S_{\mathrm{i}} \in \Omega_N \leftrightarrow AC_{\mathrm{i}} > 95\,\% \wedge AC_{\mathrm{i}} \leq 100\,\%$
Slight	95 %	$\forall S_{\mathrm{i}} \in \Omega_S \leftrightarrow AC_{\mathrm{i}} > 60\,\% \wedge AC_{\mathrm{i}} \leq 95\,\%$
Moderate	60 %	$\forall S_{\mathrm{i}} \in \Omega_M \leftrightarrow AC_{\mathrm{i}} > 30\,\% \wedge AC_{\mathrm{i}} \leq 60\,\%$
Extensive	30 %	$\forall S_{\mathrm{i}} \in \Omega_E \leftrightarrow AC_{\mathrm{i}} > 0\,\% \wedge AC_{\mathrm{i}} \leq 30\,\%$
Complete	0 %	$\forall S_{\mathrm{i}} \in \Omega_C \leftrightarrow AC_{\mathrm{i}} = 0\,\%$

3.3. Methodology

3.3.1. General methodology

In this part, we use a probabilistic methodology with four stages to simulate the hazard (including its occurrence and spatio-temporal propagation profile) and its impacts on the power system (i.e., the system response and quantification of system resilience). Following the proposal in [42], we refer to these stages as follows: 1) Hazard modeling, 2) Vulnerability of the system components, 3) System response, and 4) Resilience quantification. These four stages are run sequentially in a Monte Carlo method in order to obtain a detailed simulation of the power system during the natural hazard. The methodology for seismic resilience analysis is depicted in Fig. 3.2. The description of each of the stages is detailed below.

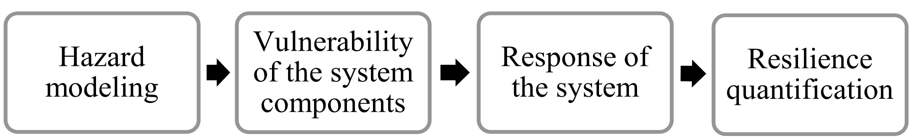

Figure 3.2: Methodology to seismic resilience analysis.

3.3.2. Hazard modeling

In the first stage, we simulate the seismic hazard using the peak ground acceleration (PGA) profiles as a seismic intensity parameter for each of the locations of the system components. To calculate PGA attenuation, we use the model proposed by Boroschek [102] (suitable for Chile) as follows (3.1):

$$\begin{aligned} \log_{10}(PGA(x, y; \mathrm{e}x, \mathrm{e}y, h, M)) = -1{,}55 + 0{,}26M \\ +0{,}01h - 0{,}01R - (1{,}52 - 0{,}10M)\log_{10}(R) \end{aligned} \tag{3.1}$$

where M is the moment magnitude and h is the focal depth. Given the hypocenter $(\mathrm{e}x, \mathrm{e}y, h)$, then $r = \sqrt{(\mathrm{e}x - x)^2 + (\mathrm{e}y - y)^2}$ and R is $\sqrt{r^2 + (0{,}07 \cdot 10)^{0{,}36 \cdot M}}$. The results is on units of [g], the gravity acceleration constant.

The Boroschek PGA model offers the key advantage of being calibrated with strong-motion records from the 2010 Mw 8.8 Maule earthquake, making it well suited for Chilean subduction-zone conditions. Its formulation captures magnitude, depth, and distance effects, providing realistic spatial estimates of seismic intensity. However, the model is derived from a single major event and does not account for site-specific amplification or long-period ground-motion effects, which may influence the performance of large electrical infrastructure. Despite these limitations, it remains an appropriate and regionally validated choice for large-scale seismic hazard simulations in Chile.

3.3.3. Vulnerability assessment

We assess the vulnerability of system components by using fragility curves [101], which are hazard intensity dependent. In this stage, we incorporate the two frameworks for substation outage modeling. For both the monolithic approach and the bay-level approach, we use fragility curves for power substations, as shown in Fig. 3.3, which correspond to a substation of medium voltage (150 kV to 350 kV).

We then determine the hazard-dependent failure probabilities of every network component. After we have determined the outage/state probability of every network component, we use Monte Carlo simulations to generate various scenarios where network components are outaged/derated. In details, the failure probability obtained from fragility curves is compared with a uniformly distributed random number $r \sim U(0, 1)$ for each component at each simulation. If the failure probability is equal or greater than the random number, the damage state is assigned. After we have determined the damage state of every network component, we fix the condition (outaged/derated) for each one. For these network conditions (where each may present several simultaneous outages), we model the system response as explained below.

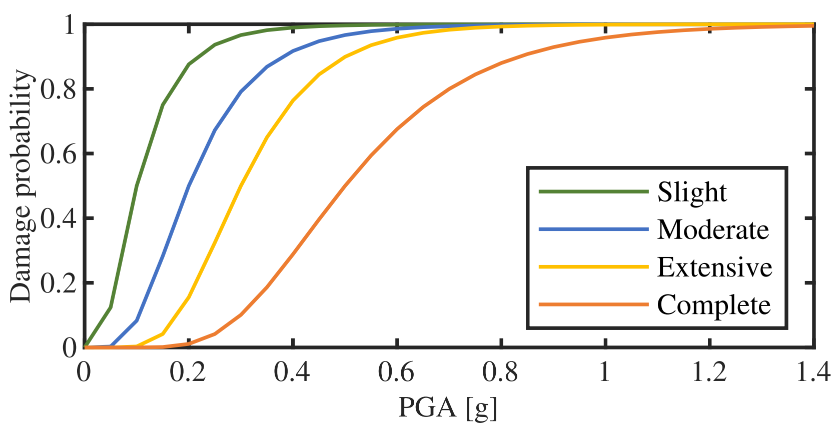

Figure 3.3: Fragility curves for medium voltage substations.

It is important to clarify that the fragility curves shown in Fig. 3.3 are not updated after a contingency occurs. In this work, fragility curves are used exclusively to determine the initial hazard-dependent probability of each damage state during the Monte Carlo sampling stage. Once a component is assigned to a given damage state, that state remains fixed for the entire simulation of the cascading process. This modeling choice is consistent with standard applications of static fragility functions in large-scale power system risk assessments, where damage is assumed to occur independently of subsequent electrical or operational contingencies and where post-contingency degradation would require detailed mechanical or structural models that fall outside the scope of this study. Therefore, no curve shifting, degradation progression, or post-event updating of fragility functions is performed; rather, the system response is evaluated based on the initial sampled damage configuration.

3.3.4. System response

We determine the system response through two power system models: a pre-contingency optimal power flow (OPF) and a post-contingency OPF, where the latter is subject to the results obtained by the former. We first run the pre-contingency OPF model in order to define the intact system condition. After such intact system operation has been obtained, a set of input outage scenarios due to earthquakes are defined. We model the system response considering optimal corrective actions by means of the post-contingency OPF model. In fact, this OPF model is used for undertaking corrective actions right after the outages occur (by using generation changes, e.g., ramp rate limits or load shedding). The amount of load shedding in all buses represents the energy not supplied (ENS) in this study.

In the post-contingency OPF, several elements obtained from the pre-contingency OPF are kept fixed to ensure consistency between the intact operating point and the corrective actions taken after the earthquake-induced outages. Specifically, the pre-contingency OPF provides the initial generation dispatch, voltage magnitudes, branch flows, and the status of transmission assets and operational limits (e.g., ramp-rate constraints, generator capacity bounds, and load levels), all of which define the feasible operating region before the disturbances occur. These variables are not re-optimized in the post-contingency model; instead, they serve as the initial condition from which corrective actions can be applied. The post-contingency OPF then adjusts only the controllable variables—such as generation outputs within allowable ramping limits and load shedding—according to the outages sampled in the vulnerability stage. In this way, the pre-contingency OPF establishes the reference operating state, while the post-contingency OPF captures the system's capability to recover feasible operation under the new damaged topology.

3.3.5. Resilience quantification

To quantify the system resilience, we use the expected energy not supplied (EENS) and the $\Phi\Lambda E\Pi$ framework [103] as resilience metrics. On the one hand, EENS is defined as the expected amount of energy not being served to consumers by the system during the period considered due to system capacity shortages or unexpected severe power outages [104]. The metric is detailed in (3.2), where ENS_k is the energy not supplied with a probability π_k of occurrence of outage scenario k during the time frame of the study.

$$EENS = \sum_{k=1}^{N_k} ENS_k \cdot \pi_k \tag{3.2}$$

On the other hand, the $\Phi\Lambda E\Pi$ framework allows measuring the performance of the different phases that a power system may experience during an extreme event. For seismic analysis, when the power systems are hit by an earthquake whose duration is seconds to minutes, a sharp and immediate resilience decrease occurs. Hence, we select Λ-metric that measures how low resilience drops when the extreme event hits a power system. For this, Λ-metric represents the difference between the pre-disturbance resilience state indicator (R_0) and post-disturbance resilience state indicator (R_{pd}) as shown in (3.3).

$$\Lambda = R_0 - R_{pd} \tag{3.3}$$

In addition to providing a direct measure of the immediate resilience drop, the $\Phi\Lambda E\Pi$ framework offers a structured way to analyze how power systems perform across the different temporal phases of an extreme event—pre-event, disturbance, and recovery. One of its key strengths is that it separates the instantaneous degradation caused by fast-onset hazards, such as earthquakes, from the gradual restoration processes that follow. This makes $\Phi\Lambda E\Pi$ particularly suitable for HILP-type events where most of the performance loss occurs within seconds to minutes. Furthermore, the framework supports both operational and infrastructure assessments by allowing different state indicators to be incorporated into R_0 and R_{pd}. In the context of this study, lost production and lost load are used as operational indicators, while outaged lines and substation outages represent infrastructure degradation. This flexible structure enables the $\Phi\Lambda E\Pi$ framework to capture the multidimensional impacts of seismic events and to complement probabilistic metrics such as EENS, providing a broader and more interpretable characterization of system performance under extreme conditions.

3.4. Results and discussion

To demonstrate the applicability of the proposed substation modeling approaches in the seismic resilience analysis methodology, two case studies are analyzed: i) the IEEE RTS 24-bus system and ii) Chilean transmission system.

3.4.1. IEEE RTS 24-bus system

Input data

The case study described in this section is based on the IEEE RTS 24-bus system. This test system consists of 24 buses, 33 transmission lines, 5 power transformers. and 33 generators with a total capacity of 3405 MW. Using the substation bay considerations described in

Section II-B, the bay-level RTS 24-bus system will consist of 20 substations. Buses 9, 10, 11 and 12 formed a substation, and buses 3 and 24 formed another substation. The electrical data and network component locations on the map can be found in [105].

For the seismic resilience analysis, we use the probabilistic methodology introduced in Section III. To calculate the PGA for each of the locations of the system components, we evaluate an earthquake with a magnitude of 7.5 M_W and a depth of 20 km. The epicenter at $(60, 60)km$ on a fictitious map with an area of 210×210 km^2. We then generate 10,000 scenarios to simulate network outages triggered by earthquakes, via Monte Carlo simulation. Once the status of the components (outaged/derated) is obtained, we model the system operation during peak demand. The analysis allows to quantify the resilience of the power system. The methodology is implemented in MATLAB, making use of MATPOWER, which is an open-source power system optimization library [106].

Results and discussion

Table 3.3 shows the resilience metrics obtained for the IEEE RTS 24 bus system. These metrics are divided into three groups to visualize how the system is affected in terms of EENS, operational resilience, and infrastructure resilience. On the one hand, the proposed bay-level approach provides an EENS value that is approximately 49 % higher than the monolithic approach. To illustrate the EENS results, Fig. 3.4 shows that the number of scenarios where ENS values are highest (placed in the right "tail" of distribution) is caused by the bay-level approach (see Fig. 3.4(b)) and is significantly higher compared to the monolithic approach (see Fig. 3.4(a)). On the other hand, the results obtained for the infrastructure (outaged lines and outaged substations) and operational (lost production and lost load) resilience indicators show that the bay-level approach caused more significant resilience drops than the monolithic model.

The results demonstrate that the bay-level approach causes greater degradation in infrastructure and operation resiliency metrics due to a greater number of simultaneous network component outages caused by the failure of individual bays, and thus, increases the number of higher ENS scenarios.

Table 3.3: Resilience quantification for IEEE RTS-24-bus system.

Approach	EENS (MWh)	*Operational resilience*		*Infrastructure resilience*	
		Λ-lost production (% MW lost)	**Λ-lost load (% MW lost)**	**Λ-outaged lines (% Lines tripped)**	**Λ-outaged substations (% subs. outaged)**
Monolithic	478.73	16.53	15.24	7.79	7.74
Bay-level	935.01	26.75	24.16	31.11	15.10

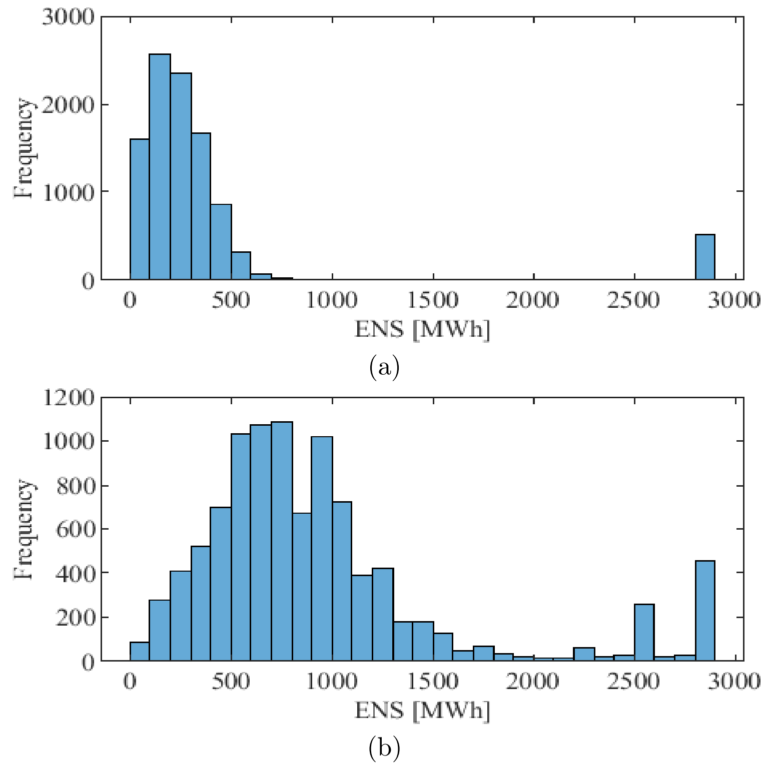

Figure 3.4: ENS Histogram for IEEE RTS 24-bus system (a) Monolithic approach, (b) Bay-level approach.

3.4.2. Chilean transmission system

Input data

The case study described in this section is based on the Chilean transmission system [105], considering its infrastructure in 2018. For that year, the total installed generation capacity is 24 GW, and generation supply included mainly hydro [23 TWh (30 %)], coal [30 TWh (39 %)], and gas [11 TWh (15 %)] units, with minor participation from wind [4 TWh (5 %)] and solar resources [5 TWh (7 %)]. The electricity peak demand is approximately 10 GW. The Chilean transmission system is represented by nodes/substations, with their real geographical coordinates; and links are the transmission lines connecting substations as shown in the Fig. 3.5.

For the seismic resilience analysis, we use a earthquake intensity equal to 8.8 M_W and a depth of 35 km, the epicenter of the event was located at the coordinates latitude: -35.846° and longitude: - 72.719°, equalizing the conditions of the most recent 2010 earthquake (which was one of the worst earthquakes experienced in Chile). The PGA is determined at the location of each system component as shown in the Fig. 3.5.

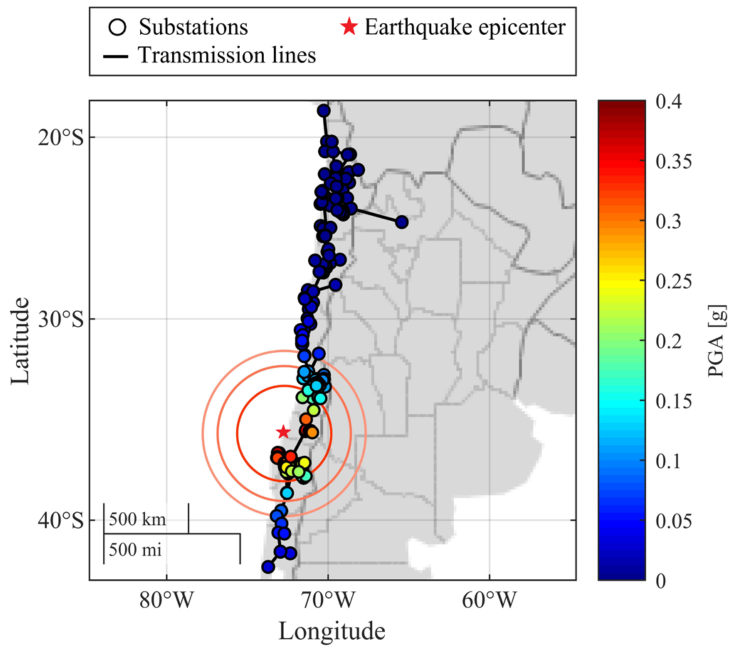

Figure 3.5: The Chilean transmission network diagram considering earthquake of 2010.

Results and discussion

Table 3.4 shows the resilience metrics obtained for the Chilean transmission system. These metrics are divided into three groups to visualize how the system is affected in terms of EENS, operational resilience, and infrastructure resilience. The amount of EENS for the bay-level approach is approximately 48 % greater than the monolithic approach. Furthermore, Fig. 3.6 shows the ENS histograms for both approaches, it is observed that for the bay-level approach (see Fig. 3.6(b)) the critical scenarios increase and present a greater amount of ENS compared with critical scenarios obtained by the monolithic approach (see Fig. 3.6(a)). On the other hand, the operational and infrastructure resilience results show that the bay-level approach caused greater drops in resilience indicators than the monolithic approach.

A noteworthy result emerges from the validation perspective: the percentage of outaged substations obtained with the proposed bay-level approach closely matches empirical observations from the 2010 Chile earthquake, during which approximately 25 % of transmission-level substations were damaged. This agreement reinforces the argument that modeling substation outages at the bay level provides a more realistic representation of system behavior during extreme seismic events. Moreover, these findings highlight the applicability and scalability of the proposed approach for large power networks.

In the Monte Carlo framework, each sampled earthquake realization k produces a specific outage pattern and its corresponding post-disturbance system state. For each scenario, the post-disturbance resilience indicator $R_{\text{pd},k}$ is computed using the same operational and infrastructure indicators used to evaluate R_0—namely, lost production, lost load, outaged lines, and outaged substations—applied to the damaged network configuration. Consequently, Eq. (3.3) is evaluated on a scenario-by-scenario basis, yielding the resilience loss $\Lambda_k = R_0 - R_{\text{pd},k}$ for each realization. The overall resilience degradation is then obtained by averaging these Λ_k

values across all Monte Carlo samples, weighted by their occurrence probabilities.

For comparison with empirical evidence from the 2010 Chile earthquake, we isolate the subset of Monte Carlo scenarios whose magnitude and hypocentral characteristics align with that event. Within these scenarios, we assess the proportion of substations reaching extensive or complete damage states. The resulting distribution converges to values close to the reported 25 % substation damage ratio, providing strong validation for both the hazard–vulnerability modeling and the bay-level substation representation employed in this study.

Table 3.4: Resilience quantification for Chilean transmission system.

Approach	**EENS (MWh)**	***Operational resilience***		***Infrastructure resilience***	
		Λ-lost production (% MW lost)	**Λ-lost load (% MW lost)**	**Λ-outaged lines (% Lines tripped)**	**Λ-outaged substations (% subs. outaged)**
Monolithic	1846.00	20.00	16.50	9.40	9.37
Bay-level	3538.00	34.30	27.60	29.40	26.20

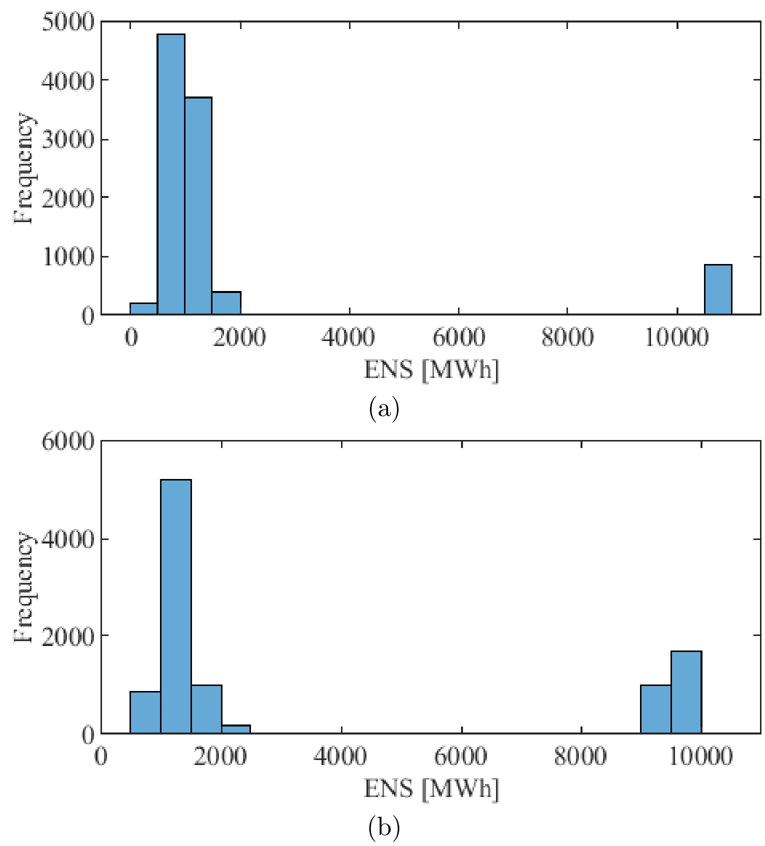

Figure 3.6: ENS Histograms for Chilean transmission system (a) Monolithic approach, (b) Bay-level approach

4. The impact of cascading outages on system response and investment decisions

4.1. Overview

This chapter explores the impact of cascading outages on both system operational response and investment decision-making by using a simple yet illustrative power system. The objective is to provide a transparent comparison between conventional contingency analysis and a more comprehensive cascading failure simulation, thereby highlighting the consequences of neglecting failure propagation in power system planning and operation. Unlike traditional approaches that only evaluate the immediate effects of single contingencies, the proposed assessment incorporates protection-driven failure propagation, islanding conditions, and dynamic load and generator disconnections.

To achieve this, a compact 3-bus test network is developed, which includes three generators, three loads, and three existing transmission lines. Candidate enhancement options include new transmission lines, a reactive power compensator, and battery energy storage systems. Two case studies are conducted using this system: the first focuses on comparing system responses to an initiating outage using an AC-OPF-based post-contingency analysis versus a detailed cascading failure simulation model; the second evaluates the effect of these cascading outages on the ranking and effectiveness of network enhancement strategies.

This chapter aims to demonstrate how investment recommendations can significantly change when cascading outages are explicitly considered. Using the concept of Expected Load Not Supplied (ELNS) as a risk metric, different enhancement alternatives are evaluated under all single-line outages. The results reveal that, in contrast to traditional contingency analysis, cascading failure simulations may prioritize entirely different investment options due to their ability to capture multi-stage disruptions and the activation of protection mechanisms such as underfrequency load shedding or generator tripping.

Overall, this chapter provides an essential link between detailed failure modeling and investment planning. It underscores the necessity of incorporating cascading outage simulations to support more robust and informed infrastructure decisions, particularly under systemic risk scenarios where standard reliability criteria may fall short.

4.2. Illustrative example (3-bus system)

This network serves to: (i) illustrate the effects of cascade outages in the system response by means of a simple example and (ii) demonstrate how network enhancement decisions may change when cascading outages are included in network planning through an understandable case. For these assessments, the cascading failure simulation tool is compared with an AC-OPF tool with standard contingency analysis that does not include cascading failures (as described in Appendix A). Here, the OvS approach is not used.

The proposed framework is initially applied to a test system composed of three buses (N1, N2 and N3), three generators (G1, G2 and G3), three existing lines (L12, L13 and L23) and three loads (D1, D2, D3). In order to mitigate the consequences of outage scenarios, the system can be expanded through two new lines (L'12, L'23), a reactive power compensator (C3), and two battery storage devices (B2, B3). This test system is illustrated in Figure 4.1, whose data can be found in Appendix B.

Two case studies are performed to demonstrate the effects of cascading outages within the system response and network decision-making process. In the first case, the evaluation of the system response is undertaken before and after the triggering disturbance occurs. For this assessment, the cascading failure simulation tool is compared to an AC-OPF tool with standard contingency analysis that does not include cascading failures. In the second case, the evaluation of different enhancement propositions in a network planning problem is performed. For illustration purposes, the cost of any network enhancement is assumed to be the same. These enhancement propositions fulfill the following functions:

- New lines and transformers to create alternative routes to transfer power and provide redundancy.
- Reactive power compensators to maintain voltage within allowable range during and after cascading events.
- Battery storage devices to make the system more flexible in order to adapt to different postfault conditions, helping to mitigate the consequences of frequency problems.

In both case studies, all single outages in existing lines are considered as the triggering event for simulating cascading failures. It is important to mention that the battery storage units and reactive power compensators can only react and operate in an outage condition and thus cannot interfere with the dispatch in the intact system when no failure occurs.

The pre-contingency operating condition of the system is calculated with an optimal power flow that minimizes the cost of supplying the load. The results of the generation dispatch and power flows are shown in Figure 4.2.

In order to compare the system response with and without cascading failures, the test system is subjected to a single line outage and the post-contingency condition is evaluated. Then, Figure 6 illustrates the system response without cascading failure analysis after the line L12 outage occurs. In this case, the system response is simulated considering optimal

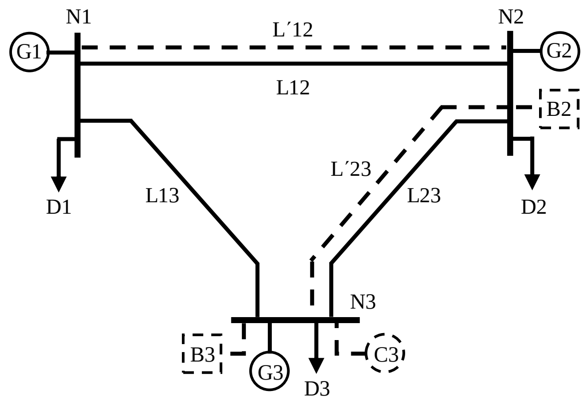

Figure 4.1: 3-bus system topology, where candidate assets for investment are shown in dashed lines.

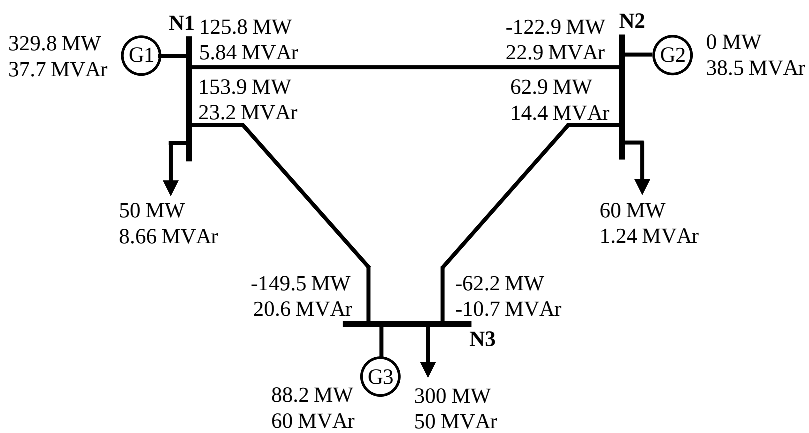

Figure 4.2: Illustration of results of generation dispatch and power flows for pre-contingency condition.

corrective actions (by using generation re-dispatch and load shedding) by means of a post-contingency OPF. Hence, the generators are re-dispatched and the load shedding in bus 3 results in approximately 10 % (from 300 MW to 271.4 MW).

On the other hand, the cascading failure simulator is applied to demonstrate the effect of cascading outages on system response after the triggering events take place. In this case, Figure 7 shows the system response considering cascading failures after the line L12 outage occurs. Next, the triggering events are detailed as follows:

- Once line L12 is tripped, as a subsequent event, the power flow on line L13 exceeds the maximum power capacity value (see Figure 7(a)), i.e., this line is overloaded, which would cause its disconnection due to the action of the system protections.

- When the two lines are disabled, two islands are formed (see Figure 7(b)).

- In island 1, the underfrequency load shedding (UFLS) is performed.

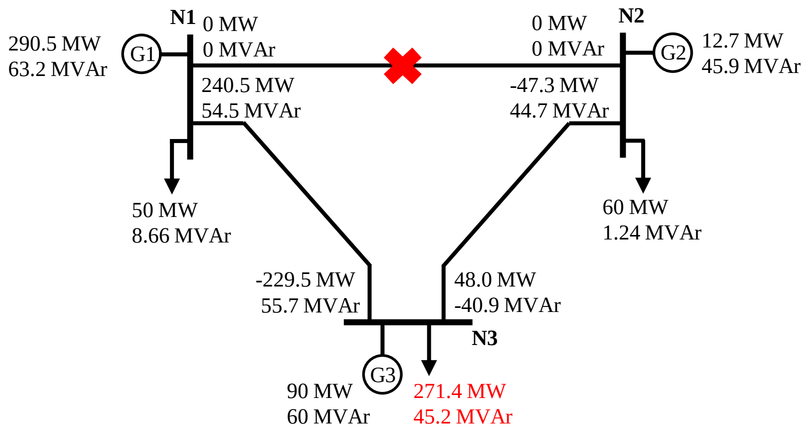

Figure 4.3: Illustration of results post-contingency without cascading failures for the outage of line L12.

- In island 2, the overfrequency generator shedding (OFLS) is performed.

The total load shedding of the system is 76.84 %.

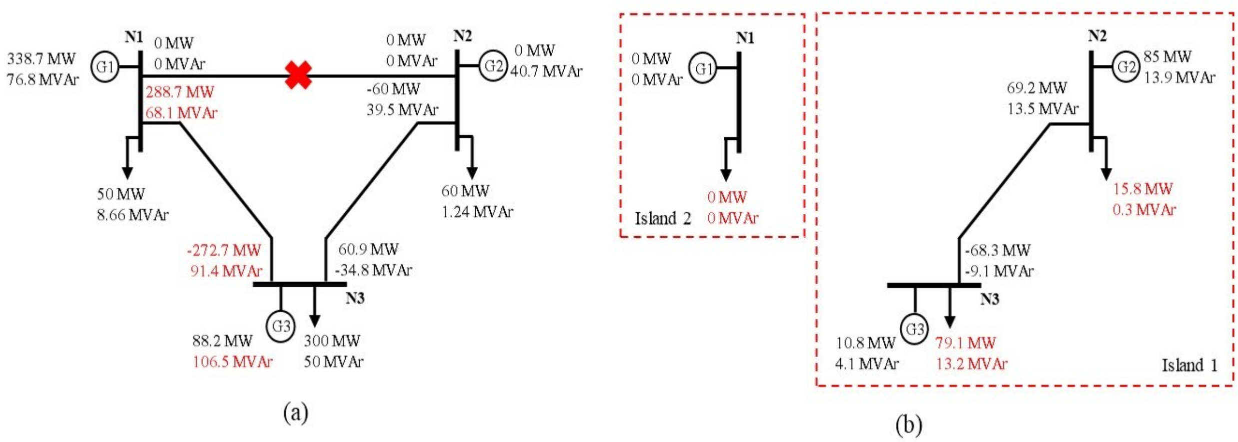

Figure 4.4: Illustration of results post-contingency considering cascading failures for (a) initial system topology and (b) end system topology after the outage of line L12.

These results show two fundamental differences between the cascading failure simulation tool and an AC-OPF tool without cascading failure analysis within the system response. First, the total load shedding is significantly higher with the cascading failure simulation tool due to the activation of the protection mechanisms. Second, the number of equipment outaged increases with the cascading failure simulation tool because this tool can simulate cascade disconnections, whereas the AC-OPF tool considers a standard contingency analysis (i.e., only simulating the triggering event without the possible propagation). Therefore, the simulation of cascading outages cause changes in system response, even increasing the risk of load shedding and the number of equipment outaged compared to the AC-OPF tool without cascading analysis.

4.3. Results and discussion

Table 4.1 shows the results of the ranking of the network enhancement propositions considering both cascading failure analysis (left) and without cascading failure analysis (right). In this particular case, the enhancement propositions correspond to a single action that includes adding new lines, battery storage devices and reactive power compensators. Hence, Table 4 presents, from left to right, the ranked enhancement proposition and its respective load shedding averaged across all outage scenarios. In both cases, with and without cascading failure analysis, all network enhancement propositions are assessed under all single outages in existing lines. In this case, the proposed assessment is simple since the complete set of feasible solutions presents only 5 elements (2 line propositions, 2 battery storage systems and 1 reactive power compensator), plus the base case with no enhancement. More details of the results of this assessment can be found in Appendix C.

Table 4.1: Rankings of network enhancement propositions with and without cascading failures.

Ranking	**With cascading failures**		**Without cascading failures**	
	Solution	**ELNS (MW)**	**Solution**	**ELNS (MW)**
1	L'12	20.2	B3	0
2	B3	27.7	L'12	8.4
3	B2	43.7	B2	8.7
4	L'23	51.2	C3	12.7
5	C3	52.1	L'23	13.1
6	Base case	54.5	Base case	15.3

The noticeable insight from these results is that the best enhancement proposition is different in both cases. For the case with cascading failure analysis, the best enhancement proposition corresponds to the installation of the line (L'12), which offers an alternative route to transfer power between generation in bus 1 (cheaper and with greater capacity) and bus 2 connecting to the more expensive generator, and provide redundancy. Instead, the installation of battery storage unit 3 (B3) is the most efficient proposition for the case without cascading failure analysis, since it is placed in order to secure supply for large energy demand volumes (in bus 3) in post-fault conditions. Interestingly, the second best alternative under the case with cascading failure analysis is the installation of the battery storage unit 3 (B3), which present the largest energy consumption. Evidently, adding this battery supports a more resilient supply in bus 3, ensuring the supply-demand balance in case a cascading outage occurs.

For illustration purposes, Figure 4.5 shows the installation of the battery storage device 3 (B3) in order to mitigate the effects of the L12 contingency previously evaluated in section 4.1.2. For the case without cascading failure analysis, Figure 4.5(a) shows that the battery storage unit can totally mitigate the load shedding caused by the given outage scenario. This is because the battery participates in post-fault dispatch, injecting its maximum capacity (under the assumption that the battery is fully charged during the emergency). Instead, for the case with cascading failure analysis, Figure 4.5(b) shows that the battery storage unit partially reduces load shedding in island 1, mitigating the effects of the underfrequency load shedding mechanism. Therefore, it is important to highlight that this example demonstrates how network enhancement decisions change when cascading outages are included.

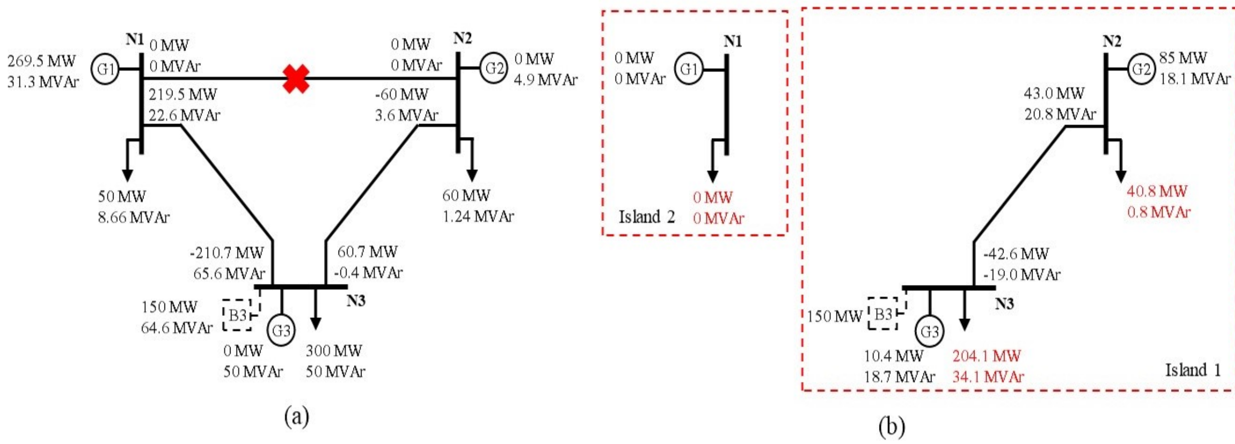

Figure 4.5: Illustration of results post-contingency considering a battery storage system located in bus 3 and the outage of line L12 (a) without cascading failures and (b) with cascading failures.

AC-CFM can facilitate key improvements of power network resilience in three ways. First, the model provides insights into how cascading failures propagate within power networks, for instance by providing visualisations of cascades [107]. It highlights the need for and contribution of various protection mechanisms in cascading failures. The capability of AC-CFM to handle large contingencies is vital for such investigations. Secondly, by using cascade visualisations, the model can identify network components, such as lines or buses, that are involved in large cascades and the type of issues that arise, such as undervoltages or overloads. Thus, improvement strategies can be developed, for instance for the location of shunt devices or additional transmission line capacity. Thirdly, the model can assess the resilience of a power network after such improvement strategies have been developed, particularly for future network scenarios such as increased loading or deployment of distributed generation.

5. Simulation-based optimization framework for planning under cascading outages

This chapter presents the methodological framework developed in this thesis to identify cost-effective network investments that mitigate the risk of cascading outages. The framework is based on an OvS approach that integrates detailed system failure simulations into the decision-making process. It is structured around three interdependent modules: a sampling module that selects representative $N-k$ contingency scenarios; an optimization module that determines the most effective combination of network enhancements, including battery storage, reactive power compensation, transmission lines, and transformers; and a simulation module that evaluates system performance using a detailed AC cascading failure model. The chapter describes the logic, mathematical formulation, and implementation of each module, emphasizing the integration of protection mechanisms and the quantification of outage risk through metrics such as Expected Load Not Served (ELNS) and Conditional Value-at-Risk (CVaR).

5.1. Overview

The proposed framework employs an OvS approach, that integrates detailed system failure simulations into the investment planning model. The framework operates through three interconnected modules (see Figure 5.1). First, the sampling module aims at the appropriate selection of a set of contingencies. These contingencies are then passed to the optimization module, which identifies the most cost-effective network enhancements from a set of candidate options, including transmission lines, power transformers, reactive power compensation devices, and battery storage units.

Since no analytical optimization function can fully capture the complexity of cascading outages, the optimization process relies on the simulation module to evaluate the performance of the selected network investments. The outputs from the simulation, which reflect how the network behaves under various failure conditions, are used as input to the optimization model. This ensures that investment decisions are based on representative system behavior in response to cascading outages, which cannot be easily modeled using conventional mathe-

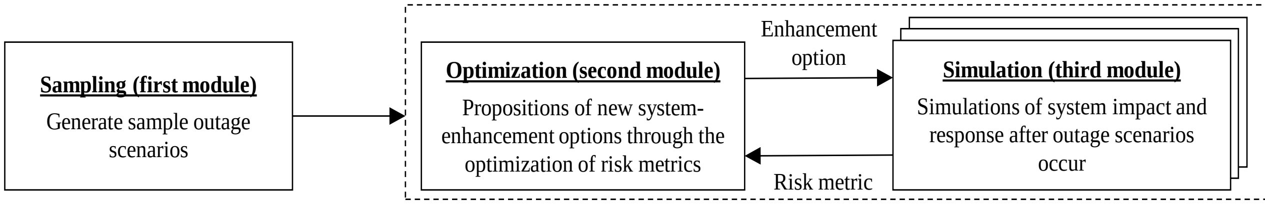

Figure 5.1: Overview of the proposed methodological framework.

matical techniques.

Additionally, parallel computing can be used in the simulation module to evaluate multiple scenarios simultaneously, speeding up the process. By iterating through these modules, the framework determines the optimal portfolio of network investments, ensuring that the final solution is both cost-effective and capable of mitigating the risks associated with cascading outages.

The description of each module is detailed below.

5.2. Methodology

5.2.1. Sampling module

This module aims to generate potential trigger scenarios for cascading outages, with a specific focus on N-k outages. Since cascading outages often involve the simultaneous failure of k elements, analyzing all possible combinations in a large-scale network would be computationally prohibitive. To address this challenge, the sampling module employs a sampling-based strategy that selects a representative subset of N-k outages [108], prioritizing those with the highest probability of initiating cascading outages. This sampling approach ensures that the most critical scenarios are captured while avoiding the computational burden of analyzing a full set of N-k outages. These selected outage scenarios are then used in the OvS approach to identify necessary network enhancements.

5.2.2. Optimization module

This module identifies the most effective network enhancements to mitigate cascading outages. Given the complexity of cascading failures, which cannot be expressed by an analytical function, this module relies on outputs from detailed system failure simulations. As a result, the objective function has an unknown structure, and the goal is to minimize the expected risk across various outage scenarios, formulated as follows:

$$\min_{\mathbf{x}\in\Theta} \; \mu(\mathbf{x}) = \mathbb{E}[F(\mathbf{x},\xi)] \tag{5.1}$$

where $F(\mathbf{x}, \xi)$ is the simulation output for a given enhancement configuration $\mathbf{x}$ and scenario ξ. The set of possible enhancement decisions is defined by $\mathbf{x} \in \Theta$, where Θ represents the feasible solution space. The expectation $\mathbb{E}[F(\mathbf{x}, \xi)]$ is estimated through simulation, as the cascading behavior of the system cannot be captured analytically.

In this module, network enhancements are selected based on their effectiveness in reducing the severity of cascading failures, as measured by the Expected Load Not Served (ELNS). Prioritization is subject to a budget constraint, favoring enhancements that deliver the highest risk reduction per unit cost. Battery storage and reactive compensation devices are prioritized when they improve system flexibility, particularly by mitigating voltage or frequency instability. In addition, enhancements are strategically placed in network locations where cascading failures are more likely to originate or propagate.

The problem (5.1) is subject to a budget constraint, represented as:

$$\sum_{\mathrm{i} \in Q} c_{\mathrm{i}} \mathbf{x}_{\mathrm{i}} \leq b, \tag{5.2}$$

where c_{i} represents the cost of each enhancement $\mathbf{x}_{\mathrm{i}}$ and b is the total budget available. The optimization ensures that the allocated budget is directed toward the enhancements that most effectively minimize the risk of cascading outages.

The optimization procedure involves evaluating different portfolios of network enhancements through simulation experiments. The expected risk of each portfolio is estimated by averaging the results across the sampled outage scenarios, as follows:

$$\bar{F}(\mathbf{x}) = \frac{1}{\Omega} \sum_{j=1}^{\Omega} F(\mathbf{x}, \xi_j). \tag{5.3}$$

where Ω represents the number of simulation replications used to approximate the expected value of the objective function.

Since the problem (5.3) involves evaluating system performance through simulations, a genetic algorithm (GA) is used as part of the OvS approach. Genetic algorithms are well-suited to this type of optimization problem due to their ability to efficiently search large, complex solution spaces without requiring an explicit mathematical representation of the objective function [109]. This approach helps to identify (near) optimal solutions within reasonable computational times.

Due to the probabilistic nature of GA, the results may vary between runs. To ensure robustness, we use a two-step strategy to finally identify the best network enhancement solution [110]. First, a set of good candidate solutions is built by running the optimization process multiple times (e.g., 10 iterations). In the second step, a large number of evaluations/simulations are performed on each candidate solution to determine the best one.

5.2.3. Simulation module

This module evaluates the impact of cascading outages by simulating the behavior of the power system under various failure conditions. To do so, this module uses detailed system failure simulations to quantify load shedding and assess the effectiveness of the selected network enhancements.

Each simulation begins with a security-constrained AC optimal power flow (SC-ACOPF), which determines the initial operating conditions while ensuring N-1 security. This step takes into account the network configuration, the proposed enhancements, and all single outages. After this initialization, each triggering scenario is simulated in three sequential stages as shown in Figure 5.2.

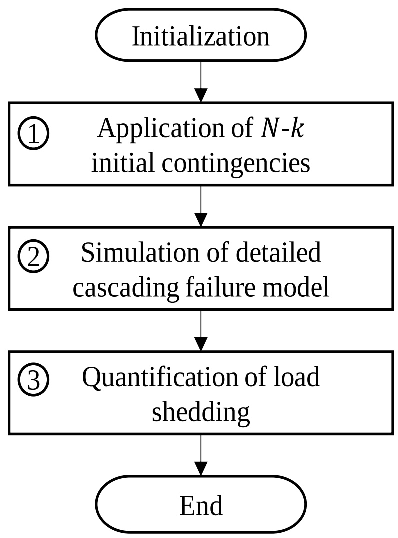

Figure 5.2: Flowchart of the simulation module.

Application of N-k initial contingencies

Each of the N-k outages, from the previously defined set of scenarios, is applied to the test network with N components. k is the number of electrical components that fail. In this work, such contingency is particularly related to branch outages. However, generator outages can also be evaluated. These triggering outages serve as inputs for the subsequent analysis of cascade simulations.

Simulation of detailed cascading failure model

Once the initial outages are applied, the cascading failure model simulates the sequence of dependent failures that follow. The model, based on a detailed AC power flow simulation [107], employs a recursive approach, analyzing cascading failures within each island individually. The simulation begins with an in-depth analysis of power flow in each island, applying protection mechanisms dynamically to prevent failures from escalating. These protection mechanisms include:

- *Under- and Overfrequency:* Protects the system from sudden imbalances between electrical and mechanical power, such as unintentional islanding. By employing Underfrequency Load Shedding (UFLS) or Overfrequency Generator Shedding (OFGS), the system restores the balance between mechanical and electrical power, ensuring frequency remains within acceptable limits.

- *Over- and Underexcitation:* Prevents damage to generators caused by fluctuations in reactive power demand. Using Overexcitation Limiters (OXL) and Underexcitation Limiters (UXL), the model constrains the generator's field current, adjusting terminal voltage.

- *Undervoltage:* Mitigates voltage drops caused by inadequate reactive power flow, preventing voltages from falling below safe limits. Undervoltage Load Shedding (UVLS) is applied to gradually reduce demand until voltage levels are restored to within acceptable limits.

- *Overload:* Ensures safe operation of transmission lines by tripping those that exceed their load rating. Overload Line Protection (OLP) is activated to prevent damage from overheating and stop the cascading failure from escalating.

- *Voltage Collapse Load Shedding (VCLS):* This mechanism is triggered when the AC power flow solver fails to converge, often due to voltage collapse. By converting all loads to dispatchable, the model uses an Optimal Power Flow (OPF) solver to identify the minimum amount of load shedding required to restore solvability and avoid voltage collapse.

When protection mechanisms are insufficient to stabilize the network, emergency protection measures are applied to prevent further destabilization of the grid:

- *Island Tripping (nOPF):* This is applied when the network reaches a point where it is beyond its physical capabilities. If non-convergence persists even after applying protection mechanisms like load shedding or OPF, the entire island is disconnected to ensure the stability of the rest of the system. Island Tripping occurs when no feasible solution exists, even after reducing all loads to zero.

- *Tripped Load Shedding (TLS):* This occurs when buses or lines are disconnected due to other protections, such as OLP or generator tripping. It typically results from buses being part of an island with insufficient generation or from lines being tripped by overload protection, causing associated loads to be shed to maintain network balance.

Figure 5.3 illustrates the sequence of protection mechanisms in the detailed AC cascading failure simulation model with network enhancements highlighted in red. These enhancements include battery storage units (BSU), reactive power compensation (RPC) devices, new transmission lines, and power transformers, have been incorporated through extensions to the original model [107] and contribute to a more comprehensive analysis of cascading failures. BSU are modeled to inject or absorb active power and reactive power. These units are integrated into the cascading failure process by stabilizing frequency imbalances before load shedding or generator tripping occurs, supporting frequency-related protection mechanisms such as UFLS and OFGS. RPC devices are modeled to inject reactive power and are used to stabilize voltage levels during cascading failures, providing voltage support. These devices are incorporated into protection mechanisms to prevent undervoltage conditions. New transmission lines are modeled to redistribute power across the network, reducing stress on existing lines during cascading failures. These assets help prevent overloads and limit the cascading effect, supporting OLP by providing alternative routes for power flow. Power transformers are modeled with tap changers for voltage control and load balancing during cascading failures. Transformers can reduce the need for actions such as UVLS by maintaining system voltage and supporting power flows.

Furthermore, parallel computing can be used to accelerate the simulation by processing multiple scenarios simultaneously. This allows for a more efficient evaluation of the network response to cascading failures.

Compared with related works that employ cascading-failure models, particularly [79, 80], this work goes further by embedding a detailed failure simulation into an OvS framework, enabling investment decisions to be evaluated explicitly under HILP-driven operating conditions.

Quantification of load shedding

After the cascading failure simulation concludes, the total load shedding is quantified. The key metric used is the ELNS, which measures the average amount of energy not supplied due to cascading failures. This metric is derived from the probability-weighted average of load shedding across all contingencies, capturing both the likelihood and impact of each event. Additionally, the Conditional Value-at-Risk (CVaR) is computed to assess the expected impact of worst-case scenarios. These probabilistic metrics are critical for comparing the effectiveness of different network enhancements and identifying solutions that minimize the risk of severe outages [99].

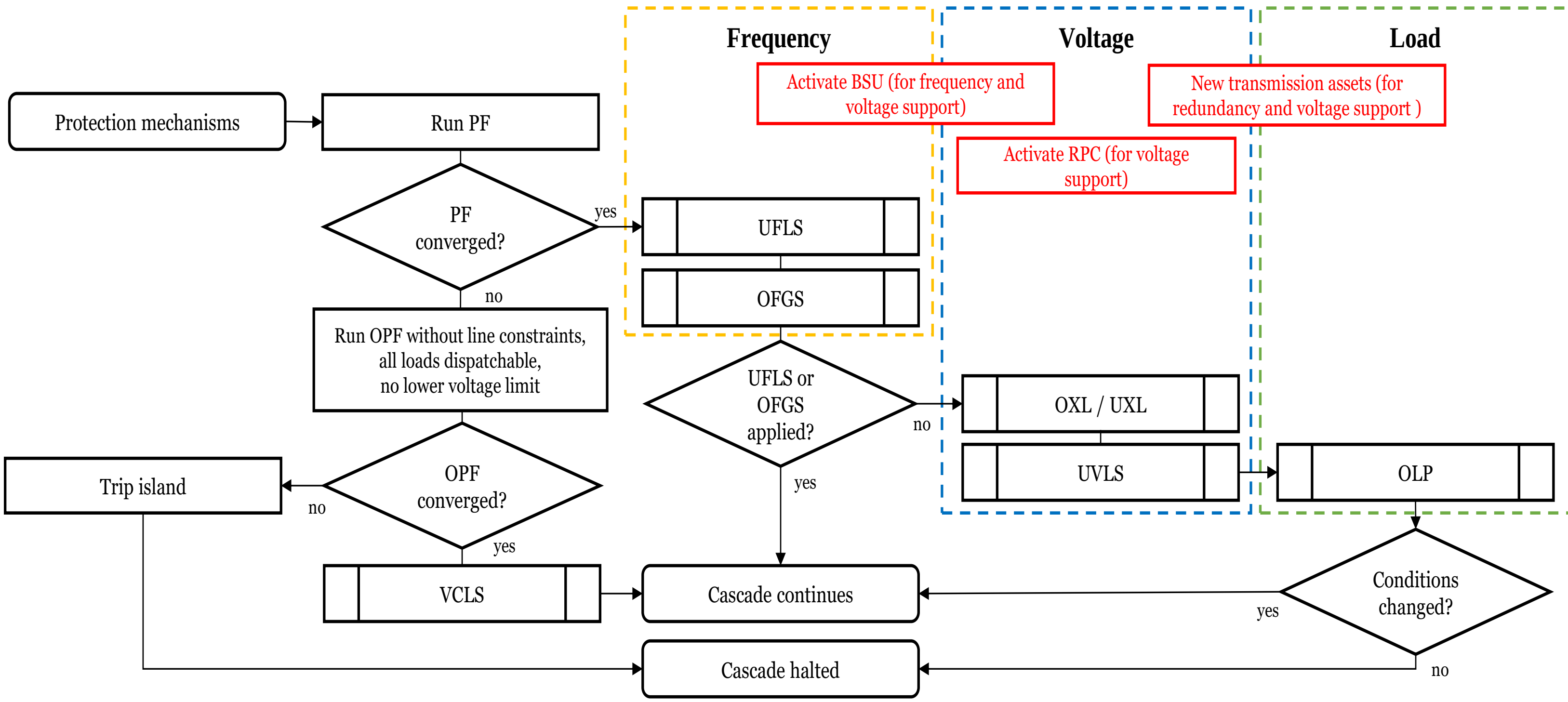

Figure 5.3: Flowchart of detailed AC cascading failure simulation model with protection mechanisms and network enhancements highlighted in red. Adapted from [106].

5.3. IEEE 24-bus test network

This section extends the fundamental analysis performed in a 3-bus test system and analyzes the proposed framework in a modified IEEE 24-bus test network. This test network serves to verify and validate the OvS model and demonstrate its applicability in network investment planning problems for larger budgets.

5.3.1. Description of the test network

We modified the IEEE 24-bus test network described in [111] by adding four additional lines connected in parallel to the original lines (6-10, 7-8, 14-16, and 15-24), totaling 42 existing branches. We also changed the installed generation capacity and peak demand conditions for each bus. Further details of these data can be found in [105]. For planning purposes, the following set of 15 candidate network enhancements are considered:

1. New transmission assets (line (L) and power transformer (T)): L12-23, L15-21, L3-9, L17-22, T10-12;

2. New battery storage units (B) in buses 1, 7, 13, 18, 21;

3. New reactive compensation devices (C) in buses 3, 5, 6, 10, 19.

Each battery storage unit has a capacity of 200 MW, and each reactive compensation device has a capacity of 200 MVAr. For illustrative purposes, we assume a uniform cost of 1 for each network enhancement ($a_k = 1$), simplifying the budget (b) to an integer representing the feasible simultaneous enhancements. This simplification aids in conceptual clarity and allows for a straightforward representation of the budget constraints in our analysis. In addition, all $N-2$ double line outages are considered to trigger cascading failures.

The settings used for the GA search (which have been enumerated through extensive simulations) are a population size of 200, with an 80 % probability of crossover and reproduction.

The proposed framework is implemented in MATLAB on a laptop with an Intel Core (TM) i7 2.60 GHz CPU with four processors and 16 GB of memory.

Two case studies are performed to verify and validate the OvS model and demonstrate its applicability in network investment planning problems for larger budgets. In the first case, as validation, the OvS model is compared with the results of a Complete Enumeration (CE) approach. In the second case, the OvS model is tested to identify optimal portfolio solutions for different budgets for both the cascading failure simulation tool and the AC-OPF tool with standard contingency analysis.

In both case studies, a security-constrained OPF model is run in which all single line (N-1) outages are considered to determine the pre-contingency conditions. Note that no single outage will cause cascading failures. Then, all double-line outages in each bus are modeled as triggering events. In this case, a list of 101 outage scenarios is used to evaluate

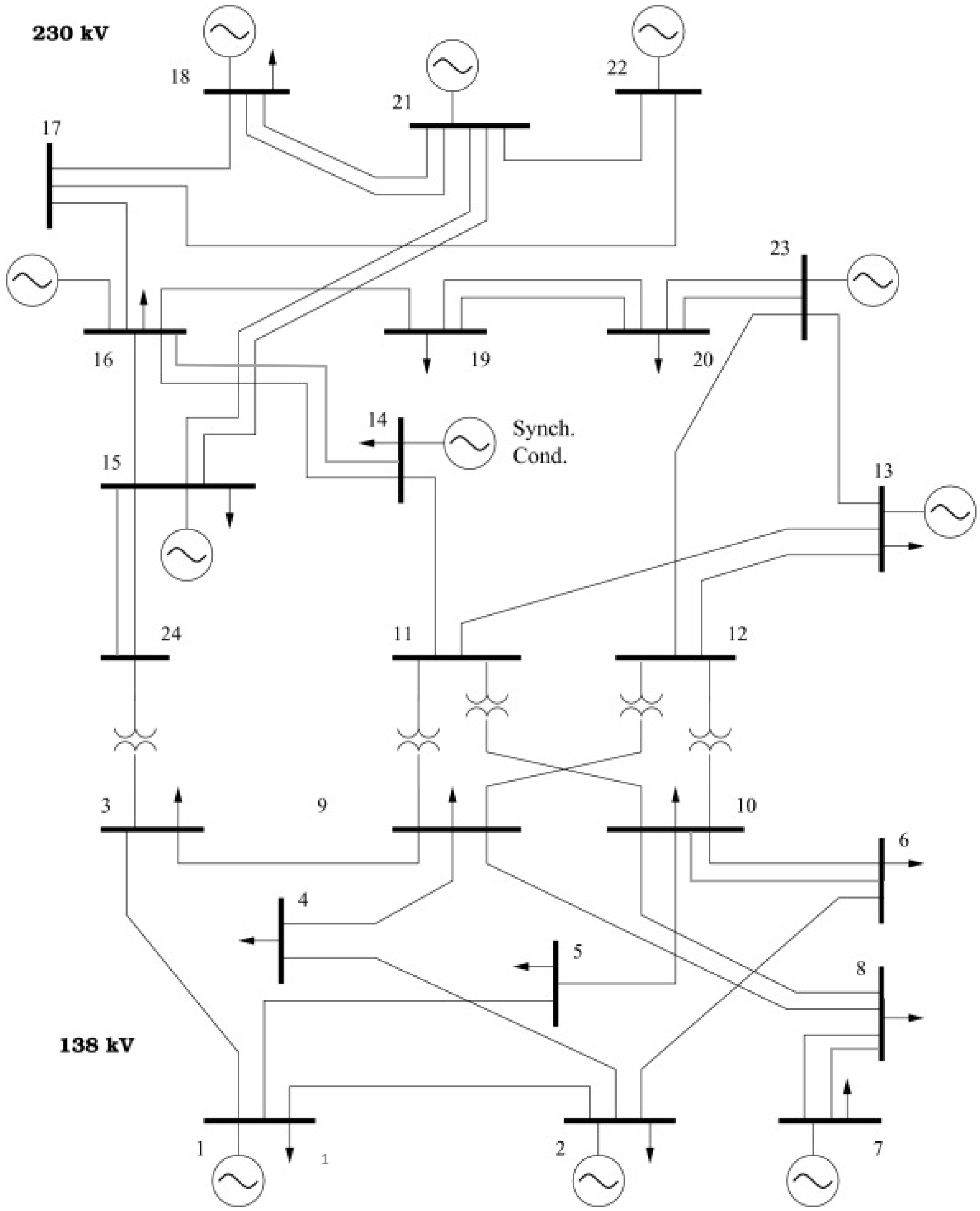

Figure 5.4: Modified IEEE 24-bus test system.

the operating condition (i.e., peak demand), resulting in 101 cascading failure simulations for each evaluation of the objective function, i.e., execution of the cascading failure simulator. In the algorithm properties, the population is 100 individuals, the maximum number of iterations is 200 and the maximum stall iterations is 10. Moreover, the values of the different operators for selection, crossover, and mutation are detailed in Table D.1, Appendix D.

The OvS framework is developed in MATLAB and executed on a personal computer with an Intel(R) Core (TM) i7-10750H with 2.6 GHz and 16 GB of RAM.

5.3.2. Validation of the proposed OvS

We validate the proposed OvS approach by comparing its results with those from the Complete Enumeration (CE) method, which systematically evaluates every possible feasible solution (combination of candidates). Although the CE method guarantees comprehensive coverage, it is highly computationally expensive, especially as the size of the budget increases. Furthermore, CE is not scalable and thus it can only be applied in small-scale problems. The aim of this analysis is to demonstrate that the OvS approach provides a more efficient alternative. It avoids the need for exhaustive testing, yet still delivers consistent and robust outcomes comparable to the CE method.

Table 5.1 compares the portfolio solutions obtained between the CE method and the proposed OvS approach for different budget sizes (ranging from 1 to 5). For each budget, the table details the ELNS and CVaR metrics, the number of feasible solutions, the number of evaluations, and the corresponding computation times for both methods. It also includes a measure of robustness for the OvS approach [110], which evaluates the number of times that an OvS solution hits the optimal value (or is, at most, 10 % different from it). As mentioned above, the OvS model is run 10 times and the best solution is finally selected.

Table 5.1: CE vs. OvS portfolios.

Budget	Solution	ELNS (MW)	CVaR (MW)	No. of feasible solutions	CE No. of Eval.	CE Time (sec)	Proposed OvS No. of Eval.	Proposed OvS Time (sec)	Proposed OvS Rob.
1	B1	96.3	781.4	16	13,776	128	110,000	811	1
2	T10-12, L12-23	36.7	441.1	121	104,181	763	130,000	2,378	1
3	T10-12, L12-23, L15-21	23.9	296.9	576	495,936	3,292	150,000	4,927	0.7
4	T10-12, L12-23, L15-21, B1	19.2	234.2	1,941	1,671,201	10,782	180,000	6,281	0.6
5	T10-12, L12-23, L15-21, L3-9, B1	16.2	212.3	4,944	4,256,784	27,709	200,000	7,910	0.6

As the budget increases, both approaches show improvements in ELNS and CVaR. For example, ELNS reduces from 96.3 MW at a budget of 1 to 16.2 MW at the highest budget of 5, while CVaR decreases from 781.4 MW to 212.3 MW. This demonstrates that a set of enhancement options (portfolio) provides a better hedge against cascading failures. However, even for this small-scale problem, the computational effort required by the CE method increases significantly with the budget. For a budget of 5, CE performs 4,256,784 evaluations, taking more than 27,000 seconds (around 7.7 hours). In contrast, the OvS approach requires only 200,000 evaluations and completes in approximately 7,910 seconds (around 2.2 hours) at the same budget level. This highlights the efficiency of OvS, which significantly reduces computational requirements while delivering similar results. Figure 5.5 further illustrates this comparison, showing the sharp rise in computation time for the CE method as the budget increases, while the OvS approach maintains a more moderate and stable growth.

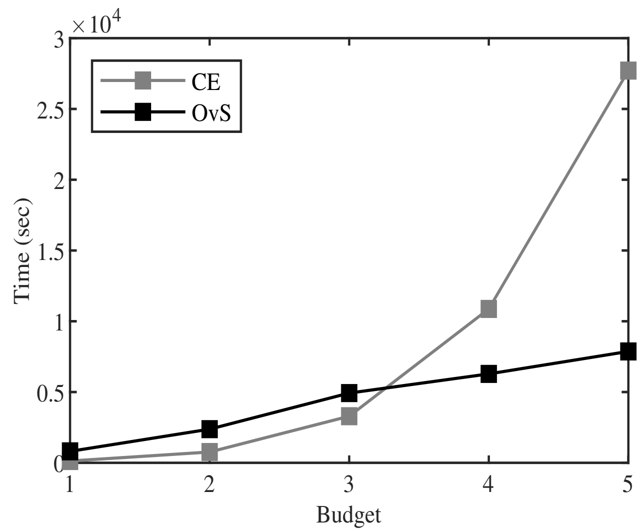

Figure 5.5: Computation time comparison between CE and OvS for different budget sizes.

In addition, the OvS approach shows the robustness for each budget. While robustness is initially high (1.0) for lower budgets (1 and 2), it slightly decreases as the budget increases, reaching 0.6 for a budget of 5. Despite this slight decrease in robustness, the computational savings and reduced risk levels make the OvS approach a promising option as the budget grows larger.

The results highlight the trade-offs between the exhaustive CE method and the more computationally efficient OvS approach. While the CE method provides comprehensive solutions, its high computational cost makes it increasingly impractical for larger budgets. In contrast, the OvS approach provides a balance between efficiency and performance, delivering robust solutions within reasonable computational times. This makes it a promising alternative for network investment planning, especially as budget size increases.

It is worth noting that, to the best of our knowledge, no existing framework directly compares network expansion and battery storage optimization using detailed AC cascading failure simulations. As a result, direct comparisons with alternative methodologies are limited. Instead, we validate our approach by comparing it to a complete enumeration method, which provides an exhaustive solution benchmark. Our OvS method achieves nearly identical solutions while significantly reducing computational effort, thereby supporting the robustness and practicality of the proposed framework.

5.3.3. OvS results and analysis for larger budgets

Table 5.2 presents a comparison of the investment portfolios identified by the proposed OvS approach, plus the base case with no enhancement, for both the investment planning model with cascading failures and the model without cascading failures, across different budget sizes. For each budget size, the table shows the solution, the ELNS, and CVaR (which represents the average unsupplied demand across the 5 % worst cases).

Table 5.2: Comparison of budget solutions from proposed OvS: Portfolios with and without cascading failures.

Budget	**With cascading failures**			**Without cascading failures**		
	Solution	**ELNS (MW)**	**CVaR (MW)**	**Solution**	**ELNS (MW)**	**CVaR (MW)**
0	Base case	113.9	1,382.5	Base case	17.9	148.3
1	B1	96.3	781.4	B1	7.7	62.9
2	T10-12, L12-23	36.7	441.1	B1, C6	5.4	56.6
3	T10-12, L12-23, L15-21	23.9	296.9	L3-9, B1, B7, C6	3.4	47.0
4	T10-12, L12-23, L15-21, B1	19.2	234.2	L3-9, B1, B7, C6	1.9	46.0
5	T10-12, L12-23, L15-21, L3-9, B1	16.2	212.3	L3-9, B1, B7, C3, C6	1.7	46.0
6	T10-12, L12-23, L15-21, L3-9, B1, B7	12.4	190.6	L3-9, B1, B7, C3, C6, C19	1.6	75.3
7	T10-12, L12-23, L15-21, L3-9, B1, B7, C6	10.2	151.8	T10-12, L3-9, B1, B7, C3, C6, C19	1.5	75.3

As the budget increases, the portfolio solutions incorporate different combinations of network enhancements. These combinations differ between the model that includes cascading failures and the model that does not, reflecting the distinct decisions required to address the respective risks. For example, the solution for cascading failures with a budget of 7 includes three transmission lines (L12-23, L15-21, and L3-9), one power transformer (T10-12), and two battery storage units (B1 and B7), and one reactive power compensation devices (C3, C6, and C19). On the other hand, the solution without cascading failures includes a combination of one transmission line (L3-9), one power transformer (T10-12), two battery storage units (B1 and B7), and three reactive power compensation device (C6).

When cascading failures are considered, both ELNS and CVaR are significantly higher. For instance, in the base case, the ELNS is 113.9 MW with cascading failures, compared to 17.9 MW without cascading failures. As the budget increases, the ELNS and CVaR decrease consistently in both models, reflecting the effectiveness of the network enhancements. For a budget of 7, ELNS drops to 10.2 MW with cascading failures compared to 1.5 MW without cascading failures.

Hence, the portfolio solutions for network enhancements differ depending on whether cascading failures are taken into account. This difference highlights the importance of considering cascading failures in network investment planning.

Furthermore, Figure 5.6 illustrates the load shedding associated with different protection and post-fault mechanisms (UFLS, UVLS, VCLS, nOPF, and TLS) triggered by cascading failures. For a budget of 1, the inclusion of battery storage unit B1 significantly reduces the load shedding associated with frequency instability. As the budget increases to 2, investments in power transformer T10-12 and transmission line L12-23 effectively mitigate voltage related load shedding (UVLS and VCLS). At a higher budget level of 7, the portfolio consists of a combination of transmission assets, battery storage units, and reactive power compensation devices, effectively addressing load shedding across all post-fault mechanisms. These results highlight how an optimal mix of network enhancements can significantly reduce the impact of cascading failures.

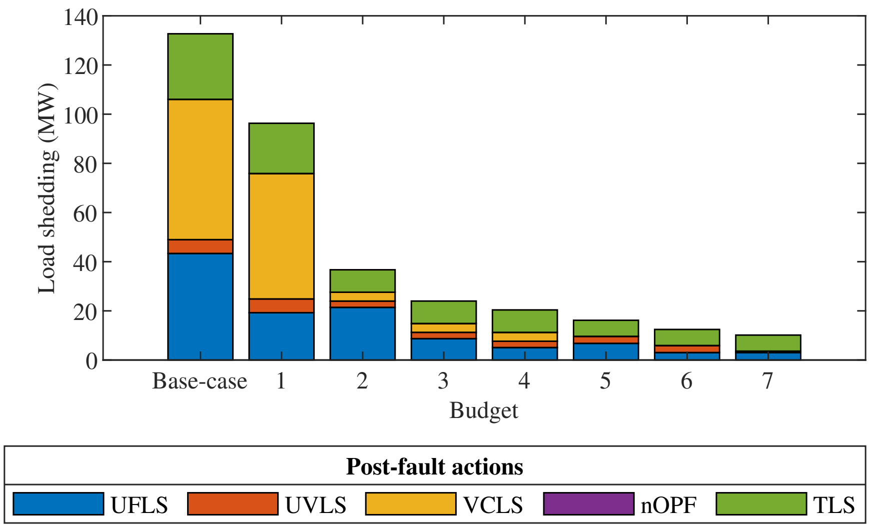

Figure 5.6: Load shedding by protection mechanism across various budget sizes in the IEEE 24-bus test system.

In order to prove the importance of incorporating cascading outages in network investment planning, Table 5.3 compares the selected investment portfolios for budget 7 from Table 5.2, alongside the base case with no enhancements. These portfolios and the base case are evaluated using the detailed cascading failure simulator to measure their effectiveness in mitigating cascading outages. The assessment is based on ELNS, CVaR, and the percentage reduction in both metrics compared to the base case.

To better illustrate the advantages of the proposed framework over conventional planning approach, Table 5.3 provides a quantitative comparison of the resulting investment portfolios under cascading outage scenarios. The analysis considers two key reliability metrics: ELNS and CVaR, which capture both average and extreme system impacts. The results indicate that the portfolio derived from the proposed framework achieves significant reductions in ELNS and CVaR, by 91.0 % and 89.0 %, respectively, compared to the base case. In contrast, the portfolio obtained using the conventional model, which does not account for cascading failures, results in smaller reductions of 59.1 % and 59.8 %. These findings highlight the added value of explicitly modeling cascading outages in the planning process, as doing so leads not

Table 5.3: Comparison of best portfolios for the IEEE 24-bus test system.

Solution	**ELNS (MW)**	**CVaR (MW)**	**Reduction ELNS (%)**	**Reduction CVaR (%)**
Base case	113.9	1,382.5	-	-
T10-12, L12-23, L15-21, L3-9, B1, B7, C6	10.2	151.8	91.0	89.0
T10-12, L3-9, B1, B7, C3, C6, C19	46.6	556.2	59.1	59.8

only to distinct investment decisions but also to demonstrably better outcomes in terms of risk mitigation and system reliability.

5.4. German transmission network

In this chapter, a 489-bus test system (German transmission network) shown in Figure 5.7 is used to further verify the applicability of the proposed framework for a larger system.

5.4.1. Description of the test network

We test the proposed framework on the German transmission network to demonstrate its scalability. The network, reduced to high and extra-high voltage levels as defined by the SciGRID project [112], consists of 489 buses, 441 generators, and 852 lines. From the PyPSA toolbox [113], both loads and generators are incorporated, with loads scaled proportionally to reach a peak load of 80 GW. Additionally, 21 candidate enhancements are considered for investment planning, including 7 new transmission lines, 7 battery storage units, and 7 reactive power compensation devices. Each enhancement option is assigned a different cost, with investment constrained by budget limitations. The capacities and investment costs associated with the various enhancement options considered in this study can be found in [105].

Similar to the previous test network, $N-2$ line outages serves as the triggering events for simulating cascading failures. However, the considerable size of this network, with 852 lines, makes it computationally infeasible to perform an exhaustive $N-2$ contingency analysis. Specifically, performing such an analysis for a network of this size would require over $3{,}393{\cdot}10^5$ rounds of simulation, a computational challenge that may even be considered impractical. To address this, we use an appropriate selection of a set of 1,000 contingencies as a reasonable and computationally feasible sample size for this network. Increasing the sample size to 2,000 raised the estimated risk by only 0.8 %, but doubled the simulation time, highlighting that 1,000 contingencies offer an effective balance between accuracy and efficiency.

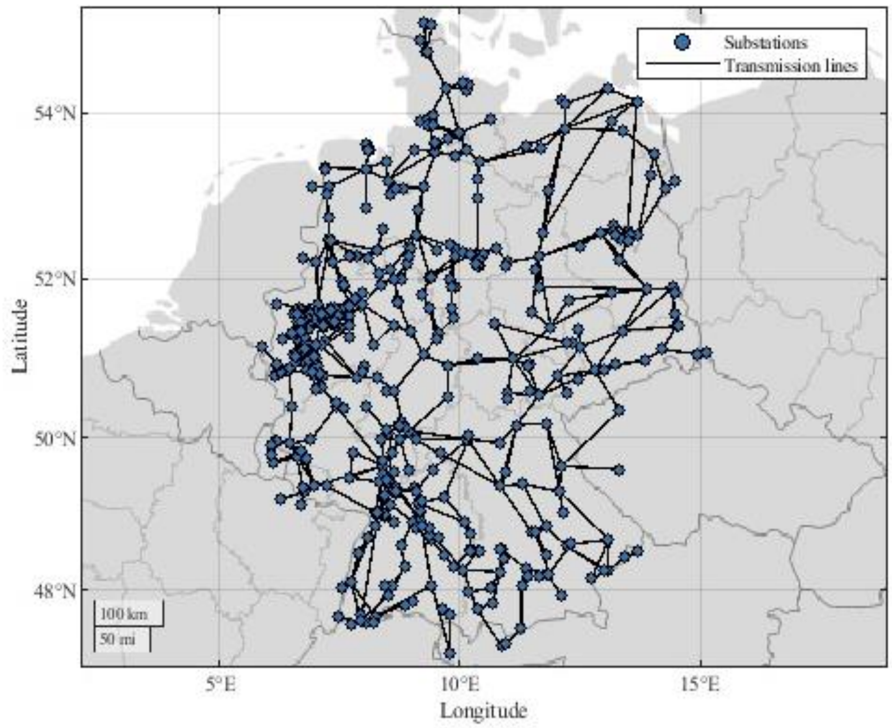

Figure 5.7: Representation of 489-bus test system (German network).

The settings used for the GA search (which have been enumerated through extensive simulations) are a population size of 300, with an 80 % probability of crossover and reproduction.

The framework is implemented on a computer with Intel(R) Xeon(R) CPU E5-2620 with 2.4 GHz and 32 GB of RAM. For the German transmission network, the optimization process required between 2 to 8 hours, depending on the budget constraint and the number of scenarios evaluated. Each AC cascading failure simulation took approximately 1-3 minutes per scenario, depending on the number of protection mechanisms triggered. Parallel computing is used to improve computational efficiency, reducing computation times by up to 60 % compared to sequential execution. For even larger networks, implementing the framework on high performance computing clusters or dedicated servers with increased parallel processing capabilities would further improve scalability.

5.4.2. OvS results and discussion

Table 5.4 presents the investment portfolios for the German network, considering cascading failures at different budget levels, while Table 5.5 shows the results without accounting for cascading failures at the same budget levels. Both tables show details of the budget, portfolio solution, investment cost (IC), ELNS, and CVaR (which represents the average unsupplied demand across the 5 % worst cases).

In both tables, as the investment budget increases from 100 M$ (million) to 900 M$ (million), different portfolios emerge with corresponding improvements in ELNS and CVaR. For example, in the 900 M$ case, the portfolio with cascading failures includes a mix of transmis-

Table 5.4: Budget-specific solutions considering cascading failures in the German network for various sizes (confidence intervals are negligible, thus omitted).

Budget (M$)	**Solution**	**IC (M$)**	**ELNS (MW)**	**CVaR (MW)**
100	B150, B226, C207	83	13,127.9	75,982.5
300	L594, B150, B226, C207	256	10,574.9	69,158.1
500	L594, L484, B150, B226, C207	485	8,462.3	55,429.0
700	L74, B150, B226, C207	681	6,848.0	42,755.9
900	L74, L484, B150, B226, C207	855	6,786.5	39,850.0

Table 5.5: Budget-specific solutions without considering cascading failures in the German network for various sizes (confidence intervals are negligible, thus omitted).

Budget (M$)	**Solution**	**IC (M$)**	**ELNS (MW)**	**CVaR (MW)**
100	BXX, B150, C38, C207	95	4,275.4	28,627.2
300	L484	299	3,854.2	24,112.8
500	L484, L376, C38, C207	498	2,758.6	22,985.7
700	L74, B150, C38, C207	659	2,565.3	22,671.2
900	L74, L376	898	2,368.9	22,505.1

sion lines (L74, L484), battery storage units (B150, B226), and reactive power compensation device (C207). In contrast, without cascading failures, the focus is mainly on transmission lines (L74, L376). In terms of ELNS, the portfolio considering cascading failures achieves a significant reduction from 13,127.9 MW (corresponding to 100 M$) to 6,786.5 MW. Without cascading failures, the ELNS decreases from 4,275.4 MW to 2,368.9 MW (corresponding to 100 M$) to 2,368.9 MW, but this overlooks the potential risks of cascading failures.

The CVaR values further emphasize the difference between the two approaches. When cascading failures are considered, the CVaR ranges from 75,982.5 MW to 39,850.0 MW, significantly higher than the range of 28,627.2 MW to 22,505.1 MW range when cascading failures are ignored. This demonstrates the increased risk exposure when cascading events are considered and highlights the limitations of conventional planning models.

To validate the results obtained for the German transmission network, we conducted a statistical consistency analysis across all Monte Carlo simulations. For each evaluated investment portfolio, the estimated metrics (ELNS and CVaR) were computed over a sufficiently large number of sampled contingencies, ensuring stable convergence of the sample mean and variance. We observed that the confidence intervals around the ELNS and CVaR estimates were negligible—typically below 5 % of the point estimates—which indicates that additional samples would not materially change the results. Moreover, repeated simulations with different random seeds produced virtually identical outcomes, further confirming the robustness of the results. Overall, the negligible confidence intervals and consistent convergence behavior provide evidence of the statistical reliability and internal validity of the results for this case.

No convergence issues were observed in either the optimization or the Monte Carlo stages.

For the German network, repeated runs with different initialization seeds yielded consistent portfolios, and the objective function stabilized within the expected number of generations. Likewise, ELNS and CVaR estimates converged quickly as the number of sampled contingencies increased, confirming stable and reliable convergence throughout the analysis.

Additionally, Table 5.6 presents a comparison of the selected investment portfolios from Table 5.4 and Table 5.5, alongside the base case with no enhancements. These portfolios and the base case are evaluated using the detailed cascading failure simulator to measure their effectiveness in mitigating cascading outages. The assessment is based on ELNS, CVaR, and the percentage reduction in both metrics compared to the base case.

Table 5.6: Comparison of investment portfolios in the German network under cascading failures.

Solution	**ELNS (MW)**	**CVaR (MW)**	**Reduction**	
			ELNS (%)	**CVaR (%)**
Base case	13,630.6	76,019.3	-	-
L74, L484, B150, B226, C207	6,786.5	39,850.0	50.2	47.6
L74, L376	9,573.1	57,682.0	29.8	24.1

The first portfolio, comprising L74, L484, B150, B226, and C207, achieves notable reductions of 50.2 % in ELNS and 47.6 % in CVaR. Conversely, the second portfolio, consisting of two transmission lines, L74 and L376, yields smaller improvements of 29.8 % in ELNS and 24.1 % in CVaR. These results clearly demonstrate that the portfolio obtained through the proposed framework leads to more substantial improvements in risk mitigation and system reliability when compared to the conventional approach.

This analysis highlights the superior performance of the first portfolio, which effectively addresses cascading failures by incorporating a mix of enhancement options (network expansion and batteries). Moreover, the first portfolio addressing cascading risks is more cost-effective, delivering greater reductions in ELNS at a lower investment cost (see Table 5.4).

These findings underscore the benefits of explicitly considering cascading outages in network planning, as the second portfolio, obtained without accounting for cascading effects, results in less robust decisions and smaller improvements in system reliability. The comparison not only demonstrates the importance of incorporating cascading failure modeling into investment planning models, but also validates the scalability and practicality of the proposed framework when applied to a large-scale power system such as the German transmission network.

6. Conclusions

6.1. Main findings

This thesis presents a comprehensive planning framework that integrates detailed system failure simulations into transmission network expansion and storage planning. The research focuses on addressing the limitations of conventional contingency-based approaches by modeling simultaneous failures, such as cascading outages and localized disruptions within substations, through probabilistic methods. Two major methodological contributions are presented: a substation-level failure model based on bay-level configurations for seismic resilience assessment, and an Optimization via Simulation (OvS) framework for transmission planning under cascading failure risk. Together, these tools enhance the ability to evaluate system vulnerability and support the identification of infrastructure strategies that minimize the impact of HILP-type events.

The first contribution is a novel substation-level modeling approach that represents electrical bays as the basic unit of analysis in the simulation of seismic impacts. Unlike traditional monolithic models that assume a full substation outage, the bay-level model enables partial and conditional failures within substations, improving the resolution of simulated outages and the accuracy of expected energy not supplied calculations. This modeling granularity is essential to properly capture the effect of seismic hazards, which often cause localized failures across several components. The methodology was validated using a modified IEEE 24-bus system and the Chilean transmission network. The results revealed significant differences in both outage patterns and estimated system performance, demonstrating that monolithic assumptions can underestimate vulnerabilities. By reflecting the internal topology of substations, the bay-based approach allows a more realistic identification of critical components, aiding both operational response and investment prioritization.

The second major contribution of this research is the development of a simulation-based planning framework that incorporates cascading failure dynamics into investment decision-making. The proposed framework couples probabilistic failure sampling, an AC power flow-based cascading simulator, and a genetic algorithm for optimizing portfolios of transmission lines, transformers, battery storage units, and reactive compensation devices. This integrated approach goes beyond deterministic N-1 security standards by capturing sequential failure propagation mechanisms, such as overloads, frequency instability, and islanding. Through detailed simulation of cascading outages, the OvS framework enables the evaluation of network portfolios based on their ability to reduce risk metrics, such as EENS and CVaR.

The validation of the framework was conducted using two test systems. First, the IEEE 24-bus network was used to benchmark the OvS-based approach against a Complete Enumeration method. The comparison showed that the OvS model could identify solutions with similar or better reliability performance at a fraction of the computational cost. Furthermore, the results showed that when cascading failures are not considered, the planning outcomes differ substantially, often underestimating the benefits of flexible technologies and overinvesting in less effective reinforcements. The second case study applied the framework to the German transmission system, consisting of 489 buses. Despite the system's complexity, the framework demonstrated its scalability and robustness, identifying optimal investment portfolios under a set of contingencies. Across both case studies, the results confirmed that including cascading failure modeling in the investment loop leads to more effective and cost-efficient planning.

These findings support three key conclusions aligned with the hypotheses of this thesis. First, the representation of initial outages using detailed failure models significantly alters the risk profile and should replace monolithic assumptions in future assessments. Second, optimization approaches that incorporate cascading failure simulations outperform conventional static planning models by better capturing the value of redundancy, flexibility, and resilience. Third, the explicit inclusion of cascading risks within the planning loop enables the identification of optimized infrastructure portfolios that achieve higher reliability and lower blackout impacts at similar or reduced investment levels.

Therefore, this research demonstrates that probabilistic modeling of simultaneous failures, including localized substation disruptions and system-wide cascading outages, is critical to support the resilience assessment and planning of modern power systems. By bridging vulnerability modeling and optimization under uncertainty, this thesis contributes a scalable and flexible decision-support tool capable of addressing emerging threats under realistic operating conditions. Future research may extend this work to include other HILP-type events, adaptive protection schemes, and interdependent infrastructure networks.

Finally, although the methodology offers high modeling detail, its integration into utility planning requires considerations related to data availability, computational effort, and compatibility with existing regulatory and operational practices. In practice, applying substation-level failure modeling and simulation-based investment analysis would require coordinated data collection, scenario-reduction strategies, and selective use of high-fidelity simulations in studies where extreme-event risk is a priority. This discussion clarifies the pathway for real-world adoption and highlights the main practical challenges that planners may face.

6.2. Future works

Future research can build on the outcomes of this thesis by addressing several methodological and practical aspects not fully explored in the current framework. A first line of improvement involves the integration of the two main contributions of this work, substation-level seismic modeling and cascading failure simulation, into a unified framework. While these components have been addressed separately to ensure clarity and depth in their respective analyses, future work should consider the compounding effects of localized failures within substations on the initiation and propagation of cascading outages. Modeling both mechanisms jointly would enable more accurate assessments of vulnerability, especially in systems where substation fragility can act as a trigger for widespread collapse.

Another important direction concerns the treatment of uncertainty. The current implementation uses a scenario-based sampling method for initial outages, but it does not incorporate probabilistic representations of hazard frequency, duration, or intensity. Integrating hazard models with system response simulations would enable more comprehensive risk quantification, supporting the prioritization of investments under budget constraints and uncertainty. Additionally, further work is needed to evaluate the sensitivity of results to fragility assumptions, protection system settings, and load response behavior. These factors may significantly affect the resulting blackout size and investment recommendations.

The inclusion of resilience metrics beyond load shedding (such as system restoration time, critical load coverage, or customer impact indices), represents another promising avenue. These indicators can provide a more holistic perspective on system performance during and after extreme events, complementing traditional energy-not-served-based metrics. Embedding such metrics into the optimization loop could lead to investment decisions better aligned with long-term reliability and recovery objectives.

From an application standpoint, the framework should be tested on additional large-scale networks that reflect real-world complexities, including the presence of renewable generation, meshed topologies, and interdependencies with other infrastructures. In particular, renewable-rich systems present unique challenges due to their variability, limited inertia, and spatial dispersion. Extending the framework to incorporate time-varying resource profiles, forecast uncertainty, and dynamic control schemes (e.g., inertia emulation or adaptive protection) could enhance its applicability in future grid scenarios.

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Appendix A: ACOPF model

This appendix describes the basic mathematical formulas used in Alternating Current Optimal Power Flow (ACOPF) model and in this thesis.

The optimal AC power flow problem is a nonlinear optimization model that optimizes the power flow dispatch in an electrical network in a single period, given the state of the system in the previous period. The optimization problem is solved using MATPOWER package that allows computing power flows and optimal power flows in MATLAB. The standard version of the ACOPF optimization problem takes the following form [114]:

$$\underset{\Theta,V,P^G,Q^G}{\text{mín}} \sum_{\mathrm{i}\in\Omega^G} \left(f_{\mathrm{i}}^P(P_{\mathrm{i}}^G) + f_{\mathrm{i}}^Q(Q_{\mathrm{i}}^G) \right) \tag{A.1}$$

$$P_b^B(\Theta, V) + P^D - P^G = 0 \quad \forall b \in \Omega^B \tag{A.2}$$

$$Q_b^B(\Theta, V) + Q^D - Q^G = 0 \quad \forall b \in \Omega^B \tag{A.3}$$

$$|F_l^{from}(\Theta, V)| - \bar{F}_l \leq 0 \quad \forall l \in \Omega^L \tag{A.4}$$

$$|F_l^{to}(\Theta, V)| - \bar{F}_l \leq 0 \quad \forall l \in \Omega^L \tag{A.5}$$

$$\theta_b^{ref} \leq \theta_b \leq \theta_b^{ref} \quad \forall b \in \Omega^B \tag{A.6}$$

$$\underline{v_b} \leq v_b \leq \bar{v_b} \quad \forall b \in \Omega^B \tag{A.7}$$

$$\underline{p_{\mathrm{i}}^G} \leq p_{\mathrm{i}}^G \leq \bar{p_{\mathrm{i}}^G} \quad \forall \mathrm{i} \in \Omega^G \tag{A.8}$$

$$\underline{q_{\mathrm{i}}^G} \leq q_{\mathrm{i}}^G \leq \bar{q_{\mathrm{i}}^G} \quad \forall \mathrm{i} \in \Omega^G \tag{A.9}$$

The objective function (A.1) is the summation of cost functions f_{i}^P and f_{i}^Q of active and reactive power injections, respectively, for each generator i. The equality constraints (A.2) and (A.3) are the power balance equations for active and reactive power balance as nonlinear functions, respectively. The inequality constraints (A.4) and (A.5) are the branch flow limits as nonlinear functions of the bus voltage angles and magnitudes, one for the from end and one for the to end of each branch. The variable limits (A.6)- (A.9) include an equality constraint on any reference bus angle and upper and lower limits on all bus voltage magnitudes and active and reactive generator injections.

Appendix B: Input data of 3-bus test system

Table B.1: Generators data

Bus	$\bar{P}$ (MW)	p (MW)	$\bar{Q}$ (MVAr)	q (MVAr)	c_2 (\$/MWh^2)	c_1 (\$/MWh)	c_0 (\$/h)
G1	1	425	0	170	0	7.5	0
G2	2	85	0	50	0	14	0
G3	3	90	0	60	0	10	0

Table B.2: Buses data

Bus	P_D (MW)	Q_D (MVAr)
1	50	8.66
2	60	1.24
3	300	50

Table B.3: Existing branches data

From Bus	To Bus	BR_R (pu)	BR_X (pu)	BR_B (pu)	$\bar{S}$ (MVA)
1	2	0.02	0.2	0.001	126
1	3	0.02	0.2	0.001	250
2	3	0.02	0.1	0.001	130

Table B.4: Candidate branches data

From Bus	To Bus	BR_R (pu)	BR_X (pu)	BR_B (pu)	$\bar{S}$ (MVA)
1	2	0.02	0.2	0.001	150
2	3	0.02	0.1	0.001	130

Table B.5: Candidate battery storage device data

Bus	$\bar{P}$ (MW)	$\bar{Q}$ (MVAr)
2	100	50
3	150	50

Table B.6: Candidate reactive power compensator data

Bus	$\bar{Q}$ (MVAr)
3	50

Appendix C: Detail results of the 3-bus test system

Table C.1: Results of single line outages with cascading analysis

Contingency (From-To Bus)	Base case	B2	B3	C3	L′12	L′23
1–2	76.84	58.33	40.26	76.84	0.00	76.84
1–3	79.41	65.43	42.82	79.41	53.21	76.61
2–3	7.32	7.32	0.00	0.00	7.32	0.00
Average value	54.52	43.69	27.69	52.08	20.18	51.15

Table C.2: Results of single line outages without cascading analysis

Contingency (From-To Bus)	Base case	B2	B3	C3	L′12	L′23
1–2	7.00	0.00	0.00	5.20	0.00	6.50
1–3	33.00	20.30	0.00	33.00	20.30	32.80
2–3	5.80	5.80	0.00	0.00	4.90	0.00
Average value	15.27	8.70	0.00	12.73	8.40	13.10

Appendix D: Input data of IEEE 24-bus test system

Table D.1: Buses data

Bus	P_D (MW)	Q_D (MVAr)
1	108	22
2	97	20
3	180	37
4	74	15
5	85.2	16.8
6	136	28
7	150	30
8	171	35
9	175	36
10	234	48
13	265	54
14	194	39
15	380.4	76.8
16	120	24
18	399.6	81.6
19	181	37
20	128	26

Table D.2: Generators data

Number	Bus	$\bar{P}$ (MW)	p (MW)	$\bar{Q}$ (MVAr)	q (MVAr)	c_2 (\$/MWh^2)	c_1 (\$/MWh)	c_0 (\$/h)
1	1	20	0	10	0	0	130	400.6849
2	1	20	0	10	0	0	130	400.6849
3	1	76	0	30	-25	0.0141	16.0811	212.3076
4	1	76	0	30	-25	0.0141	16.0811	212.3076
5	2	20	0	10	0	0	130	400.6849
6	2	20	0	10	0	0	130	400.6849
7	2	76	0	30	-25	0.0141	16.0811	212.3076
8	2	76	0	30	-25	0.0141	16.0811	212.3076
9	7	100	0	60	0	0.0527	43.6615	781.5210
10	7	100	0	60	0	0.0527	43.6615	781.5210
11	7	100	0	60	0	0.0527	43.6615	781.5210
12	13	591	0	240	0	0.0527	43.6615	832.7575
13	14	0	0	200	-50	0	0	0
14–18	15	12	0	6	0	0.3284	56.5640	86.3852
19	15	155	0	80	-50	0.0083	12.3883	382.2391
20	16	155	0	80	-50	0.0083	12.3883	382.2391
21	18	400	0	200	-50	0.000213	4.4231	395.3749
22	21	400	0	200	-50	0.000213	4.4231	395.3749
23–28	22	50	0	16	-10	0	0.001	0.001
29	23	155	0	80	-50	0.0083	12.3883	382.2391
30	23	155	0	50	-50	0.0083	12.3883	382.2391
31	23	350	0	150	-25	0.0049	11.8495	665.1094

Table D.3: Branches data

Number	**From bus**	**To bus**	$\mathbf{BR_R}$ (pu)	$\mathbf{BR_X}$ (pu)	$\mathbf{BR_B}$ (pu)	$\bar{F}$ (MVA)
1	1	2	0.0026	0.0139	0.4611	70
2	1	3	0.0546	0.2112	0.0572	70
3	1	5	0.0218	0.0845	0.0229	105
4	2	4	0.0328	0.1267	0.0343	88
5	2	6	0.0497	0.1920	0.0520	70
6	3	9	0.0308	0.1190	0.0322	131
7	3	24	0.0023	0.0839	0.0000	240
8	4	9	0.0268	0.1037	0.0281	88
9	5	10	0.0228	0.0883	0.0239	105
10	6	10	0.0139	0.0605	2.4590	175
11	7	8	0.0159	0.0614	0.0166	158
12	8	9	0.0427	0.1651	0.0447	175
13	8	10	0.0427	0.1651	0.0447	70
14	9	11	0.0023	0.0839	0.0000	300
15	9	12	0.0023	0.0839	0.0000	300
16	10	11	0.0023	0.0839	0.0000	300
17	10	12	0.0023	0.0839	0.0000	300
18	11	13	0.0061	0.0476	0.0999	300
19	11	14	0.0054	0.0418	0.0879	280
20	12	13	0.0061	0.0476	0.0999	300
21	12	23	0.0124	0.0966	0.2030	300

Number	**From bus**	**To bus**	$\mathbf{BR_R}$ (pu)	$\mathbf{BR_X}$ (pu)	$\mathbf{BR_B}$ (pu)	$\bar{F}$ (MVA)
22	13	23	0.0111	0.0865	0.1818	300
23	14	16	0.0050	0.0389	0.0818	300
24	15	16	0.0022	0.0173	0.0364	400
25	15	21	0.0063	0.0490	0.1030	360
26	15	21	0.0063	0.0490	0.1030	360
27	15	24	0.0067	0.0519	0.1091	400
28	16	17	0.0033	0.0259	0.0545	400
29	16	19	0.0030	0.0231	0.0485	300
30	17	18	0.0018	0.0144	0.0303	240
31	17	22	0.0135	0.1053	0.2212	400
32	18	21	0.0033	0.0259	0.0545	120
33	18	21	0.0033	0.0259	0.0545	120
34	19	20	0.0051	0.0396	0.0833	210
35	19	20	0.0051	0.0396	0.0833	210
36	20	23	0.0028	0.0216	0.0455	400
37	20	23	0.0028	0.0216	0.0455	400
38	21	22	0.0087	0.0678	0.1424	300
39	6	10	0.0139	0.0605	2.4590	175
40	7	8	0.0159	0.0614	0.0166	158
41	15	24	0.0067	0.0519	0.1091	400
42	14	16	0.0050	0.0389	0.0818	300

Table D.4: Candidate battery storage device data

Bus	$\bar{P}$ (MW)	$\bar{Q}$ (MVAr)
1	200	50
7	200	50
13	200	50
18	200	50
21	200	50

Table D.5: Candidate reactive power compensator data

Bus	$\bar{Q}$ (MVAr)
3	100
5	100
6	100
10	100
19	100