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From Reliability to Resilience

1.1 Why Power System Resilience?

Extreme events – primarily natural disasters and climate-driven severe weather – have increasingly exposed the limitations of current, traditional reliability frameworks in power system design and operation. Historically, power system planners, regulators, and policymakers have not accounted for such events in network reliability standards. Instead, the design and operation of electric power infrastructure have centered on so-called credible (or "average") outages, such as single or double faults – commonly referred to in power system terminology as N–1 or N–2 contingencies [1]. While these approaches have ensured continuity of supply during minor, everyday disruptions, they fall short in addressing the challenges posed by extreme events.

Recent disasters have underscored the inadequacy of traditional methods. Bushfires in Australia, the Americas, and Greece; flooding events in the United Kingdom; storms in the Americas; and earthquakes in Pacific Ring of Fire countries have caused disruptions far beyond the scope of N–1 or N–2 outages. For example, Chile experiences more than 300 earthquakes exceeding 4.5 Mw annually, resulting in significant power interruptions each year. In the United Kingdom, severe storms and floods have led to prolonged outages, such as the 56-hour interruptions caused by flooding in North West England in 2016. Table 1.1 provides an overview of how natural events have triggered significant power outages. Globally, the World Meteorological Organization reports over 11 000 weather- and climate-related disasters between 1970 and 2019, resulting in 2 million deaths and $3.64 trillion in economic losses [2].

The need for change is urgent: power systems must evolve to address high-impact, low-probability (HILP) events, which are often underestimated or neglected by traditional reliability frameworks. This necessity is further amplified by aging infrastructure, increasing societal dependence on electricity, and emerging threats such as climate change. To meet these challenges, decision-makers must adopt resiliency-driven and risk-aware engineering practices that explicitly integrate resilience into operational and planning standards. This shift is critical to addressing both existing vulnerabilities and the growing challenges posed by climate change and other stressors.

The Intergovernmental Panel on Climate Change (IPCC) emphasizes the urgency of this transformation for all critical infrastructure. Projections indicate a rise in extreme heat, fire weather, heavy precipitation, flooding, and severe windstorms across Europe, alongside similar global challenges [3]. Therefore, resilience must become a cornerstone of future power system design and operation.

This book seeks to address pivotal questions: How can resilience-thinking be effectively incorporated into power system methodologies? What constitutes the optimal portfolio of measures for

Fundamentals of Power System Resilience: Disruptions by Natural Causes, First Edition.
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Table 1.1 Significant blackouts caused by natural hazards.

Country	Date	Disaster name	Size of blackout	Effects on society
United States	August 25, 2005	Hurricane Katrina	2.7 million people without power, 10+ days	Major displacement, economic loss, and deaths due to lack of power for critical infrastructure like hospitals
Japan	March 11, 2011	Tōhoku Earthquake and tsunami	21 GW, several weeks	Nationwide economic disruption, rolling blackouts, and societal stress after the Fukushima nuclear disaster
India	July 30, 2012	2012 India blackouts (Monsoon flooding)	32 GW, affected 620 million people	Largest power outage ever, massive economic disruption, halted transportation, and widespread societal stress
Puerto Rico	September 20, 2017	Hurricane Maria	3.7 million people without power, ~11 months	Longest blackout in US history; major humanitarian crisis, public health emergencies, and infrastructural collapse
Philippines	November 08, 2013	Typhoon Haiyan	1 month	16 million people affected; loss of livelihoods and severe societal disruption
China	May 12, 2008	Sichuan Earthquake	4 million households without power, ~15 days	Infrastructure damage, agricultural and industrial losses, and disrupted supply chains
Chile	February 27, 2010	2010 Maule earthquake	4522 MW loss, 2 weeks	Severe disruption to infrastructure, widespread blackouts, and difficulty restoring electricity
Italy	September 28, 2003	2003 Italy blackout (storm-induced grid overload)	177 GWh of energy not supplied (ENS), 13 hours	Nationwide disruption, halted trains and airports, and emergency services stretched
Canada	January 05, 1998	North American ice storm of 1998	5 million people without power, up to 1 month	Severe economic impacts, fatalities due to cold, and reliance on emergency shelters
Australia	September 28, 2016	2016 South Australian blackout (severe storms)	~1.1 million people, 8 hours	South Australia-wide blackout; economic impact on manufacturing and agriculture
Mexico	September 19, 1985	Mexico City earthquake	1/3 of the city hit by power outages	Infrastructure collapse, humanitarian crisis, and significant rebuilding costs
United States	February 10, 2021	2021 Texas winter storm	~4.5 million people, ~7 days	Severe disruption in Texas, major fatalities (246+), loss of heating during extreme cold, and economic impact of ~$195 billion

enhancing power grid resilience? And how can we build power grids that are both robust and flexible enough to withstand unprecedented disruptions? By presenting a resilience-driven framework that bridges theory and practice, this book equips decision-makers with the tools to enhance power system resilience worldwide. It offers methodologies, regulations, theories, and real-world examples to inspire informed and practical solutions for the energy sector.

1.2 The Historical Approaches to Power System Reliability

1.2.1 The Historical N-k Network Security Criterion

The N-k (deterministic) network security criteria or standards require that networks withstand the loss of one or two circuits (i.e. N–1 or N–2) without causing overloads on other circuits, and that such outages do not compromise the integrity of system operations [1]. These standards are applied across both short-term operational and long-term planning time horizons. In short-term operations, network security is maintained by limiting power transfer across the network, often through generation re-dispatch. For long-term planning, security is ensured through investments in network reinforcements. Both approaches generally justify network redundancy (in the form of network congestion in the short term and network investments in the long term) for the provision of security.

Within this framework, outages beyond those deemed credible – and their associated consequences – are generally not analyzed. Network security is achieved through a combination of preventive and corrective control actions. These include managing network congestion and implementing post-contingency controls such as adjusting generation setpoints and utilizing flexible AC/DC network components like HVDC lines, line switches, series compensators, and phase-shifting transformers. However, deterministic security standards are typically biased toward preventive control measures, emphasizing network redundancy.

Furthermore, traditional deterministic standards assume that the system should remain stable under any credible contingency without requiring load shedding. While these rules were designed with transparency and cost-effectiveness in mind, their adequacy must now be reassessed in the face of extreme events that go far beyond N–1 or N–2 contingencies. Furthermore, deterministic standards have been historically criticized for their lack of economic optimization. Specifically, they do not account for the social costs of post-fault demand curtailment (and corrective control actions) in comparison to the costs of preventive control measures (network congestion and investment). This imbalance fosters a probabilistic approach that explicitly evaluates the trade-offs between preventive actions and the expected costs of energy not supplied (ENS) as well as other costs such as generation tripping actions with the associated revenue losses.

To address these limitations, researchers and academics have proposed probabilistic approaches to network security, which are discussed next.

1.2.2 The More Advanced Probabilistic Network Security

A probabilistic network security approach allows for post-fault demand curtailments by appropriately balancing them against the up-front costs incurred in the pre-fault condition due to network congestion and investments. From the perspective of operation, improving the reliability of a power system through network congestion should continue only until the costs associated with such congestion exceed their benefits in terms of reduction in the unsupplied demand costs. This approach

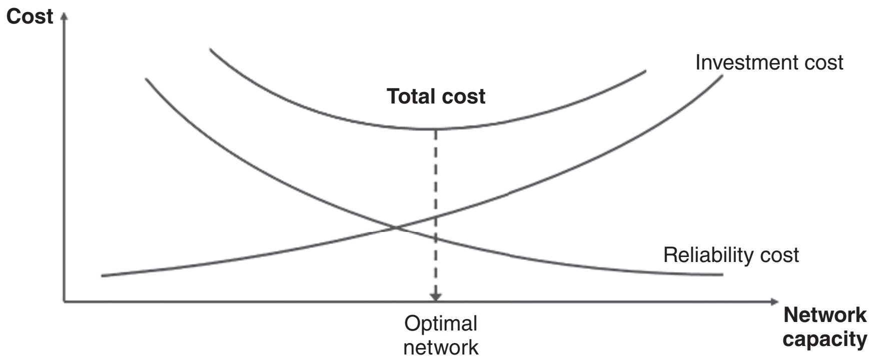

Figure 1.1 Optimal balance between investment and reliability costs.

ensures that operational decisions, such as power transfer levels, are optimized to minimize total costs. These costs include operating expenses, such as congestion and losses, as well as the expected costs of unsupplied demand. The optimization is performed over an array of operating states (i.e. outages), weighted according to their probabilities, resulting in efficient network utilization and a balanced level of risk for specific operating conditions. This means that more congestion can be justified to control reliability levels. Mathematically, the optimization of total cost (operation and unsupplied demand) is performed over an array of operating states (i.e. outages), weighted according to their probabilities, resulting in efficient network utilization and reliability levels.

Similarly, from the perspective of infrastructure planning, network redundancy can be created through new investments rather than simply increasing congestion. In this case, investments are justified only when the marginal savings in demand curtailment costs (and pre-contingency congestion costs) outweigh the marginal costs of the new investments.

In probabilistic reliability assessment, as pioneered by Billinton and Allan [4], the estimated costs from expected ENS are averaged (weighted by probability) across all modeled scenarios and optimized against additional investment and operational costs. Network investments are therefore well justified as a trade-off between economic efficiency and security of supply. If operational costs (e.g. congestion and losses) are simplified or neglected, investments are made until the marginal cost of additional investment equals the marginal benefit of enhanced reliability. This relationship is graphically represented in Figure 1.1, where reliability costs are measured as the product of expected energy not supplied (EENS) and the Value of Lost Load (VoLL). However, while effective for standard reliability challenges, this probabilistic approach has fundamental limitations in addressing HILP events. These limitations and their implications for operational and investment decisions are explored in Section 1.3.

1.3 Need for a (Tail)Risk-Aware Approach

HILP events are, by definition, rare, and their impact on average indicators like EENS is consequently minimal. For example, our analysis indicates that, on average, it would be economically optimal to endure the consequences of very large earthquakes in Chile every 15 years rather than invest in additional infrastructure to reinforce and harden the power system [5]. This raises an important question: Why should we be concerned about events that, on average, have a relatively small effect?

The answer lies in the risk attitudes of electricity consumers and policymakers (and by extension, network planners who serve them). Empirical evidence suggests that both consumers and policymakers strongly dislike the risks associated with the severe consequences of HILP events and therefore seek to minimize them as much as possible. This preference raises critical questions: How can we model this risk attitude? And what assumptions about risk are embedded in the probabilistic assessments currently used?

In risk analysis, attitudes toward risk are generally classified into three categories, which are illustrated as follows:

- *Risk-neutral:* The consumer is indifferent between two options with the same total expected cost.
- *Risk-averse:* The consumer prefers an option with higher predictability and fewer adverse outcomes, even if it is slightly more expensive (on average).
- *Risk-seeking:* The consumer prefers the option with higher variability and larger adverse outcomes, even if it is less predictable.

Consider an electricity consumer choosing between two network services:

1) The first option costs $90, rarely fails, and has minor ENS-related losses totaling $10.
2) The second option costs $50 and fails more frequently, with larger ENS-related losses totaling $50.

In both cases, the total cost is the same, and thus a risk-neutral consumer would view these options as equally attractive. In contrast, most consumers are risk-averse and would prefer the stability and predictability of the first option, even at a slightly higher cost (which is not the case in this example, as both cost the same). This mirrors consumer behavior in other industries, where individuals are willing to pay for insurance to mitigate the impacts of rare but catastrophic events.

This preference for risk aversion is evident even in less extreme scenarios. For instance, during the January 2019 heatwaves in Australia, sporadic rolling load-shedding events occurred in several areas, including central Melbourne. Although these outages had only a minor overall impact, many consumers deemed them unacceptable, illustrating a widespread aversion to uncertainty and disruptions.

Governments, too, often adopt risk-averse stances, as their responsibility extends to ensuring public welfare. For political and societal reasons, they may prioritize actions to hedge against HILP events, regardless of the purely economic risk-neutral rationale. For example, regulatory and market responses were implemented following the South Australia black system event in September 2016, and additional measures were set in response to the widespread bushfires in January 2020.

The key takeaway is that risk-averse approaches and metrics, essential for addressing HILP events, are often absent from current power system planning practices. Incorporating these approaches will require a paradigm shift, moving beyond traditional reliability frameworks to account for the complex interplay of economic, social, and political factors associated with rare but devastating disruptions.

1.4 Inspiration from Other Economic and Engineering Areas

1.4.1 Risk Hedging and Portfolio Optimization

The concept of risk hedging, originating in financial portfolio theory, offers valuable insights for determining an optimal mix of investments to enhance power system resilience. In finance, Harry Markowitz's modern portfolio theory revolutionized decision-making by proposing diversification as a strategy to maximize returns for a given level of risk [6]. This approach introduced the efficient frontier or Capital Asset Pricing Model (CAPM) balancing risk (represented by the standard deviation) and return (represented by the expected return) across a portfolio of assets.

Building on Markowitz's work, subsequent advancements in risk assessment, such as conditional value at risk (CVaR), have provided robust tools for quantifying and managing risk. CVaR, pioneered by Rockafellar and Uryasev, focuses on minimizing potential losses in the tail-end of a probability distribution [7], making it particularly suited for addressing HILP events. Notably, CVaR integrates seamlessly with linear programming, a critical asset in modern decision-making processes.

Applying these principles to power systems, resilience strategies can be viewed as portfolios of measures – including system expansion, hardening, and smart technologies – that balance cost and risk. Just as financial portfolios are designed to hedge against market volatility, resilience investments aim to mitigate the impacts of extreme events on energy infrastructure. Decisions informed by risk-hedging methodologies ensure that resources are allocated efficiently, targeting the most vulnerable points in the system while optimizing long-term benefits.

For example, investing in microgrids (MGs), distributed energy resources (DERs), and adaptive control systems diversifies the resilience portfolio, reducing reliance on any single strategy and enhancing overall system robustness. By adopting a portfolio optimization approach, decision-makers can better navigate the trade-offs between upfront costs and the potential benefits of reduced downtime, improved recovery, and sustained service delivery during crises.

1.4.2 Risk-Aware Design in Structural and Civil Engineering

The field of structural and civil engineering offers a wealth of practices that can inspire resilience strategies in power systems. One cornerstone concept is the "return period" [8], a metric used to design structures to withstand extreme conditions that may occur once every 50, 100, or even 1000 years. This approach ensures that critical infrastructure remains robust against rare but catastrophic events. Central to this approach is the key question: How rare is the event we need to protect against?

In structural engineering, risk-aware design involves tailoring buildings, bridges, and other infrastructure to endure specific environmental threats such as earthquakes, hurricanes, and floods. These designs integrate both probabilistic and deterministic models, assessing historical data to predict the likelihood and intensity of extreme events. For example, earthquake-resistant buildings are designed to absorb seismic forces based on data about the most severe quakes recorded in a region over centuries.

This philosophy aligns closely with resilience planning in power systems, where strategies must also account for HILP events. By incorporating ideas from structural engineering, power system planners can adopt a similar mindset, designing grids and components to handle worst-case scenarios over long time horizons.

Furthermore, structural engineering emphasizes redundancy and flexibility. Just as bridges are often designed with multiple load paths to prevent collapse in the event of a localized failure, power systems can enhance resilience by creating alternative energy pathways and resources, such as MGs and additional transmission lines. Similarly, flexibility in materials and construction techniques enables buildings to adapt to dynamic forces – a principle mirrored in power systems through adaptive protection schemes and demand response mechanisms.

Another critical parallel is the integration of risk-based decision-making. Structural engineers use tools like fragility curves to assess how different materials and designs perform under stress, enabling cost–benefit analyses for resilience investments. In power systems, similar probabilistic concepts can support the optimization of investments in infrastructure hardening, operational measures, and smart technologies.

By learning from the structured, risk-aware practices of structural and civil engineering, power system resilience can advance toward a more robust and proactive approach. This cross-disciplinary inspiration underscores the importance of designing for long-term challenges, ensuring that both systems and structures are prepared for the uncertainties of an evolving world.

1.5 From Reliability to Resilience Paradigm

The transition from a reliability-centered approach to a resilience-oriented paradigm marks a significant shift in how energy systems are designed, managed, and evaluated. Traditionally, reliability has been the cornerstone of power system planning and operation, ensuring a consistent and uninterrupted supply of electricity to meet consumer demand. While reliability standards have been effective in minimizing routine disruptions, they are insufficient to address the growing complexities and uncertainties of the modern energy landscape. Emerging challenges such as climate change, increased frequency of extreme weather events, cyber-physical threats, and the integration of renewable energy necessitate a broader framework – one that prioritizes not only prevention but also adaptation and recovery.

Reliability in power systems focuses on ensuring that generation, transmission, and distribution networks perform their intended functions under normal operating conditions. Reliability metrics, such as the System Average Interruption Duration Index (SAIDI) and the System Average Interruption Frequency Index (SAIFI) in distribution networks, have traditionally been used to evaluate reliability. These metrics emphasize steady-state performance and the likelihood of equipment or system failures within a given timeframe.

Resilience, by contrast, encompasses the ability of a system to anticipate, absorb, adapt to, and recover from disruptive events [9]. It extends beyond the steady-state analysis of reliability to address the dynamic and often unpredictable nature of threats. Resilience emphasizes three key capabilities [10]:

1) Robustness – the ability to withstand shocks without significant degradation.
2) Adaptability – the capacity to adjust operations in response to changing conditions.
3) Rapid recovery – the ability to restore normalcy quickly and efficiently after an adverse event.

1.5.1 Key Differentiators Between Reliability and Resilience

While reliability and resilience share overlapping goals, the resilience paradigm is broader in scope. Reliability focuses on minimizing the probability of failure, whereas resilience acknowledges that failures are inevitable and seeks to mitigate their consequences. The complementary nature of these concepts is evident in the following areas:

1) *Proactive risk management:* Reliability standards traditionally rely on deterministic approaches, such as the N–1 contingency criterion, which ensures that the system can withstand the failure of a single component without widespread disruptions. However, resilience incorporates

probabilistic and scenario-based analyses to address low-probability, high-impact events. This shift enables planners to account for compounding factors and cascading failures that are not captured by conventional reliability metrics.

2) *System flexibility and redundancy:* Resilience emphasizes building flexibility and redundancy into the system. For example, DERs such as rooftop solar panels and battery storage can enhance resilience by providing localized energy supply during grid outages. Similarly, MGs equipped with advanced control systems can operate autonomously in islanded mode, ensuring continuity of service for critical loads.
3) *Real-time monitoring and adaptive control:* Advances in digital technologies, such as the Internet of Things (IoT), artificial intelligence (AI), and machine learning, enable real-time monitoring and adaptive control of power systems. These technologies enhance both reliability and resilience by providing early warning of potential failures and enabling dynamic responses to evolving conditions.
4) *Interdisciplinary collaboration:* The resilience paradigm requires a multidisciplinary approach that integrates engineering, economics, environmental science, and social dimensions. Unlike traditional reliability standards, which are often narrowly defined, resilience planning engages a broader set of stakeholders, including policymakers, community leaders, and emergency management agencies.

1.5.2 Expanding Resilience Practices

1.5.2.1 Broadening the Scope of Contingencies

Reliability-driven standards focus on managing credible contingencies, such as single- or double-circuit outages (commonly referred to as N–1 or N–2). Resilience, on the other hand, considers a broader range of simultaneous outages that could be triggered by natural events. By encompassing these extreme scenarios, resilience provides a more comprehensive framework for mitigating cascading failures and widespread disruptions.

1.5.2.2 Focusing on High-Risk Scenarios

Traditional reliability metrics often rely on averages, across all scenarios, to quantify system performance. While these averages provide a baseline understanding, they fail to capture the full impact of rare but catastrophic events. Resilience, in contrast, emphasizes a risk-focused approach that considers the tail-end of probability distributions, where the most severe consequences reside. By prioritizing the mitigation of high-risk scenarios, this approach ensures that power systems are better prepared for extreme events.

1.5.2.3 Incorporating Environmental Interactions

Traditional reliability approaches often treat power systems as isolated entities, ignoring the broader environmental context. In contrast, resilience explicitly accounts for the interactions between power systems and their surrounding environment, recognizing that external factors such as storms, floods, or earthquakes directly influence system performance. This holistic perspective enables more effective planning and response strategies tailored to specific environmental threats.

1.5.2.4 Tailoring Strategies to Natural Threats

Resilience is inherently dependent on the nature of the threats faced by a specific region. Areas prone to storms, for instance, require different resilience measures than regions vulnerable to earthquakes. This adaptability ensures that resilience strategies are context-sensitive, addressing the unique risks and vulnerabilities of each location.

1.5.2.5 Integrating Diverse Measures and Technologies

While reliability-driven standards primarily rely on $N-1$ or $N-2$ redundancy to ensure security, resilience incorporates a diverse array of measures. These include system expansion, infrastructure hardening, and enhancing responsiveness through advanced technologies and operational practices. This multi-faceted approach provides greater flexibility and adaptability in dealing with extreme events.

1.5.2.6 Emphasizing Dynamics and Recovery

Reliability standards traditionally focus on robustness, aiming to withstand outages through snapshot-type analyses. Resilience, however, emphasizes a dynamic approach that accounts for the entire lifecycle of an event. This includes the ability to “fail gracefully” immediately after a disruption and recover rapidly, as illustrated by the resilience trapezoid curve. By prioritizing recovery alongside robustness, resilience ensures that power systems can adapt and respond effectively to evolving threats.

1.6 Fundamentals of Power System Resilience

The aim of this book is to provide power system engineers and scholars with the fundamentals of power systems resilience. The overview of the book is captured in Figure 1.2.

Before moving to the technical discussions, Chapter 2 first introduces in detail the concept of power systems resilience, outlines the features and characteristics of the concept, and compares it with traditionally used concepts, including reliability and robustness. Further, popular resilience frameworks are presented, including the resilience triangle and trapezoid, where the relation of the time-series performance of a system exposed to an extreme event to the key resilience characteristics is outlined. Hence, Chapter 2 lays the basis for the subsequent book chapters.

Chapter 3, on system resilience assessment and quantification, presents different resilience metrics and provides illustrative examples on real-world systems of how these metrics can be applied to measure the spatial and temporal resilience of a power system. Further, recognizing the need to capture the cascading impacts of weather-induced asset outages, a novel AC cascading fault model is

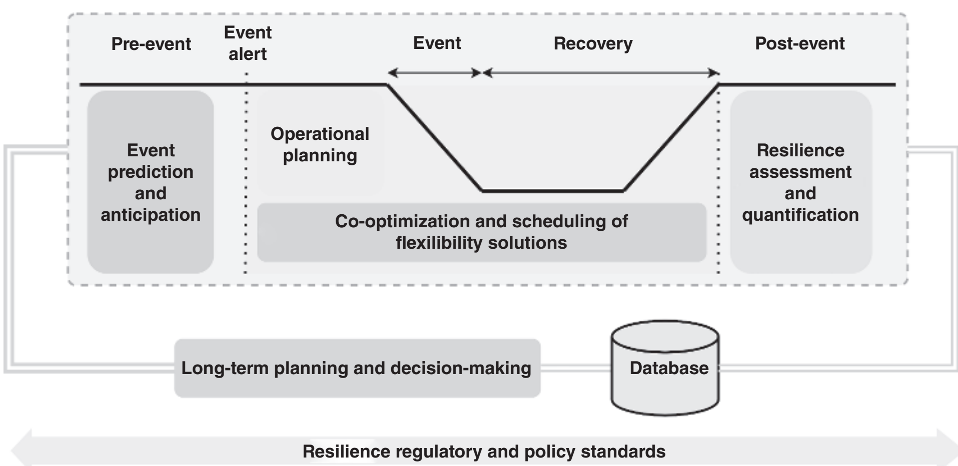

Figure 1.2 Overview of the book context.

presented, highlighting its capability of seamlessly integrating to various resilience metric systems. The resilience assessment models introduced in Chapter 3 are subject to the high uncertainty of the data inputs to these models.

In this context, Chapter 4 next addresses the data granularity and ambiguity, shedding light on methodologies for linking failure rate data, network-branch data, and weather data together for the purpose of visualizing overhead line failure probability for the purpose of providing quantitative assessments of system risk.

Chapter 5 then builds on Chapters 3 and 4 to explore strategies for enhancing power systems' resilience against natural hazards. It incorporates HILP events into investment planning and decision-making, introducing mathematical models for resilient network design. It discusses the need for a balanced investment portfolio between network expansion, infrastructure hardening, and smart grid technologies, emphasizing the significance of probabilistic analysis and risk metrics like CVaR in decision-making. Additionally, it also reviews alternative modeling approaches that use stochastic and robust optimization. Further to investment planning.

Chapter 6 delves into introducing advanced concepts on operational resilience planning and flexibility solutions. This chapter discusses the operational measures applied to enhance power system resilience in all the phases of a progressing extreme event and how the impact on the power system can be modeled to be taken into account during its operation. The use of machine learning techniques and the resilient operation of low-inertia power systems with high penetration of renewable resources during extreme events is also analyzed.

Chapter 7 explores the role of DERs as one of the most effective operational measures for enhancing power system resilience and flexibility. MGs in particular, applied during pre-event, during-event and post-event phases are able to enhance resilience of both transmission and distribution systems, due to their ability to operate connected to the main power grid or islanded. This chapter highlights practical cases in which MGs have been used for enhancing resilience during major natural disasters in the past.

Finally, Chapter 8 aims to discuss, with the aid of several real-world case studies, general economic, market, regulatory, and policy aspects of power system resilience. It also concludes with a discussion on the links between decarbonization policies and resilience, and the potential role and opportunities for DERs and grid digitalization to enhance power system resilience.

1.6.1 Contribution to the Field

Power system resilience is an evolving field that requires interdisciplinary collaboration and innovation. This book contributes to the discourse by presenting a techno-economic perspective that integrates engineering principles with economic and policy considerations. By addressing resilience from both a conceptual and practical standpoint, it aims to inspire new research and inform strategic decision-making in the energy sector.

1.6.2 Closing Remarks

The challenges facing modern power systems are formidable, but so are the opportunities to transform them into resilient and sustainable infrastructures. This book invites readers to engage with these challenges critically and creatively, contributing to a resilient energy future that can withstand the uncertainties of a rapidly changing world.

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