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Review

Survey of Reliability Challenges and Assessment in Power Grids with High Penetration of Inverter-Based Resources

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Abstract: Decarbonization is driving power systems toward more decentralized, self-governing models. While these technologies improve efficiency, planning, operations, and reduce the carbon footprint, they also introduce new challenges. In modern grids, particularly with the integration of power electronic devices and high penetration of Renewable Energy Sources (RES) and Inverter-Based Resources (IBRs), traditional reliability concepts may no longer ensure adequate performance due to systemic restructuring. This shift necessitates new or significantly modified reliability indices to capture the characteristics of the evolving power system. Ensuring converter reliability is essential for effective planning, which requires precise, component-to-system-level modeling, as different converters impact system performance indicators. However, the existing literature in this field faces a significant limitation, as most studies focus on a singular perspective. Some examine reliability at the device-level, others at the component-level, while broader reviews in power systems often emphasize system-level analysis. In this paper, we aim to bridge these gaps by comprehensively reviewing the interconnections between these levels and analyzing the mutual influence of power converter and system reliability. A key point to highlight is that, with the rapid evolution of modern power grids, decision-makers must adopt a multi-level approach that incorporates insights from all levels to enable more accurate and realistic planning and operational strategies. Our ultimate goal is to provide an in-depth investigation of studies addressing the unique challenges posed by modern power grids. Finally, we will highlight the gaps in the literature and suggest directions for future research.

Keywords: reliability; power system; modern power grid; microgrid; active distribution network; power electronics; power converter; renewable generation; inverter-based resources

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1. Introduction

In recent years, there has been a significant shift in electrical power devices and systems, driven by the increasing focus on achieving carbon-zero generation. Power systems are transitioning from traditional centralized power generation to new decentralized architectures. With the growing use of Distributed Generations (DGs) in distribution systems and the rising penetration of Renewable Energy Sources (RES) at both the transmission and distribution levels, Inverter-Based Resources (IBRs), such solar, wind, and batteries, are becoming central to future power systems. As shown in Figure 1, traditional power systems have been dominated by synchronous generators with high rotational inertia and relatively low integration of IBRs. In future systems, a significant portion of generation will be interfaced with power electronics and inverters [1]. In these modern grids, traditional reliability concepts may no longer ensure adequate performance due to systemic restructuring. The conventional approach, which primarily emphasizes adequacy and security indices, is now being challenged by the evolving landscape of power generation and distribution. DG utilizing RES and control switches may significantly enhance grid reliability, save costs, and alleviate environmental impacts [2]. In the context of power converters, reliability fundamentally pertains to the system's capacity to function effectively without failure and within established performance boundaries over a specified time frame.

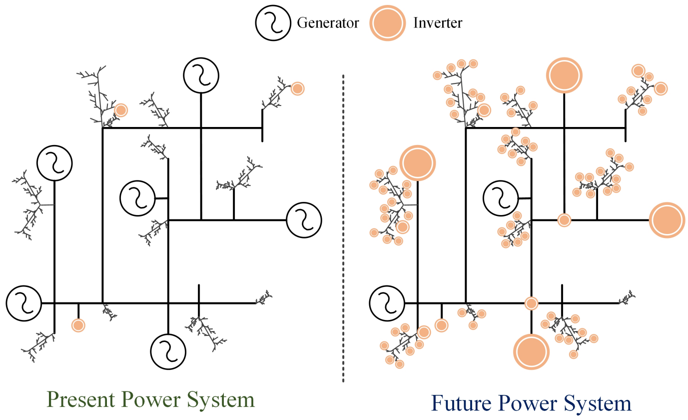

Figure 1. Changes in the electric power system due to the integration of IBRs [1].

Studies on reliability assessment can generally be categorized into two layers: (1) system-level assessments and (2) component-level assessments. Both face distinct challenges, such as issues arising from Microgrid (MG) operations, the integration of RES and IBRs, and the complexities introduced by power electronic devices. System-level studies focus on assessing, enhancing, or modeling the overall reliability of power systems by evaluating various components, such as lines, transformers, buses, converters, and loads. These studies treat the components as part of a unified system, without delving into the specific reliability or aging processes of individual elements. This approach prioritizes the performance and robustness of the system as a whole. In contrast, component-level reliability assessments aim to evaluate, model, and improve the reliability of specific components, such as converters, by examining their failure modes, aging mechanisms, and operational stress factors. By focusing on individual components, these studies provide critical insights into how component-level performance can influence overall system reliability.

Integrating any type of resource into the distribution network transforms it into an Active Distribution Network (ADN), providing several benefits, such as reduced power losses, improved voltage profiles, enhanced stability and reliability, and cost savings. However, there are also disadvantages due to the uncertain nature of RES, which can introduce protection issues and lead to reliability issues due to varying operating conditions. As mentioned, reliability is defined as the ability to supply load without interruption and ensure a reliable power supply for electricity customers within the grid. In addition to the characteristics of ADNs, the concept of Smart Grids (SGs) includes the implementation of Demand Response (DR) programs and consideration of a new communication layer in the system. While these advancements enhance the reliability and functionality of the grid, they also introduce cybersecurity challenges and increase the overall complexity of the system.

Recent years have seen a rapid advancement in MG study, development, and deployment, with particular emphasis on control, protection, operation, and planning techniques being researched more comprehensively. MGs are ADNs that incorporate Distributed Energy Resources (DER), including DG and Energy Storage (ES), and may function in both grid-connected and autonomous island modes [3]. The primary objectives of MGs are to enhance the reliability of the distribution system, facilitate the integration of RES, provide islanding capability, and increase generating efficiency within a sustainable power grid. Power systems researchers generally have been encouraged to use state-of-the-art technology in the design of reliable MG systems by the improvement of power electronics research efforts and control methodologies for their inverters and hybrid AC-DC MGs [4,5]. Enabling the increase in RES integration rate is one of key advantages of MGs, which simultaneously reduces grid energy demand and dependency on fossil fuels. Additionally, MGs can enhance system reliability by supplying power to local loads during upstream grid failures through islanding operations [6].

As mentioned, Energy Storage Systems (ESS) has a crucial role in reliability enhancement. ESS are among the best solutions for supplying load during periods when RES are insufficient. It is important to note that the performance of both ESS and RES is heavily dependent on the reliability of their inverters. This highlights the critical importance of inverter reliability in modern power grids with high penetration of RES and ESS. The authors of [7] investigated this impact and generally categorized that (1) ES significantly improves system reliability and reduces transmission upgrade costs and (2) policies promoting a shift from fossil fuels to RES support the development of ESS. There has been a transition from fresh batteries to Second Life Batteries (SLBs) in recent years. SLBs can fulfill the requirements of modern grids for frequency management, power smoothing, and peak shaving. Furthermore, these retired batteries may also be utilized for generating income through Energy Arbitrage (EA) and saving in terms of the capital cost of acquiring the ESS. The authors of [8] proposed a comprehensive review of the SLB's role in the power grid and their reliability influence. Electric vehicles (EVs) are considered a key solution for reducing global warming and advancing battery technology. Their adoption is expected to lower emissions in both transportation and power sectors, driven by rising fuel prices and fossil fuel limitations, especially in industrialized cities over the past decade [9]. The authors in [10] address the allocation problem of electric vehicle parking lots by incorporating their ancillary services into both reliability and operational planning. EVs play a significant role in modern power systems and can impact system reliability by imposing substantial demand on the grid. Their integration adds further complexity to reliability assessments in these evolving systems. This influence has been studied by [11], which also includes a techno-economic evaluation of the system reserves required for reliable operation.

In addition to the challenges and opportunities introduced by the high penetration of IBRs and modernization of the grid, many studies have evaluated the reliability of new power system components in isolation. In the system-level perspective, identifying critical components in a power system reliability evaluation has raised much scholarly interest [12–16]. These include most critical components such as ESS [14], transformers [12,13], and load points [15]. The reliability of power systems with RESs such as Wind Turbines (WTs) [17] or solar Photovoltaics (PVs) is investigated in [18]. Nevertheless, the reliability of converters has rarely been considered as a potential factor contributing to system failures in previous studies. The influence of converter reliability on overall system reliability has been discussed in only a few studies [19,20]. The authors in [20] proposed a kind of sorting for multiple converters due to their influence on the system-level reliability. However, the reliability relation between different converters and components has not been investigated. In this concept, the expected end-of-life of converters is really important for the advancement of power systems [21].

In addition to research papers, review papers have been thoroughly investigated here, with a summary of these studies provided in Table 1. To compare, the studies of [7,22,23] provide high-quality investigations into ESS and power electronic devices technologies within SG and MG reliability assessment methods. However, these studies lack a system-level reliability perspective. On the other hand, review papers such as [24–29] focus on evaluating power system reliability but tend to overlook the critical importance of component reliability modeling, which is essential for comprehensive system reliability assessment.

The introduction of new technologies in modern power systems—such as DG, ESS, MG, DR, and EV—offers new opportunities to enhance reliability but also poses significant challenges for reliability assessment methods. A key challenge in systems with high integration of IBRs is the need to evaluate both component-level and system-level reliability within the same study; a gap identified in the current literature. As shown in Table 1, even review papers tend to focus on one perspective, either addressing converter reliability modeling or power system reliability assessment, but rarely both, while in this study, we comprehensively review reliability modeling and evaluation methods for both power electronic devices and power systems. Additionally, we examine research that investigates the interconnections and dependencies between equipment and system reliability, highlighting gaps in the literature and suggesting future research directions to support the development of zero-carbon power systems with renewable energy integration. We aim to explain the challenges of future power grids while introducing solutions for enhancing system reliability in terms of operation and planning.

Table 1. Summary of key review papers on power system reliability and limitations regarding IBRs.

Refs.	Domain	Focus	Limitation Regarding IBR
[7,22]	Impact of ES on reliability and its applications	ES	System-level reliability consideration
[23]	Reliability assessment methods for SG and MG components	New reliability assessment method and modern power system component	
[24,25]	Impact of DG integration on reliability	DG	Lack of focus on power converter reliability modeling
[26]	Reliability assessment methodologies	Comparison of various reliability evaluation methods	
[27]	Power systems reliability regarding adequacy and security enhancement	Power system maintenance	
[28]	Impact of DER on distribution system reliability	Control, protection and communication technologies	
[29]	Impact of information and communication technologies integration on system reliability	Cyber system integration	Component-level reliability considerations
This review	IBR-penetrated grids with a multi-level perspective	Modern power system reliability challenges and IBR reliability modeling	Addressing this gap in the literature

The remainder of this manuscript is organized as follows: Section 2 provides a detailed explanation of the modern power grid and the challenge of reliability assessment in it. An overview of reliability concepts and metrics, along with power system and power converter assessment methodologies, is thoroughly presented in Section 3. Section 4 provides a detailed outline of various reliability enhancement approaches, with a focus on the system levels. Finally, Section 5 summarizes the key findings and future directions, and Section 6 provides the conclusion of this paper. It should be mentioned that the authors also acknowledge the use of ChatGPT-4, Quillbot, and Grammarly for English writing assistance and grammar checking throughout the preparation of this manuscript, ensuring that the language is accurate and professional.

2. Modern Power Grid

2.1. Power Grid Architecture

Conventional power systems rely on large-scale thermal power plants to generate electricity, which is then delivered to customers through centralized transmission and distribution networks. System operators centrally manage operations and planning, handling tasks like market regulations, energy management, unit commitment, power flow, and protection strategies. On the other hand, in recent years, planners have also incorporated renewable energy generation into their long-term strategies at both the generation [30,31] and distribution levels [32].

The rapid growth of renewable energy technologies has significantly reshaped the power and energy markets, leading to a transformation in power system architecture. DG has gained prominence, with large-scale renewable installations, such as solar parks and wind farms, now integrated into transmission and medium-voltage distribution networks [24]. This integration has transformed distribution systems into ADNs and SG [33], shifting from traditional, one-directional power flow to a more dynamic, bidirectional system. With the increasing integration of RES, the need for ESS to smooth power and voltage fluctuations becomes essential. Additionally, EVs will have a significant impact on modern power systems. Figure 2 highlights the key differences and features between conventional and modern power systems.

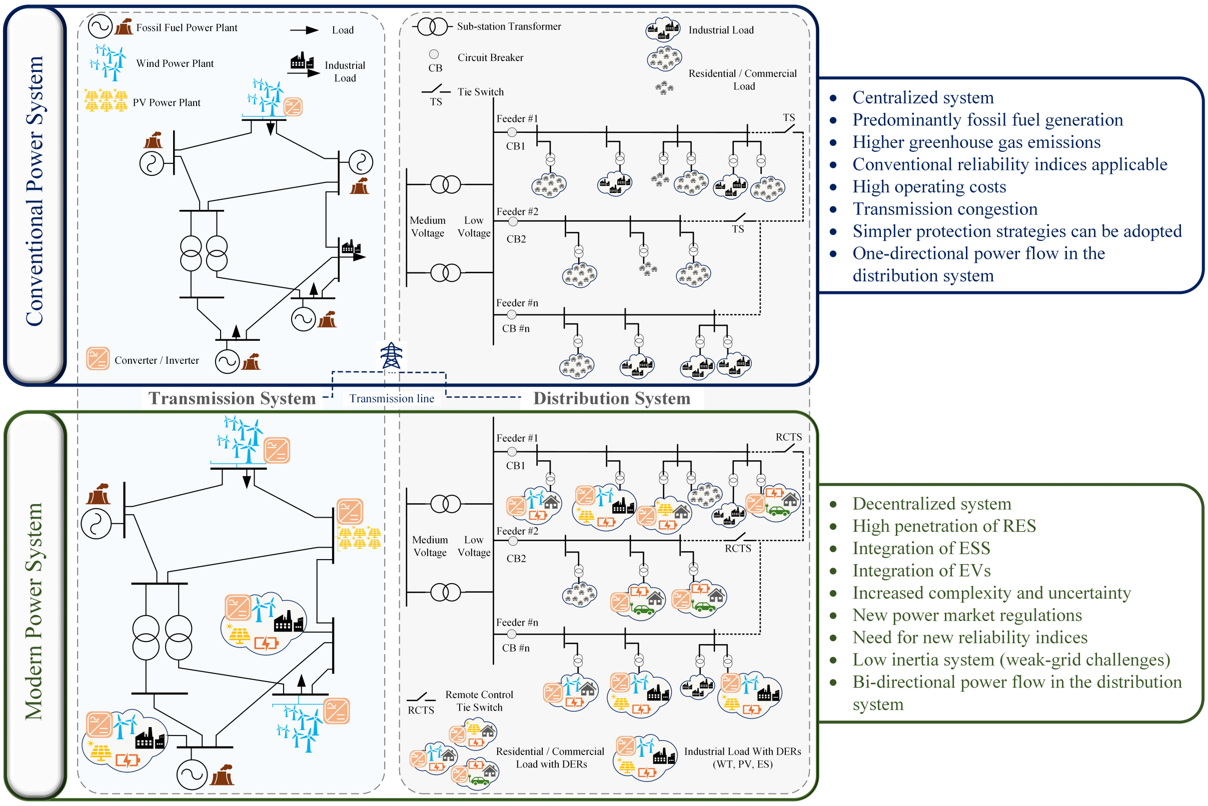

Figure 2. Key differences and features between conventional and modern power systems.

The uncertainties in the planning and operation of the distribution networks rooted in the high penetration of RES and DGs could carry a destructive impact on reliability. Accordingly, appropriate actions should be taken to maintain the reliability parameters within the specified limits [24]. Instability in the RES supply combined with unpredictable changes in demand over time has created a significant risk for sustaining system dependability in terms of an adequate supply of customers [22]. A MG, as a cyber-physical system, relies heavily on the cyber system for coordinated control of its units. Any performance degradation in the cyber system, such as outages or transmission delays, can compromise the stable operation of the MG [34]. In addition to conventional, single-owner ES in the grid, Cloud Energy Storage (CES), which aggregates grid-scale storage resources, can significantly improve the cost-effectiveness and reliability of MG operations [35].

The unpredictability associated with RES and loads can significantly undermine MG reliability and adversely impact its capacity to deliver power to consumers with adequate quality [36]. Under these circumstances, DR programs can significantly contribute to managing demand loads and improving the reliability of MGs [37]. The development of intelligent devices in SG enables the active involvement of responsive loads in demand response programs [38]. In these SGs with high integration of RES, DR is always one of the beneficial solutions to deal with uncertainty in production DGs production [39]. The authors in [40] also highlighted the reliability benefits of DR programs, discussing how they enhance network utilization and improve system reliability.

2.2. Integration of Power Electronics Devices

As a key component of future power grid upgrading, power electronics reliability has recently attracted a lot of attention [41]. It is essential to emphasize the significance of power electronic converters and examine their possible impacts while evaluating the stability of a power system among the development of RES and power electronic interfaces [20]. EVs, ESS, high- and medium-voltage direct current (DC) transmission and distribution systems, and RES all rely on power converters as their primary energy conversion mechanism [42]. Nevertheless, based on industry knowledge, it appears that the converters are the weakest parts of the system regarding reliability issues.

Effective planning, including cost-effective design and replacement scheduling, relies on the converter's lifetime [21]. Since converter failure rates impact availability and operational efficiency, proper reliability modeling is essential for scheduling maintenance, repairs, and replacements. Additionally, reliability modeling is crucial for designers to ensure optimal and reliable converter manufacturing [19]. The decision-making for investment in manufacturing, system-level planning, operation, and maintenance of power electronic systems emphasizes the value of predicting converter reliability [43]. Nonetheless, failures arising from power electronic converters linked to RESs in the system-level assessing still do not attract much interest in the majority of current research. Experimental data and practical experience reveal that power converters frequently contribute to failures in different electrical applications [44]. As further converters are incorporated into the system, interactions among them will increasingly arise, hence raising issues over overall system reliability. However, causal relationships regarding reliability have not often been investigated and articulated clearly. The authors in [45] utilized a Bayesian Network (BN) structure to visualize the causal relationships in a converter-based power system.

2.3. Reliability in MG Operations

The growing prevalence of DERs and the consequent decentralization of power generation have fostered the concept of MG in Electricity Distribution Systems (EDS) as autonomous entities capable of functioning independently from the primary grid [46]. Furthermore, MGs are rapidly gaining attention as a method of improving reliability and security [47]. They have the advantage of employing RES and DGs in the grid. In addition to the shift toward interconnected MGs in the system, current power infrastructure also integrates DC-based DERs, including DG and ES. Moreover, a significant portion of modern electrical loads, including variable speed drives and EV chargers, operate on DC power. The DC characteristics of DER technologies have driven the development of DC microgrids (DC-MGs), leading to their rapid adoption [48,49]. The reliability analysis of DC-MGs that are mostly powered by renewables is investigated by [47]. In theory, MG reliability specifies that the local power supply must be enough to fulfill local-load reliability requirements during islanding [50]. Nevertheless, unexpected failures could leave the local generation inadequate to meet the total demand, so providing loss of load or load shedding inevitable. Moreover, during islanding, renewables-dominated DC-MGs may have little alternative but to reduce their renewable energy output during times of generating surplus and when ES units are unavailable or fully charged. Subsequent partial reduction in the renewable power supply may become unavoidable during islanding. The authors of [51] address the stability and reliability challenges in island power systems with high levels of IBRs, focusing on short timescales and discussing the role of ES, modeling techniques, and advanced control methods in stabilizing grids with high shares of RES.

The reliability of MGs has been investigated by numerous studies [34–36,52–58]. Ref. [34] demonstrated that features of cyber systems, including topology, failure rates, communication-link time delays, and attack-based data manipulation, may significantly impact MG reliability. Incorporating CES into EDS, especially in scenarios involving multi-MGs alongside RES and micro-turbines, significantly enhances reliability and reduces electricity costs for the MGs [35]. The authors in [52,53,58] focused on the reliability of AND with AC-MGs. Ref. [53] offers methods for grouping ADN into a group of MG with optimal supply-adequacy and reliability indices. The impacts of protection-related issues on MG reliability have been investigated in [54,55].

Furthermore, [56] examined the reliability of decentralized vs. centralized MGs, with an emphasis on how decentralizing the control architecture may improve MG reliability. In [57], the influence of the control method is evaluated in the short-term reliability evaluation, precisely representing the short-term reliability level of the islanded MG. Ref. [36] proposed short-term optimal scheduling of autonomous MGs to assess the impact of DR programs on reliability and economic factors concurrently. Ref. [58] proposed a new evaluation framework for ADNs with multi-MGs reliability assessment. Another study [59] aims to propose a model for the reliability of self-controlled DER-rich MGs from the EDS prospect. An overview of reliability evaluation studies that considered DG integration is presented in Table 2.

Table 2. Summary of reliability assessment studies with MG consideration.

Refs.	Test System	Reliability Indices	Including
	IEEE Bus Systems		
[59]	Modified IEEE 33-bus (EDS)	CAIDI, ENS, SAIDI	RES and ESS
[35]	Modified IEEE 33-bus (EDS)	ENS	RES and ESS
[53]	IEEE 69-bus (EDS)	SAIFI, SAIDI, MAIFI	RES and ESS
[58]	RBTS-Bus6 F4 and EDS in Northwest China	ASUI, ASAI, EENS, SAIDI, SAIFI	RES and ESS
[60]	RBTS-Bus2 (EDS)	SAIDI, SAIFI, CAIDI, ASAI	RES and ESS
[47]	IEEE 15-bus with islanded DC-MG	LOSE, RIVE, ROPE, LOLE	RES (No ESS)
[49]	RBTS-Bus6 F4 (EDS)	ASUI, ASAI, EENS, SAIDI, SAIFI	RES (No ESS)
[52]	IEEE 37-bus (ADN)	Maximum power mismatch	ESS (No RES)
	Standalone MG Systems		
[54,55]	Modified 0.4 kV MG network	SAIFI, SAIDI, ENS	RES and ESS
[61]	Standalone MG (Kandla, India)	EENS, LOLE	RES and ESS
	Cyber-Physical Systems		
[34]	MG network with cyber-physical layer	EENS, LOLP, SAIDI	RES and ESS
[62]	Cyber-physical MG	SAIDI, EENS, LOLOP	RES and ESS

2.4. Challenges in Modern Power System

Significant research has been conducted on power system reliability, with many methods improved to account for RES contingencies and variable load demands in the new power system structure. However, outages caused by RES-connected power converters remain underexplored. Converter reliability is evaluated based on the performance of its critical components [63], involving two layers: the device level and the converter level. Challenges related to the reliability of power electronic devices, including semiconductors, switches, and overall converter performance, are often overlooked. In many studies, the failure rates of these components are either assumed constant or largely ignored.

Additionally, several studies have developed reliability models for various power system components, taking into account the impact of mission profiles and operating conditions on their reliability. For example, the aging effects of power transformers were considered in [12], though other components were assumed to be fully reliable. The authors in [44] conducted a reliability assessment for critical components of a WT converter, taking into account the thermal stress of each component. Reliability assessment for a DC-DC boost converter integrated with PV panels was conducted to improve efficiency in [64]. In another study [65], a time-varying reliability model for generation units with high WT integration was proposed, but potential failures in WT-connected converters were not addressed. Given that power converter failures are among the most frequent in IBR-penetrated grids [41], more attention should be directed toward modeling their reliability. This will be thoroughly examined in Section 3.3.1.

2.4.1. Distribution System Reliability

As previously mentioned, there has been a dramatic rise in research on EDS reliability due to the increasing reliance of modern society on electric energy [66]. The expansion of RES has been closely accompanied by the integration of various power electronic converters, which play a critical role in energy conversion [21]. As a result, the modern power system is much more complex than a typical power system from the reliability aspect. In particular, the reliability of the EDS is critical to the overall satisfaction of customers, making it more important than any other sections of the power system. Minimizing outages for EDS customers is therefore a key focus of reliability enhancement policies. This can be performed by reducing the outage duration and failure rate of the components. The EDS components failure rate can be reduced by maintenance actions [67].

The transition of EDS toward ADN and SG with the integration of MGs have made their reliability assessment more challenging. Evaluating the system's reliability in such a complicated environment calls for developed methods that are tailored to the new characteristics of EDS. In this context, the challenge of modeling MGs in a reliability-oriented manner has been addressed by [59]. The authors in [63] proposed an inclusive methodology for power system reliability evaluation taking into account the impact of uncertainties in different power convert. Although the complexity of RES-integrated power systems makes it difficult to assess the reliability of the whole system, authors in [18] proposed a reliability model for grid-connected PV power systems.

2.4.2. Voltage Related Issues

Furthermore, DC-MGs are vulnerable to failures, which can result in poor voltage quality during islanding. A key issue is the potential for voltage spikes caused by the high penetration of RES, especially since renewable-based DG systems often operate in Maximum Power Point Tracking (MPPT) mode, leading to unregulated voltages during periods of surplus power [68]. High voltages are undesirable as they can damage sensitive equipment and increase the risk of droop-based DER failures due to reverse power flow [50]. These challenges complicate reliability evaluations and hinder both effective islanding and stable MG operation, where maintaining proper voltage levels and ensuring supply adequacy during islanding are crucial. In addition, it requires voltage-controlled DERs, which can achieve voltage regulation through voltage droop control. The benefit of this method is that DERs use only local voltage and current measurements, allowing them to adjust their reference voltages to stabilize system voltage and evenly distribute the load [50]. The authors in [69] presented a new method for active Power Factor Correction (PFC) using a dual-purpose inverter, aiming to reduce Total Harmonic Distortion (THD), improve power factor, and enhance converter reliability under both normal and outage conditions.

3. Overview of Reliability Concepts and Metrics

3.1. Reliability Assessment Methods

The primary objective of reliability assessment in power systems is to propose quantitative analysis through various indices to enhance system operation and future planning [70]. In other words, reliability studies are conducted to increase system adequacy and system security. System adequacy studies are frequent in generation and transmission sectors, while system security studies predominantly focus on the distribution network. This assessment is often conducted by simulation methods, analytical techniques, or a combination of both approaches [24].

3.1.1. Analytical Methods

Analytical methods, including Markov Process (MP) modeling, Fault Tree Analysis (FTA), BN, scenario reduction techniques, Reliability Block Diagram (RBD), Failure Mode and Effects Analysis (FMEA), minimal cutset, etc., are used. In these types of methods, the computing effort grows in proportion to the system's complexity. Table 3 provides a summary of studies that have utilized this approach. The authors in [71] conducted FTA analysis for optimal planning of transmission system. A probabilistic multi-state model for reliability evaluation of hybrid systems considering ES and MG has been explained by [61]. In [72], the authors examine the impact of DG units on reliability enhancement and use series-parallel reduction equations to evaluate reliability.

In [73], BN is employed for the reliability evaluation of modern power systems, highlighting the significance of system components and their impact on system reliability. The study showcases the BN's data-driven learning capability, enabling its application in large-scale power systems. Also, reliability analysis for IBR-integrated power systems based on BN-structure was the goal of [45]. The authors in [47] aimed to create a BN-based probabilistic graphical method for the reliability analysis of DC-MGs that are mostly powered by renewables.

Reliability assessment of the system based on minimal path has been proposed in [74]. The integration of the minimal cutset approach and FMEA is employed for the reliability evaluation of radial distribution systems in [75]. A Stochastic Infrastructure Damage Evaluation (SIDE) method for state sampling in EDS is the goal of [76]. SIDE simplifies system complexity by utilizing the concept of minimal cutsets. It focuses on critical groupings within the complex space of component failures and replaces equipment-based event trees, a type of FTA, with Partition-Based Event Trees (PBET), reducing the complexity to lower-order trees.

Table 3. Classification of research papers which utilizes analytical methods.

Refs.	Analytical Method	Test System	Including
[61]	Probabilistic upper reservoir multi-state model	Standalone MG (Kandla, India)	RES and ESS
[56]	MP	MG network with a decentralized control architecture	
[45]	BN	Modified IEEE RTS 24-bus	
[47]		15-bus islanded DC-MG	RES (No ESS)
[77]	Analytical with MILP *	RBTS-Bus4	
[75]	FMEA	IEEE 33-bus	-

* Mixed-Integer Linear Programming.

3.1.2. Simulation-Based Methods

Simulation-based methods, including Monte Carlo Simulation (MCS), effectively simulate the random behavior of the system. The simulation period is divided into basic time intervals which are selected randomly [67]. MCS is performed by Non-Sequential MCS (NS-MCS) and Sequential MCS (S-MCS). In NS-MCS simulation, sampling is conducted randomly, or it is time-independent, while in S-MCS chronological sequences are conducted at different time intervals [78]. The authors in [79] utilized MCS to identify the power system components state. Table 4 presents the classification of MCS in reviewed studies.

Table 4. Classification of research papers utilized simulation-based methods.

Refs.	Evaluation Method	Test System	Including
[80]	Sequential MCS	IEEE RTS 79-bus	RES (No ESS)
[60]		RBTS-Bus2	RES and ESS
[34]		MG network with cyber-physical layer	
[35]	Non-Sequential MCS	Modified IEEE 33-bus	
[81]	Mission-profile-based MCS	DC-MG	
[62]	Developed MCS-based	Cyber-physical MG	
[52]	Simulation-based MG topology planning	Maximum power mismatch	ESS (No RES)
[82]	MILP-based reliability-oriented planning	Dättwil district (Switzerland)	RES and ESS

MG reliability modeling for EDS has been developed in studies such as [58,83,84]. However, the method proposed in [58] is not well-suited for analytical approaches. Additionally, the models presented in [58,83,84] are oversimplified, which may lead to inaccuracies in reliability quantification. To address this, ref. [59] provides a novel approach that combines analytical and simulation-based methods to produce a quick and effective way to assess the reliability of EDS that use multiple MGs.

3.1.3. Hybrid and Data-Driven Methods

This category includes hybrid methods, which combine the two previously mentioned approaches, along with data-driven and intelligent methods, such as Artificial Neural Networks (ANN). Table 5 provide a brief review of papers in this category.

Table 5. Examples of hybrid and data-driven methods.

Refs.	Method	Test System	Research Focus
[85]	Hybrid	Brazilian EDS	DER impact
[86]		IEEE 69-bus (EDS)	EDS automation
[55]		400 V microgrid system	Protection system operation for MG
[54]	Scenario selection and enumerative analysis combined method	Modified 0.4 kV MG network	Short-term outage model for MG
[87]	ANN	EDS network	PV plant

3.2. System Reliability Indices

Reliability indices are used to quantify system reliability and can be divided into two categories: classic and modern indices. The classic indices, often referred to as customer-oriented indices, focus on traditional power systems aiming at characterizing the impact of system failures on the customers [88,89]. In contrast, modern indices have been developed specifically for modern power systems with high penetration of IBRs. Some of the reviewed reliability indices are presented in Figure 3. The most important indices include Expected Energy Not Supplied (EENS), System Average Interruption Duration Index (SAIDI), System Average Interruption Frequency Index (SAIFI), and Customer Average Interruption Duration Index (CAIDI) from the conventional indices, as well as Loss of Supply Expectation

(LOSE) and Rise in Voltage Expectation (RIVE) from the newer indices. These indices can be obtained using Equations (1)–(6).

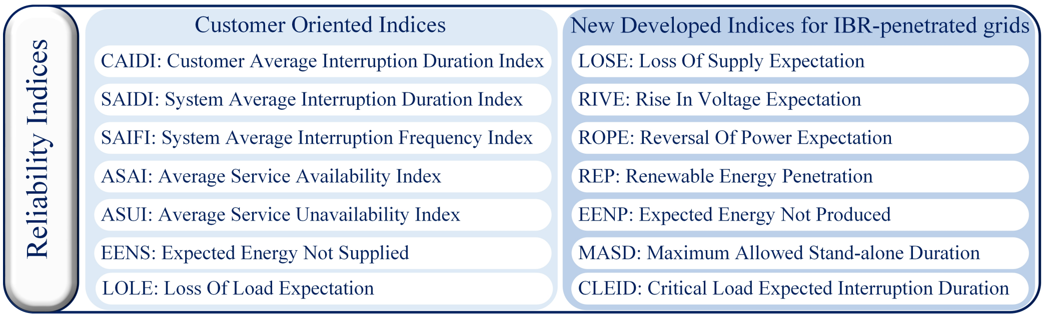

Figure 3. Overview of classic and newly developed reliability indices for power system reliability evaluation.

$$\text{EENS} = \sum_{i=1}^{N} P_{\text{outage,i}} \times E_{\text{outage,i}} \quad (1)$$

where $P_{\text{outage,i}}$ is the probability of an outage at component i, and $E_{\text{outage,i}}$ is the energy not supplied during that outage.

$$\text{SAIDI} = \frac{\sum_{i=1}^{N} U_{\text{i}} \times N_{\text{i}}}{N} \quad (2)$$

where U_{i} is the unavailability duration of component i, N_{i} is the number of customers affected by component i, and N is the total number of customers.

$$\text{SAIFI} = \frac{\sum_{i=1}^{N} \lambda_{\text{i}} \times N_{\text{i}}}{N} \quad (3)$$

where λ_{i} is the failure rate of component i, N_{i} is the number of customers affected by component i, and N is the total number of customers.

$$\text{CAIDI} = \frac{\sum_{i=1}^{N} \frac{U_{\text{i}}}{\lambda_{\text{i}}}}{N} \quad (4)$$

where U_{i} is the unavailability, and λ_{i} is the failure rate of component i.

$$\text{LOSE} = \sum_{i=1}^{N} P_{\text{curtail,i}} \times T_{\text{curtail,i}} \quad (5)$$

where $P_{\text{curtail,i}}$ is the curtailed renewable power at bus i, and $T_{\text{curtail,i}}$ is the duration of curtailment. The nodal LOSE takes the value "True" when the renewable power at the bus cannot be fully delivered and "False" otherwise. This measure helps assess the adequacy of supply in islanded microgrids, particularly during light loading conditions.

$$\text{RIVE} = \sum_{i=1}^{M} \Delta V_{\text{i}} \times P_{\text{V,i}} \quad (6)$$

where ΔV_{i} is the rise in voltage at renewable-based bus i, and $P_{\text{V,i}}$ is the probability of voltage rise at that bus. Nodal RIVE is specifically defined for renewable-based buses, as these buses are prone to voltage rise due to fluctuations in renewable power generation, especially in islanded microgrids.

3.3. Reliability Analysis of Power Converters

3.3.1. Modeling and Challenges

The reliability of power converters is greatly influenced by operating and environmental conditions [43,81,90,91]. For instance, ref. [43] focuses on adjusting the loading on converters to mitigate the aging process, while [81] highlights failure-prone converters from a wear-out perspective. In this section, we address the challenges in reliability modeling for power converters by reviewing the development of methods that accurately model their reliability. This is crucial for optimal power system planning and operation.

Assessing new converter structures [92–94], control strategies and switching methods [43,94–96] along with studying the influence of control and operational variables on the converters functionality necessities adequate reliability models [81,97]. The authors in [92] examined the impact of different topologies on the reliability of the DC/DC boost stage in PV applications, utilizing mission profile-based modeling techniques. The reliability of two-stage and three-stage interleaved converters in PV generation systems was investigated by [93]. Ref. [94] proposed a reliability assessment approach for modular multilevel converters with redundant structures and techniques. Additionally, ref. [95] introduced a reliability assessment method that employs a combined system-level reliability model to optimize control strategy selection and enhance reliability assessment performance. There have been various methods to model converter reliability [91–95,98–101]. Most of them utilize Military Handbook 217 (MIL-HDBK-217), which lacks data for new technologies and does not account for varying operational conditions. In addition to MIL-HDBK-217, manufacturers and companies have developed other handbooks, such as Telcordia SR-322, Siemens SN29500, and RDF-2000, all of which share similar limitations, even with updates [19]. All of these proposed a constant failure rate during the lifetime use and they avoid the wear-out phase which is not a real representation of the converter reliability. To address these issues, the International Electrotechnical Commission (IEC) introduced IEC TR-62380 [102], which aims to predict converter failure processes by considering mission profiles. However, it faces the same limitations as previous models. IEC 61709 [103] has since replaced IEC TR-62380 [102], offering basic guidelines for failure rate prediction based on mission profiles.

Both the failure mechanisms and the physical processes of failure are inadequately modeled in all the mentioned handbooks. Developing an accurate reliability model for a robust design is challenging, and identifying areas with low reliability adds to the difficulty. Therefore, MIL-HDBK-217 was updated by FIDES group, in which the failure rate is dynamic based on the physical condition [104]. For many years, ref. [104] served as the updated standard for failure rate prediction. Later, several chapters of the document were revised in [105].

Conversely, there have been recent efforts to use failure mechanics to analyze wear-out in converter components [91,100,106,107]. Specifically, ref. [100] investigates the prediction of wear-out probability in converter components, utilizing MCS for device aging modeling. However, a scalability issue arises with using MCS for power converters in large IBR-integrated power systems, as components experience varying mission profiles across different locations [19]. In addition, for control reasons, online reliability monitoring necessitates a method for rapid reliability prediction [43]. At the same time, during the design phase, reliability methods that rely on repeated MCS are time-consuming. The authors in [106] examined system-level reliability of converter taking into account the wear-out failure of semiconductor devices (SDs) and capacitors (Caps). Refs. [91,100,106,107] explored the wear-out modeling for lifetime prediction. Reliability design and end-of-life prediction for power converters are both aided by the aging failure probability, while converter availability, which is affected by wear-out and useful lifespan failure rates and mission profile, must be modeled for system design and maintenance purposes. As a result, efficient converter design and operation depend on accurate failure rate prediction, which is the goal of [106].

Figure 4 illustrates the failure rate behavior of a converter at various stages of its lifetime [19,106]. The first stage, infant mortality, represents failures during manufacturing and debugging, which are resolved prior to use. The second stage covers random failures during the converter's lifespan, while the final stage, the wear-out phase, reflects component aging, applied stress, and the impact of mission profiles. Optimal converter design and operation require a thorough understanding of behavior during both the useful life and wear-out periods. Predicting wear-out failures is crucial for cost management and system longevity, as wear-out failures are more common than random failures over the useful life [106]. The mathematical approach for modeling a variable failure rate will be explained in the following.

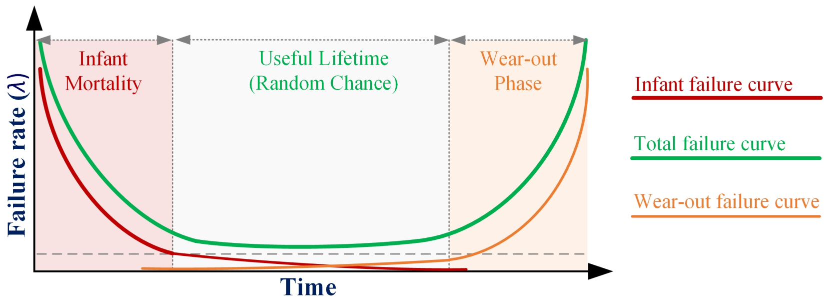

Figure 4. Typical bathtub curve describing failure rate of a component.

3.3.2. Mathematical Modeling

In most cases, the component failure rate is assumed to be constant. For components availability calculation MP can be utilized. System states can be defined as being in either a normal state or a failure state through MP as shown in Figure 5I. System availability is described as the probability of being in the normal state, which can be achieved by Equation (7) [108].

$$A = 1 - \text{FOR} = \frac{\mu}{\lambda + \mu} \tag{7}$$

where λ and μ represent the failure and repair rates within the useful lifespan, respectively. The Forced Outage Rate (FOR), which defines unavailability, can also be calculated from Equation (7). The MP cannot be applied to systems with non-constant failure rates (Figure 4). As shown in Figure 5II, an additional time-varying term must be introduced in such cases for failure rate modeling. As previously mentioned, a converter's capacitors and semiconductor devices are prone to both random failures due to abnormal operation and unexpected over-stressing, as well as wear-out failures from material degradation over time. Consequently, a system with a non-constant failure rate provides a more accurate representation of a converter's real reliability model.

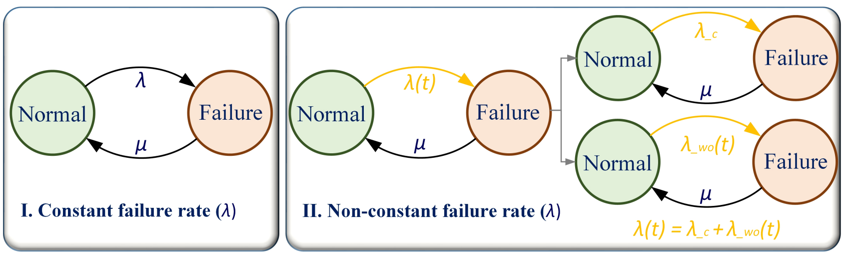

Figure 5. Modeling of state samples of a component: (**I**) MP used to define state with constant failure rate (λ); (**II**) state space modeling with non-constant failure rate ($\lambda(t)$).

3.3.3. Dynamic Failure Rate

To provide an overview of RES-connected converter reliability modeling, Equation (8) calculates the reliability $R(t)$, where λ represents the failure rate. In this model, λ is considered time-dependent but assumed to be a constant value [88].

$$R(t) = e^{-\lambda t} \tag{8}$$

However, as mentioned, in reality λ will be influenced by different uncertainties and different mission profiles on the component [89]. To address these challenges, the FIDES [105] method is the most updated one, which will be expressed in the following equations:

$$\lambda = \Pi_{PM}\Pi_{Process}\lambda_{Phy} \tag{9}$$

$$\lambda_{Phy} = \sum_{i}^{States}\left[\frac{t_{annual}}{T}\right]_i \Pi_i\lambda_i \tag{10}$$

where Π_{PM} represents failures due to quality and technical control during component manufacturing, while $\Pi_{Process}$ encompasses every step of the process, from specification to maintenance and operation. These two parameters, Π_{PM} and $\Pi_{Process}$, are considered as λ_c in Figure 5. λ_{Phy} is the key variable that represents all possible states of the components, and it corresponds to $\lambda\_wo(t)$ in Figure 5. In Equation (10), t_{annual} is i^{th} state duration over the lifespan T and λ_i is the user-defined, component-specific induced overstress electrical factor [99]. In conclusion, the reliability model is expressed as shown in (11), where $\lambda_{j,t}$ represents the failure rate of each component j at time t.

$$R(t) = e^{-\left(\sum_{j=1}^{N_j}\lambda_{j,t}\right)t} \tag{11}$$

where λ_i is detailed in Equations (12)–(18). Factors contributing to physical stresses are addressed in Equation (12). Equation (13) calculates thermal stress factors, while temperature cycling factors are covered in (14). Equation (15) addresses junction temperature factors, (16) models mechanical stress, and finally, Equation (18) calculates the impact of humidity stress on failure rate modeling [20,104,105]. Mission profile variables definitions are provided in Table 6.

$$\lambda_i = \lambda_{0\text{TH}} \times \Pi_{\text{Thermal}} + \lambda_{0\text{TCyCase}} \times \Pi_{\text{TCyCase}} + \lambda_{0\text{TCySolderJoints}} \times \Pi_{\text{TCySolderJoints}} + \lambda_{0\text{RH}} \times \Pi_{\text{RH}} + \lambda_{0\text{Mech}} \times \Pi_{\text{Mech}} \tag{12}$$

$$\Pi_{\text{Thermal}} = \begin{cases} \exp\left[\frac{11604\times 0.7}{T_{\text{Ref}}+273} - \frac{1}{T_{\text{j-component}}+273}\right] & \text{In an operating phase} \\ 0 & \text{In a non-operating phase} \end{cases} \tag{13}$$

$$\Pi_{\text{TCyCase}} = \frac{12 \times N_{\text{cy}}}{T_{\text{phase}}} \times \left(\frac{\Delta T_{\text{cycling}}}{20}\right)^4 \times 1414 \times \exp\left[\frac{1}{313} - \frac{1}{T_{\text{max-cycling}} + 273}\right] \tag{14}$$

$$\Pi_{\text{TCySolderJoints}} = \frac{12 \times N_{\text{cy}}}{T_{\text{phase}}} \times \left(\frac{\min(\theta_{\text{cy}}, 2)}{2}\right)^{\frac{1}{3}} \times \left(\frac{\Delta T_{\text{cycling}}}{20}\right)^{1.9} \times 1414 \times \exp\left[\frac{1}{313} - \frac{1}{T_{\text{max-cycling}} + 273}\right] \tag{15}$$

$$\Pi_{\text{Mech}} = \left(\frac{G_{\text{RMS}}}{0.5}\right)^{1.5} \tag{16}$$

$$\Pi_{\text{RH}} = \begin{cases} \left(\frac{RH_{\text{ambient}}}{70}\right)^{4.4} \times \exp\left[11604 \times 0.9 \times \left[\frac{1}{293} - \frac{1}{273+T_{\text{ambient-board}}}\right]\right] & \text{In a non-operating phase} \\ 0 & \text{In an operating phase} \end{cases} \tag{17}$$

Table 6. Mission profile variables definitions.

Parameter	Description
T_{amb}	Ambient Temperature (°C)
T_{Ref}	Reference temperature (60 °C)
$T_{\text{ambient-board}}$	Mean temperature of the board during a state (°C)
$\Delta T_{\text{cycling}}$	Amplitude of temperature variation associated with a cycling phase (°C)
$T_{\text{max-cycling}}$	Maximum temperature on the board during a cycling phase (°C)
RH_{ambient}	Humidity level associated with each state (%)
N_{cy}	Number of cycles associated with each cycling state (cycles)
$T_{\text{j-component}}$	Component junction temperature during an operating phase (°C). The maximum value of this temperature will be 175 °C.
θ_{cy}	Cycle duration (hours)
G_{RMS}	Vibration amplitude associated with each random vibration state (Grms)

3.3.4. IGBT and Diode Loss Calculations in WT and PV Converters

In the reliability modeling of RES-connected converters, particularly those linked to WT and PV systems, different models are applied based on the converter topology (Figure 6), as the mission profile impacts converter devices differently depending on the specific topology. To do so, power losses are calculated based on the converter's topology. For WT converters, both conduction and switching losses contribute to overall power loss, influenced by factors such as the resistance and voltage drop of an IGBT or diode (affecting conduction loss) and the switching frequency (affecting switching loss) [109]. Similarly, for PV panel DC-DC boost converters, power losses include conduction and switching losses, with calculations comparable to those used for WT converters. After determining the dynamic failure rate model of the IGBT and diode within the converter, the overall reliability model for WT and PV can be derived using Equation (18) and Equation (19), respectively.

$$\lambda_{\text{WT}}(t) = \sum_{i=1}^{N_{com}} \left[N_{IGBT} \times \lambda_{WT_{IGBT}}(i) + N_{Diode} \times \lambda_{WT_{Diode}}(i) \right] \tag{18}$$

$$\lambda_{\text{PV}}(t) = \sum_{i=1}^{N_{com}} \left[N_{IGBT} \times \lambda_{PV_{IGBT}}(i) + N_{Diode} \times \lambda_{PV_{Diode}}(i) \right] \tag{19}$$

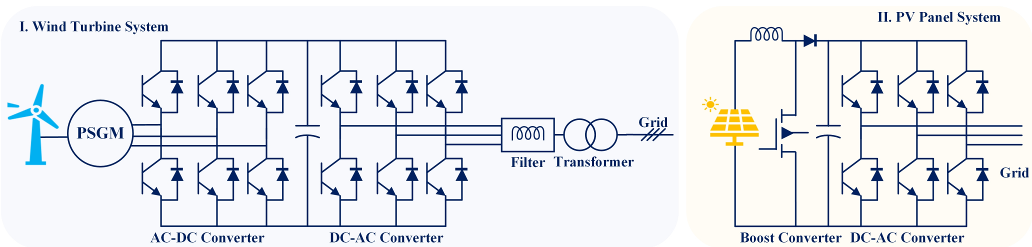

Figure 6. (**I**) A typical WT system with a generator-side inverter, a DC link, and a grid-side inverter. (**II**) A typical PV (**II**) system with DC-DC boost converter and DC-AC and AC-DC inverter.

Conduction losses for the IGBT and diode in the WT-connected converter are derived from Equations (20) and (21). Following this, the switching losses are calculated using Equations (22) and (23). The total IGBT and diode losses, as well as the overall converter losses, can then be obtained using Equations (23) and (24), respectively. Finally, the junction temperature is determined using Equation (26).

$$P_{WT,con_{IGBT}}(t) = I_{\text{WT}}(t) \times V_{\text{CEO,WT}} \left(\frac{1}{2\pi} + \frac{M_{\text{WT}} \cos \phi_{\text{WT}}}{8} \right) + [I_{\text{WT}}(t)]^2 \times r_{\text{CE,WT}} \left(\frac{1}{8} + \frac{M_{\text{WT}} \cos \phi_{\text{WT}}}{3\pi} \right) \tag{20}$$

$$P_{WT,con_{Diode}}(t) = I_{\text{WT}}(t) \times V_{\text{F0,WT}} \left(\frac{1}{2\pi} - \frac{M_{\text{WT}} \cos \phi_{\text{WT}}}{8} \right) + [I_{\text{WT}}(t)]^2 \times r_{\text{F,WT}} \left(\frac{1}{8} - \frac{M_{\text{WT}} \cos \phi_{\text{WT}}}{3\pi} \right) \tag{21}$$

$$P_{\text{WT,sw}}(t) = \frac{1}{\pi} \times f_{\text{sw,WT}} \times \left[\frac{E_{\text{on,WT}} + E_{\text{off,WT}}}{V_{\text{ref,IGBT,WT}} \times I_{\text{ref,IGBT,WT}}} + \frac{E_{\text{rec,WT}}}{V_{\text{ref,Diode,WT}} \times I_{\text{ref,Diode,WT}}} \right] \times I_{\text{WT}}(t) \times V_{\text{DC,WT}} \quad (22)$$

$$P_{Loss,WT_{IGBT/Diode}}(t) = P_{WT,con_{IGBT/Diode}}(t) + P_{WT,sw_{IGBT/Diode}}(t) \quad (23)$$

$$P_{\text{WT,Conv,Loss}}(t) = N_{\text{IGBT,WT}} \times P_{Loss,WT_{IGBT}}(t) + N_{\text{Diode,WT}} \times P_{Loss,WT_{Diode}}(t) \quad (24)$$

$$T_{\text{j,WT}}(t) = T_{\text{amb}}(t) + R_{\text{sa,WT}} \times P_{\text{WT,Conv,Loss}}(t) + R_{\text{jh,WT}} \times P_{\text{Loss,WT}}(t) \quad (25)$$

Similarly, for a PV-connected converter, the adjusted IGBT saturation voltage is determined using Equation (26), which accounts for the temperature dependency of the IGBT. Equation (27) then calculates the IGBT conduction loss based on this adjusted voltage and the current through the PV panel. The switching loss of the IGBT is determined in (28), using the on and off energy values and the switching frequency. The total IGBT loss, combining both conduction and switching losses, is expressed in (29). For the diode, its conduction loss is given in (30), while the forward resistance and reverse recovery losses are calculated in Equations (31) and (32), respectively. These losses are aggregated in (33) to provide the total diode loss. The overall converter loss, which sums the losses of all IGBTs and diodes, is presented in (34). Subsequently, the junction temperatures of the IGBT and diode are calculated using Equations (35) and (36), respectively, considering ambient temperature and thermal resistances, as well as the respective converter and component losses. Descriptions of these parameters are presented in Table 7.

$$V_{\text{CE,sat,temp,PV}}(t) = V_{\text{CE,sat,PV}} + V_{\text{CE,sat,temp,coeff,PV}} \times (T_{\text{amb}}(t) - 25) \quad (26)$$

$$P_{\text{PV,IGBT,con}}(t) = V_{\text{CE,sat,temp,PV}}(t) \times I_{\text{PV}}(t) \quad (27)$$

$$P_{\text{PV,IGBT,sw}}(t) = (E_{\text{on,PV}} + E_{\text{off,PV}}) \times f_{\text{sw,PV}} \quad (28)$$

$$P_{\text{Loss,PV,IGBT}}(t) = P_{\text{PV,IGBT,con}}(t) + P_{\text{PV,IGBT,sw}}(t) \quad (29)$$

$$P_{\text{PV,Diode,con}}(t) = V_{\text{F,PV}} \times I_{\text{PV}}(t) \quad (30)$$

$$P_{\text{PV,Diode,fr}}(t) = [I_{\text{PV}}(t)]^2 \times R_{\text{F,PV}} \quad (31)$$

$$P_{\text{PV,Diode,rr}}(t) = Q_{\text{rr,PV}} \times V_{\text{DC,PV}} \times f_{\text{sw,PV}} \quad (32)$$

$$P_{\text{Loss,PV,Diode}}(t) = P_{\text{PV,Diode,con}}(t) + P_{\text{PV,Diode,fr}}(t) + P_{\text{PV,Diode,rr}}(t) \quad (33)$$

$$P_{\text{PV,Conv,Loss}}(t) = N_{\text{IGBT,PV}} \times P_{\text{Loss,PV,IGBT}}(t) + N_{\text{Diode,PV}} \times P_{\text{Loss,PV,Diode}}(t) \quad (34)$$

$$T_{\text{j,IGBT,PV}}(t) = T_{\text{amb}}(t) + R_{\text{sa,IGBT,PV}} \times P_{\text{PV,Conv,Loss}}(t) + R_{\text{jh,IGBT,PV}} \times P_{\text{Loss,PV,IGBT}}(t) \quad (35)$$

$$T_{\text{j,Diode,PV}}(t) = T_{\text{amb}}(t) + R_{\text{sa,Diode,PV}} \times P_{\text{PV,Conv,Loss}}(t) + R_{\text{jh,Diode,PV}} \times P_{\text{Loss,PV,Diode}}(t) \quad (36)$$

Table 7. IGBT and diode loss calculations parameter descriptions.

Parameter	Description
M_{WT}	Modulation Ratio (Typically equal to 0.85)
V_{CEO}	Threshold Voltage of IGBT (V)
V_{F0}	Threshold Voltage of Diode (V)
r_{CE}	Resistance of IGBT (Ω)
r_{F}	Resistance of Diode (Ω)
$V_{\text{CE,sat}}$	Saturation Voltage of IGBT (V)
$V_{\text{CE,sat,temp,coeff}}$	Temperature Coefficient of IGBT Saturation Voltage (V/°C)
V_{F}	Forward Voltage Drop of Diode (V)
R_{F}	Forward Resistance of Diode (Ω)
Q_{rr}	Reverse Recovery Charge of Diode (C)
E_{on}	Turn-on Energy Loss of IGBT (J)
E_{off}	Turn-off Energy Loss of IGBT (J)
E_{rec}	Reverse Recovery Energy Loss of Diode (J)

4. Reliability Improvement in Modern Power Systems

At the converter level, reliability is influenced by operating conditions and component lifespan. Ensuring long-run performance of the component with an acceptable level of reliability can be achieved by designing power converters with a suitable mission profile in mind [101]. By doing so, the thermal and physical stress imposed on components can influence the sizing of converters for each specific application scenario. As discussed in previous sections, converter reliability can be affected by various factors, including control strategy, converter topology, application type, operating conditions, and environmental factors [41,43,69,92,110]. Hence, to ensure reliable converter design and subsequent reliable operation, these factors must be carefully considered.

At the system level, there are various categories of actions and strategies that can be employed to enhance overall system reliability. In the following, we examine these different strategies and their potential impact on improving reliability across the system. The deregulation and competition within the electric utility sector necessitate efficient management of existing equipment while minimizing operational costs. Asset management is typically divided into long-term, mid-term, and short-term categories, with maintenance being a critical part of mid-term management. The maintenance and modernization of infrastructure are expected to become increasingly important, with maintenance demands predicted to double in the next two decades due to asset degradation [111]. Effective oversight of maintenance activities is crucial for reducing equipment failure rates, which in turn enhances system reliability by minimizing outages in EDS [112,113]. There is typically a natural monopoly in EDS that makes it difficult to achieve a balanced trade-off between reliability insurance with financial success. To counteract this monopoly, several studies have recommended Performance-Based Regulation (PBR) which identifies utilities that receive incentives based on their reliability and financial performance [114,115]. Incorporating Reward–Penalty Schemes (RPS) into regulatory frameworks is one of the most practical approaches in PBR. However, the application of RPS in reliability, specifically as a measure of service quality, has received less attention. In RPS, when the reliability level is below a certain standard, utilities are rewarded, and when it is beyond that benchmark, utilities are penalized. Utilities normally aim to increase the reliability level in order to earn greater rewards [114].

Another solution to improve the reliability of EDS is Reliability-Centered Maintenance (RCM) which takes both reliability and cost of the system into account. RCM includes two main approaches: Corrective Maintenance (CM) and Preventive Maintenance (PM). As an example, [116] defines the optimal RCM and their duration time in EDS. However, given the inherent uncertainty in failure rates, deterministic RCM models are unable to provide any guarantee on the global optimality or practicality of their proposed solutions. This uncertainty in failure rates and its effect on RCM has been addressed by a robust model in [117].

In addition, the installation of Remote-Control Switches (RCS) is an effective solution for improving EDS reliability and resilience. RCS can quickly isolate outage areas in the grid. Their use makes the Fault Location, Isolation, and System Restoration (FLISR) process more feasible [118]. The authors in [77] optimally located RCS in EDS by considering the uncertainty in load to enhance system reliability. In developed EDS and SG, distribution system automation is achievable and it is performed by RCS and can perform FLISR with functioning service restoration [119,120]. In this content, ref. [10] has also investigated the uncertainty of service restoration to enhance reliability. The authors in [121,122] aim to increase the system's reliability by optimally allocating RCS and manual switches in EDS while minimizing the planning expenses. EDS reconfiguration, which defining the status of switches in the network, is another effective approach to improve reliability, reduce loss, enhancing the penetration of RES, improvement of voltage profile, and service restoration [123–125]. For instance, Ref. [75] optimizes the distribution system switch states to achieve the best reconfiguration of the system for obtaining the maximum reliability index. In this context, the Bus-Line Feeding Matrix (BLFM) is a crucial tool in reliability studies, used to represent the connectivity between buses and lines in power systems, helping to assess the impact of faults on power flow and supply continuity. By incorporating BLFM, models can simulate power flow paths, conduct contingency analysis, and design reconfiguration strategies, enhancing system resilience and fault tolerance. For instance, the authors in [126] proposed a robust preventive–corrective security-constrained optimal power flow model to enhance power system reliability, especially under extreme weather events and outages.

Various numerical Sensitivity Analysis (SA) approaches were used by [127] to examine the most significant uncertainty on power system reliability. Hence, to understand the behavior of system reliability and the impact of new power converters on system reliability, it is crucial to use a suitable SA. Identifying the key uncertainties, such as the most impactful RES and power converter pair on system reliability, enables operators and stakeholders to optimize RCM scheduling and facilitate system operations. SA is defined at the Local SA (LSA) level and the Global SA (GSA) level. EDS reconfiguration is one of the diverse applications of GSA [128]. Other applications include increasing transmission capacity [129] and allocating voltage control devices [130]. On the other hand, conventional GSAs do not take into account the uncertain nature of RESs and unknown parameters of power converters, hence the results of system reliability cannot be very accurate. To answer this, variance-based GSA has been proposed [131].

Additionally, several uncertain parameters, which are caused by intermittent RESs and the new operation configuration, may have a significant influence on the system's reliability. Decision-makers would not implement careful power system evaluation or not achieve optimal maintenance solutions if spatiotemporal unpredictable parameters are disregarded [132]. This phenomenon, along with existing challenges, has expressed concerns about the secure and reliable operation of energy systems. To address this, the Energy Hub (EH) structure, which integrates the generation, conversion, storage, and consumption of diverse energy carriers, has emerged as a promising solution for future energy systems [133,134]. EH is one of the practical solutions for future energy systems to achieve high-reliability and economical smart city energy systems [82].

5. Key Aspects and Scope for Future Directions

Many recent studies have developed advanced methods to evaluate the reliability of modern power systems. However, this section will address key aspects and outline future directions to address the remaining limitations and gaps in this field.

5.1. Summary of Key Findings

- The majority of the investigations, according to the reviewed literature, have employed simulation-based methodologies, while these methods can be effectively adapted to complex systems, their processing time increases significantly as system size grows.
- Most reliability assessments assume protection devices to be 100% reliable, with few studies addressing their potential failures in EDS. Even fewer have explored the impact of maintenance outages, overlapping failures, or backup protection on system overall reliability. Additionally, protection coordination is a critical factor that should be considered in reliability evaluations.
- Long-term reliability evaluations for islanded MGs often use the MCS method due to its ability to scale the sampling space to include most operating conditions. However, MCS is not suitable for short-term reliability assessments, as it overlooks low-probability events. Analytical methods, which involve identifying system states and performing consequence analysis with probability calculations, provide clear physical states and accurate models. Yet, the traditional analytical approach struggles to account for all possible states due to the vast sample space of islanded MGs.

5.2. Identified Gaps and Suggestions for Future Research

The identified gaps and future research directions within the domain of reliability assessment are discussed below. Figure 7 provides a graphical summary of the key points presented in this section, each of which will be explained in detail.

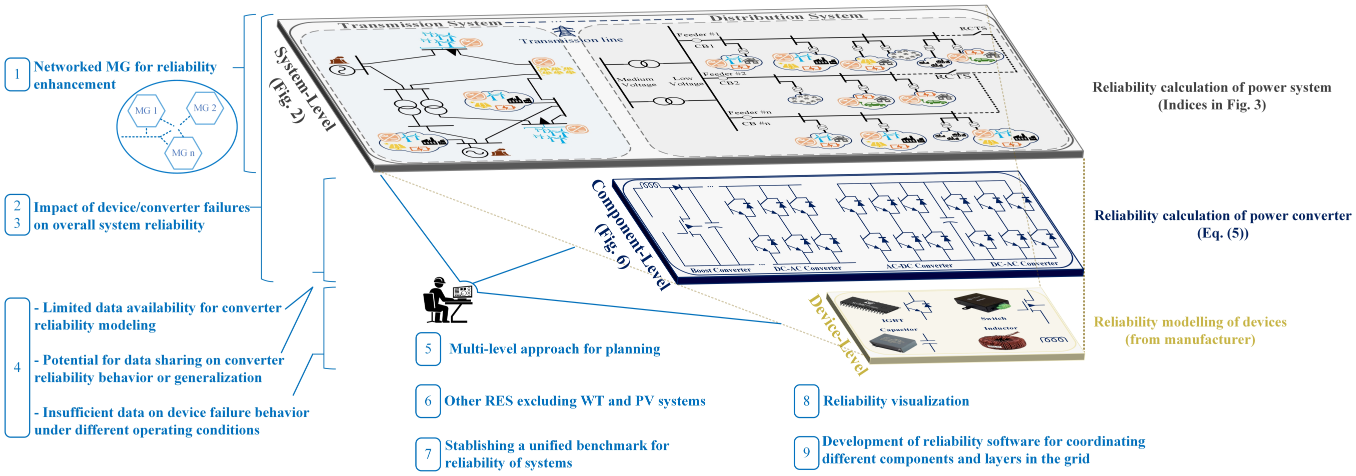

Figure 7. Layers of power system reliability evaluation and future research directions.

1. The potential of networked MGs to improve the reliability of EDS has not been thoroughly investigated, despite its growing popularity in recent years. Effective coordination between different MGs can significantly enhance reliability while reducing operational and outage costs for both utilities and customers.
2. Future research should focus on bridging the gap between system-level uncertainties and component-level reliability by developing integrated models that account for both, with particular emphasis on precise power converter modeling given their critical role in maintaining reliable power delivery. This would allow for more accurate assessments of system performance under real-world conditions and better inform strategies for outage prevention, system reinforcement, and RCM planning.
3. The growing complexity and uncertainty in modern power systems, caused by variable RES outputs and dependence on power conversion interfaces, remain insufficiently addressed. Although progress has been made in reliability assessments for large-scale RES-integrated systems, the impact of mission profiles and climate conditions—key factors contributing to power electronic converter failures—remains frequently overlooked.
4. A significant challenge in converter reliability modeling is the lack of sufficient data. Typically, mathematical methods are used to model converter reliability; however, these approaches often lack accuracy and are not well-suited to accommodate varying operating conditions and diverse converter topologies. The most recent method for converter reliability modeling, ref. [105], could be further enhanced through the integration of experimental data. Alternatively, developing a more robust approach that combines physical modeling with data-driven techniques could more accurately capture the behavior of converters under different conditions.
5. Studying the reliability of power systems primarily aims to guarantee that the system can adequately fulfill the whole load demand by providing probabilistic analysis to evaluate different reliability indices. Outage analysis, system reinforcement, maintenance scheduling, and expansion planning are all ways to increase system reliability, but it is also important to rank the influence of individual components on system reliability. Developing a method to determine the importance degree of each component in IBR-penetrated power systems, particularly at the distribution level, remains an open research question. This is especially relevant with the emergence of new paradigms like SGs and ADN in power systems.

6. Most existing studies have focused on wind and solar energy, neglecting other renewable sources. Future research should broaden the scope to include these underexplored energy sources, as well as develop more comprehensive models that consider the unique characteristics and operational challenges of each.
7. The primary objective of system reliability assessments is to minimize reliability indices and identify optimal solutions for system design, RCM, and operations. However, a standardized testbed for evaluating system reliability remains absent. Although various reliability indices have been proposed, there is no clear standard or preferred index, leaving the selection largely dependent on the specific application. Establishing a unified benchmark for reliability evaluation across different systems presents a promising area for future research.
8. "Reliability visualization" represents a promising area of research, offering the potential to present grid reliability through a more detailed and dynamic lens. Instead of relying on a single, aggregate value for system reliability, this approach could visually depict reliability metrics based on regions, component types, maintenance schedules, and other critical factors. Developing a comprehensive visualization tool, alongside a reliability assessment framework, would enable the clear representation of the relationships between various grid components, particularly RES-connected converters, and their collective impact on overall system reliability. Such a tool could greatly enhance the ability to assess and manage grid reliability in a more nuanced and actionable manner.
9. Ensuring the reliability of power converters is crucial for power system design and planning. Equally important is the reliability of the software controlling these systems, especially given the increased complexity introduced by IBRs and decentralized control mechanisms. Future research could focus on how software can enhance overall system reliability by verifying the correctness of control algorithms and their architectures. This approach would help bridge the gap between hardware reliability and software assurance.

6. Conclusions

Reliability modeling and assessment in modern power systems require fresh considerations, particularly in accounting for component-level failures and their impact on system-wide reliability. Although progress has been made in evaluating the reliability of large-scale RES-integrated systems, the role of power electronic converter failures remains largely underexplored. Many studies fail to sufficiently address the connection between system reliability and converter-level reliability. This review bridges this gap by examining reliability modeling methods in both levels. We provide a comprehensive evaluation of studies focused on developing accurate reliability models for power converters, while also reviewing research on system reliability in RES-penetrated grids. Additionally, we highlighted the limitations of current assessment tools and reviewed the state-of-the-art methods for precisely evaluating the reliability of IBR-integrated grids. Our analysis explores the interconnections between equipment and system reliability and offers directions for future research to support the evolution of zero-carbon power systems with renewable energy integration.

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Abbreviations

ADN	Active Distribution Network
ANN	Artificial Neural Network
BLFM	Bus-Line Feeding Matrix
BN	Bayesian Network
CES	Cloud Energy Storage
CM	Corrective Maintenance
DC-MG	DC Microgrids
DG	Distributed Generation
DR	Demand Response
EA	Energy Arbitrage
EDV	Electric-Drive Vehicles
EDS	Electricity Distribution Systems
EH	Energy Hub
ES	Energy Storage
ESS	Energy Storage Systems
EV	Electric Vehicles
FLISR	Fault Location, Isolation, and System Restoration
FTA	Fault Tree Analysis
GSA	Global Sensitivity Analysis
IBR	Inverter-based Resources
IEC	International Electrotechnical Commission
LSA	Local Sensitivity Analysis
NS-MCS	Non-Sequential Monte Carlo
MCS	Monte Carlo Simulation
MP	Markov process
PBR	Performance-Based Regulation
PBET	Partition-Based Event Trees
PFC	Power Factor Correction
PM	Preventive Maintenance
PV	Photovoltaics
RES	Renewable Energy Sources
RCM	Reliability-Centered Maintenance
RCS	Remote-Control Switches
RPS	Reward–Penalty Schemes
S-MCS	Sequential Monte Carlo
SA	Sensitivity Analysis
SG	Smart Grids
SIDE	Stochastic Infrastructure Damage Evolution
SLB	Second Life Battery
THD	Total Harmonic Distortion
WT	Wind Turbines

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