Expert and Intelligent Systems for Assessment and Mitigation of Cascading Failures in Smart Grids: Research Challenges and Survey

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Abstract

Network instability conditions in a smart grid may lead the network to cascading failure events (CFEs) which ultimately lead to blackouts. Examination of these CFEs at an early stage will help the network operators to mitigate the further propagation of these events in the power system network. There are many artificial intelligence-based topologies to identify, analyze, and prevent these types of events. Selecting an appropriate topology by looking at the power network architecture is one of the critical research issues that needs to be resolved. For this purpose, this review study provides a thorough examination and evaluation of intelligent assessment methodologies in smart grids to avoid CFEs, including an exploration of both their advantages and shortcomings. In contrast to existing review studies, this research focuses on a wide range of advanced topologies, i.e., quasi-steady state methods, dynamic methods, artificial intelligence (AI), probabilistic approach, digital twin method, blockchain techniques, metaverse, and the advance control methods in smart grids to avoid CFEs. Similarly, the mitigation strategy we highlighted includes several optimal power flow algorithms based on advanced machine learning that can be integrated into smart grid infrastructure to compensate against CFEs in smart grids. The objective is to pave a decision-making path for the scientific researchers who want to contribute to this research area. Through a comparative analysis of a wide range of these cascading failures assessment and mitigation topologies, the network operators easily identify the proactive approaches that can be utilized at the early stages to detect and mitigate cascading failure vulnerabilities, thus ensuring the resilience of the smart grid. Moreover, this research work indicates areas where further research is needed, and suggesting potential directions for future investigations.

Keywords Cascading Failure Analysis, Power System Vulnerability, Energy Infrastructure Security, Grid Stability Assessment, Risk Mitigation in Distributed Energy Systems, Micro grid Resilience.

Nomenclature

Table 1: List of Abbreviations

Abbreviation	Description
CF	Cascading failure
CFEs	Cascading failure events
RESs	Renewable energy sources
DERs	Distributed energy resources
BESS	Battery energy storage systems
FACTS	Flexible AC transmission
UPFC	Unified Power Flow Controller
MG	Microgrid
MGCC	Microgrid central controller
MGS	Microgrid stabilizers
PCC	Point of common coupling
PLC	Programmable logic controller
PID	Proportional integral derivative
SMC	Sliding mode control
LQI	Linear Quadratic Integrator
IB-RERs	Inverter-based renewable energy resources
FRT	Fault Ride-Through
RIPGs	Renewable integrated power grids
COFs	Cascading overload failures
MPPT	Maximum power point tracker
FCCM	Fuzzy Co-operative Control Mechanism
WSN	Wireless sensor networks
SCADA	Supervisory control and data acquisition
PMU	Phasor measurement units
QSS	Quasi-steady-state
TLR	Transmission loading relief
IoT	Internet of things
PSO	Particle swarm optimization
UVLS	Under-voltage load shedding
UFLS	Under-frequency load shedding
DVR	Dynamic voltage restorer
DSTATCOM	Distributed static compensator
TD	Temporal difference learning
CNN	Convolutional neural network
DNN	Deep neural network
GCN	Graph Convolutional network
SVM	Support vector machine
ANFIS	Adaptive neuro-fuzzy inference system
DFS	Depth-first search

GBR	Gradient boosting regression
PTDF	Power transfer distribution factors
DT	Digital twin
NIST	The National Institute of Standards and Technology
UCTE	Union for the Coordination of Transmission of Electricity

1 Introduction

The growing expansion of renewable energy sources and their inherent variability are contributing to the rising complexity of the modern power system. The electricity grid is characterized by its complex network structure, which is formed by a combination of ring and radial network topologies. In this representation, substations are represented as nodes, while transmission lines are represented as edges. As a consequence of this factor, interconnected networks exhibit a significantly higher vulnerability to catastrophic failures. The increasing intensity of interdependencies among various components within a system has significant ramifications for the functionality and functioning of other constituent pieces. As the complexity of the electrical grid continues to increase, the task of accurately representing cascading failures becomes increasingly challenging. This research highlights the fundamental significance of examining cascading failures, which arise from chain reactions, due to their potential to shut down entire power systems or substantial portions of them.

A wide range of systems, including ecosystems, transportation networks, power grids, and wireless sensor networks (WSNs), are prone to cascade failures[1],[2]. Typically, there is a certain degree of physical or logical interconnection between the different components of these systems. This study examines the prevalence of cascading failures in interconnected domains and analyzes their occurrence and consequences. Due to the interdependent nature of systems, the failure of one component necessitates the collaboration of other components to make up for the loss. Conversely, these components may get overwhelmed and experience malfunction due to this correction. This occurrence triggers a cascade of events, known as a domino effect. If appropriate and timely efforts to mitigate and control cascade failures are not taken, there can be significant repercussions for public health, the economy, the environment, and/or human society[3]–[5]. The 2003 Northeast blackout was initiated by a transmission line collapse, triggering a chain reaction that led to a widespread and substantial power outage throughout the entire region. This instance underscores the significant consequences that can result from a solitary vulnerability in a broader electrical network. The power outage resulted in about $6 billion in economic losses, impacting over 55 million individuals[6]. An additional instance that might be cited is the outage of Amazon Web Services in October 2012. The occurrence in question was triggered by a memory leak fault in a data collection agent, resulting in the disruption of numerous websites such as Reddit, Foursquare, Pinterest, and others[7].

Based on the findings of earlier studies, it has been established that cascading failure plays a pivotal role in the occurrence of large-scale blackouts[8]–[10]. On certain occasions, a cascade failure may be initiated by a multitude of disruptions. Within the domain of power systems, it is frequently noted that certain cascade failures can be halted before causing significant consequences. However, it is not unusual for catastrophic catastrophes to occur. The prevailing approach in the electric power grid domain for practical implementation primarily focuses on meeting the N-1 secure criteria. This provision functions as a protective measure, ensuring the system's ability to maintain regular functioning in the event of a single malfunction. This study explores the intricacies of cascading failures, analyzing situations in which mitigation takes place and highlighting the pivotal significance of the N-1 secure requirement in enhancing the resilience of systems[11]. However, it is important to consider that other potential failures could occur, such as concealed relay failures or errors made by operators. These failures have the potential to prolong the initial failure and activate further components, ultimately leading to a cascade failure. In conventional practices, the occurrence of component loss within a power system typically initiates a process of power redistribution[12]. The following redistribution of resources has the potential to cause an overload in transmission lines or trigger dynamic instability in generation units. The consequences of these cascade failures have far-reaching implications, indicating a substantial and interrelated influence on the overall power grid. This study explores the consequences of component loss in power systems, analyzing the subsequent cascade effects and their wide-ranging consequences on a large scale.

Each instance of a blackout is subjected to a comprehensive analysis, to identify the underlying cause of the substantial interruption and outline the measures required to prevent similar catastrophic occurrences within the stressed power grid [13]. The post-disturbance study focuses on understanding the temporal sequence of line losses, component failures, and associated events. The precise determination of the date of the disturbance is of utmost importance, as it allows network operators to promptly restore stability. The present analysis utilizes data obtained from supervisory control and data acquisition (SCADA) systems, energy management systems (EMS), Digital Fault Recorders, and Wide-Area Measurement Systems (WAMS) [14]. Wide Area Measurement (WAM) systems offer real-time monitoring capabilities to study system behavior and identify issues at an early stage. These technologies provide enhanced visibility of the electric grid. Phasor measurement units (PMUs) play a vital role in wide-area measurement systems (WAMS) by offering time-synchronized measurements at reporting rates typically ranging from 25 to 50 frames per second[15]. Contemporary power system research has transitioned from conventional approaches that heavily rely on rough mathematical models to measurement-based methodologies, facilitated by the rapid expansion in data accessibility. The detection of aberrant behavior in the power system network can be effectively achieved by examining oscillatory modes, which can be identified using PMU data [16]–[18]. In reference [19], the authors provide a comprehensive review of various techniques and instruments employed to estimate and detect oscillatory patterns. The paper by [20] discusses the importance of utilizing synchro phasor technology for the real-time monitoring of power system networks. This technology can be used to create advanced visualization and analysis capabilities that help operators effectively manage significant disruptions.

1.1 Causes of Cascading Failure

The occurrence of cascading failures in smart grids is a significant concern that can have extensive and consequential impacts. The aforementioned failures can be classified into discrete categories, each presenting specific obstacles to the resilience and dependability of the grid infrastructure. To begin with, component failures refer to the occurrence of problems in discrete devices or parts present in the smart grid. These components can include sensors, communication nodes, and power electrical devices. Furthermore, communication failures encompass instances where there are interruptions in the network connections that enable the interchange of information between various components of the grid, hence impeding the grid's capacity to react dynamically. Furthermore, operational failures can arise due to deficiencies in control and management procedures, which can have a detrimental effect on the decision-making processes that are vital for maintaining grid stability. Lastly, physical failures encompass the deterioration or malfunctioning of power equipment, such as transformers or transmission lines, resulting in a ripple effect on adjacent components. Comprehending and effectively dealing with these many classifications of cascading failures is crucial for augmenting the resilience and general efficacy of smart grids, thereby guaranteeing a sustainable and reliable energy future.

The primary factor contributing to cascading failures is the excessive stress placed on a singular and pivotal device or node, resulting in the device's failure. Cascading failures can also be triggered by the deliberate shutdown of a device for maintenance or upgrading. The redistribution of the load from the malfunctioned device to other components within the system is initiated by a singular initial occurrence. This study investigates the consequential impacts of such occurrences, elucidating the mechanisms of load redistribution and its ramifications for the overall functioning of the system. Consequently, these other devices may be subjected to excessive strain, perhaps exceeding their operational capacity. This chain reaction of overloading might continue to propagate throughout the system. The aforementioned failure process exhibits rapid propagation within the system, akin to the spreading of ripples on a pond. The process of propagation persists until a significant majority of the devices within the system have been compromised, or until there is a functional separation between the system and the source of the load. This study investigates the persistent character of this dissemination and its implications, analyzing the circumstances in which the system experiences compromise or detachment from the source of the load[21]. Table 2 displays a comprehensive compilation of significant power outages that have occurred worldwide.

Various factors that could potentially contribute to the beginning of cascade failures are numerous and diverse, not limited to:

1. The occurrence of operator errors has been documented in references[22], [23].
2. Human-induced physical attacks, such as bombings, shootings, and electromagnetic pulse attacks, have been documented[24].
3. Malicious cyber assaults can target the availability of essential data by employing denial-of-service attacks, which aim to limit or prohibit access to such information. The integrity of data can be compromised through attacks like as spoofing and tampering, which undermine the accuracy and reliability of the data. Additionally, confidentiality can be breached by eavesdropping techniques that allow unauthorized access to sensitive information. References [24], [25]are cited in support of the preceding statement.
4. Dynamic environmental conditions, such as high temperature, have been seen[26].
5. Extensive efforts have been dedicated by scientists to comprehending the origins and ramifications of natural calamities and extreme meteorological phenomena, including

seismic activities, electrical discharges, tropical cyclones, floods, storms, excessive heat, and drought[27]–[33].

Table 2: List of Major blackout in the World

Blackout Location	**Date**	**Affected People (Millions)**	**Loss of Power (MW)**	**Loss in Million Dollars**	**Time duration**	**Counter measure after blackout**
Pakistan	23 January 2023	230	N. A	100	10-12h	N. A
Bangladesh	4 October 2022	130	N. A	N. A	7h	Improve protection system
Pakistan	9 January 2021	200	N. A	200	8-12h	N. A
Sri Lanka	17 August 2020	22	N. A	N. A	7-9h	N. A
Argentina	16 June 2019	48	2000	N. A	6-8h	Trained Operator
Kenya	7 June 2016	44	N. A	N. A	3h	N. A
Sri Lanka	13 March 2016	21	800	N. A	4h	N. A
Turkey	31 March 2015	70	32	700	7h	Enhancing control and protection measures
India	31 July 2012	670	48	6000	3-8h	New load-shedding schedule
Brazil	4 February 2011	40	8884	N. A	3h	New protection scheme
Brazil	11 November 2009	87	24436	N. A	4-6h	Adopt house load policy
Pakistan	24 September 2006	160	11.16	N. A	6-12h	N. A
Europe	04 November 2006	45	14.5	N. A	2h	Amend the UCTE policy
Italy	28 September 2003	57	24	1200	5-9h	Implement the day-ahead forecast
London	28 August 2003	0.5	728	N. A	30min	Improve the utilities communication

North America	15 August 2003	50	61.8	1000	5-72h	Introduce new reliability standards

Figure 1 provides a comprehensive overview of the primary elements contributing to cascading failures as addressed in this section. These components are categorized into two main groups: behavioral factors and environmental factors.

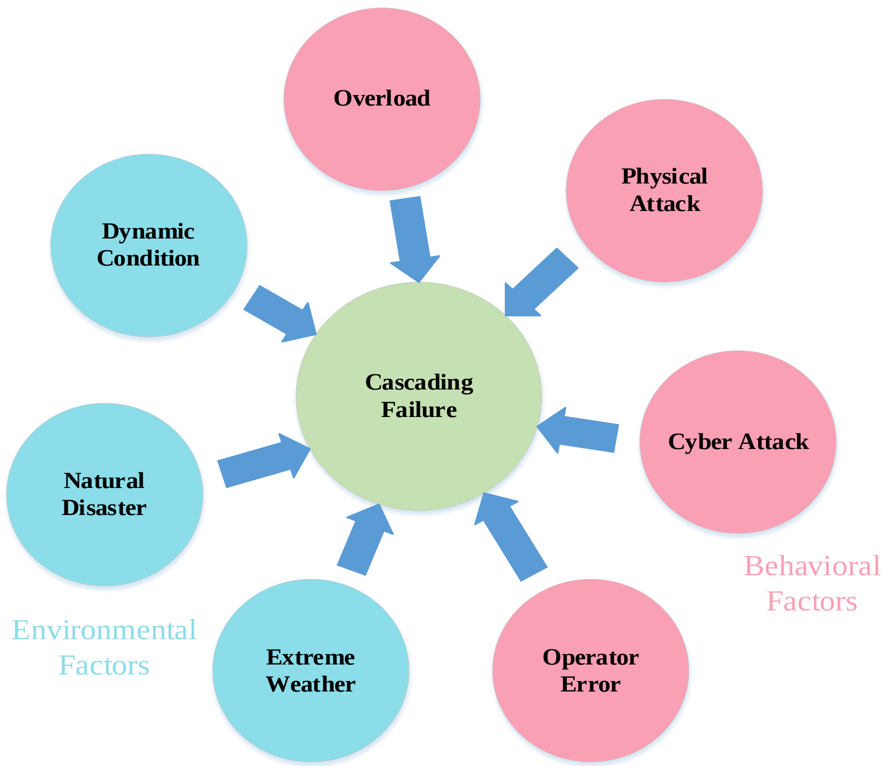

Figure 1: Overview of the primary elements contributing to cascading failures

1.2 Cascading Failure Mitigation

Cascading failure mitigation reduces the impact of localized failures and prevents system collapse in complex systems. Common cascading failure mitigation methods include:

1. Redundancy: Critical components and subsystems should have redundancy to ensure a backup system if one fails.
2. Isolation: Separating the problematic system element helps prevent problems from spreading. Circuit breakers, critical node isolation, and power grid protective relays can do this.
3. To maintain stability after a failure, load shedding may require unplugging non-critical system components.
4. Monitoring and control: Real-time system monitoring and automated control systems can detect early failure and prevent cascading effects.

5. Robust design: Fault tolerance and resilience in components and systems can reduce cascading failures.
6. Changing the structure of electricity grids helps reduce cascading failures. This may require smaller grid portions or power distribution changes.
7. Communication and coordination: System components and operators can better manage and minimize failures by communicating and coordinating.

Cascading failures can cause blackouts, transit interruptions, communication challenges, and other major issues. Therefore, mitigating methods are essential for complex system stability and functionality. Within the domain of cascading failure mitigation, this article explores two discrete strategies: selective edge protection and adaptive power balance restoration. The objective of adaptive power balance restoration is to prevent the spread of nonlocal cascade failures through the preservation of local power equilibrium. On the contrary, selective edge protection is engineered to protect particular geographic regions. The present study investigates the complexities and efficacy of these measures concerning the prevention and management of cascading failures. In addition, we put out a proposition for severity measures that can be utilized to evaluate the potential dangers associated with the spread of cascading failures, both at a local and nonlocal level[34].

1.3 Research Questions

Researchers may undertake an examination of the complex interplay of several components, including component failures, grid topology, control algorithms, and communication systems, to acquire a more profound comprehension of the mechanisms via which cascading failures propagate and to explore strategies for their efficient management.

1. Which fundamental variables are responsible for the initiation of cascade failures in power systems?
2. How can advanced modeling approaches be utilized to forecast and evaluate the incidence of cascading failures in power grid systems?
3. What are the effective control strategies and measures that may be utilized to mitigate the spread of cascading failures in the electrical grid?
4. What are the necessary infrastructure changes and design improvements required to mitigate cascading failures and increase the overall reliability of power systems?
5. In what ways may real-time monitoring and communication systems be enhanced to efficiently identify and promptly address initial indications of cascading failures within power grids?
6. This inquiry pertains to the economic and societal ramifications associated with cascading failures, as well as potential avenues for mitigating such consequences through enhanced stability and prevention techniques.

The occurrence of cascading failures in power systems offers significant challenges owing to the complex interconnections among system components, the requirement for precise predictive modeling, the formulation of efficient control strategies, and the economic ramifications associated with such failures. To effectively manage these issues, power system operators and regulators must address several crucial areas, namely enhancing grid resilience, guaranteeing robust communication and data integration, combating cybersecurity threats, and maintaining public trust in the system's reliability.

This comprehensive article delves into the factors contributing to and potential solutions for the occurrence of cascading failures inside intricate systems. The paper begins by explaining cascading failures' initiation, propagation, and effects, revealing the complex dependencies that can cause disasters. We then examine how these failures affect electricity grids, financial services networks, and transportation systems, showing their widespread hazard to society. The study analyses many mitigating methods, from system hardening and redundancy to advanced monitoring and control systems. The study examines how machine learning and AI may predict and prevent cascading failures. Overall, this paper provides a thorough grasp of cascading failures and the many ways to mitigate their potentially fatal consequences.

1.4 Contributions

The key contributions of this study are given below.

i. An extensive evaluation of intelligent cascading failure methods in smart grids.
ii. Examining digital twin, blockchain, and metaverse-based control methods for CFEs.
iii. Comparative analysis of different expert methods for CFE assessment and mitigation.
iv. Paving future research directions in the field of CFE assessment and mitigation.

1.5 Organization

Section I includes the introduction of the paper, in which the causes of cascading failure, its mitigation, and research questions are examined. Section II provides power system stability and dynamics of cascading failure, in which power system stability and dynamics are discussed. Section III provides categories for cascading failures in power systems. Section IV provides the aspect of cascading failure in which topological models, dynamic simulation models, interdependent models, probabilistic and stochastic simulations, and high-level stochastic models of cascading failures. Section V includes an assessment of cascading failure techniques for venerability analysis in which alternative and renewable energy techniques, machine learning techniques, fuzzy logic based, affinity propagation clustering, self-propagation graph, and hybrid methods are discussed. Section VI covers blockchain technology, digital twins, and metaverse technology. Future directions and comparisons of different topologies of cascading failure assessment and mitigation methods are discussed. Section VII covers the control methods, in which conventional and intelligent control methods for microgrids are discussed. Section VIII covers cascading failure mitigation in microgrids for stability enhancement. Section IX covers the conclusion and future trend of the paper.

2 Stability and Dynamics in Power Systems

Within the complex domain of power systems, a cascading failure manifests as a progressive and unmanageable deterioration of system elements initiated by one or more disruptive occurrences [9]. The complex interplay of power system dynamics and stability parameters significantly impacts the spread of cascading failures. These factors include voltage stability, transient stability, small-signal stability, frequency stability, and the redistribution of power flow. This study examines the essential components, as depicted in Figure 2, illustrating the various categories of power system stability.

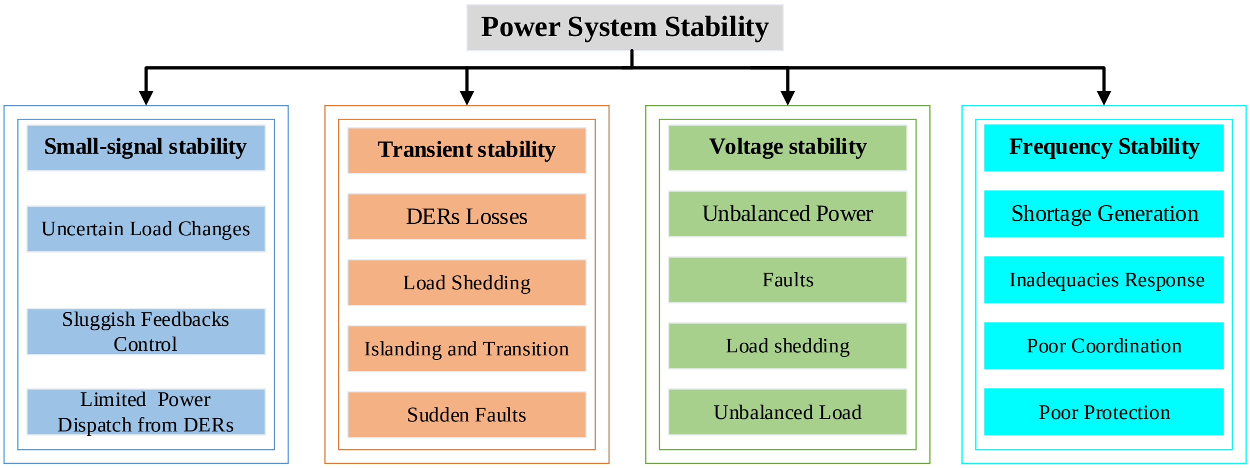

Figure 2: Power system stability types

2.1 Voltage Stability

The investigation of voltage stability requires an examination of the resolution of steady-state power flow equations to ascertain the thresholds of voltage collapse. Voltage instability is a phenomenon that, when manifested, possesses the capacity to initiate system failures, and in extreme cases, can result in total power outages. Historical instances of power outages, such as the blackout that occurred in the United States and Canada in 2003 [35], as well as the blackout in Brazil in 2009, highlight the considerable significance of voltage stability. Multiple models[36], [37] have been developed as a consequence of research investigating the influence of voltage stability on the propagation of cascading outages. This study aims to conduct a comprehensive assessment of voltage stability, highlighting its significance in ensuring the reliability of power systems and minimizing the occurrence of major disruptions.

2.2 Transient Stability

Assessing the ability of the system to stay synchronized over various times of disruption is a crucial aspect of evaluating transient stability in power system dynamics. Transient stability analysis is a comprehensive and intricate method that utilizes both algebraic and differential equations. The field of power system control design extensively utilizes this technology[38]. Numerous previous research has extensively examined the influence of transient stability on the analysis of cascading failures in the power system, as evidenced by the cited publications [39]–[41]. This paper explores the complex field of transient stability analysis, elucidating its importance in comprehending the dynamics of power systems and its function in preventing cascade failures.

2.3 Small Signal Stability

The assessment of oscillation stability in a power system can be conducted by the application of small signal stability analysis, following minor disturbances such as interarea and intermachine oscillations. Despite the limited availability of research on the influence of small-signal stability on cascading failures, the significance of considering this factor in the analysis of power system failures is growing. The increased integration of renewable energy sources such as wind and solar can be attributed mostly to the advancements in power electronic inverters. The integration of renewable energy sources into the power grid is facilitated by the utilization of inverter-based renewable energy resources (IB-RERs). These IB-RERs employ electronic controllers to deliver both active and reactive power. All of the aforementioned controls are dependent on a reference signal that is provided by a trustworthy power system. The impact of inverter control dynamics on the behavior of the system becomes more significant as the stability of the reference signal deteriorates. The reliability of the grid is compromised due to various factors, including but not limited to, the detrimental effects on system equipment, reduced power generation, and concerns regarding electricity quality. Consequently, the whole stability of the system is jeopardized, perhaps leading to its ultimate collapse[42].

2.4 Frequency Stability

Frequency stability is the term used to describe the power grid's capacity to sustain a consistent frequency in a steady-state condition, even in the event of a significant disturbance resulting in a substantial disparity between power generation and demand [43]. The ability to efficiently restore system generation and achieve load balance while minimizing load loss is of paramount importance. The occurrence of persistent frequency oscillations resulting from frequency instability has the potential to activate protection mechanisms, such as the tripping of generating units or loads. The potential destabilization of the system's frequency can be attributed to various factors, with the loss of generation being one of them. In instances where there is an abrupt disparity between the output of the system and the demands of the load, power is dissipated in the manner described by reference [44]. Various studies have put forth cascading models to examine the correlation between the frequency characteristics of a system and the redistribution of power flow. The aforementioned models have been extensively discussed in existing scholarly literature, as evidenced by the citation [45]. The increasing penetration of intermittent renewable energy resources (IB-RER) and the retirement or displacement of synchronous generators have led to the emergence of low-inertia operating conditions in the power system. Power systems characterized by low inertia are susceptible to significant frequency fluctuations when there is a disparity between power generation and demand. The implementation of a grid-scale battery energy storage system (BESS) for the provision of primary frequency response (PFR) has the potential to mitigate cascade failures [46]. This phenomenon is supported by a recent occurrence in the Australian National Electricity Market (NEM) grid. As a result of a series of failures stemming from this event, the states of South Australia and Queensland experienced a disconnection from Australia's national power grid, known as the National Electric Market (NEM).

2.5 Protection and Relay

The primary objective of protective relaying within the realm of power systems is to expeditiously deactivate a specific component of the power system upon identification of any deviation from its standard operational state. These variances have the potential to result in detrimental effects or disrupt the overall functioning of the system. Power outages can result in significant repercussions, and the power protection system assumes a crucial function not only in the potential initiation of an occurrence but also in its future propagation. During the specified time period, the Western Systems Coordinating Council (WSCC) had a high incidence of outages primarily attributed to erroneous trips of line protection relays or generator protection devices. One instance of seismic activity worth noting is the North Ridge earthquake that occurred on December 14, 1994. Additional dates of significance encompass July 2 and 3, 1996, as well as August 10, 1996. Hence, it is imperative to conduct an inquiry into the underlying defects that are inherent in the protective system. The concept of "hidden failures" pertains to security systems that exhibit either susceptibility to attacks or have already experienced failures, however, their vulnerabilities remain undetected until extraordinary circumstances occur. Furthermore, the progress of blackout development is of utmost importance concerning the effective incorporation of system protection and controls alongside system dynamic stability. The cascading failure model with system protection has been proposed in the literature, as evidenced by references [47] and [48]

3 Categories of Cascading Failure

Cascading Failure (CF) is a widely observed occurrence in various intricate infrastructures, including but not limited to the power grid[49], water system[50], gas system[51], and IoT network[52]. The primary cause of CF is the interdependence and coordination among the components inside a complex network, which enables the network to perform its intended functions. Consequently, a malfunction or problem in a single component might have a cascading effect on the operations of other components, leading to their failure. The earlier procedure may start with a modest network failure and after that progress to the breakdown of multiple components, thereby acquiring the designation of cascading failure. In the last stages of a computational framework, a substantial portion of the network may experience failure, resulting in the remaining segment being unable to adequately fulfill the requirements of network managers and end users.

The components of a power grid, mainly generator and load buses, can be conceptualized as nodes, whereas transmission line transformers can be seen as connections within a complicated network. Every node within the network receives an equal quantity of electrical power, which is distributed to its neighboring nodes by a combination of transmission lines and transformers. The voltage phase angles at the sending node i and the receiving node k are represented by the variables i and k, respectively. The term "Xik" denotes the series reactance of the link that connects nodes i and k. The power between vertices i and k [53] can be conceptualized as a connected line.

$$P_{ik} = -P_{ki} = \frac{|V_i||V_k|}{X_{ik}} \sin\left(\delta_i - \delta_k\right) \tag{1}$$

Three primary types of optimal power flow (OPF) methods are commonly utilized to analyze cascading failures. The mentioned models can be categorized into three distinct subcategories, namely quasi-steady state, quasi-dynamic, and dynamic. The findings of various static models were compared and evaluated for benchmarking purposes [54]. The dependency of cascade risk assessment on the modeling method employed has been a subject of challenge[55]. The concept of quasi-steady-state refers to how a system responds to circumstances, wherein a series of distinct steady states are sequentially established due to the occurrence of component failures. These models achieve a favorable equilibrium between the precision of the simulation and the computational effort required for its execution. Nevertheless, they fail to achieve smooth transitions between states, such as frequency instability during the ramp-up of a generator or oscillations between different regions. All of these categories are succinctly examined in the article review.

4 Aspects of Cascading Failure

The occurrence of cascading failures within microgrids encompasses a range of factors that are of utmost importance to comprehend in order to improve the dependability and adaptability of these decentralized energy systems. The examination of many review studies highlights the importance of the complex interaction between different components in the microgrid topology. The vulnerability of a system arises from the interdependence of its constituent pieces, wherein the failure of a single component can have cascading effects, leading to successive failures throughout the system. Furthermore, the presence of deficiencies in fault detection and isolation techniques exacerbates the cascade effect by enabling the unrestricted propagation of localized problems. The presence of intrinsic unpredictability in renewable energy sources, such as solar and wind, creates complexity in the system by introducing modifications that create a challenge to the stability of the microgrid. Furthermore, the presence of insufficient communication and control techniques across distributed energy resources poses a significant obstacle to achieving effective coordination, hence exacerbating the potential for cascading failures. A comprehensive comprehension of these factors is crucial for the advancement of robust microgrid systems, and in the ensuing part, we will explore the various configurations that contribute to both the difficulties and possible remedies in addressing cascading failures in microgrids.

4.1 Topological models of cascading failure

Various strategies have been suggested to mimic cascading failures to achieve a wide range of approaches. Nevertheless, as far as the author is aware, there is currently no method that can comprehensively capture all the mechanisms involved in a cascade failure. Each model possesses distinct concentration and advantages, although the simulation still needs information regarding the whole phenomenon. This section will provide a concise overview and synopsis of the most advanced cascading failure analysis models and approaches.

4.1.1 Topological model

The study of cascading failure analysis has experienced significant advancements due to the quick progress in complex network analysis in recent years. Given the prevalence of cascading failure in complex networks, researchers are actively endeavoring to integrate this phenomenon into investigations pertaining to electrical grids. The preliminary study presented a range of models that depict the sequential failure of a power system. Nevertheless, these models exhibited a certain level of simplicity and were unable to adequately represent the fundamental physical characteristics of the electrical grid [56]–[58]. The phenomenon of cascading failure was initially elucidated through the utilization of betweenness centrality models. In this situation, the loads and capabilities of vertices and arcs were assessed using betweenness centrality [59]–[61]. If the defined threshold is surpassed, a further computation will be executed. A model for node capacity was subsequently suggested [62]. The maximum load of each node in this model has a direct proportionality to its initial load. The concept of capacity, which is frequently employed in many models, becomes particularly relevant when the capacity of a node or line is not known.

The initial studies focused on investigating node degrees, betweenness centrality, distribution analysis, and path length analysis as significant topics of research. These above publications mostly examined complex networks of a broader nature, rather than specifically focusing on electric power grids. Nevertheless, these models that focus solely on topology may yield deceptive outcomes as they fail to take into account electrical characteristics[63].

After this, several topological models incorporating electrical components have been suggested as a potential resolution to this issue. Prior studies have examined the possibility of cascading failure in power grids resulting from complex network applications. However, the aforementioned research only classified the models based on the specific analysis features they examined, including vulnerability, robustness, risk assessment, dispersion, node and line criticality, attack-based resilience, and evolution. An explanation of the distinctions between these models or their evolutionary trajectory was not provided by the authors [64]–[69]. The subsequent discourse provides a concise summary of three distinct categories of topological models: those characterized by modified topologies, those based on maximum flows, and those exhibiting intricate network dependencies.

4.1.2 Modified Topological model

Modern topological models encompass several elements such as line capacities, impedances, and fluxes, which are derived from electrical principles such as Kirchhoff's law, line impedances, and reactance. The aforementioned models possess the capacity to partially depict the characteristics associated with cascading failure inside the power system. The early analysis of the power grid involved the modeling of the system as a collection of generators, transmission lines, and load nodes. The study also analyzed the network's susceptibility [70]. Another model, as illustrated in reference [71], examines the dynamic redistribution of flow and the impact of failed nodes on the network. In a subsequent investigation [72], the authors put forth an altered topological framework wherein resistance distance was employed instead of the conventional topological distance, intending to elucidate electrical characteristics. The consideration of load flow was incorporated in several models, as evidenced by the references listed in [73], [74]. In a previous study [75], novel metrics such as entropy degree, electrical betweenness, and net-ability were proposed. These metrics were developed by integrating electrical features with complex network analysis in order to achieve comparable impedance. The study also took into consideration the inclusion of power transfer distribution factors (PTDF) [76]–[78].

The utilization of these three criteria has been extensively employed in the analysis of power network vulnerability and the identification of important components. The investigation also examined the structural elements that contribute to a cascading failure, including an analysis of the positioning of generators. Figure 3 illustrates the structural arrangement of the electrical networks within the IEEE 118-bus test system. The location of dispersed generators is depicted in panel (a), whereas the placement of concentrated generators is illustrated in panel (b). The red squares seen in this diagram[79] represent the generators. The findings indicate that the strategic positioning of decentralized generators can significantly enhance the resilience of the power grid, albeit contingent upon the presence of a specific proportion of generators within the power system. In a recent study [80], a novel topological model was proposed, considering the occurrence of node overload failures and disguised failures. In their study, the authors employed a model based on alternating current (AC) power flow to examine the influence of topology on the propagation of cascades [81]. The introduction of a new vulnerability analysis model has been facilitated by utilizing the reactance matrix to represent the power grid as a weighted graph [82]. The concept of load has been changed by incorporating power angle information and considering power flow constraints.

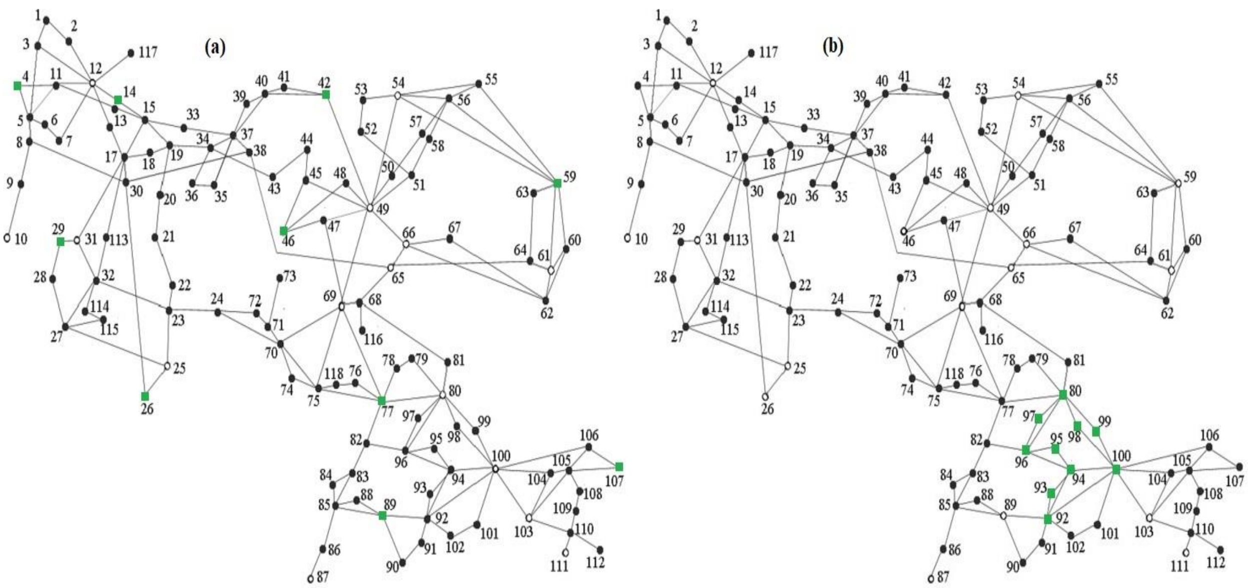

Figure 3: IEEE-118 bus network topology (a), it is decentralized (b), it is centralized

4.1.3 Maximum flow model

The concept of maximum flow theory was first proposed by Harris in 1955 as a means to tackle the problem of optimizing traffic flow on railway systems. In the subsequent year, specifically in 1956[83], Ford undertook further investigation pertaining to the aforementioned topic matter. The original integration of this technology into the electrical grid was initially documented in [84]. The primary objective of this study is to determine the maximum flow between the source nodes (generators) and the sink nodes (loads) while considering the impedance of the transmission lines. The model was employed for the computation of the grid's susceptibility. Subsequently, in reference [85], the author introduced an enhanced model for maximum flow, incorporating the consideration of node weight. The approach successfully tackled maximum flow challenges by reducing complex scenarios involving several sources and sinks to simplified circumstances involving only two. The validity of the model was assessed through simulation in the power system of western Denmark, and a comparative analysis was conducted with the results obtained from the previous model. A recent study has introduced a methodology based on maximum flow to assess the vulnerability of electricity grids [86]. The susceptibility of the system was found to be significantly influenced by an adjustable parameter, which exerted control over the initial load distribution. The model referenced as [87] was employed to construct a method that utilizes the Gini coefficient for assessing the importance of multiple attributes within a single node.

4.2 Dynamic Simulation model

Dynamic simulation models share similarities with traditional approaches that prioritize the analysis of power system dynamic characteristics. However, the key distinction lies in the ability of dynamic simulation models to effectively replicate interactions in multi-contingency scenarios during cascading failures, which is a challenge for conventional methodologies. Modern dynamic simulation models excel at accurately capturing unique system dynamics during the cascading process. Furthermore, the majority of mechanisms can be incorporated into dynamic simulation models across several instances of power failures, enabling a rather precise forecast. Nevertheless, the computing speed will be problematic due to the extensive number of details that need to be considered. Currently, these models primarily contribute to the understanding of complex cascading failure processes, rather than offering immediate real-time prediction and analysis for industrial applications.

4.2.1 OPA model

The dynamic model, which is founded on the principles of DC power flow, was introduced by a group of researchers affiliated with esteemed institutions such as Oak Ridge National Laboratory (ORNL), Power System Engineering Research Center (PSerc) at the University of Wisconsin, and Alaska University [88]. Initially, a pre-solved sample problem was presented to novice individuals. In the case of an unforeseen line failure, conventional linear programming methods would be employed to restore the equilibrium between power generation and demand. To mitigate the occurrence of superfluous load shedding, the cost function has been duly considered. The presented model provides a simplified representation of a dynamic process involving cascading failure, enabling the examination of self-organization in the evolution of a power system. The OPA system underwent validation on a 1553-bus WECC network, and the simulation results demonstrated a satisfactory level of agreement with historical WECC data, hence justifying the need for additional investigation [89]. Nevertheless, a limitation of this approach is its inability to accurately simulate actual occurrences of transmission line failures and subsequent updates, as well as the distribution of blackout probability based on different sizes.

The initial model's constraints prompted the subsequent development of a more intricate OPA model, which was subsequently released [90]. The enhanced OPA model integrated the impacts of dispatching, automation, communication, relay protection, operating mode, and planning. In order to assess the magnitude of risks associated with cascading failures, two measures, namely Value at Risk and Conditional Value at Risk, were formulated. The proposal was validated using the 570-bus Northeast Power Grid in China. A depiction of an ORNL-PSerc-Alaska (OPA) alternating current (AC) system was presented in reference [36]. The simulation encompassed both rapid dynamics, characterized by a sequence of power failures occurring in quick succession, and slow dynamics, which captured the gradual evolution of the power grid over time. The study also examined the matter of voltage stability and the corresponding enhancement methodology. The findings derived from the simulations performed on the IEEE 118-bus test system indicate that the relationship between the overall load demand and the effective transmission capacity of the system, along with the fractional overloads, can serve as indicators for inferring self-organized criticality (SOC). Modifications were implemented in the model described in reference [91] to enhance the efficiency of the cascade failure process. This study examined the effects of tree contact and line heating on line failure, as well as the significance of utility vegetation management (UVM).

4.2.2 Manchester Model

The Manchester model, a highly refined AC power flow modeling approach, was developed at the prestigious University of Manchester in the United Kingdom [92]. The inclusion of certain factors such as power outages resulting from tripped transmission lines, unstable generators, low-frequency load shedding, and emergency load shedding after a crisis, facilitated the process of studying. Additionally, it took into consideration the potential occurrence of defects in the processes of generation, transmission, and concealment. The Monte Carlo method was employed by the model to compute the potential for a cascading failure chain reaction. Multiple studies [93]–[95] have conducted assessments on the economic consequences of power outages and have put forth preventive measures based on the Manchester model.

4.2.3 COSMIC Model

The recently introduced Cascading Outage Simulator with Multiprocessor Integration Capabilities (COSMIC) is a novel nonlinear dynamic model [96]. COSMIC, being a quasi-steady-state (QSS) model, effectively employs a combination of discrete and continuous differential-algebraic equations to faithfully replicate the behavior of power networks. Additionally, the machine's dynamics and safety aspects were considered. The employed model incorporates nonlinear power flow equations to effectively handle a diverse range of operations, including spinning machines, exciters, governors, and power flows. Additionally, it included load voltage responses and discrete events, like as component failures and load shedding. COSMIC employed a recursive technique to compute differential algebraic equations that reflect several mechanisms. The model[97] encompasses various representations, including constant power (P), constant current (I), constant impedance (Z), exponential (E), and any combination thereof (ZIPE). The validity of the model was confirmed by comparing the outcomes of simulations conducted on the IEEE 9-bus test system with the findings produced by the extensive commercial software PowerWorld [98]. The outcomes of a novel simulation were compared by employing a straightforward direct current power-flow quasi-steady-state model. Initially, there existed a consensus between the cascades of the two models. However, as the simulation advanced, they exhibited a significant divergence.

4.2.4 Multi timescale quasi dynamic Model

The multi-timescale quasi-dynamic model is a recently released dynamic simulation model [55]. To address the issue of temporal uncertainty included in traditional cascading failure analysis models, this model has employed a quasi-dynamic method. The system offered dynamic simulations encompassing load variation and generator excitation protection. A proposed approach has been introduced to enhance the re-dispatch process by incorporating sensitivity analysis. This observation is motivated by the practical requirement that the processes of transmission loading relief (TLR) and re-dispatch often necessitate a time frame ranging from 10 to 30 minutes [99]. The study primarily focused on examining the impacts associated with the utilization of dispatchers. To assess the efficacy of the model in safeguarding generators and identifying the distinctive features of cascading failure stages, an experimental evaluation was carried out using the IEEE 30-bus test system. Furthermore, the verification of this claim has been supported by the utilization of data obtained from the electrical grid in the northeastern regions of the United States and Canada. With a cumulative capacity of 162,121 MW, the testing infrastructure comprised a fleet of 410 buses, 882 branches, 200 generators, and similar components. The findings align with the known instance of cascade failure during that particular year.

4.2.5 ASSESS Model

The commercial cascading failure analysis program ASSESS[100] was created by Reseau de Transport d'Electricite (RTE) in France, in collaboration with the National Grid Company in the UK. The methodology facilitated the integration of a diverse range of unlikely elements. The model incorporates four primary features. The primary model employed in this study was an AC optimum power flow with security restrictions, as outlined in reference [101]. Furthermore, the study incorporated a quasi-steady state model, which possesses the capability to accurately replicate the dynamic characteristics of intricate systems [102]. The third component encompassed a comprehensive domain simulator, facilitating the modeling of various system controllers with ease. Zone 3 relays and field current limiters on generators were implemented as protective measures for overloaded transmission lines[103]. One further advantage was the wide array of statistical techniques that were accessible. The models available on the ASSESS platform encompass a diverse array of subjects, spanning from event sequences and protective settings to line ratings and fault clearance times. The approach exhibits certain limitations, such as the requirement for skilled operators and a substantial time investment in simulation activities.

4.2.6 TRELSS Model

The analysis of cascade failures in large-scale systems can be facilitated through the utilization of a commercially accessible tool known as the Transmission Reliability Evaluation of Large Scale Systems (TRELSS). The collaborative efforts of EPRI and Southern Company Services resulted in its creation [104]. The model is capable of replicating the event by characterizing the cascade process as a series of quasi-steady state system conditions. The Protection and Control Group (PCG) has been conceptualized as a series of interconnected safety devices. The issue of voltage issues has been addressed by the utilization of a quasi-steady state AC power flow model. The model was employed by the researchers to identify the most severe initial occurrences that were simulated on the Western Interconnection power flow model, which encompassed around 16,000 buses [105].

4.2.7 Dynamic PRA Model

The study conducted by[106], introduced a probabilistic risk assessment (PRA) model consisting of two stages of complexity in their study. The study divided the cascading failure method into two distinct components. Two distinct models were developed to facilitate the understanding of cascading failure phenomena. The model investigated many power system variables, including fluctuations in international power flows, the integration of wind energy, and the maintenance and shutdowns of power plants. The model was subjected to testing using the New England Test System (NETS) and New York Power System (NYPS) 69-bus test system, employing Monte Carlo methods. The influence of temperature parameters on the incidence of cascade failure has been empirically demonstrated. A recent study has presented an enhanced PRA approach [107]. The research divided two breakdown models into distinct phases, namely slow and fast cascade phases, and subsequently conducted an individual analysis of each step. The findings facilitated the computation of the occurrence rate of hazardous incidents and the degree to which each event was attributable to energy deficiency. In order to facilitate the computational administration of dynamic analysis, a clustering methodology was developed to effectively group choices in the latter stages of slow cascade phases. Prior studies [108] have examined dynamic models of the generators.

4.3 Interdependent Model

The concept of interdependent networks has been extensively examined across various disciplines for a significant period of time[109]. The integration of smart grid technology facilitates the interconnection of traditional power systems with computer cyber networks, resulting in the formation of an interdependent network. Nevertheless, the utilization of smart grid technology presents numerous practical advantages; however, it concurrently exposes the network to novel security vulnerabilities. The occurrence of cascade failures can be intensified by the malfunction or failure of interconnected systems within the cyber infrastructure, including Supervisory Control and Data Acquisition (SCADA) systems. Numerous instances of cyber-attacks on smart grids have been documented[110]. In the year 2003, an incidence of note transpired with the "Slammer" Internet worm. This particular occurrence resulted in the disruption of monitoring computers and effectively impeded the execution of directives utilized in the operation of additional power utilities[111]. Another instance, as previously indicated, pertained to the occurrence of a cyber network attack in Ukraine in the year 2015[112]. The SCADA distribution management system was subjected to remote control by an unauthorized individual, resulting in the disconnection of multiple substations for an extended period of time. The initial failure triggered a cascade of subsequent outages throughout Ukraine. In practical scenarios, the occurrence of a failure inside a cyber network can result in direct consequences on the operational state of physical equipment. This is mostly attributed to the coupling effect, which serves to amplify the cascade phenomena. In the past decade, numerous studies have been conducted to evaluate the hazards associated with cyber networks[113]–[116]. However, there is a dearth of research focusing on interdependent models, mostly due to the intricate mechanisms involved and the challenges associated with real-world validation.

4.3.1 Interdependent models for complex network

Interconnected infrastructures are prevalent in several practical networks, including transportation and economic networks, and have been extensively examined through the lens of complex network theory[11], [117]. The integration of electrical systems with cyber networks was first documented in a subsequent publication by reference[118]. The reason for distinguishing complex network-based interdependent networks from complex network models is to underscore the importance and evolving nature of these models.

The interdependent models were proposed by Buldyrev et al. in their study[119], where they examined the resilience of interconnected networks in the face of cascading failures. The model utilized in this study contained empirical data obtained from an authentic power network and a genuine Internet network. These networks were directly implicated in the cascading failure incident that took place in Italy in 2003. This study presents an analytical solution that demonstrates the cascading impact of removing critical nodes, resulting in the fragmentation of two interconnected networks. In contrast to the behavior exhibited by a singular network, the study discovered that the dispersion of resources is directly proportional to their susceptibility to random malfunction. The author provides an updated version of the existing model as referenced in [120]. In order to assess the dependability of the power grid, the researchers employed a model that integrated stochastic multi-support dependent interactions. The findings demonstrated a high degree of consistency with the outcomes derived from simulations conducted on various independent networks. In the given reference[121], the author has introduced an alternative framework that utilizes data from the Italian communication system and power network in order to analyze the blackout event that took place in 2003. The suggested model offers a method for effectively managing cascading failures in a linked network by strategically selecting a limited number of autonomous nodes. One limitation of these models is their inadequate incorporation of electrical characteristics, as they predominantly focus solely on topological factors.

The model outlined in reference[122] places significant emphasis on the concept of interdependence and incorporates considerations of electrical characteristics. The model incorporated the substation, generator, and router, together with the electrical grid and the Control and Communication Network (CCN). The investigation conducted by researchers focused on the determination of the maximum number of nodes that might be removed from both networks while ensuring the continued functionality of each network. The researchers provided evidence to support the assertion that this particular activity exhibits the same computational complexity as an NP-hard issue. The dataset obtained from the power outage incident in Italy in 2003 was utilized to suggest and evaluate an approach that is considered to be close to optimal. Following this, the author [123] introduced a novel model that combines three separate subnetworks: the power grid, communication network, and interdependency network. The effectiveness of the mitigation method employed by the model was assessed by a sensitivity analysis. The model was subjected to a load control policy simulation, with a particular focus on the load factor and level of interdependence.

Recent work has introduced a more complete approach [124]. The employed model integrated a mesh network architecture that considered power supply specifications. In the modeling phase, the integration of two-way connections was implemented to facilitate the exchange of both data and commands. The objective of establishing these connections was to establish a tangible node within electrical grids that aligned with the digital nodes present in the network. A variety of cyberattacks, including denial-of-service (DoS) attacks, replay attacks, and fake data injection attacks, have been employed to assess the vulnerability of the coupling model. The model incorporates load shedding and relay protection.

4.3.2 Interdependent models for Markov chain

The analysis of cascade failure was conducted utilizing the probabilistic framework offered by the Inter-Dependent Markov Chain (IDMC) model. The model was specifically developed to comprehensively address the interdependencies that arise between physical networks and the power system[125]. The IDMC model offers the ability to create predictions at a system-level by considering the interdependencies across different systems. Additionally, it allows for tracking particular parts of the system. In the hypothetical scenario of a breakdown in the communication system, it is postulated that there is a corresponding rise in the probability of an electrical grid failure. Nevertheless, in the event of electrical system malfunctions, there exists a potential for the compromising of digital infrastructure. The IDMC model illustrates the impact of interdependence between two systems on the distribution of failure sizes in each system. The simulation results indicate that both systems exhibit power-law distributed failure sizes, suggesting that systems with exponentially scattered failure sizes are less resilient.

4.3.3 Hierarchical cyber-physical model flocking theory

In [126], [127], the authors introduce a cyber-physical multi-agent model of a smart grid that is informed by flocking theory. The model being discussed incorporates phasor measurement units (PMUs), a local cyber-controller, and dynamic nodes, specifically generators. The generators were designed to incorporate many physical factors, including frequency and phase angle. The PMU and the local cyber-controller were both key cyber entities responsible for executing diverse functions. The main aim of the model was to examine strategies for enhancing the robustness and resilience of a coupling system. The New England 39-bus power system was subjected to testing in order to evaluate the impact of performance enhancements. This involved simulating various fault circumstances and creating communication delays.

4.4 Probabilistic and Stochastic simulation models

Numerous simulation tools prioritize deterministic techniques, which provide a comprehensive depiction of the precise sequence of triggering events. Nevertheless, the occurrence of cascading failure often deviates from anticipated outcomes. Given the many uncertainties that trigger and intensify the cascading effect, it becomes imperative to employ a stochastic simulation, sometimes referred to as a probabilistic simulation, that accounts for all potential factors. Additionally, certain elements contribute to the occurrence of cascading events that are difficult to replicate in simulations. These factors include human errors and instances where transmission lines come into touch with overgrown trees as a result of the relatively high flow of current. Therefore, it is imperative to employ stochastic methodologies in order to simulate a greater number of potential occurrences.

4.4.1 PRACTICE Model

The stochastic cascading simulation techniques discussed in[128] incorporate probabilistic characteristics, rendering them highly helpful for analytical purposes. This approach facilitates the utilization of both the "single-path" and "multi-path" cascading modes. The uncertainties are limited to the first events in the single-path mode, and it is possible to make predictions about the system's behavior throughout the cascade process that follows. The purpose of the multi-path mode is to accurately simulate the uncertainties and the impact of protective measures across the entire cascade process. The present study employed probabilistic models to analyze concealed failure and overcurrent relay functioning, together with a probabilistic cascade technique that relied on event trees. The validation of the model involved the utilization of data pertaining to peak and off-peak demand, which was gathered from the Italian extra high voltage (EHV) transmission system during the early 2000s. To facilitate comparative analysis, a comprehensive dynamic time domain simulator was employed, which was founded on the principle of overload. The findings indicate a high level of agreement between the two models, particularly during the initial phases of the cascade process[129]. The diversity found in the outcomes of the rapid cascade phase underscores the inherent difficulties associated with replicating the several mechanisms that contribute to cascading failures.

4.4.2 Markov chain model

A Markov chain is a form of stochastic process [94] that may be used to depict a system exhibiting a sequence of events that are all connected. The purpose of this strategy is to add stochastic elements like hidden failures or mis operations into models of power grid cascading failures. The probabilities of all states that characterize the cascading failure can be evaluated using the model's output. Magnitudes in the model tend to be quite large. A stochastic Markov chain model was initially reported in[130]. The foundation of the concept is the redistribution of existing power structures. Flaws in load management, electricity generation, and transmission lines were all factored into the study. The model was able to capture the sequence of instantaneous signals very well. The specified dimensions let us zero in on the most vital components.

In a recent study [131], a Markov chain model based on network analysis was introduced to investigate the comprehensive dynamics of power networks' propagation. A computational model has been employed to assess the reliability of the power network. The model employed an improved version of the Gillespie approach [132]. The study also showed that small-world networks facilitated the rapid and extensive propagation of cascading failures as compared to a conventional network structure. The analysis of cascade outages was conducted by employing a simulation model based on Markovian trees, as described in reference [133]. The primary objective of this model is to offer a quantitative assessment of the risks associated with a cascading sequence of failures. The study also introduced a novel strategy for forward-backward Markovian tree search, which relies on the utilization of a risk assessment index. The technique proposed by the author of the cited study [134] involves the use of continuous-time Markov chains to accurately represent the dynamics of the system. The model considered factors such as loading level, estimation inaccuracy of transmission capacity, and load-shedding limits. Furthermore, it facilitated the potential for real-time prediction of a blackout.

In a recent scholarly publication, the authors introduced a graph model that incorporates influence dynamics through the use of a Markovian chain[135]. A Markovian network model was constructed utilizing a substantial dataset obtained from simulations of cascading failures. The observed similarities between the distribution of cascading failure outcomes in our model and those obtained from previous cascading failure simulators were remarkably robust. Empirical evidence has substantiated the efficacy of employing an approach grounded in this model to ascertain the potential risk associated with implementing an upgrade to a component within the power system.

4.5 High-level stochastic models

The computational speed offers a significant challenge when attempting to predict the real-time propagation tendency and distribution of blackout magnitude, regardless of the effectiveness of popular cascading failure analysis tools in simulating detailed causes. The simulation speed of high-level statistical models is enhanced due to the omission of intricate procedures associated with cascading failure. These models have the objective of offering a comprehensive perspective on the phenomenon of cascading failure, while also being straightforward and easily manageable.

4.5.1 CASCADE model

The CASCADE model is a mathematically solvable model that is derived from the component's load[136]. In order to initiate cascading, it is assumed that a stochastic initial load is imposed upon all indistinguishable constituents. The application of this load, in conjunction with a disturbance load imposed on each component, initiates a cascading effect. In instances where the load is above a specific threshold, it is possible for certain components to experience failure, subsequently leading to a transfer of the workload onto other elements within the system, thereby initiating a cascading effect. The cascade process terminates either when all overloaded components have been resolved or when the entire system experiences a failure. The simplification of redistribution formulas has resulted in enhanced comprehensibility compared to models that represent intricate cascading failure mechanisms. Consequently, the methods provided enable the straightforward and efficient calculation of both the aggregate count of malfunctioning components and the distribution of blackout sizes. The presented model illustrates the relationship between the system's load and the probability of a chain reaction failure [137]. When the load is at a low level, the failure components demonstrate an exponential tail that is approximately observed. Hence, the probability of a catastrophic chain reaction occurring is rather minimal. Nevertheless, if the critical loads surpass their threshold, the distribution of failure components adheres to a power law, thereby significantly increasing the probability of a major blackout. The model exhibits a deficiency in realism as it fails to account for the presence of physical characteristics and internal interactions inside the power grid. Hence, its capacity to provide a comprehensive understanding of the cascading failure phenomenon is constrained.

Subsequently, the model underwent modifications and was subsequently employed to investigate additional elements of cascade failure. The analysis of the cascade motor stall was conducted using the CASCADE model, as described in reference[138]. The findings of this study demonstrate that the CASCADE model, which has superior computing efficiency, produces outcomes that align favorably with those of other dynamic models. The study outlined in citation[139] demonstrates that in instances where a failure triggers a cascading effect leading to the cessation of many motors, there exists a significant vulnerability to voltage collapse. The study described in reference[140] centers around enhancing the reliability of power systems through the utilization of a CASCADE model that has a time-dependent failure propagation component. The subsequent topic of discussion is the branching process model, which can be regarded as an enhanced iteration of the CASCADE model. The utilization of static models incorporating DC power flows has been widely embraced in numerous studies on CF analyses [141] as well as in the development of mitigation strategies [142]. The dynamic behavior of the grid is effectively represented in dynamic models during the process of computational fluid dynamics. To attain accuracy levels that are compatible with the desired outcomes, AC power flow models are frequently utilized [143].

4.5.2 Branching process models

The branching process method is frequently employed in probability theory to mimic reproduction based on a specified probability distribution [144]. This method has been employed in various academic disciplines, including genealogy, which investigates the distribution and extinction of surnames, and genetics, which examines the inheritance patterns of the Y chromosome. The utilization of branching process models for the comprehension of cascading failures is initially addressed in references[145], [146]. The models discussed in the aforementioned references[145], [146] have undergone subsequent enhancements. The utilization of models with branching processes is underscored in this study. Several new articles have emerged, presenting novel applications that utilize the mentioned models[81], [147], [148].

According to a specified distribution, the occurrence of a failure in one component within the branching process model can result in a cascading impact on subsequent phases. The results indicated a strong resemblance to the outcomes obtained by the CASCADE model and historical data[149] when taking into account the likelihood of cascade propagation through a branching process. In order to enhance the computational efficiency of predicting the distribution of propagation and blackout sizes, the researchers employed the branching process model. The use of model has also been utilized to assess the impact of topology on the average propagation of cascading failure in power systems[150]. An innovative and systematic approach has been put out for the discretization of load shedding data, facilitating the utilization of the Galton-Watson branching process with a Poisson offspring distribution for the analysis of said data[151]. In recent studies, a multi-type branching methodology has been employed to examine the statistical properties and interdependencies among several categories of cascading outages[152]. Furthermore, it has been shown that the proposed approach is efficacious, even in the absence of comprehensive data, for predicting the distribution of load shedding, identifying isolated buses, and evaluating their potential maximum outages.

The mechanics of power system cascading failures are notoriously difficult to predict, and this one doesn't do a lot of work. In the case of a chain reaction failure, the supplied data gives a ballpark figure for the range of possible blackout sizes and propagation times. An interaction model with branching processes was created to address this issue by simulating and dampening the effects of cascading failures[153].

5 Assessment of cascading failure techniques for venerability analysis

The process of vulnerability analysis in power grids entails the identification of crucial components within the system that possess an elevated likelihood of failure or whose failures can result in heightened concerns regarding dependability and more significant disruptions in service. The primary emphasis of this section's review is specifically on the literature pertaining to the identification of vulnerable components that have the potential to trigger cascade failures within power systems. The identification of these components before failure is crucial to eliminate potential risks associated with system and service impairments, as well as to establish protective measures and mitigation methods. This category covers studies that focus on the utilization of alternative and renewable energy techniques, machine learning techniques, fuzzy logic based, affinity propagation clustering, self-propagation graph, and hybrid methods to tackle challenges associated with cascades occurring within the typical operational parameters of the power system, in the absence of any disturbances or interruptions. The cascading failure assessment can be made through vulnerability analysis.

5.1 ARE methods for cascading failure assessment

The occurrence of these blackouts serves as evidence of the significant and detrimental consequences that domino effects can have on the infrastructures of renewable power systems[154]. The severity of this issue escalates when many interval faults arise inside interconnected renewable power systems, resulting in the disruption of numerous resources associated with these systems. Consequently, a series of transmission line outages ensued, leading to the vulnerability of the electrical system to cascade overload failures[155]. Therefore, it is imperative to conduct an examination of load flow balancing and transient stability in order to prevent the occurrence of cascading overload failures in renewable power systems. Nevertheless, the challenge of achieving compensating chain reaction compensation in various interconnected renewable power systems persists[156].

Failure to achieve the equilibrium between supply and demand will result in a disruption on the island. The simulation concludes when there is an absence of branch overload or active island, allowing for the estimation of overall demand loss. To summarize, Figure 4(a) depicts the simulation process of the quasi-steady-state model, specifically eliminating the voltage profile, reactive power flow, system transient dynamics, and operator action that occur within the cascade.

In contrast, the dynamic model of cascading failure emphasizes the power-frequency characteristics after contingencies, utilizing discrete event analysis as depicted in Figure 4(b). Both the quasi-steady-state and dynamic models primarily address the issue of detecting islanding events, whether they are intentional or unintentional. The term "intentional island" refers to a situation in which all splitting circuit breakers are intentionally opened, whereas "unintentional island" refers to a state in which the splitting points may inadvertently remain closed. The analysis of cascading failure in renewable power systems necessitates consideration of two significant aspects of islanding[157]. The key factors to consider when constructing a dynamic model of cascading failure:

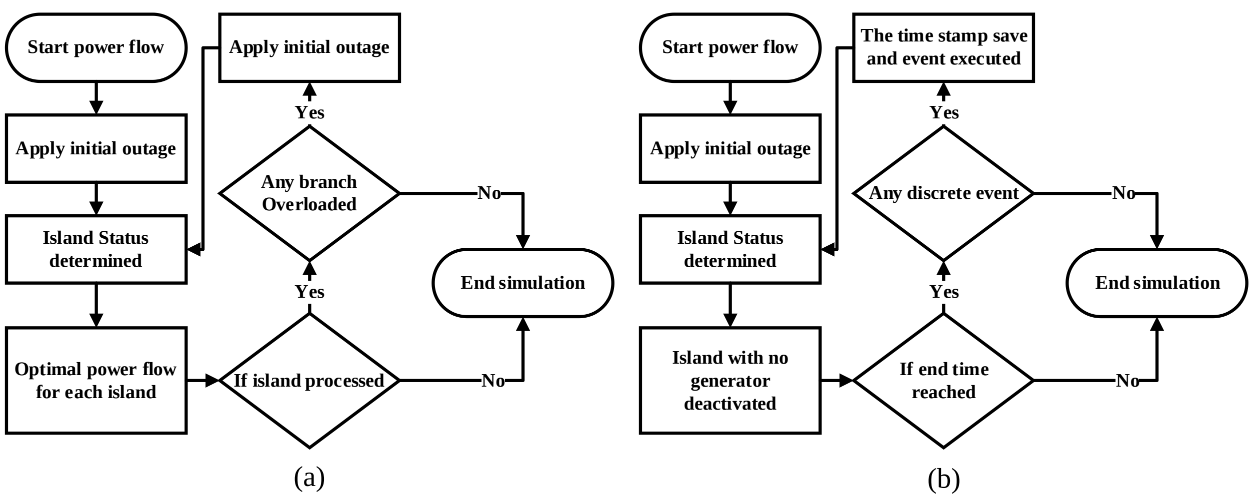

Figure 4: A standardized flowchart is presented herein to simulate both quasi-steady-state cascading failure and dynamic cascading failure.

5.1.1 Generation System modeling

In the context of generation system modeling, we are delving into the operational intricacies of solar photovoltaic (PV) and wind turbines. This includes a comprehensive analysis of the underlying dynamics and principles that control these renewable energy technologies.

5.1.1.1 Solar PV Generation System

The dynamic model analysis of a solar photovoltaic (PV) generation system is based on the assumption that solar radiation and the highest power point remain constant over an extended period of time. This assumption aids in the modeling of the short-term behavior of solar photovoltaic (PV) generation systems on a small-time scale, following the time-scale separation principle provided by[158] using the single perturbation theory. Photovoltaic (PV) arrays are typically considered to have constant power sources by utilizing the value obtained during the startup stage from the steady state computation[159], as depicted in Figure 5.

During instances of disruptions, numerous international standards, including EN50438, IEC61727, IEC62116, and IEEE1547, support the incorporation of network support functionalities in renewable power system generators. However, it should be noted that the international standards now in place offer only broad explanations of the dynamics model. These explanations do not provide specific details regarding the functionality required for integrating the grid-forming converter into the grid code of any particular country.

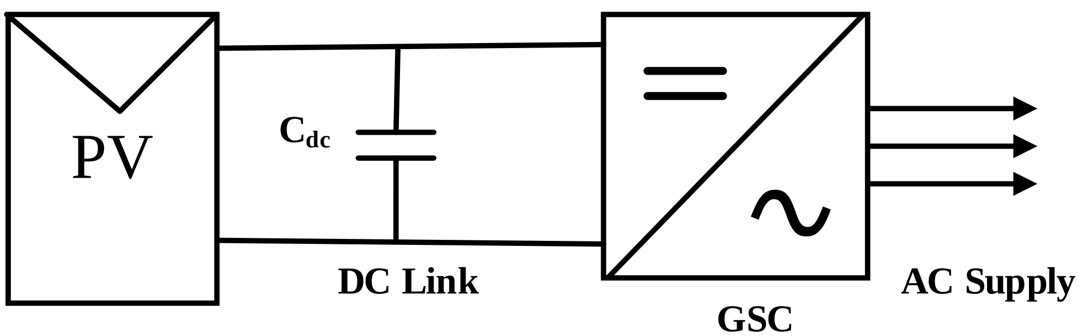

Figure 5: The topological configuration of a single-stage photovoltaic (PV) interface with a grid-side converter

5.1.1.2 DC-Link Model of Solar PV Generation System

The primary objective of the DC-link is to make a connection between the photovoltaic (PV) array and the inverter[160]. The investigation of DC-link dynamics in modeling presupposes the persistence of the stationary maximum power point[159]. Hence, the input power is equivalent to the inverter (Pdc), the output power (Ppv) of the PV array, the maximum power point (Pmpp), the inverter input (Pinv), and the active output power (Pac). The steady-state initialization required for the PV model is provided as follows.

$$P_{ac} = P_{inv} = P_{dc} = P_{mpp} = P_{pv} \tag{2}$$

In the context of a single-stage conversion system, the power generated by the photovoltaic (PV) array, denoted as Ppv, is contingent upon the voltage of the array. This voltage can be acquired straight from the inverter. Equation (3) demonstrates the correlation among the input power, Pdc, the output power, Pinv of the DC link, the capacitance of the DC link, Cdc, and the voltage of the DC link, Udc, in order to depict the dynamics of the DC link voltage.

$$\frac{dU_{dc}}{dt} = \frac{P_{dc}-P_{inv}}{C_{dc}U_{dc}} \tag{3}$$

According to equation (3), it can be asserted that the presence of an inverter active current is crucial for capturing the dynamic characteristics of the inverter's DC side.

5.1.1.3 Grid Side Converter Model of Solar PV Generation System

The AC-grid voltage is actively transformed by the grid side converter into PV DC link voltage, operating at a predetermined frequency corresponding to the power grid. The control functions of the inverter dictate the response of the solar photovoltaic (PV) generation system to network transients. According to established grid operating standards, it is required that inverter-connected producing sources actively contribute to the stability of the grid[159].

5.1.2 Wind Power Generation System

In the field of wind power systems, the configurations that have gained the most popularity are as follows:

- The fixed-speed wind turbine is equipped with a squirrel cage induction generator.
- The variable-speed wind turbine is equipped with a doubly-fed induction generator.
- The variable speed wind turbine is equipped with a direct drive synchronous generator.

The components and operation of a variable-speed wind turbine model with a direct-drive synchronous machine are detailed in[161]. Figure 6 presents a generic representation of the link between the generator system and the alternating current (AC) network. The derivation of the model involves utilizing steady-state computations to determine the inputs to the generator, which are specified in terms of the turbine's rotational speed and mechanical power. The assumption is made that the mechanical power input remains constant during the duration of dynamic simulations.

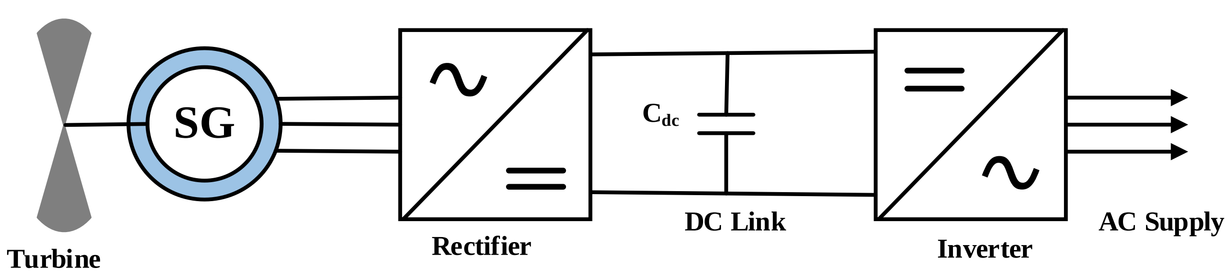

Figure 6: The topology of a wind generator comprises a wind turbine that is connected to a synchronous generator through a converter system.

This phenomenon can be attributed to the relatively stable wind speed, which plays a crucial role in determining the quantity of wind energy harnessed. Consequently, the wind speed exhibits minimal fluctuations over a brief temporal scale. The electrical side of the system involves the connection of a synchronous generator to the power grid through a full-scale frequency converter. As seen in Figure 6, the converter system consists of three main components: a generator-side converter, a DC-link, and a grid-side converter. The subsequent subsections provide a comprehensive overview of the models used to represent the distinct short-term dynamic components within the wind power generation system. The subsequent subsections delineate the component model of the short-term dynamics of the wind power generation system.

5.1.2.1 Grid side converter control of wind power generation system

The grid-side converter is comprised of insulated gate bipolar transistors (IGBTs) which are utilized for pulse-width-modulation (PWM) switching. According to the principle of time-scale separation, the high switching frequency of IGBTs has been largely overlooked in the majority of dynamics investigations. As a result of this assumption, a standard model is employed to represent the converter on the generator side. The control strategy employed in the converter is commonly referred to as the full torque control scheme[162], [163]. In order to implement this approach, it is necessary to generate the complete stator current in the q-axis of the stator, while ensuring that there is no current flowing in the d-axis[159].

5.1.2.2 Grid-side converter of wind power generation system

The wind power generation system's grid-side converter can be compared to that of the PV system, as both systems interact with the grid through an inverter. As previously mentioned, the operational principles of the inverter for grid support are derived from established grid rules that govern the regulation of power and voltage pumped into the grid. The purpose of this action is to guarantee sufficient support for the grid[159].

5.1.2.3 DC-link model of wind power generation system

The DC-link model is represented by Equation (6), where the input DC power is equal to the power of the active generator. This model, like the PV system DC link model, also presupposes a lossless DC-link, as was previously discussed. The stator terminal voltage in this equation is represented by the terms u_{ds} and u_{qs}, while the stator current in the d- and q-axes is represented by the terms ids and i_{qs}, respectively. The generator's active and reactive output powers are displayed in Equations (4) and (5), respectively.

$$P_{gen} = \frac{3}{2}\left(u_{ds}i_{ds} + u_{qs}i_{qs}\right) \tag{4}$$

$$Q_{gen} = \frac{3}{2}\left(u_{qs}i_{ds} - u_{ds}i_{qs}\right) \tag{5}$$

$$\frac{dU_{dc}}{dt} = \frac{P_{gen}-P_{inv}}{C_{dc}U_{dc}} \tag{6}$$

When taking into account the energy storage element, the wind system DC-link includes a braking chopper. When the wind energy system is unable to provide the grid with active power, this is realized. In order to keep the link voltage below the critical value and initiate FRT capabilities, the brake chopper circuit assumes control and discharges the active power. With time step, Δt, and chopper regulation time constant, τ, a first-order transfer function is utilized in Equation (7) to estimate the power change in the chopper circuit, ΔP_{chp}.

$$\Delta P_{chp} = \left(P_{gen} - P_{inv}\right)\left(1 - e^{-\Delta t/\tau}\right) \quad (7)$$

In order to deliver electricity to customers in a dependable, effective, and environmentally friendly manner, traditional power grid stations are transitioning to smart grids (SGs). This smart grid incorporates advanced communication and power networks[164]. SGs utilize interconnected clusters of renewable energy resources (RERs) in the form of multiple renewable integrated power grids (RIPGs) to achieve cost-effective electricity generation and handle unforeseen increases in power demand[165], [166]. Nevertheless, although RERs are cost-effective, ensuring reliability remains an increasing obstacle in their implementation[167]. As a result, these multiple interconnected (MIRIPGs) infrastructures experienced structural weaknesses and uncertainty[168]. Furthermore, it should be noted that the impact of a single failure that transpires at various time intervals is considerably more significant compared to the consequences of faults occurring at a single interval in a renewable power system that is interconnected[164]. All of the aforementioned models are identical in the context of a renewable integrated power system.

5.1.3 CF assessment under asymmetric faults

In this article[169], the author proposes a methodology for identifying and mitigating instability caused by asymmetrical faults in renewable integrated power grids (RIPGs) using several intervals. The suggested method utilizes real-time stability indicators to establish a criterion for identifying asymmetrical faults in RIPGs, based on numerous intervals. Subsequently, sensitivities pertaining to these stability indicators are calculated in order to pinpoint the most significant critical nodes for implementing appropriate countermeasures in RIPGs. The studies mentioned in[170]–[173] aim to identify critical nodes in power systems at an early stage by relying solely on disturbances occurring within a single interval. These disturbances can be either symmetrical or asymmetrical faults in RIPGs. In contrast, the methodology proposed in [169] builds upon the findings of[170]–[173] by presenting an optimal solution in the form of early prevention methods. This solution is designed to detect instability in power systems caused by multiple-interval symmetrical faults in RIPGs. The self-propagation graph is utilized to detect the critical node in the event of minor disruptions. However, the self-propagation graph is not suitable for larger disturbances.

5.1.4 CF assessment under multiple faults contingencies

The system is more unpredictable due to the increasing use of renewable energy resources (RERs). Load flow balancing and transient stability in renewable integrated power networks must be assessed to address cascading overload failures. When several interval faults occur in various interconnected Renewable Integrated Power Grids (RIPGs), disrupting multiple Renewable Energy Resources (RERs), this issue becomes more severe. Multiple transmission line outages caused electrical cascade overloads. This research[155] proposes hybrid probabilistic modeling to solve the problem. Load flow balance and transient stability analysis in many interconnected renewable integrated power grids are the goals. In contrast to previous algorithms that are designed to address network instabilities caused by a single interval fault, this study utilizes probabilistic modeling to mitigate network instabilities in the presence of both single interval faults and more severe multiple interval faults. These faults occur in multiple interconnected RIPGs and can result in cascading failure outages within the network. The distinction of network node failure within a complex network of interconnected RIPGs resulting from an excessively loaded situation was explicitly articulated in the study referenced as[156]. In Figure 7, an interconnection is observed across four clusters of numerous interconnected Regional Interconnected Power Grids (RIPGs), where each cluster corresponds to a distinct power grid station. The failure of a network node results from an initial node failure triggered by an excessive load condition.

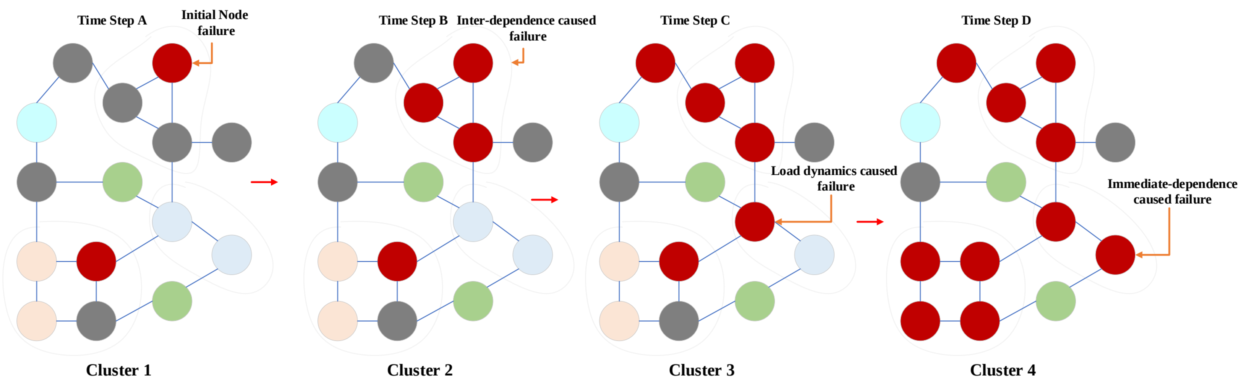

Figure 7: Cascading failure event modeling across multiple power grid stations

5.1.5 Cascading failures in communication systems

The integration of communication networks has become an integral component of contemporary civilizations. Every individual infrastructure, such as the electricity grid and water system, is equipped with a communication network that enables situational awareness and control. However, the communication network itself may experience a critical failure, leading to a decline in the performance of the infrastructures that rely on it. Communication networks facilitate the transmission of data between various devices, including both sources and sinks of data, through the utilization of links and routers. Routers are responsible for determining optimal pathways and facilitating the transmission of data between source and destination nodes across interconnected links. Both links and routers possess finite data transmission capacity and thus are susceptible to malfunctioning when the volume of data flow exceeds their respective capacities. The occurrence of component failures, such as connections and routers, first resulted in the redistribution of data flows to other active components, subsequently causing additional failures. The aforementioned procedure is iterated until a substantial proportion of the network experiences failure. This subsection will commence by presenting the approaches for CF analysis in communication networks, subsequently followed by the examination of diverse network instances, including wireless sensor networks (WSN) and the internet of things (IoT).

The models for communication networks in the context of CF can be classified into two main categories: deterministic models and stochastic models [174]. In deterministic models, the distribution of data burden from failing components to active components is carried out according to predetermined principles. An example of a load redistribution model is presented by [56]. This model redistributes the data load of a failed edge to its nearby edges, taking into consideration their weights, which are indicative of their flow capacity. The authors of this study examine the resilience of weighted networks to cascading failure and determine the optimal weights that enhance robustness in common communication network models, such as small-world and scale-free networks. In contrast, [175] utilizes a global load redistribution model wherein the load within the network is assigned to the node's betweenness centrality after an initial failure. The model employed by the authors serves the purpose of identifying the essential nodes within the network, whose failure leads to an accelerated occurrence of CF events. Nevertheless, the deterministic load redistribution merely serves as an approximation of the network load to initiate the subsequent stage of failure caused by overload. Consequently, it may not comprehensively depict the entirety or the most likely array of failures that could potentially transpire. In contrast to deterministic models, stochastic models employ a more extensive analytical approach. An article by [176] presents a conditional Markov state transition model that aims to elucidate the process of failure propagation in a network caused by node overloading. Additionally, the study demonstrates the time dependence of these failures.

This is due to the utilization of low-capacity components in these networks, each possessing unique characteristics. In recent years, there has been a significant increase in interest in the examination of techniques for managing congestion in Wireless Sensor Networks (WSN) and Internet of Things (IoT) networks, as seen by the publications of [177]. The researchers investigate the concept of cascading failure in the context of wireless sensor networks (WSN). The authors focus on the relationship between betweenness centrality and node traffic while studying the impact of traffic overload and poor connectivity on failure occurrence. A cascading failure model for Wireless Sensor Networks (WSNs) is introduced in reference [178], which takes into consideration the dynamic load variations of the network. The analysis conducted by[179]examines the incorporation of both node and link capacity in congestion control approaches. They also assume that nodes can self-recover after a specific period, which a characteristic is observed in Wireless Sensor Networks (WSNs). The increasing prevalence of the Internet of Things (IoT) has led to the interconnection of numerous devices, hence necessitating the examination of the cybersecurity aspects of IoT infrastructures. [180] Presents an extensive examination of CF analysis and dependability pertaining to IoT infrastructures, encompassing a diverse array of IoT applications. In their study, [179] examine the layered architecture and realistic attributes of the Internet of Things (IoT). They propose a congestion control model that is influenced by the overload experienced in relay nodes, base stations, and communication lines.

5.2 AI methods for cascading failure assessment

The approaches used for vulnerability analysis consist of biologically inspired optimization algorithms, machine learning, deep learning, and reinforcement learning.

5.2.1 Optimization algorithms

The optimization techniques for cascading failure assessment, which include the Greedy search algorithm, Particle swarm optimization method, and Genetic algorithm are covered in detail.

5.2.1.1 Greedy search algorithm

In this article[181], the authors present a comprehensive and rigorous framework for mathematically analyzing cascading failure in networked systems. A customized approach to the propagation mechanism is employed in order to develop a fast identification algorithm for the vulnerable set. This technique is built upon a crucial finding that uncovers the correlation structure among various N-k situations. The theoretical bottom bound of our approach is determined by examining the monotonic nondecreasing and quasi-submodular properties of the propagation process and is presented in a specific order. Optimization algorithms often utilize greedy policy[182],[183]. Solving many combinatorial problems with linear time complexity yields good results empirically. For the first time, we can guarantee the performance of a linear-time vulnerable set searching method by evaluating cascading failure in the power grid using sub modularity and monotonicity. The task of identifying vulnerabilities associated with cascading failures involves significant challenges. Therefore, it is recommended that future studies investigate the identification of sensitive line sequences in an efficient way. The AC power system model provides a comprehensive and precise representation of the condition of a power system. In order to conduct a comprehensive analysis of future cascading failures, it is recommended to utilize the AC power system model.

5.2.1.2 Particle swarm optimization method

The method described in this study utilizes particle swarm optimization (PSO)[184],[184] to efficiently seek the most vulnerable transmission for sequential attacks. Extensive simulations have been conducted to showcase the comparative advantages of our strategy in contrast to the reinforcement learning methodology. In this article[185], the authors primarily examine the line-switching sequential attack, a deliberate strategy employed by attackers to disrupt the operation of transmission lines in a predetermined sequence, resulting in substantial system failures. Our study aims to ascertain the crucial line-switching attack sequence, which holds instructional value for safeguarding the smart grid. In order to achieve our objective, we have devised a vulnerability analysis framework that utilizes evolutionary computation. Specifically, we have integrated particle swarm optimization as a means to efficiently explore and identify the essential attack sequence. In order to assess the effectiveness of our suggested method, we conducted simulation experiments on two well-established benchmark systems: the IEEE 24 bus reliability test system and the Washington 30 bus dynamic test system. It is important to acknowledge that the scope of this work is limited to the conceptual design of a vulnerability analysis framework based on particle swarm optimization (PSO). The examination of the precise effects of the hyper parameters has not yet been undertaken and will be addressed in our forthcoming research endeavors.

In article[186], the authors introduce a novel approach that integrates the distinctive characteristics of particle swarm optimization (PSO) with tabu search algorithms to identify severe high-order dependencies. The first Particle Swarm Optimization (PSO) method provides a strategic approach for exploring the solution space in a manner that demonstrates intelligence. However, it tends to primarily identify the optimal solution. The suggested methodology integrates the original Particle Swarm Optimization (PSO) algorithm with Tabu Search as shown in Figure 8, resulting in the identification of a set of top candidates[187]. This fulfills the requirement for advanced contingency screening, which might potentially serve as the input for many complex security evaluations. After this paper, the IEEE 300-bus system was tested and simulation results were released. Further research may examine how different coefficients affect speed and efficiency. A different fitness function that considers remedial actions under high-order contingent occurrences may be used.

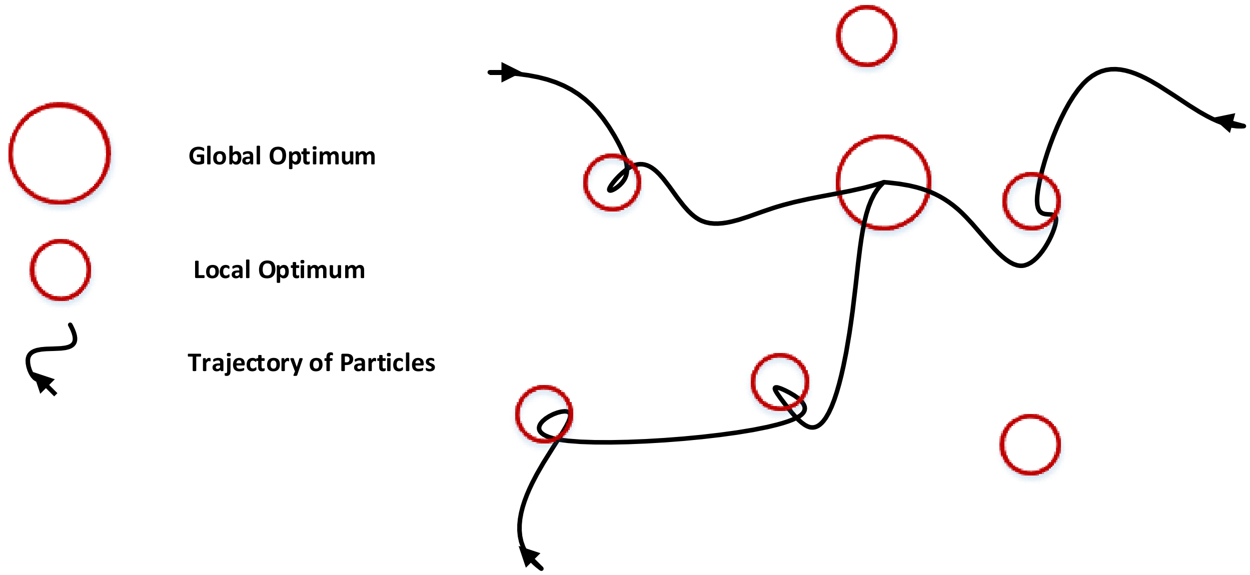

Figure 8: Particle Swarm Optimization (PSO) algorithm with Tabu Search

5.2.1.3 Genetic algorithm

In the article[194], the authors introduce a methodology for conducting vulnerability assessments in power systems by combining an AC-based cascading failure simulation model with a meta-heuristic optimization procedure. The primary aims of the assessment are twofold: firstly, to prioritize the most significant branches within the transmission grid, and secondly, to determine groupings of branches that, if tripped simultaneously, will result in the most severe cascading effect. Two criteria assessing how each branch failure affects the DNS and line overload frequency achieve the basic goal. The second goal is achieved by integrating an AC-based cascading failure simulation model with meta-heuristic optimization. The methodology helps operators create and recognize vulnerability scenarios, which they can use to develop methods to mitigate unintentional and purposeful accidents. This study's method is used on the IEEE 118-bus test system and the Swiss electrical grid. The data show that the suggested approach to power system susceptibility evaluation works. Figure 9 displays a visual depiction of the simulation method for cascading failures. The frequency deviation is computed for each island, and two measures are proposed based on these values: (i) under frequency load shedding (UFLS), and (ii) frequency control. The method currently employs the UFLS scheme, which is based on the Swiss grid grid code[189].

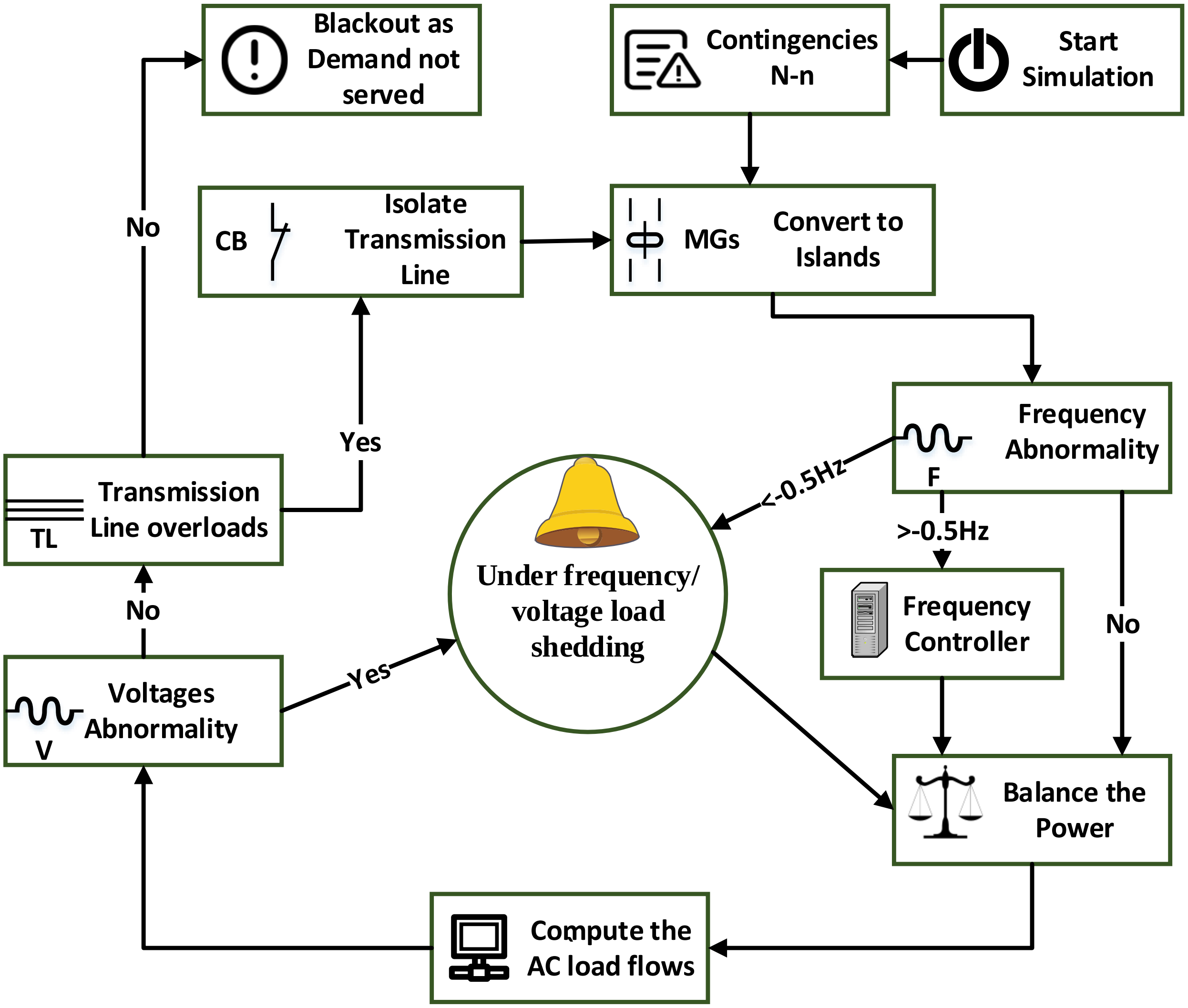

Figure 9: Diagram of cascading failure simulation. UVLS is under-voltage load shedding, and UFLS is under-frequency.

The article [195] advocates the use of an optimization methodology to systematically explore and find unanticipated interdependencies and breakdowns that may cause cascading failures and severe connectivity loss in infrastructure networks. An infrastructure network simulation model with acknowledged interdependencies is used to show the suggested methodology. The model uses a genetic algorithm to uncover unanticipated interdependencies and node failures that could cause the most infrastructure network connectivity disruption. Figure 10 presents a schematic representation of the essential infrastructure network of a case study. Large component sizes may not fully reflect failure effects in some networks, such as the electricity grid, as other components may still serve local customers. Therefore, failure implications should be measured using methods other than huge component size. The study[196] examines the susceptibility of the Italian high-voltage (380 kV) electrical transmission network (HVIET) to identify the most vulnerable links (edges, arcs) based on network topology and traffic. Betweenness centrality and network connection efficiency are used to estimate network link importance. A multi-objective optimization strategy is used to identify the most important entities, maximizing group importance while lowering size. The analysis only uses network topology information to identify the most important components, pairs, triplets, etc. The comparison with past studies shows that the suggested methodology yields valuable insights.

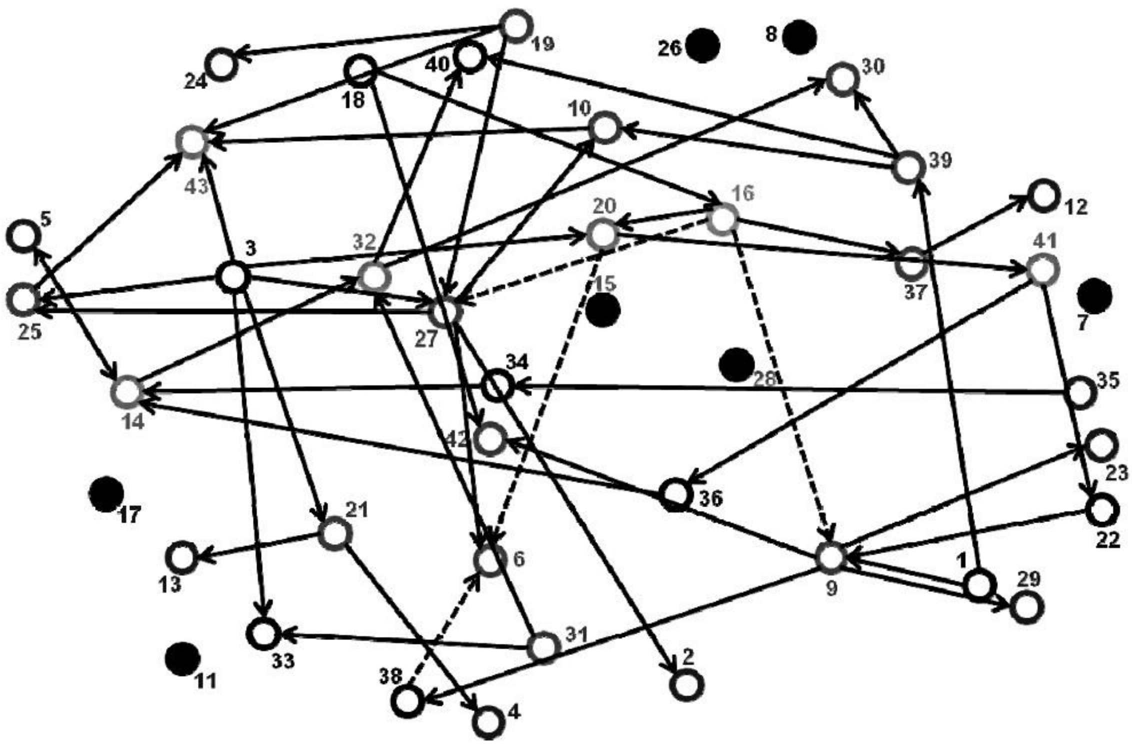

Figure 10: In the experiment, the network disintegrates when node 28 fails; the black-filled nodes are detached from the big component, reducing its size to 36.

5.2.2 Machine learning Based Approaches

The work of identifying vulnerable components in power grids that have the potential to initiate or propagate cascading failures is a challenging endeavor, primarily due to the extensive range of failure combinations that need to be examined and the likelihood of such cascades occurring. The objective of artificial intelligence (AI) based methodologies is to enhance the effectiveness and efficiency of power system search processes by facilitating more precise and efficient assessments. Numerous data-driven and intelligent algorithms have been developed to facilitate efficient search for vulnerable components and impactful attack sequences.

5.2.2.1 Classification Approach

The support vector machine (SVM) approach is used to create a blackout prediction rule[190]. The probability distribution of normal grid power flow follows a Gaussian distribution, whereas cascading events lead to a non-Gaussian distribution. Consequently, the researchers were able to enhance the training of SVM by transitioning from Gaussian to non-Gaussian probability distributions. With fewer samples, ANN approaches use observed error minimization to find local optimal solutions with limited convergence and generalization[191]. Unlike ANN, SVM solves global optimal quadratic programming problems[192]. When compared to other advanced classification algorithms, the SVM algorithm typically has a shorter training period and higher efficiency, and its architecture is shown in Figure 11. This is because of its simple structure, while still maintaining the same level of prediction accuracy[193].

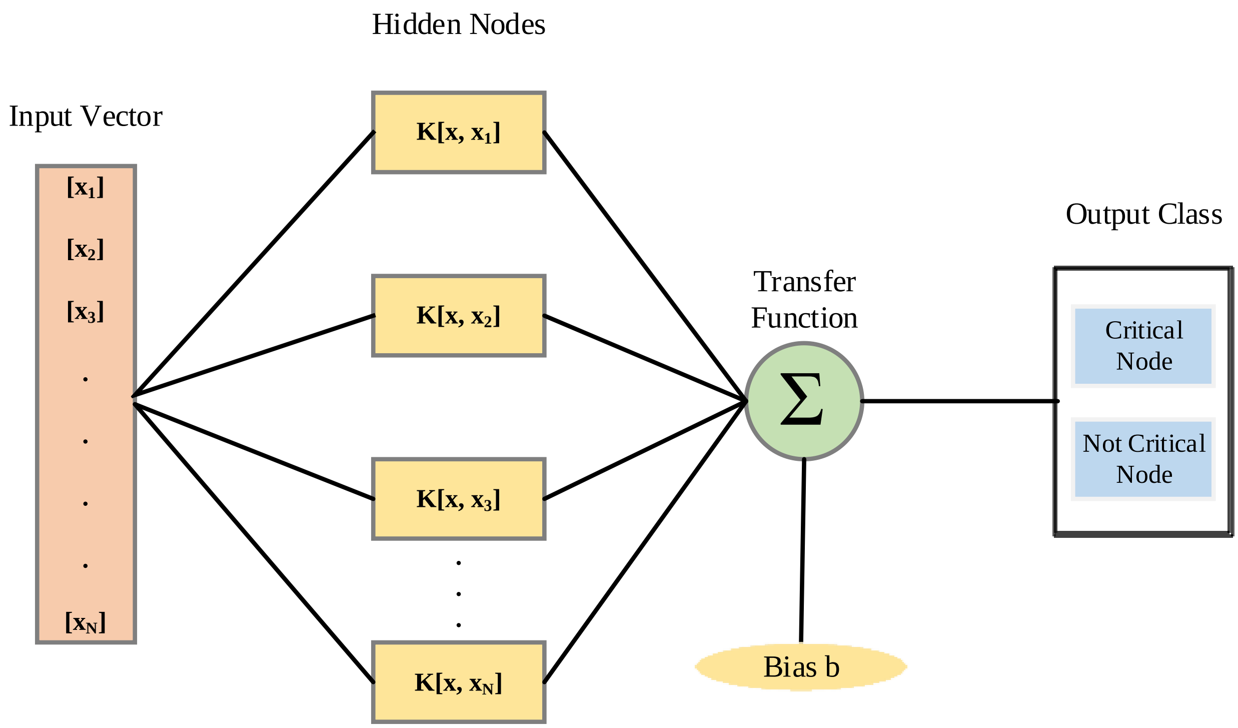

Figure 11: SVM architecture for cascading failure to identify critical nodes

A different set of studies approaches the investigation of cascade vulnerability by framing it as a classification task, wherein the various components of the system are categorized into groups such as resilient, normal, and vulnerable. In addition, the utilization of advanced ensemble learning algorithms has led to the widespread adoption of the Gradient Boosting Regression (GBR) algorithm in power system data analysis. This approach has been demonstrated to be more efficient than conventional machine learning algorithms[194], [195]. The study described in[196] employs various variables, including the centrality of buses (specifically, betweenness centrality) and power flow data, to classify the susceptibility of buses using XGboost, a distributed gradient boosting toolkit known for its optimization capabilities. In a previous study[196], the latter approach was compared to classification using logistic regression, support vector machine, and k-nearest neighbors. The authors[197] have examined a steady-state energy flow model for a combined power-gas system and have developed a hybrid classification-regression model using random forest. This model is designed to accurately categorize the susceptible power and gas components. The regression model is employed to forecast the vulnerability metric for each individual component, hence facilitating the classification of those components based on their vulnerability.

5.2.2.2 Regression Approach

The regression approach involves doing a regression-based study to determine vulnerability metrics for the various components inside a system. In a manner identical to the study conducted in[197], the research discussed[198] employs a graph neural network approach to forecast avalanche centrality. Avalanche centrality serves as a metric to gauge the influence of a node on the dynamics of an avalanche within the Motter-Lai cascading failure model. In[199], a decorrelated neural network ensemble is employed to develop a probabilistic risk index that incorporates load shedding, voltage violation, and hidden failure. This index aims to enhance the understanding of $N - k$ contingency analysis by taking into account the potential cascade-inducing outages.

5.2.3 Deep learning approaches

As artificial intelligence progresses, there is a growing trend of employing data-driven techniques to investigate cascading failures in interdependent networks [165]. A substantial training dataset is required in order to learn the cascading failure paths within and across the networks. The authors[200] have proposed a search methodology that utilizes a graph convolutional network (GCN) to effectively detect and analyze major cascade failures. The Graph Convolutional Network (GCN) model facilitates the search process by employing a classification technique to distinguish between normal outcomes and load-shedding outcomes[201]. This classification is based on the system's state, which is determined by input features such as the state of the lines. The occurrence of cascading failures is intricately linked to the graphical configuration of the system. Thus, we select the GCN model instead of the DNN model[202] and the CNN model[203] due to its explicit focus on capturing graph-structured mechanisms. Figure 12 illustrates the fundamental layers of the DNN model, the CNN model, and the GCN model.

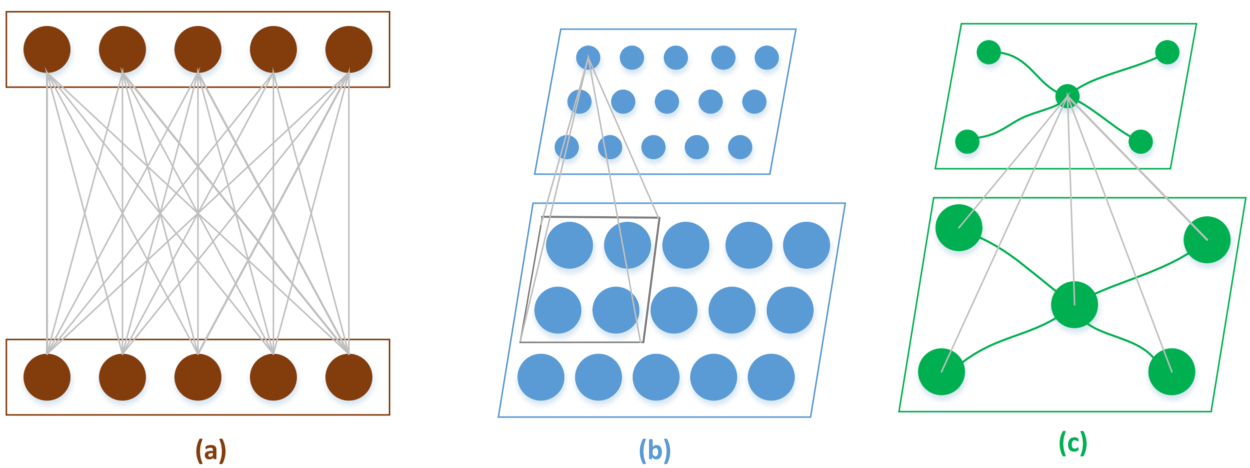

Figure 12: Illustration showing three distinct levels. (a) Dense layer in a deep neural network model. (b) Convolutional layer in a CNN model. The graph convolutional layer is a fundamental component of the graph convolutional network (GCN) model

To enhance clarity, we employ the terms "bus" and "branch" to denote the power network, whereas we utilize "node" and "edge" to signify the graph in GCN. The rectified linear unit (ReLU) layer functions as the activation function as in equation (8), introducing nonlinearity to the neural network. The output will consist only of the positive values from the inputs. xRelu and yRelu represent the input and output vectors of the Relu layer, respectively.

$$\boldsymbol{y}^{\text{Relu}} = max\left(0, \boldsymbol{x}^{\text{Relu}}\right) \tag{8}$$

The study[204] presents a comprehensive analysis of a deep convolutional neural network's use in classifying the risk level associated with transmission lines. This classification is based on the examination of both the topological and operational aspects of the lines. Additionally, the depth-first search technique is employed to effectively identify the crucial lines that have the potential to initiate cascading outages. This research presents a data-driven approach that integrates a deep convolutional neural network (deep CNN) with a depth-first search (DFS) algorithm. The purpose is to efficiently screen and assess cascading outages and associated risks in real-time, particularly in unclear situations. Prior research has focused on employing machine learning techniques, including artificial neural networks[205], convolutional neural networks[206], and deep autoencoders[207], for evaluating security in the event of contingencies. However, the specific analysis of cascading outage impacts has not been extensively explored. Power system operators can use deep CNN and DFS screening results to prevent latent outages and reduce the system's risk management costs like load shedding and generator dispatch. Future power system planning can use screening results to efficiently invest in the most susceptible transmission devices.

5.2.4 Reinforcement learning

In this article[188], the authors presented a method that uses reinforcement learning to analyze vulnerabilities in power transmission systems caused by sequential attacks. The approach assesses the impact of blackout damage caused by line-switching interdiction, taking into account cascading outages caused by overloading and undetected line breakdowns. The topic is framed within the framework of reinforcement learning and the Q-learning algorithm is used to identify crucial sequences in sequential attacks. The attack surface of smart grids encompasses both directives and measurements. Further study will detect and mitigate successive attacks. The proposed approach uses reinforcement learning to screen vulnerable topological line-switching sequences, but it can also be adapted to consider voltage and frequency.

While the heuristic algorithms outlined in the text employ direct search methods on the grid topology, reinforcement, and deep learning-based search strategies adopt data-centric ways to learn patterns. The study conducted by the authors in reference[208] proposes a temporal difference reinforcement learning approach to acquire knowledge about the association between faults and load loss. This approach aims to identify the fault chain that results in the most significant load loss. The results support the TD-learning technique and provide a new perspective on cascading failure data analysis. Initially, code attacks could modify or fabricate control commands[209],[210]. Sophisticated strategies employing tools such as the Petri-net[211] can also initiate synchronized cyber-physical assaults on transmission components like transformers and circuit breakers, and optimize their impact when ample resources and/or comprehensive knowledge of power systems are accessible.

In Table 3, we compare the various AI methods for cascading failure assessment and highlight their respective advantages and disadvantages.

Table 3: Comparison of AI methods for cascading failure assessment

Method	Pros	Cons
Greedy search algorithm	• Efficiency from local optimization • Easy installation • Useful for specific issues	• Local optima-prone • Poor backtracking • No global optimality guarantee
Particle Swarm Optimization algorithm	• Searching solution space efficiently with PSO • Outperformed reinforcement learning in sequential attack techniques • PSO-tabu search strategy for intelligent space exploration • Finding excellent prospects for advanced contingency screening • Simulations on benchmark systems show applicability.	• PSO's preference for optimal solutions • The study focused on conceptual design, not hyperparameters. • Incomplete hyperparameter effects analysis • Simulation results for the IEEE 300-bus system are pending. • A fitness function for high-order contingent events is acknowledged but not explored.
Genetic algorithm	• A complete vulnerability evaluation uses AC-based cascading failure simulation and meta-heuristic optimization. • Prioritizes transmission grid branches by essential criteria. • Aids operators in accident mitigation by identifying vulnerabilities.	• Limited methodology limits and limitations information. • Uses only Swissgrid's under-frequency load shedding (UFLS) method. • Recognizes the difficulty of reflecting infrastructure network failure impacts with big components.

Classification approach	• Blackout prediction SVM switches from Gaussian to non-Gaussian distributions. • With less training, SVM gives global optimal answers. • SVM's basic structure has good critical node identification prediction accuracy. • Traditional power system data analysis algorithms are less efficient than GBR.	• ANN methods may not converge or generalize. • SVM training efficiency is not specified. • Classifying robust, normal, and susceptible groups is difficult. • Small comparison scope since SVM is rarely compared to other algorithms.
Regression approach	• Regression measures system component vulnerability. • Graph neural network avalanche centrality predictions enhance node influence understanding. • Decorrelated neural network ensembles develop probabilistic contingency risk indices.	• Few regression model experiments. • Graph neural network interpretation and computation complexity. • No detailed validation of the probabilistic risk index's practicality.
Deep learning approaches	• Investigation of cascading failures using data driven. • GCN for detection and analysis. • For failure understanding, capture graph-structured systems. • Deep CNN and DFS classify risk by topology and operation. • Operators employ screening results to	• A large training dataset is needed for data-driven approaches. • GCN model complexity may require substantial adjustment. • Few DNN and CNN experiments. • Limited cascading outage impact study. • Limited real-time implementation

	prevent system risk, lowering expenses.	information and problems.
Reinforcement learning	• Q-learning and reinforcement learning for vulnerability analysis. • Evaluate line-switching interdiction and cascading blackout harm. • Adaptability to voltage and frequency vulnerability screening. • Data-driven pattern recognition learning.	• Few mitigation strategies for subsequent attacks. • Smart grid address surface complexity with instructions and metrics. • Complex cyber-physical attacks require enormous resources. • Insufficient code attack analysis on control commands.

5.3 Fuzzy logic-based techniques

The evaluation of cascading failures has emerged as a fundamental concern in the dynamic realm of smart grid technologies, with the aim of safeguarding the resilience and security of the grid infrastructure. This research article examines various contemporary techniques for evaluating cascading failures, each presenting novel strategies to improve the resilience of smart grids. Fuzzy cooperative control methods are employed to enhance adaptability by utilizing fuzzy logic, hence optimizing control strategies to effectively respond to dynamic situations and mitigate potential failures. The utilization of the Fuzzy co-operative control mechanism, Adaptive-Neuro-Fuzzy-Inference System (ANFIS) within the context of smart grid security involves the application of machine learning techniques to develop predictive models. Also, in the end, there is affinity propagation clustering, self-propagation graph, and hybrid method to identify the critical nodes in smart grid systems. This approach is valuable for identifying vulnerabilities and addressing them proactively.

5.3.1 Fuzzy co-operative control mechanism

In the article[212], the authors propose a cooperative control algorithm that utilizes vehicle-to-grid (V2G) technology and employs a fuzzy logic technique to prevent cascading failures without incurring any losses. The approach is applied to a conventional IEEE-30 bus system, utilizing mathematical combinations in a heuristic manner to identify essential nodes. This is achieved by employing a self-propagation graph to efficiently distribute the optimal power from vehicle-to-grid (V2G) sources. The studies in[165], [213]–[215] emphasize the superiority of the fuzzy controller over conventional controllers in detecting overloading and transient delays. The primary limitation of employing traditional controllers in a network is that their architecture is contingent upon the mathematical modeling of the system. When dealing with a complicated network, the mathematical representation of the system is insufficiently specified. Despite the presence of all established parameters, changes in parameters may nevertheless occur inside a power system network. Designing parameters accurately for a controller is difficult for this reason, and it is explained in depth in the control strategy section.

In a recent study[216], researchers presented a fuzzy logic controller that utilizes adaptive event-triggered output to handle packet dropouts and actuator failure in non-linear network systems. This study was documented in reference[217]. In[218], a geometric technique was utilized to implement an event-triggered mechanism for precise fault identification and isolation of the discrete-time system. In addition, the study in[219] examines a fuzzy logic system that utilizes a multiagent system. This system is affected by input quantization and uncertain gains while aiming to achieve a specific performance level. The authors conducted a stochastic analysis of the effects of CFEs on the power system network following (N-1) and (N-1-1) contingency occurrences, without implementing load shedding or preventive measures. Figure 13 shows a closed-loop demand response probabilistic model for this. Using cooperative control V2G technology based on fuzzy logic, network operators monitor overloaded and transient responses on lines 28, 29, and 36 of the IEEE-30 bus networks.

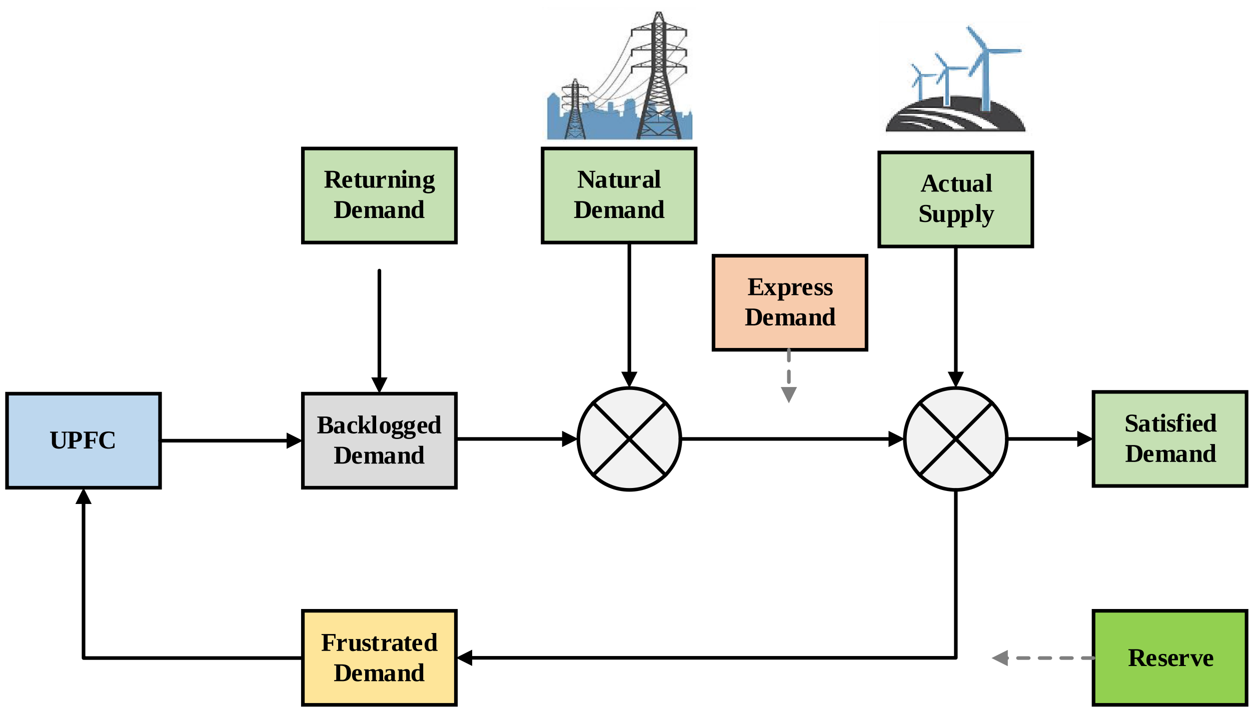

Figure 13: Probabilistic schematic model for demand response.

The fuzzy Co-operative Control Mechanism (FCCM) for smart grid cascading failures has drawbacks. The complexity of building a rule-based system that captures the intricate dynamics of a smart grid sometimes requires tremendous skill and labor. Fuzzy logic systems are sensitive to parameter changes, needing careful calibration and tweaking to adapt to grid conditions. Fuzzy logic's lack of transparency in decision-making may further lower grid operators' confidence due to the system's behaviors being hard to comprehend. FCCM increases processing overhead, which requires exact real-time data. This questions the system's timeliness and reliability. FCCM can improve power system resilience, however, there are limits. These constraints emphasize the need for ongoing research to address them and maximize FCCM efficiency in smart grid applications.

5.3.2 Adaptive-neuro–fuzzy-inference system for smart grid security

The Adaptive Neuro-Fuzzy Inference System (ANFIS) is a computational framework that combines Artificial Neural Networks (ANN) and Fuzzy Logic (FL). Figure 14 presents a model of the ANFIS organizational structure. It is designed to effectively handle non-linear and complex systems, even when training data are scarce. The system consists of two main components, namely the premise and consequence, which are further divided into five layers: fuzzification, rule, normalization, defuzzification, and summing layers[220]. Figure 14 illustrates the comprehensive configuration of the Adaptive Neuro-Fuzzy Inference System (ANFIS). The identification of unintentional islanding, which refers to the unexpected disconnection of distributed generators (DGs) from the utility grid, is a significant challenge in contemporary distribution networks. In this paper, the authors[221], provide an outline of the transition in research focus from conventional systems to intelligent islanding methods.

5.3.2.1 Intelligent islanding schemes for distributed generation system

The authors introduced a two-step Adaptive Neuro-Fuzzy Inference System (ANFIS)-based Islanding Detection Scheme (IDS) in[222]. The simulation of the distribution system was initially conducted using PSCAD software at the PCC (Point of Common Coupling) to extract five selected indices. The obtained data is subsequently transmitted to the ANFIS toolbox in MATLAB to classify instances of islanding and non-islanding during the second phase. The authors utilized energy analysis of wavelet coefficients and the Adaptive Neuro-Fuzzy Inference System (ANFIS) algorithm to create a novel Intrusion Detection System (IDS) for distinguishing between islanding and non-islanding events. This IDS was described in detail in[223]. Research is needed to fully understand the topic. Since intelligent classifier-based approaches have high-performance indices, they should be used to build islanding systems. The claim that feature augmentation improves machine learning accuracy is false. More features strain the system and reduce algorithm efficiency. Precision and preponderance should determine which qualities to reduce.

5.3.2.2 Stability enhancement in multi-machine system

The occurrence of voltage instability inside a power system gives rise to low-frequency oscillations (LFOs), which have detrimental consequences for power distribution. The utilization of Flexible Alternating Current Transmission System (FACTS) management, in conjunction with supplemental control measures, exhibits significant promise in mitigating oscillations. In their study, the authors[224], put forth a strategy known as adaptive neuro-fuzzy-based recurrent wavelet control (ANRWC) to improve power system stability. The proposed approach employs a recurrent Gaussian function as the membership function for the antecedent portion, and a recurrent wavelet function for the consequent parts. The membership function is employed to establish the definition of a fuzzy set[225]. The utilization of an adaptive neuro-fuzzy controller, incorporating a wavelet function, is proposed as a means to improve the stability of a multi-machine power system.

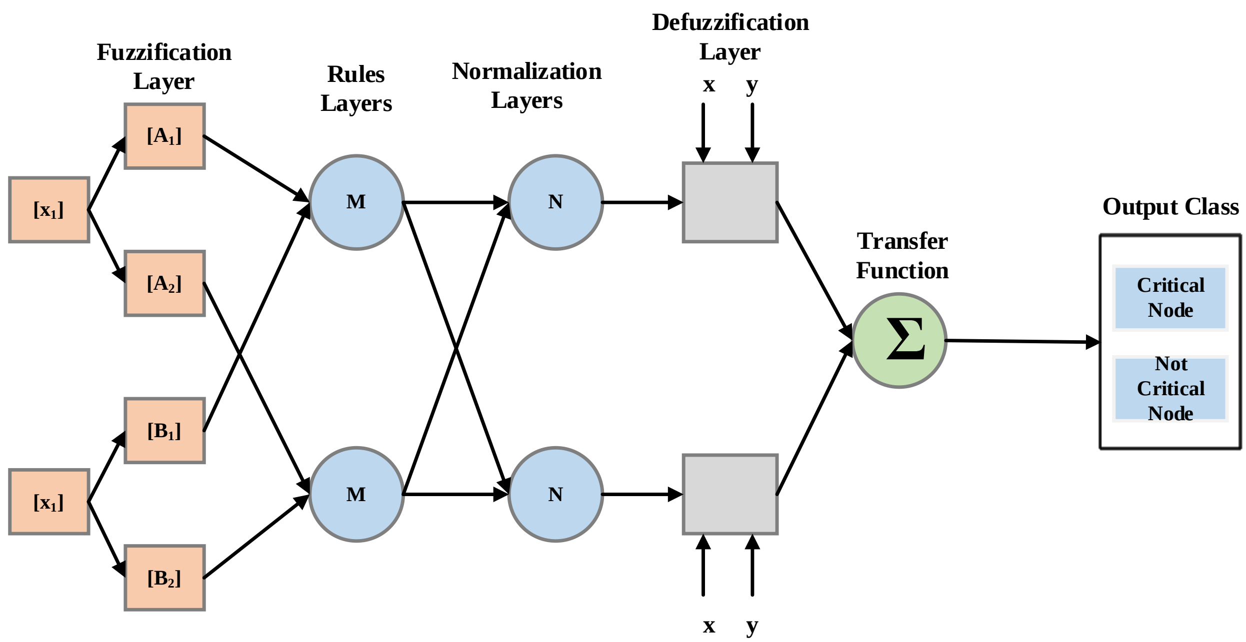

Figure 14: Complete structure of the ANFIS

The Adaptive-Neuro-Fuzzy-Inference System (ANFIS) has limitations for smart grid cascading failure resolution. Adaptive Neuro-Fuzzy Inference System (ANFIS) efficiency depends on high-quality training data. Obtaining a comprehensive dataset that accurately portrays smart grids' changing conditions can be difficult. ANFIS models also require rigorous parameter adjustment, which can be difficult, especially when smart grid dynamics change rapidly. The opaque aspect of ANFIS may make it difficult to understand the decision-making mechanism, which could lower grid operators' trust. ANFIS remains a powerful tool, and ongoing research aims to overcome these limits to improve its efficacy in the complex and ever-changing world of smart grid cascading failure mitigation.

5.3.2.3 Self-propagating graph for vulnerable nodes

In a recent study [226] the authors employ stability indicators that are generated in real-time to provide a criterion for assessing the stability of ASD. The sensitivities of these stability indicators are subsequently identified and utilized to identify the nodes with the greatest influence for implementing countermeasures. In order to enhance the efficiency of calculation, the sensitivities of just those nodes that are traversed by a self-propagating graph originating from the susceptible generator will be computed as shown in figure 15. The sensitivity matrix, denoted as S_K, is defined as a matrix in which each member can be determined using equation (9). Where index K represents the generator and index m represents load nodes. The use of sensitivity to identify nodes significantly impacting generator stability has been reviewed in[227]. However, the computational speed of speed propagation graphs increases when dealing with complicated networks.

$$S_{K_{km}} = \frac{\partial\left(\frac{Z_{th}}{\sin\phi_{th}}\right)}{\partial Y_{m,m}} \frac{\partial K_{th_k}}{\partial Y_{m,m}} \tag{9}$$

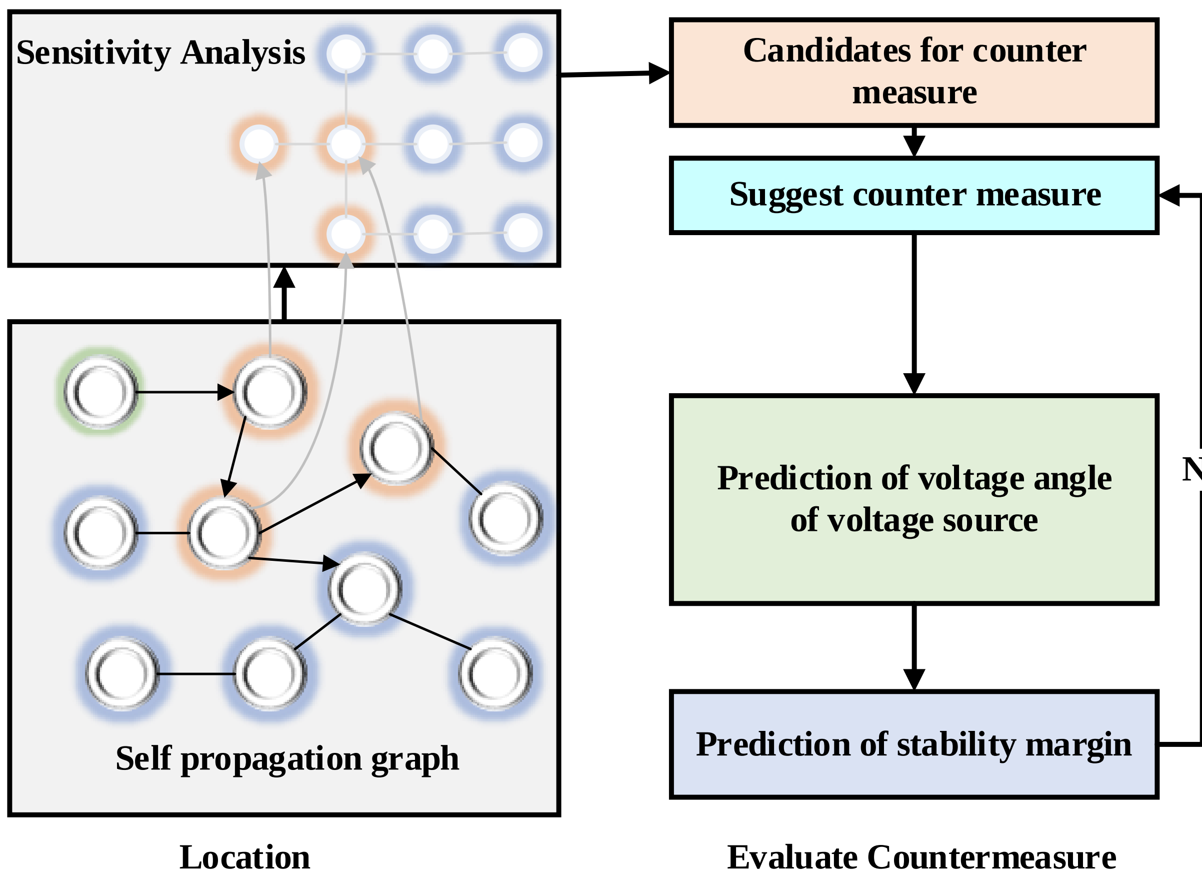

Figure 15: The present study outlines a methodology for identifying critical nodes and doing sensitivity analysis within self-propagating graphs.

5.3.2.4 Affinity propagation technique for vulnerable buses

In the context of smart grid systems, the presence of susceptible transmission lines has the potential to initiate a series of cascading failures, ultimately resulting in extensive blackouts on a wide scale. The identification of susceptible lines within smart grid systems can significantly enhance system stability and mitigate the potential for cascading failures. The identification of vulnerable lines in a smart grid system can be approached by modeling it as a directed graph and analyzing it from a clustering perspective. The authors of [228] have provided a full description of a bus clustering method based on affinity propagation, which takes into consideration both topological and electrical features. Each division is represented by the most significant bus, which serves as a representation of its cluster in this method that categorizes buses into groups.

Conducting a comprehensive vulnerability assessment is crucial in order to minimize the impact of damages and the probability of cascade occurrences. The effectiveness of preventative treatments relies heavily on the evaluation process, which is of utmost importance[229], [230]. Let F be the set that represents the impact centers of the buses in G(group). Each bus i, where i is an element of the set {1, 2,..., N_b}, is denoted by yi and is considered a center within F. This study aims to categorize buses into separate clusters in order to identify the set F that maximizes the total similarity between the buses and their respective influence centers. The similarity matrix S(i, j) indicates that bus j exerts a greater influence on bus i.

$$F = \arg_{y_1, y_2, \ldots, y_{N_b}} max\{\textstyle\sum_{i=1}^{N_b} S(i, y_i) \mid y_i = 1,2, \ldots, N_b\} \tag{10}$$

The vulnerable line identification scheme was devised based on the clustering results, as depicted in Figure 16. In order to enhance the reliability of smart grid systems, it is essential to take into account additional elements such as the vulnerability of buses other than the central bus. Failure to consider these aspects may result in the failure of affinity-based clustering, particularly in relation to the cascading failure problem.

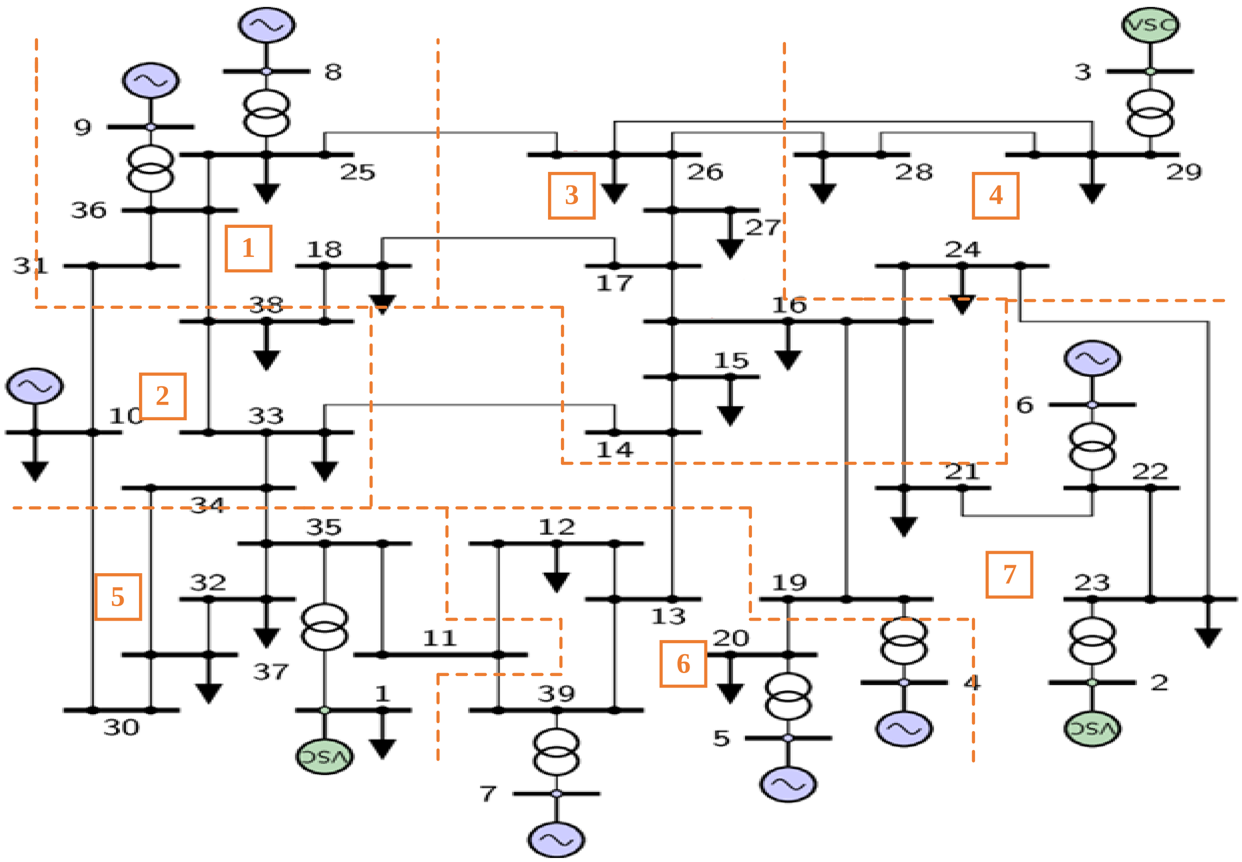

Figure 16: Single-line diagram for the analysis of the IEEE 39-bus system and the subsequent clustering outcomes

5.3.2.5 Hybrid technique for critical node identification

The examination of current approaches employed for evaluating the vulnerability of smart grids exposes notable deficiencies in both the Affinity Propagation (AP) technique and the Self-Propagating Graphs (SPG) approach. The AP algorithm, although successful in clustering buses according to their susceptibility to transmission line vulnerabilities, has been observed to exhibit sensitivity towards the central bus criterion. The AP resistance diminishes when the key node fails to fulfill this fundamental need. Conversely, the SPG technique offers precise evaluations of vulnerabilities but cannot adjust in real time due to the substantial computational resources needed for sensitivity calculations. In order to overcome these limitations, we suggest a new hybrid model that combines the clustering abilities of Affinity Propagation with the real-time stability indicators of Self-Propagating Graphs (SPG).

The hybrid approach utilizes self-propagating graphs generated from vulnerable sources to dynamically modify clustering criteria. This adaptive technique can assist in the more precise identification of key nodes. Furthermore, the utilization of SPG stability indications improves the capacity to identify vulnerabilities in real-time, hence overcoming the occasional constraints on processing time encountered during sensitivity calculations. The outcomes of this study demonstrate that the hybrid model holds significant potential for enhancing smart grid risk assessments by addressing the constraints of existing approaches.

6 Blockchain and Metaverse base assessment of cascading failure

Blockchain technology offers a reliable and decentralized network for smart grid transactions and communications, revolutionizing the current approach. Utilizing self-propagating graphs is a proactive measure to detect venerable nodes and mitigate potential points of failure. The core of affinity propagation systems lies in utilizing clustering algorithms to accurately detect crucial places within the electrical grid, with the objective of identifying vulnerable buses. Lastly, a comprehensive method for detecting and managing crucial points in the smart grid is provided by integrating different strategies in hybrid techniques. This approach holds significant potential for improving the overall dependability and security of the grid.

6.1 Blockchain technology on smart grid security

The goal of the smart grid concept is to determine the most effective way to integrate storage and renewable energy technologies by reinterpreting the traditional power system in a modern fashion. In this sense, an innovative approach to guaranteeing an intelligent grid connected to electrical energy also referred to as the energy Internet is consistently offered by big data and the Internet. Given its notable characteristics, the blockchain can be used to address security and trust-related concerns in smart grid standards. A thorough examination of blockchain applications in relation to smart grid energy data protection and cyber security perception will be provided by this study[231]. Implementation of blockchain technology in the smart grid for industry purposes[232]. The primary objective is to provide a comprehensive analysis of the integration of blockchain technology with smart grid systems and energy trading, as seen in Figure 17. Hackers employ four primary methods, namely scanning, surveillance, maintenance, and manipulation, to target devices and obtain access and control[233].

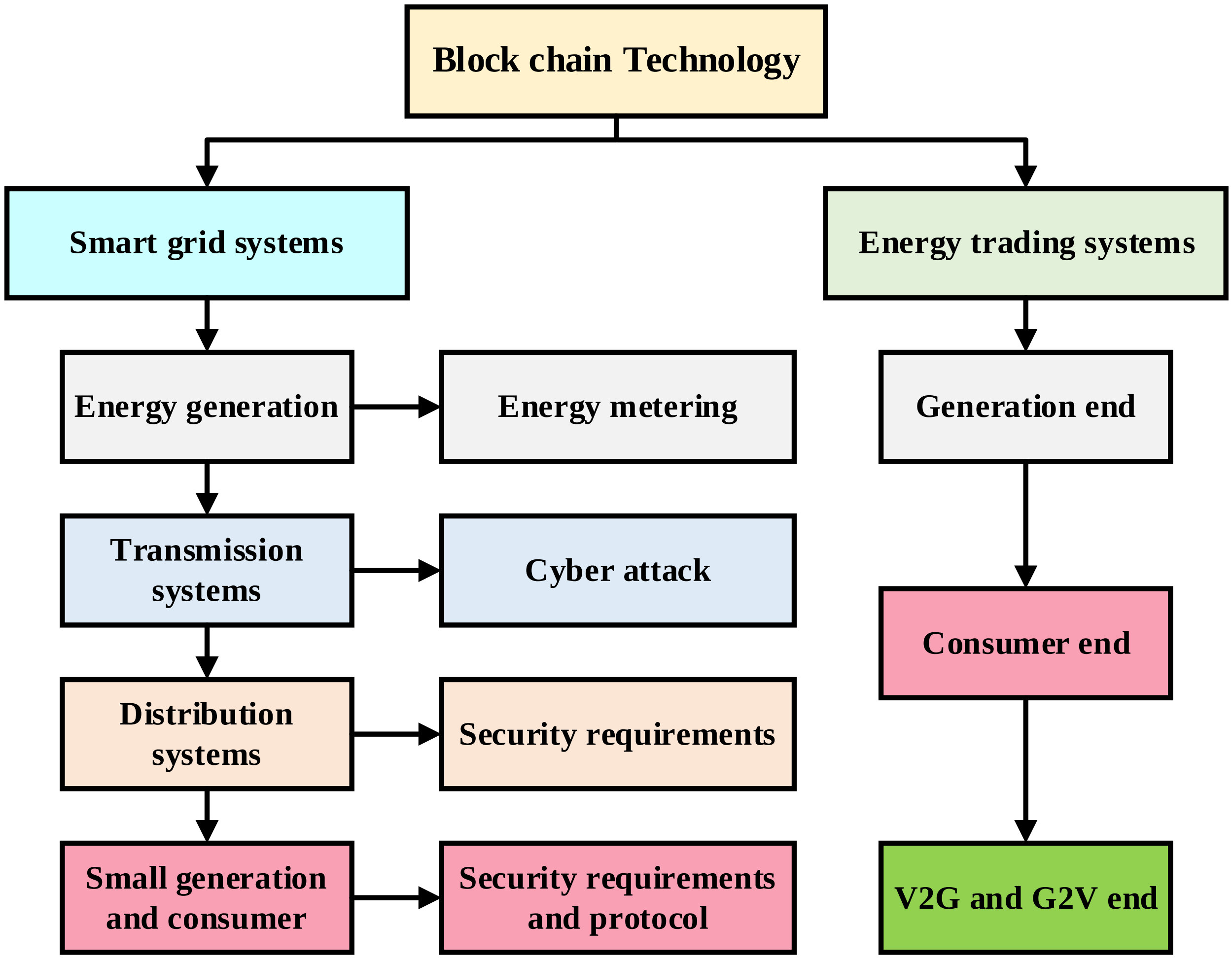

Figure 17: An overview of the integration of blockchain technology with smart grid systems and energy trading

6.1.1 Blockchain technology with smart grid systems

Energy trading is vital to BC technology research and industry use, especially in emergency SG electricity generation and distribution. BC technology reduces fraud. An energy trade certificate establishes trust and assurance between providers and consumers. Integrating blockchain technology streamlines energy trade and decreases marketing time. Experts and governments worldwide are seeking renewable energy alternatives as fossil fuels deplete rapidly. Numerous smaller firms generate energy on a lesser scale and need connectivity to the national grid to allow users to buy it[234], [235].

Customers also produce and sell energy. The BC system streamlines local peer-to-peer trading, generating some energy. The peer-to-peer topology autonomously preserves this data on the public ledger, distributing duplicates over the network. Block nodes exchange data with the SG network in BC technology. Each device shares its address and information with the previous devices[236]. The many potential, benefits, methodologies, and technical obstacles of employing blockchain technology in the smart grid[237]. An extensive examination of the utilization of blockchain technology in the context of smart grid systems[238].

6.1.2 Blockchain technology with energy trading systems

Integration of electric vehicles (EVs) with smart grids (SGs) has become a hot topic in recent years. Smart grid connectivity is the EV charging system's top priority. Charged electric vehicles that aren't needed can pressure the power grid. Thus, BC technology tackled this issue in numerous ways. Several research articles tested the EV charging with BC technology[239]–[241]. Researchers recommend integrating the electric vehicle (EV) charging system into blockchain (BC) to identify nearby EV charging outlets. Blockchain technology allows the electric vehicle (EV) to easily find the most cost-effective and best location for an EV charging station, assuring privacy and security.

In existing extensive blockchain networks like Ethereum or Bitcoin, any modification to the software code that operates in the participating nodes must undergo approval (via consensus algorithms) in order to be implemented across the whole network. Any dissent on this action might result in the creation of separate branches and divisions of the network, jeopardizing its security and the integrity of its data. It is imperative to safeguard the architecture of these blockchain networks for smart grids from such adverse impacts. Exploration of blockchain-based solutions is necessary to address many aspects of decentralized grid management and control, such as enhancing demand-supply equilibrium, automating verification of grid assets, predicting grid needs, and modifying power usage in response to price fluctuations.

6.1.3 Blockchain Technology: A Catalyst for Future-Proofing Smart grids Against Cascading Failures

The review emphasizes the crucial importance of blockchain technology in efficiently dealing with and reducing the impact of interconnected failures within smart grids, especially in identifying and reducing the vulnerability of specific nodes. The decentralized and transparent characteristics of blockchain are expected to fundamentally transform the future of microgrid resilience by offering a safe and unalterable platform for data management. Looking into the future, the utilization of blockchain technology is positioned to have a crucial impact in averting cascade failures in smart grids. Through the utilization of smart contracts and consensus procedures, blockchain technology can facilitate automated and swift reactions to emerging vulnerabilities, hence diminishing the likelihood of extensive disruptions. The capability of this technology to provide a reliable and distributed record for monitoring energy transactions and system performance will play a crucial role in improving real-time situational awareness. The potential incorporation of blockchain technology into smart grid systems offers the possibility of establishing a stronger and more flexible energy infrastructure, protecting against widespread failures and guaranteeing the dependability of microgrid networks in a rapidly changing energy environment.

6.2 Microgrid Digital Twins: Bridging Virtual and Physical Realities

An MGDT is a digital representation that accurately replicates the functioning of a physical microgrid (MG) [242]. It achieves this by utilizing sophisticated models and simulation platforms, as well as exchanging real-time data with the physical microgrid. The widespread implementation of sensor networks and Internet of Things (IoT) technologies in microgrids (MGs) results in the constant generation of a substantial amount of data. This data contains valuable information that can be utilized to improve the operation of MGs. MGDTs offer a robust solution for efficiently and securely managing large volumes of historical and real-time data. They play a crucial role in supporting the design, operation management, and maintenance of MGs. Various organizations have begun incorporating digital twinning into their solution plans, seeing its prospective benefits. General Electric (GE)[243], Siemens[244], ABB[245], and Rolls-Royce[246] are leading companies in this field[247].

6.2.1 Establishing a digital twin for smart grids

The digital twinning framework comprises three components: the physical system, the virtual system, and the data interchange between these two systems. In order to construct a digital twin (DT), accurate and detailed models are combined with many sources of data, including sensor data, historical data, technical information, and maintenance records[248]. The data is utilized to construct models of the physical system and maintain the models' precision under varying operational circumstances. Therefore, a highly accurate and current understanding of the system's operational status is accessible for the purposes of logical thinking and decision-making. The subsequent sections will outline the various stages involved in establishing DTs, as depicted in Figure 18.

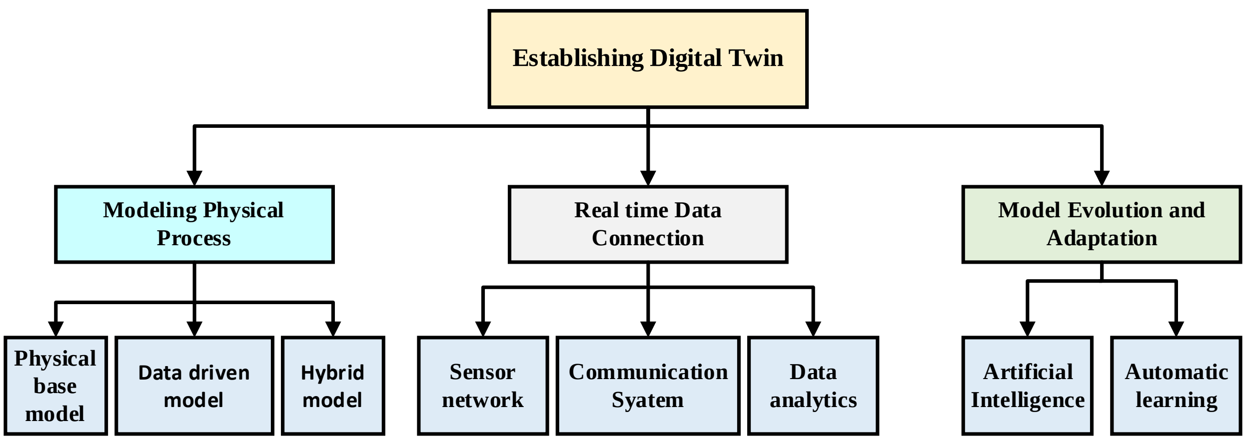

Figure 18: Creating a digital replica or virtual representation of an object or system.

6.2.2 Modeling of physical systems and processes

Modeling serves as the foundation for digital twinning[249]. The initial phase of generating a digital twin involves constructing precise models of the actual system or asset that can accurately replicate its behavior. In order to create the virtual model, it is essential to utilize and combine the most reliable understanding of the system dynamics with the available data. The data comprises previous data collected from the system under different operating situations. The comprehensive model of a system is attained through the integration of models representing all subsystems and their interactions[250].

Its ability to convey various information uniformly is notable[251]. The goal of DT implementation and its intended application allows for several models with different levels of abstraction. Complex models are more accurate, but evaluating them takes time. Therefore, simplified lower-order models with less complexity are preferred for thorough system analysis. For instance, the hierarchical control of MGs[252] does not require extensive knowledge of the dynamics of individual components at the tertiary level, called the energy management system. In this case, knowing energy flows between subsystems and the approximate power relationship between components is enough to achieve system power balance. In addition, the model gives the necessary data to assess KPIs including operational cost, pollution, reliability, and system losses. For short-term power estimation, simplified models of MG components like photo voltaic (PV) systems (equivalent circuit models or black box models) and field meteorological data work[253]. However, microscopic performance limiters must be analyzed to determine PV cell deterioration[254]. Interoperability of numerous services and efficient and safe model and data sharing are crucial DT functions. Continuous updates and synchronization ensure that the DT closely matches the real system and maintains consistency between models. The twinning rate is the rate at which the DT is updated with the latest physical system information. After building DT models, evaluate their fidelity to ensure they accurately match the physical twin before use.

6.2.3 Real-time data connection

The process of digital twinning focuses on utilizing data to establish a connection between digital models and their corresponding real objects. Data is collected from various system components, such as lines, buses, switches, transformers, loads, storage systems, etc., through field measurements, IoT devices, and smart meters. In addition, meteorological data such as ambient temperature, solar radiation, humidity, wind speed, and wind direction are gathered from many sources including field observations and data centers such as national or local weather stations and networked systems. Managing a large amount of data, which includes structured, unstructured, and semi-structured data obtained from various sources with varied levels of detail, is a difficult undertaking.

Communication is reliable and secure. The desired service and application's communication needs determine the communication technology selection. Latency, dependability, coverage, data rate, and cost are quantitative requirements, whereas scalability, interoperability, flexibility, and security are qualitative[255]. WiFi, WiMAX, 4G/5G, and satellite technologies, or a mix of these, can be used for digital transformations. A detailed examination of communication technologies and their properties. The utilization of AI techniques at the network edge and the close vicinity of the data source are discussed in reference[256].

6.2.4 **Digital Twins for Proactive Cascading Failure Prevention**

Utilizing digital twin technology is crucial in reducing the occurrence of cascade failures in microgrids. Digital twins provide a dynamic and comprehensive depiction of the microgrid system by combining precise models with a wide range of data sources. The ongoing surveillance allows for the timely discovery of abnormalities, while the identification of vulnerabilities and analysis of prospective scenarios empower the implementation of preventive steps to prevent potential chain reactions of failures. Digital twins utilize advanced analytics and machine learning to enable predictive capabilities, enabling proactive measures to mitigate hazards throughout the entire system. Moreover, the technology facilitates the advancement and experimentation of refined control techniques, guaranteeing efficient reactions to changing circumstances. Operators benefit from fast insights and informed responses by utilizing dynamic decision support through real-time data interchange, which helps prevent the escalation of errors. Digital twin integration fundamentally improves the ability of microgrid systems to withstand and maintain their performance, providing a comprehensive strategy to minimize the consequences of cascading failures.

6.3 Metaverse Technology in Micro grid

The rapid ascent of the Metaverse as an advanced virtual digital technology is driving advancements in power generation innovation. The increasing need for sustainable energy and the advent of the Metaverse have facilitated the development of a viable energy trading system that incorporates Smart Grid (SG), Virtual Power Plants (VPP), Digital Twins (DT), and Blockchain technology. The integration of Virtual Power Plants (VPP) with Smart Grid (SG) technology has the potential to optimize the use of distributed energy resources and enhance the stability and reliability of the energy supply in the metaverse. Next-Power is an innovative framework designed for the purpose of facilitating secure and sustainable energy trading within the Metaverse[257].

6.3.1 Conceptual model of a Smart Grid

The NIST's Smart Grid (SG) conceptual model outlined the whole structure (including domains and sub-domains), participants, and uses of the SG. NIST emphasizes the importance of DERs as emerging energy sources. This model is categorized into seven domains and their respective sub-domains. Figure 19 depicts the primary domains involved in the system, which consist of generation, including distributed energy resources (DERs), distribution, transmission, operations, service provider, market, and customer. After evaluating the NIST proposal, we believe that the implementation of blockchain technology will significantly alter the P2P energy trading system. Blockchain technology will guarantee the integrity, dependability, and protection of peer-to-peer energy trading networks.

6.3.2 Blockchain-based peer-to-peer trading of energy

There is significant enthusiasm for creating Peer-to-peer (P2P) energy trading systems that enable prosumers (individuals who both use and produce energy) to trade their excess energy with other prosumers in a nearby microgrid. Various peer-to-peer (P2P) energy trading schemes have been suggested in academic literature to enable such transactions, with each scheme tailored to meet individual needs and demands. Notable P2P energy trading schemes encompass direct exchange, double auction, uniform pricing, and the blockchain-based approach [258]–[261]. In order to secure the successful deployment of P2P energy trading networks, it is crucial to address the various security concerns they face, notwithstanding their potential benefits. For instance, the direct exchange arrangement is deficient in transparency and accountability, rendering it susceptible to fraud and market manipulation. Hence, it is imperative to assess the security vulnerabilities linked to any peer-to-peer energy trading system and establish suitable security measures to alleviate these risks. The security procedures encompass authentication, authorization, access control, data encryption, and secure communication protocols. P2P energy trading schemes can offer a dependable and effective method for energy trading within microgrids by tackling security challenges.

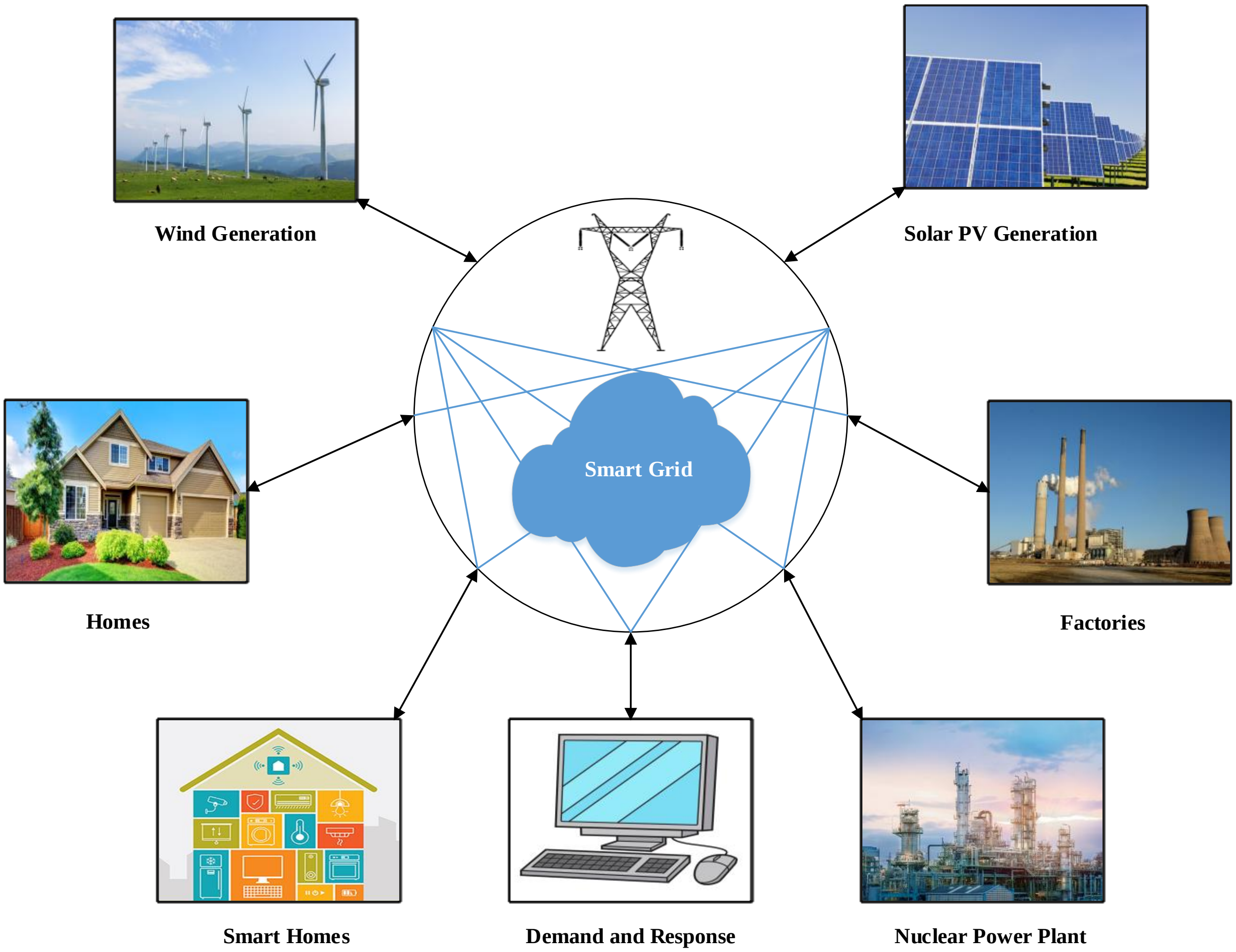

Figure 19: Conceptual model of a Smart Grid.

6.3.3 Metaverse integration to strengthen microgrids against cascading failures

Integrating Metaverse technology into microgrids offers a comprehensive strategy for averting cascading failures. Operators can utilize real-time monitoring and visualization to evaluate the status of the microgrid by generating virtual replicas and digital twins of the system. Utilizing predictive analytics and simulations in the Metaverse allows for the detection of possible sources of failure and the deployment of proactive interventions. The resilience of the microgrid is improved by Metaverse platforms, which provide decentralized control and collaborative decision-making, enabling quick solutions to emerging difficulties. Furthermore, the implementation of cybersecurity monitoring and simulated attacks in the Metaverse serves to strengthen the digital infrastructure and protect it from any interruptions. Virtual environment training and simulation effectively provide operators with the necessary skills to handle real-life situations, while dynamic load management efficiently allocates resources to minimize the likelihood of overloads. The Metaverse fundamentally changes the way microgrid operations are conducted by integrating cutting-edge technologies to actively anticipate and reduce the consequences of cascading failures.

7 Microgrid control techniques

In complicated microgrid control, distributed energy supply balance is critical for long-term stability and optimal performance. This comprehensive examination explains how classic and sophisticated control methods are used in microgrid operations. The traditional control methods for stability are proportional controllers (P, PI, PID, PR). These methods properly examine peak overshoot and settling time. Fundamentally, these control methods prevent a chain reaction of microgrid failures, eliminating flaws that could cause broad system disruptions. The Deadbeat Controller, Model Predictive Control (MPC), Hysteresis Controller, and others are cutting-edge control methods that adapt to microgrid's complexities. These methods increase the system's cascading failure detection and response. The exploration culminates by seamlessly integrating Fuzzy-PI/PID controllers with an Adaptive Neuro-Fuzzy Inference System (ANFIS). This method shows a complicated cascade failure prevention mechanism. Each solution has its own benefits and strengthens microgrid stability and resilience, reducing cascade failures in dynamic energy conditions.

7.1 Traditional Control Methods

This section covers several traditional control methods used in MG to maintain stability. There are four types of proportional controllers: proportional (P), proportional-integral (PI), proportional-integral-derivative (PID), and proportional-resonant (PR). The short characteristics and their associated parameters are shown in Table 4.

Peak overshoot, settling time, rising time, steady-state error, and other factors are among those included in the table as parameters for evaluating these controllers.

Table 4: Conventional control techniques

Controller Equation	Parameters	Remark
$P[262] \qquad \frac{U(s)}{E(S)} = K_p$	The controller's proportional gain is denoted by Kp.	• Reduces settling time and steady-state error, increases overshoot, and decreases rise time.
$PI\ [262],[263] \qquad \frac{U(s)}{E(S)} = K_p + \frac{K_i}{s}$	Controller gain can be thought of as either proportional (Kp) or integral (Ki).	• A shorter ramp-up time and smaller steady-state error • Increased overshoot and decreased settling time. • Enhanced functionality offers cross-coupling and feed-forward voltage.

		• Using current as a reference, the dq reference frame accounts for the direction of power flow at the system level.
PID [264] $\frac{U(s)}{E(S)} = K_p + \frac{K_i}{s} + sK_d$	Kp is proportional, Ki is integral and Kd is the derivative gain of the controller.	• A combination of the Kp, Ki, and Kd gain values. • Little drop in the rising time, overshoot, and settling times. • A large influence on steady-state inaccuracy. • Improved capacity to respond to sudden and unpredictable changes. Better performance with low K_d values.
PR[265]–[269] $\frac{U(s)}{E(S)} = K_p + K_i \frac{s}{s^2+w^2}$	The integral gain of the controller is denoted by Ki, the proportional gain by Kp, and the resonant frequency by w.	• Larger gain levels that get closer to the target value produce a more noticeable reduction in steady-state error. • Useful in both the reference and abc frames. • The performance of the controller can be adjusted for different scenarios. • However, it has a number of drawbacks, including a delay in transmission time, the need for precise tuning, and a heightened sensitivity to frequency shifts.

7.2 Intelligent control techniques and strategy:

Deadbeat Controller: A quick-thinking and perceptive regulator of inverter current. Due to the controller's enormous bandwidth, real-time current tracking is possible anywhere it's needed. Because they are derived from control parameters[270], [271], [271], intelligent controllers can predict the system's future state and, consequently, the control action. A deadbeat controller, which is employed in research, assists the system by correcting inverter current problems but is also sensitive to the network's features. Figure 20 depicts the schematic arrangement of the deadbeat controller, with reference signal r(z) being processed via the controller to the intended system, with y(z) serving as the principal output, where e denotes an error signal to the controller unit, Q and P denote the transfer function's polynomials, u denotes the manipulated signal, and P denotes the actual system/model.

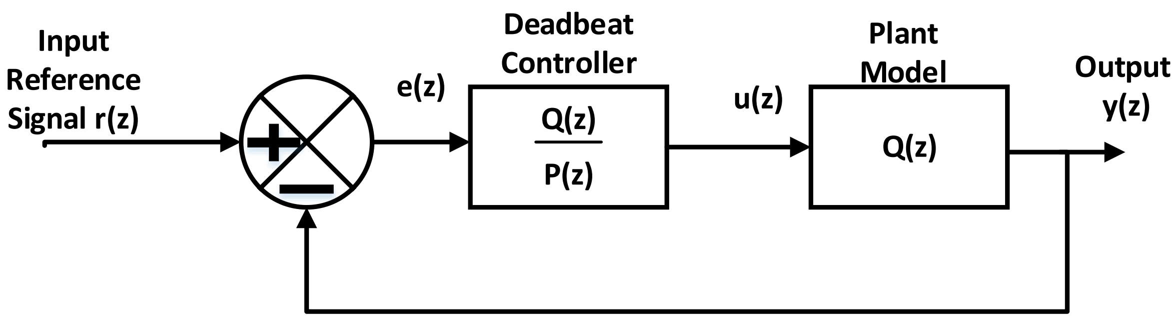

Figure 20: Deadbeat Controller techniques

Model Predictive Control (MPC): It aims to accurately track the current parameter while minimizing prediction error. One of MPC's features is that it can retain all of the network's general and nonlinear restrictions even when there are numerous inputs and outputs. The model predicts the network's future values based on the current values of several parameters to ensure its steady functioning. Additionally, the approach is subject to the presence of mathematical equations[272]–[274]. The block configuration of the MPC is shown in Figure 21, along with several restrictions and goals that serve as the controller's primary inputs and are used to process the control signal for the real system.

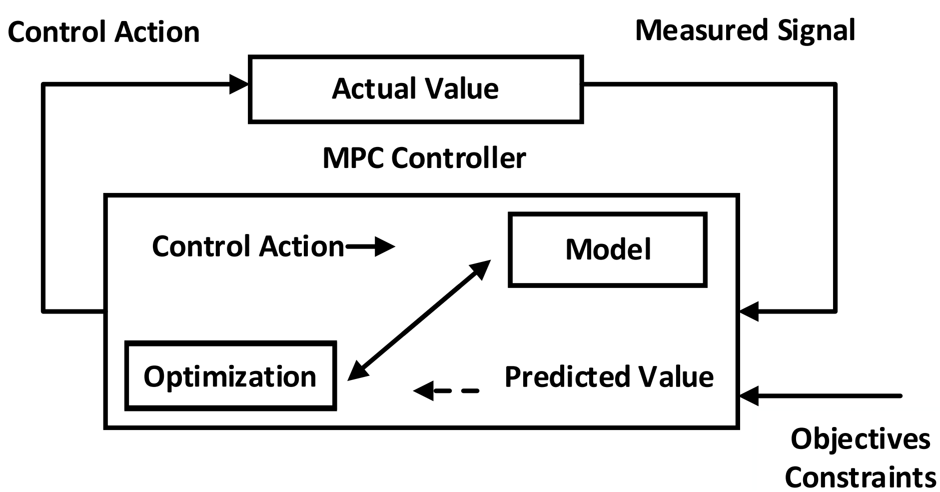

Figure 21: Model Predictive Control

Hysteresis Controller: A simpler method for comparing the reference signal and the current error signal while managing the current error signal. Hysteresis controller benefits include quick and adaptable reaction to the inverter, simple installation, etc. The controller also lowers the system's THD[275], [276] and has an intrinsic current protection method. The hysteresis controller, depicted in Figure 22, could be inactive or active, depending on the status of the relays. Signal processing for the intended system ensures reliable functioning.

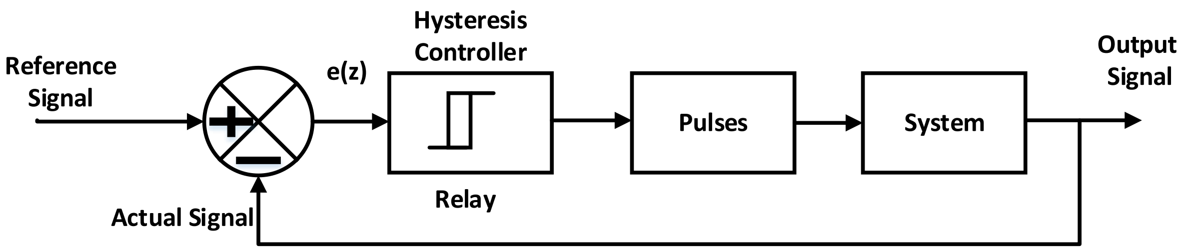

Figure 22: Hysteresis Controller

H-infinity Controller: The controller that has the capability to modify any parameter's value that disturbs the system while stabilizing the system with a quick response. Eliminating the parameter responsible for the system's disruption is the controller's main goal. Before the controller can take any action, the problem must be described in the context of optimization. The requirements of the system are determined by imposing limits on the singular values of the various transfer functions within the loops. The controller's benefits include decreased error, a simpler implementation, and robustness in the face of unknown parameters.

One disadvantage of using a controller is the need to construct and understand elaborate mathematical expressions[277]. Figure 23 depicts the fundamental H-infinity controller, whereby G(s) represents the plant or system, and k(s) is the compensator. The primary responsibility of the controller is to determine the appropriate value of k(s) that will enable the system to achieve a state of equilibrium.

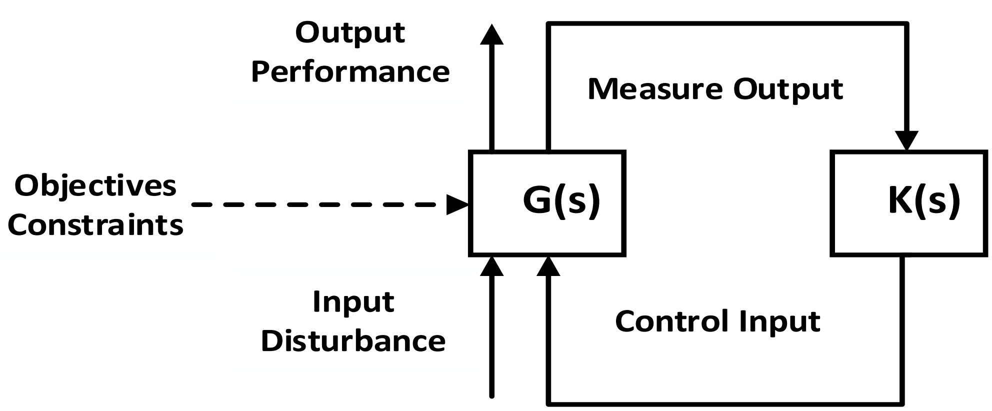

Figure 23: H-infinity Controller

Repetitive Controller: A tool for minimizing and eliminating errors that operate under the internal model concept. This theory operates by describing the error terms as pole pairs at various assigned frequencies. In the literature, a repetitive controller is defined as a parallel connection of an integral, proportional, and resonant controller. Harmonic distortion that is low over a large range of input parameters (current, voltage, etc.). When nonlinear inductive loads are present[266], [278], [279], is one of the repetitive controller's main benefits for MG stability. In the controller's block diagram shown in Figure 24, the variables are denoted as follows: r represents the raw input, e represents the error, CR represents the processed inputs, u represents the processed inputs, and y represents the major output of the system G.

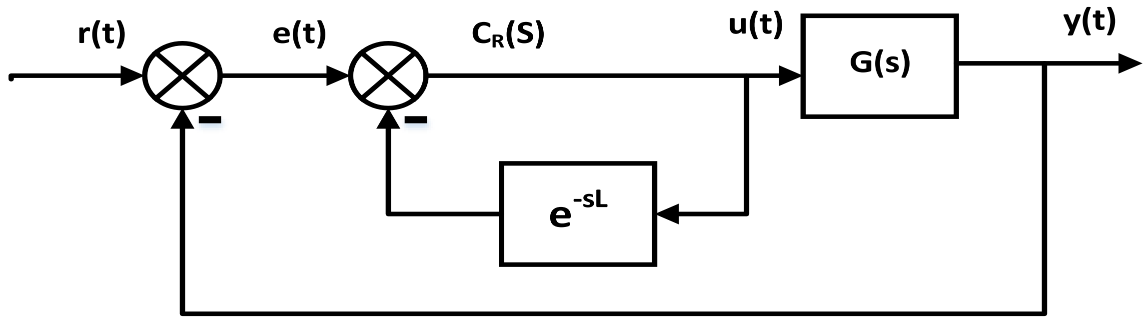

Figure 24: Repetitive Controller

Artificial *Neural Network:* The central processor, which works similarly to the human brain, receives the necessary information from the neural network-based controller with a slight delay. A closed-loop system relies on the interplay between an input/output layer, an activation function, weights, and a hidden layer to ensure accurate and error-free data flow. The neural network's ability to be an adaptable, intelligent, and self-learning controller provides for greater versatility as well as simpler design and implementation for various operating scenarios. In addition to their quick decision-making and resilient behavior, neural networks also contribute to the stability of the MG[280], [281]. The neural network-based controller's short schematic layout is shown in Figure 25. The input/hidden/output layer, regulator, and reference signal all contribute to the system's smooth operation.

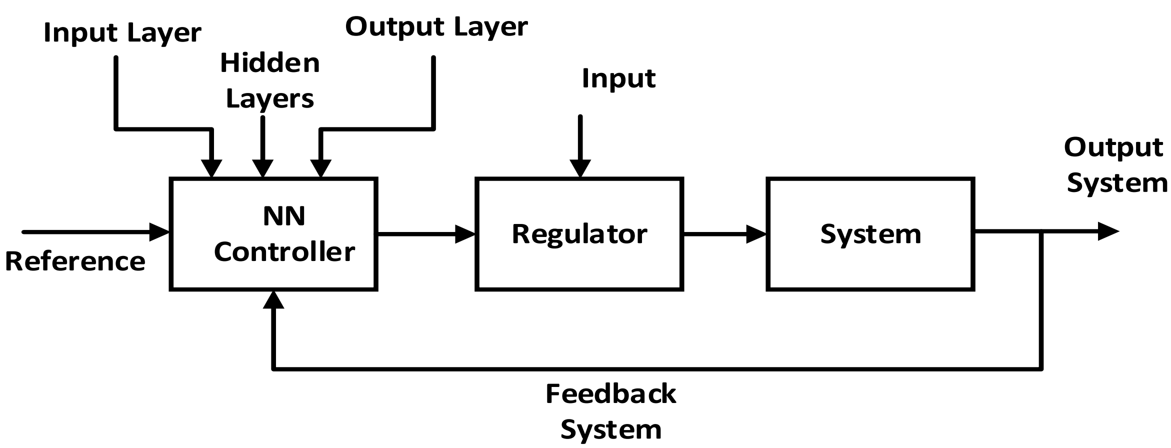

Figure 25: Neural Network Controller

Fuzzy Controller: This logical controller in Figure 26 substitutes relationships and deals with various linguistic values for the clear value's logic in decision-making. Fuzzy values range from 0 to 1. Fuzzy logic has been frequently utilized to regulate MGs because of its high level of robustness and user-friendliness. Fuzzy logic controllers have been used to improve tracking performance, as well as decision-making and robustness. [282]–[286].

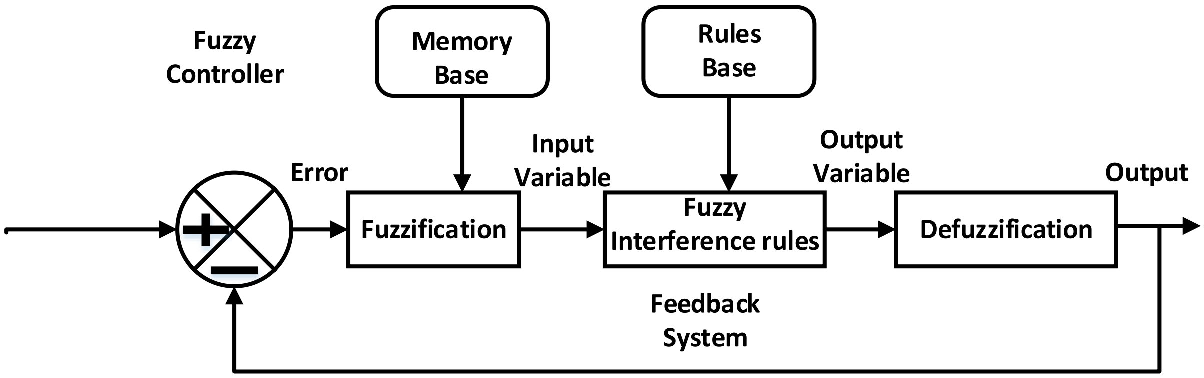

Figure 26: Fuzzy Controller

Sliding Mode Control: Depending on the operating scenarios, this dependable and flexible controller adjusts to changes in the system parameters. The system can soon become stable due to the wide range of such a modification. The key objective of the controller is to keep the system in a stable state; nevertheless, in the event of an unpredictable change, the controller is required to take an immediate control action. Because the controller struggles to adapt to the nonlinear system's unpredictable change and dynamic behavior, it optimizes the parameters based on the output ripple waves to prevent this problem. The key benefits of the sliding mode controller are its low sensitivity to changes in parameter values and its ease of integration into the MG. [287], [288].

Linear Quadratic: Maintaining MG stability in this manner is defined as a reliable and efficient controller that works well in both steady-state and non-steady-state settings. The main benefit of this approach is that it is inherently stable and not dependent on the order of the system. The shift in load type hinders efficiency in monitoring and decision-making [289], [290].

Linear Quadratic Integrator: By employing this technique, the steady-state accuracy of many parameters, including voltage, can be decreased without compromising the system's responsiveness. When subjected to uncertain load variations, as depicted in Figure 27, the controller acquires the measured real error values between the grid voltage and the reference voltage in order to reduce the error. In addition, the controller is required to minimize interruptions in the operation of the system. Considering the benefits, implementing the control technique is less difficult since finding the optimal gain that provides adequate tracking with a small steady-state error is straightforward[291], [292].

The integrator's output (xi), the state-space model (sys), the output (y) with gain (k), the input (x) to the gain block (r), the error (e), and the reference signal (r) are all represented in this expression.

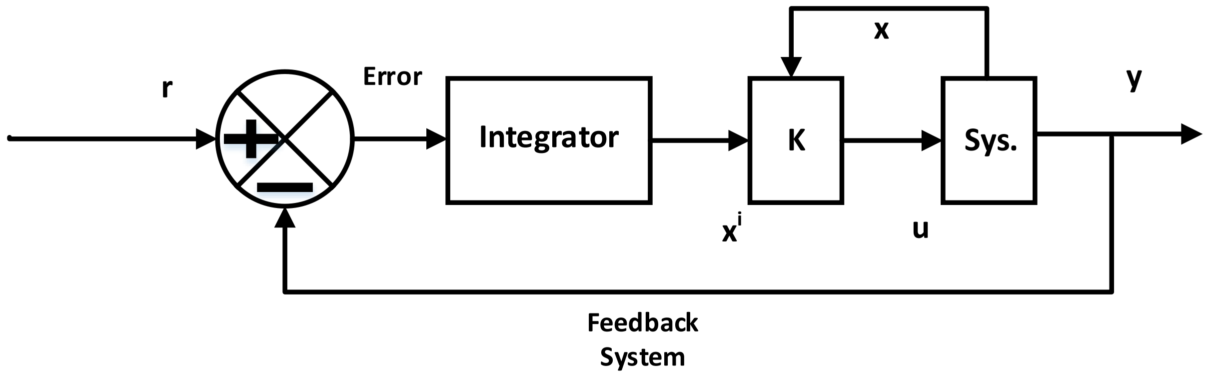

Figure 27: Linear Quadratic Integrator

7.3 Hybrid control techniques:

Fuzzy-PI/PID controller: Although the PI/PID controller's many benefits for enhancing an inverter-based MG's stability, its performance is hindered by unclear, unpredictable, and abrupt system disturbances. The fuzzy inference system is therefore ideally suited to handle such circumstances that might be used to optimize PID while compensating for system disturbances. The primary benefit of integrating fuzzy logic and the PID controller is the improved decision-making skills that result from the former's faster and more accurate decision-making and the latter's more precise tuning. It is not uncommon for the system's input to include a wide range of potential error factors [293], [294]. In Figure 28, we see the hybrid fuzzy/PID controller in action, ensuring the system runs smoothly. The fuzzy controller takes in two kinds of information: the base (x) and the derivative (E). The PID controller receives the resultant, precise value as shown in Figure 28. The gains affect the system's response to an input signal, which is also known as the output (u).

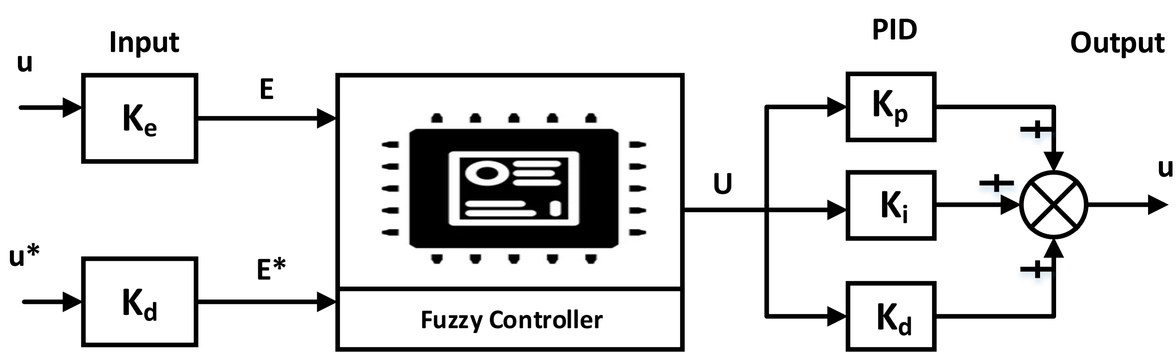

Figure 28: Hybrid control techniques

Adaptive Neuro-Fuzzy Inference System (ANFIS): ANFIS-based control approach is the combination of neural network and fuzzy technique that makes use of their advantages. The technique uses a flexible, reliable fuzzy inference system in conjunction with the learning and feedback capabilities of neural networks to more accurately represent the system's data and knowledge[295]. In order to reduce mistakes in the system and boost stability, the weights are updated depending on feedback from the input layer to the output layer using the gradient descent approach. This weight-tuning technique, which is also known as backpropagation, consists of the first layer's preliminary tuning and the fourth layer's following tuning[296], [297].

In Table 5, we compare the various MG stability-targeting controllers and highlight their respective advantages and disadvantages.

Table 5: Various MG stability controllers

Controller	**Pros**	**Cons**
P[262]	• Simple implementations. • Short rising times.	• Low stability. • High overshoots when the stage is intermittent
PI[262], [263]	• Short rising times. • Reduced steady-state error using the dq reference frame.	• An insufficient steady-state response to transients. • For uncertain systems, high steady-state error.
PID[264]	• Small overshoot. • Reduced steady-state error.	• Inappropriate for time-delayed and transient, systems with little flexibility.
PR[265]–[267]	• Reduced rising time. • Reduced steady-state error.	• Lag time. • Inaccurate gain tuning. • Sensitivity to ambiguous situations.
Deadbeat[270], [271], [298]	• Transient response that is quick and dynamic with minimum harmonics. • Distortion is appropriate for controlling harmonics.	• Difficulty of network parameters. • Exact parameters for filter and inverter models.
Model predictive[272]–[274]	• It is suitable for non-linear systems. • Requires fewer switching cycles. • Provides precise current regulation with low THD levels.	• Complex computations • Modeling of the filter and inverter that is both precise and sensitive to variations in input values.
Hysteresis[275], [276]	• Implementation is simple. • The transient reaction is quick and dynamic.	• Problems relating to resonance • Issues with harmonics.

	• Automatic current safety.	• Inaccurate current tracking
H infinity[266], [278], [279]	• Reduced tracking error • Minimized THD. • Robust performance for linear, nonlinear, and unbalanced loads.	• Demands comprehension of difficult mathematical problems. • Slow dynamics.
Repetitive[299]	• Stable performance in complex and chaotic conditions. • Reducing steady-state error across a variety of harmonic frequencies.	• Slow reaction during load variations. • Problems with system stabilization.
ANN[280], [281]	• Self-learning controller. • Excellent performance in instantaneous control.	• Complex and slow reaction. • High data requirements.
Fuzzy logic[283]–[285], [300]	• No impact from changing the parameter. • Useful for both small- and large-scale non-linear systems.	• Slow-control technique. • Complex rule production.
SMC[288]	• THD minimization. • Consistent performance during fluctuations and transients.	• Complex design process. • Chattering Phenomenon in Discrete Implementation.
LQI[292]	• Quick and dynamic action. • Simple design and construction techniques. • Accurate performance tracking.	• Voltage monitoring phase shift problem. • Difficulty in collecting model attributes and characteristics.
Fuzzy-PI/PID[289]–[291]	• The ability to self-tune gain. • Improved performance in hazy and nonlinear systems.	• Complex implementation. • Complex structure.
ANFIS[296], [297]	• Flexible and durable. • The ability to operate on both linear and non-linear systems.	• Complex data analysis and collecting.

8 Cascading Failure Mitigation in Micro Grid for stability Enhancement

While the strategies for analyzing system stability are described in the following part, the numerous ways to improve MG stability have been covered in this subsection.

8.1.1 Micro Grid stabilizer:

Similarly, to how power system stabilizers are responsible for maintaining voltage within permissible limits, MGS serves the same purpose. To conduct power factor correction, the MGS is responsible for regulating the level of reactive power within the system. The small-signal stability problems of the MG are being tackled by linking the MGS to the VSCs.

In this paper[301], the authors proposed a versatile control strategy for microgrids (MGs) operating in both islanded and grid-connected modes. This approach incorporates a nonlinear MG stabilizer to enhance the overall stability of the MG system under large-signal conditions. Instead of conventional current-voltage controllers, the controller functions within the domains of angle, frequency, and power.

The transfer function for MGS is shown in Figure 29; here, K is the block gain, and 1 + T2S/1 + T1S is the phase correction for system stability with time constants T1 and T2. In addition, the system's natural frequency is used to determine T1 and T2, and K is determined by the amount of damping necessary to maintain stability. [302]By comparing terminal voltages and reference voltages, voltage is used as a main control parameter to generate the reactive power/voltage droop control curve, which consists of the reactive power, error, and gain constant of the system.

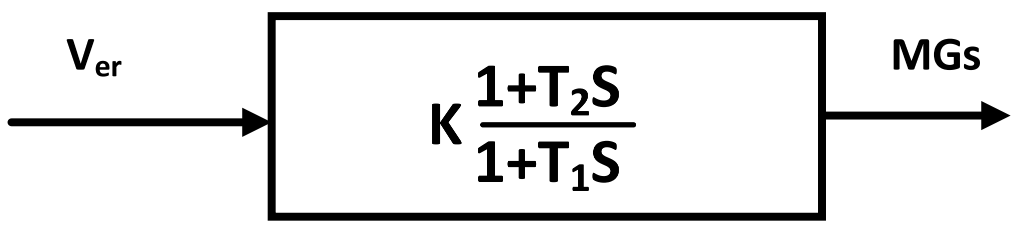

Figure 29: MGs transfer function

The role of a Microgrid Stabilizer is of utmost importance in the mitigation of cascading failures within a microgrid. The primary objective of this sophisticated control system is to optimize the stability and robustness of the microgrid through the rapid identification and effective mitigation of disturbances or faults. Through the ongoing monitoring of electrical characteristics within the microgrid, such as voltage and frequency, the stabilizer possesses the capability to detect possible concerns that may result in the occurrence of cascade failures. During instances of disruption, the Microgrid Stabilizer utilizes advanced algorithms to promptly and precisely implement remedial measures, such as regulating power distribution, activating energy storage devices, or altering the functionality of distributed energy resources. The implementation of a proactive and expeditious response strategy aids in mitigating the escalation of faults, hence minimizing their consequences and guaranteeing the overall stability of the microgrid. Moreover, the Microgrid Stabilizer enhances the dependability of the microgrid by enabling smooth transitions between grid-connected and islanded modes, hence decreasing the likelihood of cascading failures in both regular and emergency operational scenarios.

8.1.2 Electrical energy storage devices:

Electrical energy storage devices incorporate a category of electric vehicles (EVs). A drop in power production, an increase in load demand, MG islanding, etc. are just a few of the MG problems that can disrupt stability related to active/reactive power. Flywheels, batteries, and capacitor banks from ESS can be used to offset such problems. By providing active as well as reactive power, these devices try to regulate voltage while improving system stability. [302] Electrical, mechanical, thermal, and electrochemical systems are only a few of the various ESS types in Figure 30.

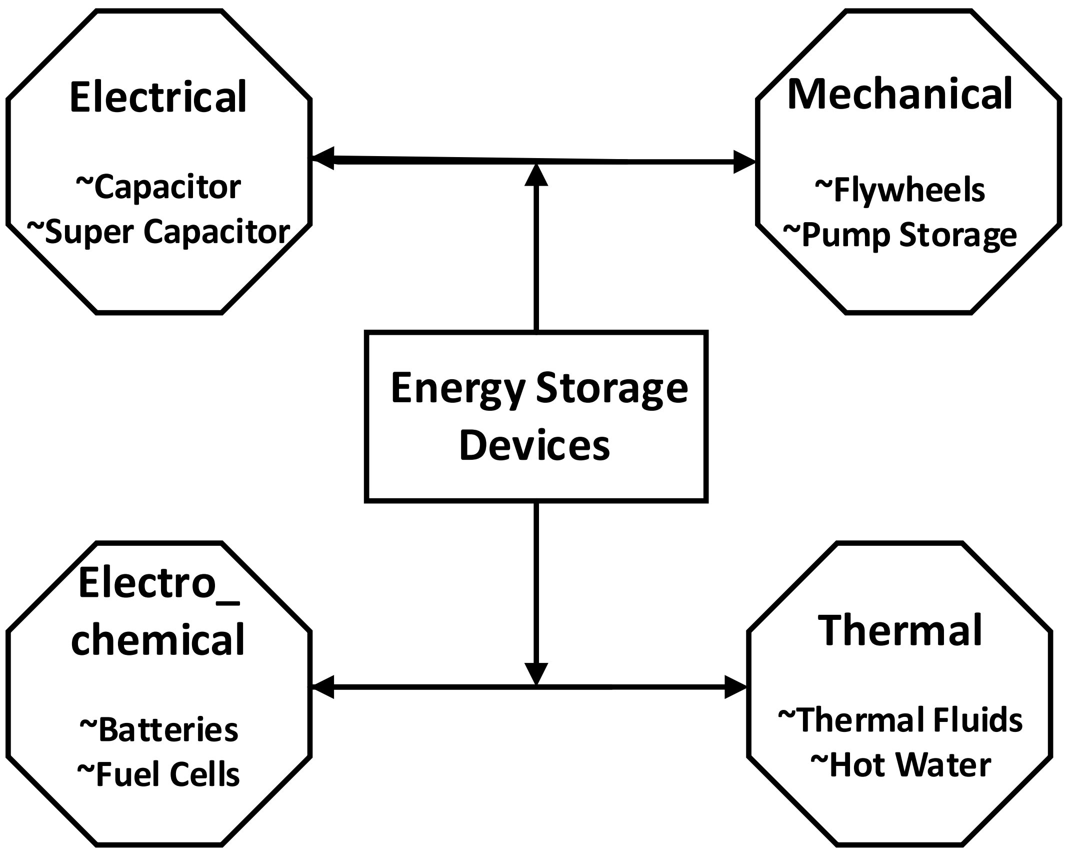

Figure 30: Energy Storage Devices

Micro grid compromise of base power generation is a diesel generator, renewable sources are solar PV and wind, loads, and EV aggregators [303]. The purpose of the home model which operates in grid-connected and islanded mode and sources are solar PV and EV. EVs are used to mitigate load sharing, load transient, and fault analysis. The droop control and virtual inertia are utilized in a unified manner this paper is a good thing. The model is implemented by MATLAB and deployed by real-time simulations by OPAL-RT simulator to validate the feasibility[304]. They use solar PV and batteries to maintain the stability of frequency and voltage it is good they are proving by simulation but they take a too small number of EVs, as overserved the battery is depleted up to 0%

SOC's not good for battery health so future work is to increase the number of EVS and then simulate the system.

This paper presents an analysis of the algorithm utilized by inverters to regulate power, voltage, and frequency when connected to a microgrid. The simulation results indicate that the power hardware-in-the-loop validation (PHV) system effectively maintains the desired frequency and voltage levels within the microgrid[305]. The working power plants are employed as the sliding-mode main controller to stabilize the frequency, adaptive dynamic programming is used in the design of the EV controller to handle a significant amount of frequency variation[306]. A reliable and recently created PI-PD cascade controller based on the Salp Swarm Optimisation (SSO) algorithm for the load frequency control (LFC) of the SMG integrated with the EVs[307].

In order to prevent the propagation of cascading failures in the IEEE-30 bus network without resorting to load shedding, the network must satisfy the following two criteria. The first step is minimizing an overloading state shortly after a contingency occurs[308]. The second approach is to mitigate the impact of transient issues at the earliest possible stage, hence reducing the risk of cascading failures and subsequent outages. This issue was emphasized in references[309] and[310]. In order to address these two crucial issues effectively, a probabilistic modeling technique is employed. This technique integrates cooperative control V2G technology with a fuzzy logic approach within the power system network. Different load-shedding procedures are applied to mitigate the losses caused by critical fault events (CFEs) in the power system network, specifically under (N-1) and (N-1-1) contingencies. This study[212], presents a collaborative control method that utilizes Vehicle-to-Grid (V2G) technology and a fuzzy controller to tackle this issue.

Electric vehicles (EVs) reduce microgrid cascade failures by providing dynamic energy storage and bidirectional power transfer. Electric vehicles (EVs) can deliver electricity to the microgrid and stabilize the grid as distributed energy resources under normal operation. Electric cars (EVs) with Vehicle-to-Grid (V2G) technology can easily release stored energy back into the microgrid in the event of a disruption or malfunction. Quickly addressing unexpected resource supply and demand reduces the disruption's effects and prevents its spread inside the microgrid. Because electric vehicles (EVs) can supply bidirectional power flow, they can change their energy contribution to maintain microgrid stability quickly and easily. EVs can also serve as portable energy storage devices, strengthening the power grid by providing emergency power. This prevents huge microgrid failures.

8.1.3 Load balancing:

Due to the great unpredictability of the demand, the system demonstrates a high degree of instability, especially for microgrids operating under islanded conditions. Rising electricity demand is primarily to blame for the current power shortage. Implementing appropriate load-shedding methods with the help of an intelligent and adaptive controller is one approach to solving this problem[311], [312]. The noncritical load may need to be drastically reduced to ensure that the microgrid's (MG) power production is sufficient to fulfill consumption during islanding. Recent research looked at the effectiveness of using circuit breakers, under-frequency or under-voltage relays, hardwired logic, and programmable logic controllers (PLC) to improve MG Island's efficiency[313].

Load balancing is an essential approach for minimizing cascade failures within a microgrid, as it guarantees a consistent allocation of electrical demand throughout the network[314]. Load balancing is a crucial technique in microgrids since it effectively manages the distribution of loads[315]. By dynamically optimizing load distribution, load balancing eliminates the occurrence of localized overloading and minimizes stress on specific components within the microgrid. This strategy aids in mitigating the accumulation of excessive demand on individual nodes or sections, hence decreasing the probability of equipment failures and averting the domino effect that may result in cascade failures. Load balancing systems employ ongoing monitoring and dynamic adjustments to effectively distribute workloads in response to real-time fluctuations in demand and supply situations[316], [317]. Load balancing techniques have the capability to promptly adjust and redistribute power in the face of faults or disruptions, ensuring the preservation of equilibrium and averting the propagation of failures inside the microgrid. The use of proactive strategies for managing electrical loads plays a crucial role in improving the overall resilience and dependability of microgrids, hence reducing the potential for cascade failures.

8.1.4 FACTs devices:

Flexible AC gearbox (FACTS) devices, which have many applications in today's power system, have been used to improve MG stability [318]These electronic devices are in charge of addressing a number of challenges that cause MG instability, such as MG power quality improvement, transient mitigation, real and reactive power compensation, voltage management, and power flow regulation. The comprehensive probabilistic model of the system was created to improve stability. Results indicated that UPFC insertion improves power system network transient stability and resilience better than other methods in the literature[319].

The classification of FACTS devices is as follows: series controller, shunt controller, series-series controller, and series-shunt controller[320]. Even so, it resulted in an enhancement of power flow quality across all the various locations within the multi-microgrid system. Furthermore, the Unified Power Flow Controller (UPFC) provided substantial transient stability in the event of a fault. The findings provide diverse perspectives on the management of power flow in multi-microgrids[321].

UPFC has better performance in rapidly stabilizing the electrical grid, particularly when faced with more frequent transients caused by numerous interval faults, as compared to other controllers[322], [323]. The study determined that algorithms based on the Unified Power Flow Controller (UPFC) were successful in effectively reducing the occurrence of cascading outages in severe fault scenarios. This concept was also prominently emphasized in reference[323]. In order to achieve load flow balancing and evaluate transient stability in numerous interconnected Renewable Integrated Power Grids (RIPGs), [155]the implementation and optimization[324] of a Unified Power Flow Controller (UPFC) is employed. The assessment of transient instabilities, as mentioned above, under multiple faults is conducted solely using the UPFC. The failure of a network node resulting from an overloaded condition is mitigated by UPFC, which is shown by the green color in clusters as depicted in Figure 31. UPFC enables efficient compensation of future contingencies caused by severe multiple-interval failures in the power system.

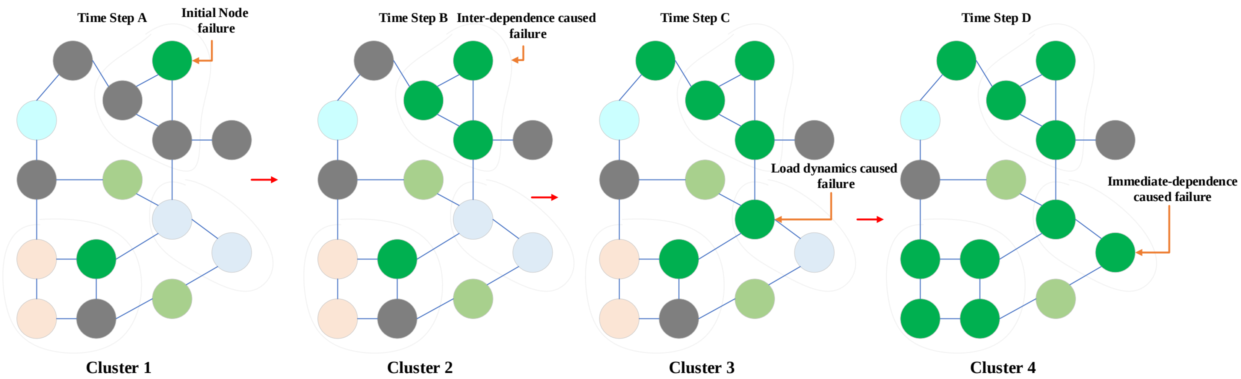

Figure 31: UPFC can be used to mitigate cascading failure events in multiple power grid stations.

Microgrids can efficiently manage cascading failures by utilizing the Unified Power Flow Controller (UPFC), a device that actively regulates power flow and enhances grid stability. The Unified Power Flow Controller (UPFC) ensures rapid and accurate regulation of voltage and power flow to prevent the exacerbation of imbalances that may trigger a cascading failure in the case of interruptions or malfunctions. The UPFC enhances power transfer efficiency and microgrid resiliency by dynamically adjusting the impedance of transmission lines, hence minimizing component stress. The Unified Power Flow Controller (UPFC) efficiently compensates for both reactive and active power, leading to enhanced voltage level stabilization and optimized overall system performance. If the device possesses the capability to mitigate temporary disturbances and promptly adapt to fluctuations in the power grid, it will have the capacity to prevent failures inside the microgrid from propagating. To proactively enhance microgrid resilience and reduce the probability of failure cascades, the UPFC employs its precision control and optimization capabilities.

8.1.5 Resource forecasting:

Due to the lack of clarity regarding RESs, it is unclear how much energy can be generated from them to meet the load demand in the islanding MG. This means that until noncritical load shedding occurs, the system will remain unstable. It is possible to use resource forecasting to deal with this problem by employing a variety of time series and AI-based algorithms for different facets, as depicted in Figure 32.

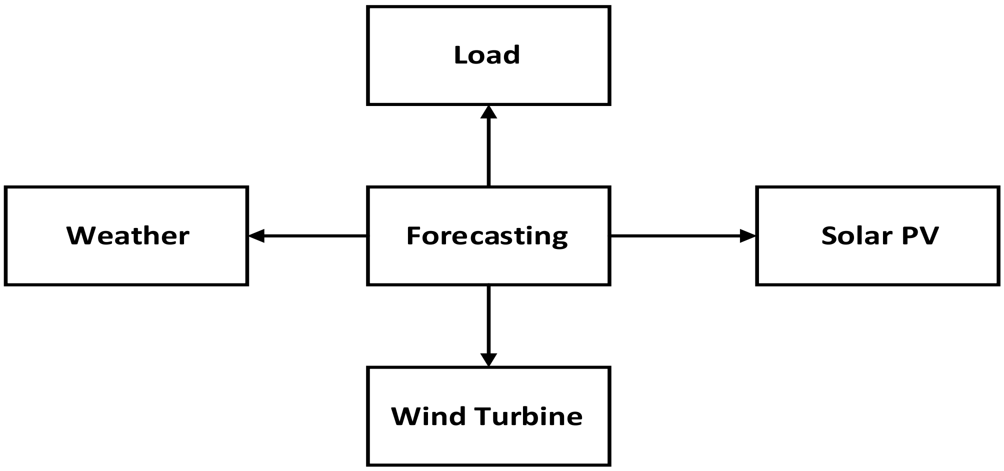

Figure 32: Resource forecasting

In order to ensure the MG's steady functioning, precise parameter estimates as well as any inherent uncertainty must be taken into account.[318] This MG stabilization is achieved by balancing the predicted power generation of the H_MG system with its total power consumption. Various techniques in the fields of Machine Learning (ML), Deep Learning (DL), and Artificial Intelligence (AI) can effectively predict electric power, and there is also ongoing research on combining different approaches[325].

The approach of resource forecasting is crucial when addressing the issue of microgrid cascade failures. Solar photovoltaic (PV) and wind power are among the numerous renewable and alternative energy solutions that necessitate consideration. Operators can enhance their decision-making about energy allocation and demand management by utilizing predictive analysis, which offers insights into how different renewable sources will contribute to power generation. Microgrid operators can effectively regulate power distribution to ensure a consistent demand by taking into account the possible fluctuations in energy supply from renewable sources like solar photovoltaic (PV), wind, and other sources. This approach allows for the efficient usage of existing resources while mitigating the possibility of overburdening system components. The use of this methodology is of utmost importance in facilitating the assimilation of intermittent energy sources, enabling the microgrid to adapt its structure in response to projected energy variations. The utilization of resource forecasting in microgrids improves their resilience by proactively mitigating imbalances, making a substantial contribution to the overall stability and guaranteeing the reliability of the microgrid's varied energy portfolio.

In Table 6, we compare the aforementioned methods for MG stability and highlight their respective benefits and drawbacks.

Table 6: Comparison of methods for MG stability

Method	**Pros**	**Cons**

Micro grid stabilizer	• Better damping. • Better dynamic stability. • Fewer power losses.	• Ineffective at various operating points. • Slow action.
Electrical energy storage devices	• Improved reliability and quicker reaction times. • Rapidly expanding technology emergency backups all help to facilitate the efficient use of RESs.	• Physical dimensions and price Effects on the environment safety concerns. • Rating and capacity problem.
Load balancing	• Maintains power balance and Enhances variable generating system stability. • Avoids rapid and dynamic frequency/voltage deviations.	• The condition of 100% load demand fulfilled not succeeding. • Fast response controllers are involved, and adaptive controllers are necessary.
FACTs devices	• Voltage regulator. • Pollution-free. • Increased system capacity and reliability. • Power compensation	• High initial investment. • High maintenance. and repair costs. • Complex installation.
Resource forecasting	• Planning and designing become easier coordination is bettered. • System performance is improved with knowledge of anticipated uncertainties • It is cost-effective.	• Time-consuming. • Inaccurate. • Resource-intensive. • Providing incomplete and incorrect data.

Table 7 provides a summary of the comparison between the linked reviews and the novelty of our review work. The review conducted previously lacked a full analysis of several cascading failure approaches, including their respective advantages and drawbacks. Our review exhibits inherent dissimilarities as a result of the comprehensive exposition of various cascading failure topologies, artificial intelligence (AI), alternative and renewable energy approaches, the Probabilistic method, the digital twin method, the metaverse, and the comprehensive microgrid control method for evaluating cascading failure within the microgrid. Additionally, we address the existing challenges, potential solutions, and prospects in this domain.

Table 7: Summary of the Comparison between the Existing Review and Our Work. Note: PY: Published Year; CF: Cascading Failure Mitigation; DSM: Dynamic Simulation Method; AI: Artificial Intelligence; RES: Renewable Energy Systems; PSM: Probabilistic and Stochastic Method CM: Control Method; BC: Block Chain; DT: Digital Twin; MV: Metaverse Ref: References

PY	Duration	CF	DSM	AI	RES	PSM	CM	BC	DT	MV	Review	Ref
2015	2001-2015	✓	×	×	×	×	×	×	×	×	Predicting natural disaster-related power system disturbances, hardening operations, and preventing cascading failures are covered.	[326]
2016	2001-2016	✓	×	✓	✓	×	×	×	×	×	Microgrids with high renewable energy penetration and failure diagnostics enable condition-based maintenance and reduce cascading failures. Various microgrid fault diagnosis methods are given.	[327]
2017	2002-2017	✓	✓	×	×	✓	×	×	×	×	An Overview of cascading failure analysis and categorization, as well as various cascading failure model advantages and disadvantages, are discussed.	[328]
2018	2011-2018	×	×	×	✓	×	✓	×	×	×	To improve grid resilience, catastrophic event features are examined, and the most investigated challenges and solutions are provided per application stage.	[329]
2019	2002-2019	✓	×	×	✓	×	×	×	×	×	Explores how environmental and man-	[330]

											made variables affect power system resilience and how smart grid technology can hasten restoration and improve resilience.	
2020	2001-2020	✗	✗	✗	✗	✗	✓	✓	✗	✗	Cyber-physical security in power systems from a microgrid perspective and related smart grid application development work are discussed.	[331]
2021	2007-2020	✗	✗	✗	✓	✗	✗	✗	✗	✗	Microgrid challenges, including protection and cyber security, and their solutions under diverse operating situations, as well as techniques, are discussed.	[332]
2022	2004-2022	✓	✗	✗	✓	✗	✓	✗	✗	✗	Various resilience microgrid challenges and distribution system resilience enhancement techniques for optimal microgrid development, scheduling, and energy management	[333]
2023	2001-2022	✓	✗	✗	✓	✗	✗	✗	✗	✗	In renewable power systems, cascading failure modeling focuses on dynamic and protection modeling and assesses methods to balance accuracy and computational complexity.	[334]
-	Up to 2023	✓	✓	✓	✓	✓	✓	✓	✓	✓	Details on cascading failure topologies, AI, alternative and renewable energy approaches, probabilistic, digital twin, metaverse, and comprehensive microgrid control	Our Work

											methods for evaluating cascading failure. We also discuss this domain's challenges, potential solutions, and future prospects.	

Table 8 provides a summary of the comparison between the linked reviews and the novelty of our review work. The review conducted previously lacked a full analysis of several cascading failure mitigation approaches, including their respective advantages and drawbacks. Our review exhibits inherent dissimilarities as a result of the comprehensive exposition of various cascading failure mitigation methods, which include microgrid stabilizers, electric vehicles, FACTS devices, load balancing, and resource forecasting to stabilize the microgrid.

Table 8: Summary of the Comparison between the Existing Review and Our Work. Note: PY: Published Year; CFM: Cascading Failure Mitigation; MGS: Micro grid Stabilizer; EV: Electric Vehicles; FD: FACTs Devices; LB: Load Balancing; RF: Resource Forecasting; Ref: References

PY	Duration	CFM	MGS	EV	FD	LB	RF	Review	Ref
2015	2001-2015	✓	×	×	✓	×	×	Statistical analysis of prior pre-event data and online monitoring of the most predictive aspects for near-future failure prediction and mitigation improve resilience and reduce maintenance costs.	[335]
2016	1998-2015	×	×	×	✓	×	×	Grid integration, power quality, and cost-effective custom power and FACTS device solutions for wind and solar energy systems are discussed.	[336]
2017	1999-2014	×	✓	×	×	×	×	Based on the microgrid characteristics analysis, which includes operating mode, disturbance types, and time frame, a stability classification approach is provided.	[337]
2018	2000-2017	×	×	×	×	✓	×	A large microgrid stabilization system classification is provided. Stabilization methods include feeder, intermediate, and load side compensation. The pros	[338]

								and cons of each generic strategy are discussed.	
2019	2007-2019	×	×	✓	×	✓	×	The use of load management and EV mitigation measures can prevent voltage variation and other power quality issues related to high PV penetration in LV networks.	[338]
2020	1995-2020	×	×	×	✓	×	×	Distributed flexible AC transmission system (DFACTS) devices like DSTATCOM and DVR help reduce power quality difficulties caused by renewable energy integration.	[339]
2021	1997-2021	×	×	✓	✓	×	×	MG control systems, challenges linked to utility grid interconnection, potential solutions, and economic and market factors for MG commercialization are discussed.	[340]
2022	1994-2022	×	×	×	×	×	✓	Hybrid machine learning (ML) methods are most prevalent for forecasting power demand. Discussed single and hybrid forecasting model pros and cons.	[341]
2023	2001-2022	×	×	✓	×	×	×	EV integration in distribution networks and power quality issues such as voltage imbalance, transformer failure, and harmonic distortion are investigated. A detailed power quality study and mitigation strategy are provided.	[342]
-	Up to 2023	✓	✓	✓	✓	✓	✓	Details on cascading failure mitigation methods, which include	Our Work

								microgrid stabilizers, electric vehicles, FACTS devices, load balancing, and resource forecasting to stabilize the microgrid.	

9 Conclusion and Future Trends

This review provides insight into the complex issue of cascading failures in smart grid systems. The paper thoroughly examines several techniques for mitigating cascading failures and also discusses the constraints of previous studies. This study offers a novel viewpoint by thoroughly examining cascading failure topologies, identifying their critical variations, and presenting the corresponding mitigation strategies. This paper will comprehensively examine several aspects of smart grid dynamics, including artificial intelligence (AI), strategies for renewable energy, the probabilistic approach, digital twins, the metaverse, microgrid control, and hybrid techniques including self-propagation and affinity propagation clustering. Addressing these areas provides a thorough understanding of the complexities of micro grid dynamics. The identification of crucial nodes and the prioritization of mitigation techniques are key components in establishing a strong basis for improving the resilience of micro grid systems.

Perform iterative optimization research to refine the parameters and methods utilized in the hybrid methodologies of self-propagation and affinity propagation clustering. This study aims to investigate machine learning methodologies for the purpose of dynamically adapting hybrid strategies to the changing conditions of micro grids. Engage in collaborative efforts with utility companies and smart grid operators to undertake comprehensive field trials, which involve simulating a wide range of scenarios and subjecting the hybrid clustering methodologies to rigorous stress-testing. This study aims to assess the scalability and adaptability of the employed methodologies in different micro grid topologies and sizes. This study aims to examine the current advancements in artificial intelligence (AI) algorithms, including deep learning and reinforcement learning, and evaluate their potential collaboration with hybrid clustering methodologies. The objective is to design adaptive algorithms capable of iteratively enhancing their performance by leveraging real-time data feedback. The establishment of industry collaborations is crucial for the collaborative development and implementation of hybrid clustering approaches within operational micro grid environments. In order to effectively tackle practical difficulties and enhance the procedures, it is imperative to integrate feedback received from industry stakeholders. Participate in collaborative standardization initiatives with pertinent organizations to provide comprehensive industry-wide protocols for the integration of hybrid clustering methodologies inside micro grid systems. This proposal aims to effectively resolve interoperability concerns and guarantee seamless integration with established smart grid standards and protocols.

This paper aims to investigate the utilization of augmented reality (AR) and virtual reality (VR) technologies in the metaverse for the purpose of conducting immersive analysis of smart grid data and cascading failure scenarios. This study aims to explore the possibilities of metaverse technologies in the context of training and simulation for grid operators. It is imperative to closely observe the progress made in energy storage technologies, including sophisticated battery systems and supercapacitors, in order to enhance the incorporation of renewable energy sources into intelligent power grids. This study aims to explore novel approaches for demand response and load balancing within smart grid systems that are abundant in renewable energy sources. It is imperative to remain updated on advancements in the field of explainable artificial intelligence (AI) in order to augment the interpretability and reliability of AI models employed in smart grid applications. This study aims to investigate the utilization of swarm intelligence and ensemble learning approaches to enhance the robustness and adaptability of artificial intelligence (AI) systems in the domains of cascading failure prediction and mitigation. This study aims to investigate adaptive control systems that possess the capability to dynamically adapt to various disturbances, including cyber-attacks and physical failures, in order to maintain the resilience of microgrid operations. This study aims to examine the integration of energy-efficient and fault-tolerant components inside microgrid control frameworks. This paper aims to investigate the incorporation of blockchain technology and smart contracts to provide secure and transparent energy transactions within smart grid systems. This study aims to examine privacy-preserving blockchain systems that can effectively safeguard sensitive smart grid data, while also assuring data integrity and traceability. Facilitate collaborative research initiatives involving computer scientists, power systems engineers, cybersecurity experts, and policymakers to address the diverse challenges of smart grid resilience. Promote knowledge exchange through workshops and conferences, fostering a holistic approach to cascading failure mitigation in smart grids.

10 References

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