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(Review Article)

Power grid reliability and fault detection using Artificial Intelligence

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Abstract

Extreme natural hazards, climate change, and human-caused disruptions are making it harder to keep electric power systems reliable and resilient worldwide. This article reviews and analyzes how well power systems perform during events like cyclones, floods, heat waves, earthquakes, and intentional attacks. It brings together ideas about resource adequacy, operational reliability, and resilience to see how power systems handle disruptions, adapt to new risks, and recover after major events. Drawing on international research, disaster case studies, and experiences from regions prone to hazards, the study examines weaknesses in generation, transmission, and distribution networks, with a focus on how extreme events, especially, affect distribution systems and customer service. The article also reviews engineering, operational, and institutional strategies, such as grid hardening, decentralized energy resources, microgrids, underground cables, GIS and SCADA decision-support systems, emergency response, and governance, that can help strengthen systems and speed recovery. It pays special attention to how climate change increases risks and why resilience should be part of long-term planning and investment in the power sector. The article concludes by highlighting research gaps and policy needs, calling for a shift from traditional reliability planning to a broader resilience-based approach that prepares for rare but severe events and supports a secure, reliable electricity supply in a world of growing risks.

Keywords: Power System Resilience; Artificial Intelligence; Grid Reliability; Electric Power Infrastructure

1. Introduction

Artificial intelligence (AI) is used for fault detection in smart grids to improve the reliability and efficiency of modern power systems (Aman Choudhary & Pathania, 2025). Smart grids use advanced methods to quickly and accurately find faults by analyzing large amounts of data (Zhang et al., 2018). Techniques like Deep Reinforcement Learning (DRL) help detect anomalies and predict errors with high accuracy (Arshad et al., 2022). This study examines different AI algorithms and their effectiveness for real-time monitoring and fault detection in smart grids. Case studies and simulations show that AI-based methods outperform traditional approaches in response time, accuracy, and flexibility. Using AI in smart grid management can improve grid stability, reduce downtime, and optimize energy distribution. This study provides a detailed analysis of how AI supports fault detection and discusses future developments and practical applications in smart grid systems.

2. Fundamentals of Power Grid Reliability

Keeping the bulk power system reliable is a key goal for those who plan, operate, and oversee the electric grid [1]. As we bring in more clean energy sources like wind, solar, and batteries, regulation is needed to maintain system reliability. Figure 1 breaks down the power grid into two main systems: the bulk energy system, which has generators and high-

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voltage transmission lines, and the distribution system, which uses local, lower-voltage lines to deliver electricity to homes and businesses. NERC defines resource adequacy as "the ability of the electricity system to supply the aggregate electrical demand and energy requirements of the end-use customers at all times, taking into account scheduled and reasonably expected unscheduled outages of system elements"[2]. This means the system must deliver enough electricity where it is needed, even during bad weather or unexpected problems. Sometimes power plants and transmission lines fail, but a reliable system has enough backup to cover these situations or maintenance. Figure 1 is based on an original from the Energy Systems Integration Group. NERC defines operating reliability as "the ability of the Bulk-Power System to withstand sudden disturbances, such as electric short circuits or the unanticipated loss of system elements from credible contingencies, while avoiding uncontrolled cascading blackouts or damage to equipment." In other words, the system can keep supply and demand balanced in real time, even just seconds or minutes after a major problem. This helps keep the lights on during unexpected outages. Operational reliability also includes normal, random changes in supply or demand, which is sometimes called the system's flexibility [3]. While resource adequacy and operational reliability can overlap, resource adequacy primarily focuses on ensuring there are enough generators and transmission capacity.

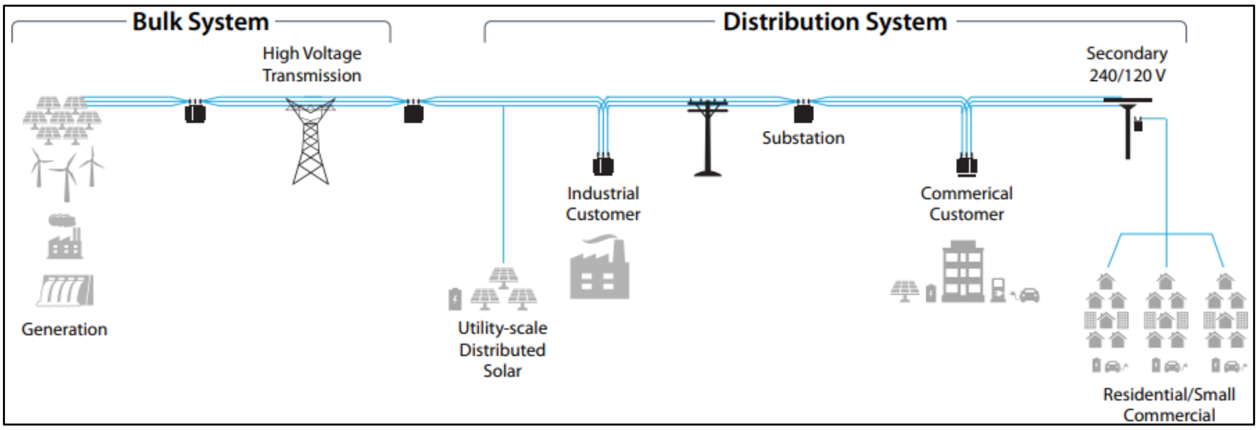

Figure 1 Major components of the grid [4]

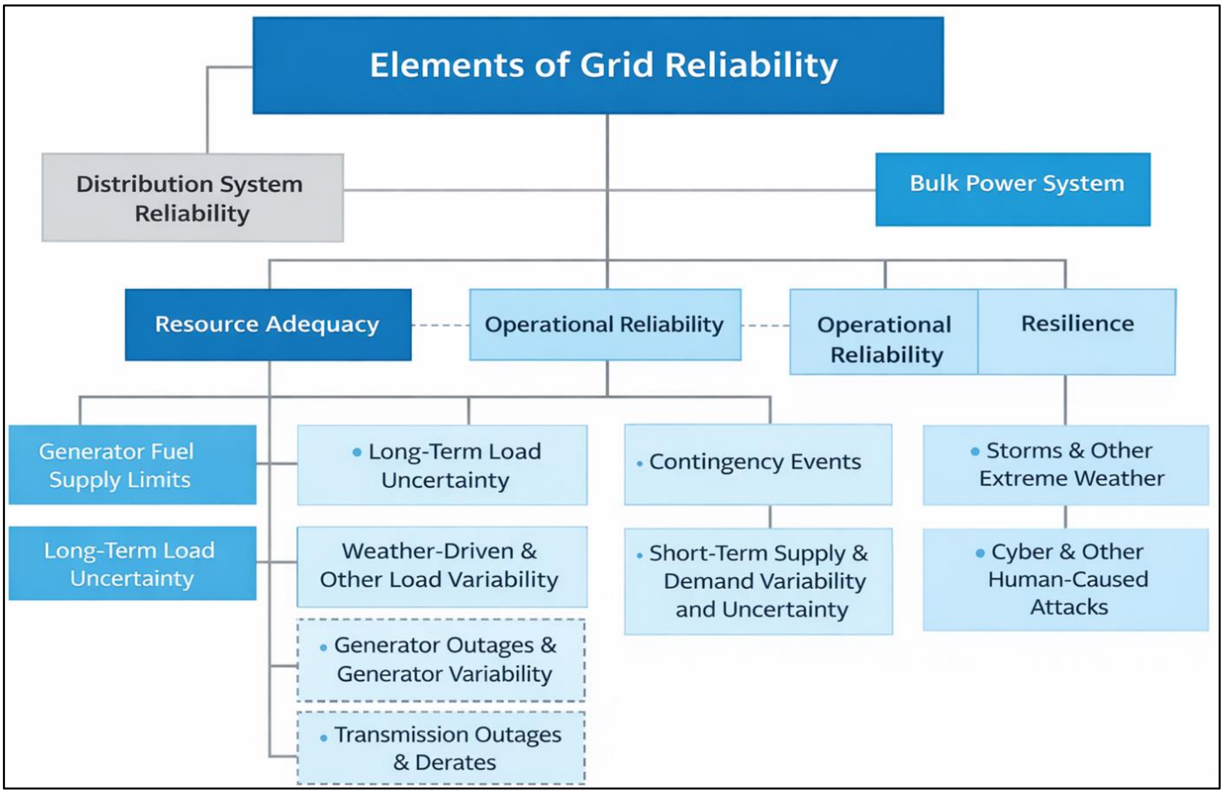

Figure 2 Reliability framework [5]

2.1. Causes of power grid failures and disturbances

Power grid failures can result from various causes, including natural events, human error, and technological limitations[6].

2.1.1. Inclement weather is the main reason for power outages.

Strong winds or flying debris from winter storms, snowstorms, tornadoes, and hurricanes can knock down transmission lines [7]. When this happens, the power grid in that area may stop working for some time. Very cold or hot weather can also cause people to use more electricity at once, potentially overloading the system. Ice storms and other winter weather often cause power lines to fall.

2.1.2. Earthquakes and Other Natural Disasters

Earthquakes often damage infrastructure, especially in California, where they happen more frequently [8]. While every state has experienced an earthquake at some point, they are less common outside California. The New Madrid fault runs through the center of the United States. Between 1811 and 1812, the Midwest had a series of large earthquakes[9]. Flooding is another major natural disaster that can cause power outages. Strong winds and heavy rain during storms can knock over poles or damage equipment(Sony Paul et al., 2013).

2.1.3. Increased Demand

In the last 10 years, rolling blackouts and brownouts have occurred because electricity demand exceeds the power supply [11]. We have not built many new baselines power plants, and many existing ones have been shut down. Instead, more peaking plants that use wind and solar have been built, but these cannot keep the power running if the baseline plants are offline [12].

2.1.4. Intentional Outages

To reduce the risk of fires, government and power companies sometimes intentionally turn off power in certain areas. Electricity may also be shut off during repairs or maintenance.

2.1.5. Human Error/Disasters

In 2003, a software bug caused a major power outage that left about 10 million people in Ontario and 45 million people in eight U.S. states without electricity. The events of 9/11 also disrupted many services, such as regional phone networks, transportation, and the power grid.

2.1.6. Renewable Energy Problems

Solar and wind power systems only work when the sun is shining or the wind is blowing (Solar_PKB_IJCEE, 2024). In January 2022, Germany faced energy shortages because it relied too much on these sources [14]. Renewable energy and other backup plants need a steady 'baseline' sine wave to connect to the power grid. This baseline usually comes from large nuclear or coal power plants. If these main sources are offline, smaller solar and wind systems have nothing to sync with, so they can't supply power even if conditions are good. Some newer systems can make their own sine wave, but that brings other challenges. Electric cars add another concern, since charging them uses a lot of electricity. In California, power companies have already asked people not to charge their cars at certain times.

2.1.7. Physical Attack

There are more than 2,000 extra-high-voltage (EHV) transformers in the United States[15], and most lack adequate protection. It takes 12 to 24 months to manufacture an EHV transformer, and only a few spares are kept in stock[16]. Utilities and the government do not have enough transformers available to replace damaged ones in the event of a large-scale attack.

Tennessee Valley Authority had five incidents between 2011 and December 2014 [17]. On April 16, 2013 a PG&E's 500 kV substation (EHV transformers) in Coyote, California were attacked. Gunfire destroyed one of the larger transformers and damaged 16 others. Cabot outages in August and Scott in Sept and Oct 6 of 2013 in Arkansas[18] (all by the same person). In 2017 a Garkane Energy's (Utah) substation was attacked [19]. December 2017 in Arizona. In 2019 Randolf County, NC, a man was arrested for shooting an electrical transformer. In February 2022, three men were caught and pleaded guilty to planning grid attacks. July 2022, Huron, South Dakota, had transformers "vandalized." On Saturday, December 3rd, 2022, two substations in North Carolina were attacked[20].

2.1.8. Cyber Attacks

The US utility grid is under constant cyberattack, and it seems likely that hackers will eventually breach it and cause serious harm [21]. In 2007, Idaho National Laboratory conducted the Aurora Generator Test, demonstrating that a cyberattack could physically destroy key components of the electric grid [22]. The rapid development of information and communication technologies, especially the Internet, has brought significant benefits.

However, it has also introduced new challenges to information system security. The frequency of cyber threats continues to rise, including unauthorized access and data breaches, highlighting the digital landscape's growing vulnerability[23].

In May 2021, hackers carried out a successful attack on Colonial Pipeline. At Christmas in both 2015 and 2016, Russia cut power to 250,000 people in Ukraine. The attacks also caused a denial-of-service attack on Ukraine's emergency services and disrupted electrical systems. RedEcho, a group based in China, launched widespread cyberattacks against India's power sector, including in DLT and Telangana. The Colonial Pipeline attack. The thwarted Saudi Aramco attack. The 2014 Korea Hydro and Nuclear Power (KHNP) hack.

2.1.9. Solar CME and Nuclear EMP

In 1989, a small CME or solar flare struck Canada and parts of the northern United States, damaging a section of the power grid. If a larger event like the 1869 Carrington event happened today, the impact would be much worse. Experts believe it is only a matter of time before a major coronal mass ejection affects us. In 2012, we narrowly avoided a solar flare at least as strong as the Carrington event by just nine days.

2.1.10. Nuclear EMP (electromagnetic pulse)

A nuclear explosion creates a blast that sends out a pulse, which can seriously damage the power grid[24]. In 1994, Russian scientists revealed details about a nuclear test designed to study the effects of an EMP[25]. The test took place over an industrial area in Kazakhstan, where 148,000 people lived. The explosion destroyed a 600-kilometer underground power line and caused fires at the city's power plant. It also damaged or ruined generators and transmission lines. The Starfish Prime nuclear test could be seen from 900 miles away, and its EMP damaged radios and telephones. On the island of Oahu, even streetlights stopped working. Fewer people know that six satellites were also harmed by the EMP[26]. Any large CME or EMP could lead to widespread power grid failures.

2.2. Impact of reliability issues on economic and social systems

This study examines the economic effects of power disruptions caused by damaged utility infrastructure, rather than the direct property damage to utilities, households, or businesses from natural disasters (from orange painted box on the right side of Figure 3). Regulatory and planning processes for utilities typically do not account for damage to households or businesses caused by disasters[27]. Instead, they focus on damage to the utility system and how it might affect customers later. Utilities and their regulators use this information to make decisions aimed at reducing future impacts. Recent research shows that business interruption costs are more than nine times higher than property damage costs. Because of this, we focus on the economic and social effects of power disruptions, given the limited information available. There are established ways to estimate the direct costs of short, local power outages, and these estimates are often used to support investments in reliability. However, the costs of long-duration, widespread interruptions (LDWIs) are often excluded from planning, partly because there is no standard way to measure the value of resilience. To include LDWI costs in planning, better methods are needed to describe these costs. Most current models use average costs per event or static values per kilowatt-hour, which do not change as the outage continues. These static values are not suitable for analyzing resilience investments, which are meant to address the costs of LDWIs. It is better to use cost estimates that increase with the length and size of the outage, such as duration-dependent customer damage functions (CDFs). When available, these duration-dependent costs typically cover only outages shorter than 24 hours (for example, the Interruption Cost Estimate (ICE) Calculator). To improve this, researchers at the National Renewable Energy Laboratory (NREL) created a framework that uses a duration-dependent approach to the value of lost load (VOLL). This framework separates power interruption costs into three types:

- fixed costs that do not depend on how long the outage lasts;
- flow costs, which add up as the outage goes on;
- stock costs, which are losses of perishable goods after a certain point.

While this approach is better for modeling longer outages, it has three main problems. First, the data used to build the CDFs is not very detailed. Second, the CDFs are based on hypothetical and fixed models. Third, there is insufficient customer data to estimate the required parameters and combine individual CDFs at the sector level. In this study, we focus on island communities, which face special challenges with energy security and resilience because their infrastructure has limited backup options.

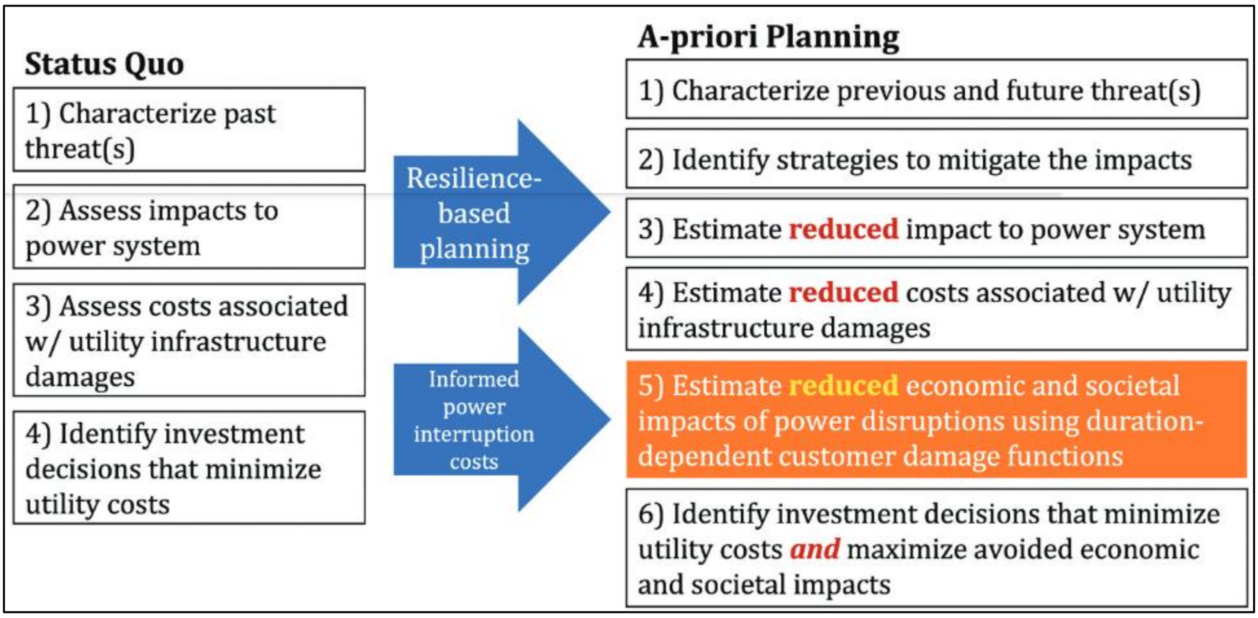

Figure 3 Investments to reduce the risks of power interruptions without and with resilience-based planning and informed power interruption cost estimates [28]

3. Power Grid Faults: Types and Characteristics

Power grid faults are physical problems that stop a circuit element from working as it should[29]. These include short circuits, open circuits, failed devices, and overloads. In practice, most faults are some kinds of short circuit, so the terms' fault and short circuit are often used to mean the same thing. A short circuit is an abnormal connection that lets current flow along a path it shouldn't. Short-circuit faults can have very low impedance, called bolted faults, or higher impedance[30]. Usually, bolted faults cause a protective device to trip, resulting in a power outage for some customers. High-impedance faults, or high-Z faults, have sufficient resistance to prevent protective devices from operating. These faults might not cause outages, but they can create power quality problems and damage equipment. If a power line falls but stays energized, high-impedance faults can also be dangerous. The IEEE also defines open-phase faults, in which a conductor is disconnected without creating a short circuit[31]. Open-phase faults can occur if a conductor fails or due to a bolted-phase fault, such as when a lateral-phase fuse blows and disconnects that phase. These faults can cut off service to customers and pose a hazard, since a line that appears disconnected might still have power due to backfeed. Open-phase faults often occur due to a poor connection at a pole-top switch(Gahan et al., 2020). Any fault can change type due to physical instability, arcing, wire burn-down, or electromagnetic forces. These are called evolving faults, and utility engineers are interested in detecting how faults change over time. Our goal is to detect, classify, and locate faults as accurately as our equipment allows. This process uses different measurements and event-correlation logic, which we will explain later. Figure 4 shows a breakdown of grid faults. We sort bolted faults into momentary (self-clearing) or sustained (which need a protective device to cut power until crews fix the problem). For high-impedance faults, we separate them into intermittent (occurring regularly but infrequently) and persistent (occurring randomly but almost all the time). Faults can also be static or evolving, meaning they change type or involve additional phases over time. For example, a Single Line to Ground (SLG) fault might blow a line fuse. If the plasma moves up into other lines, a phase-to-phase fault can develop from the original SLG fault.

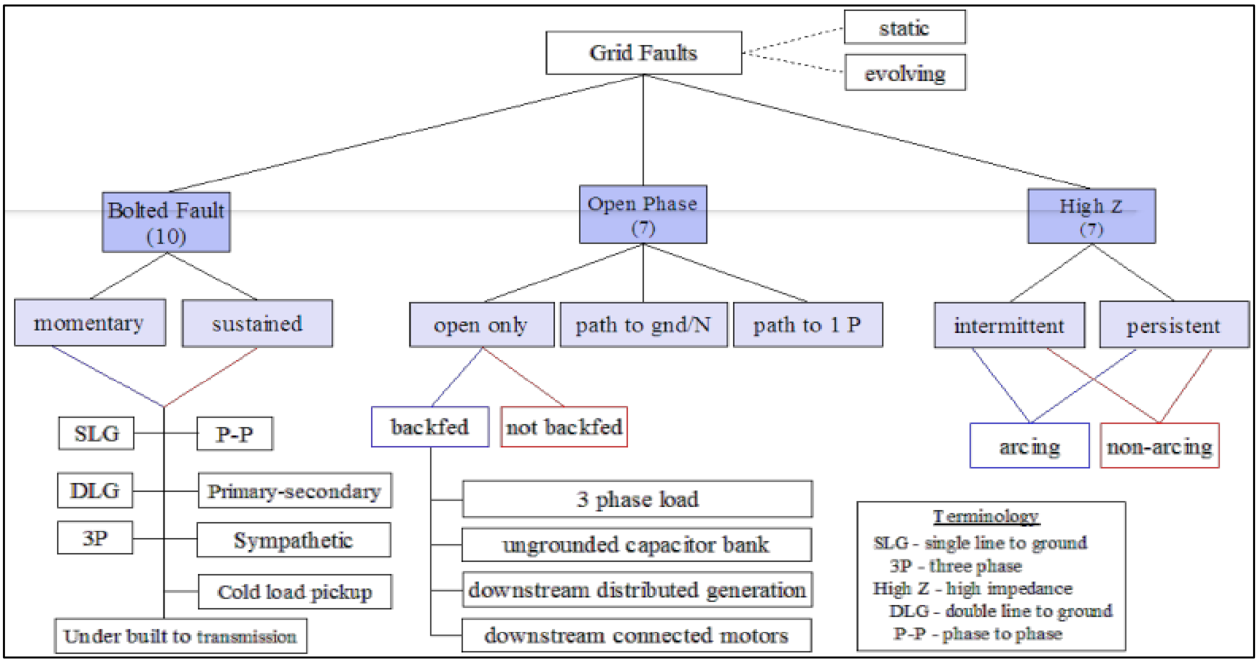

Figure 4 Grid Fault Taxonomy [5]

Table 1 Fault Types and Grid State Indicators

Fault Types	Phase Involvement	Grid State Indicators
Bolted Fault (distribution primary)	SLG	The voltage on the affected phase drops and can reach zero at or below the fault point. If a Neutral Grounding Resistor (NGR) is installed on the transformer, the voltage on non-faulted phases rises above normal levels. The phase current upstream of the fault on the affected line increases sharply until the protection system trips. The neutral current upstream of the fault on the affected line also rises quickly until the protection system trips. The current on the affected line displays a DC offset that gradually decreases over time. Current downstream of the fault on the affected line drops to zero. Meters downstream of the fault send Power Outage Notifications (PONs). After the protection system trips, all meters on the affected line send PONs if they have not already. There is a shift in the impedance phasors. If a fuse interrupts the fault, both phase and neutral currents temporarily rise, which can sometimes trip the circuit breaker. This is known as a sympathetic trip. The voltage on affected lines drops, reaching zero at and behind the fault. Currents upstream of the fault on affected lines increase sharply until the protection system trips.
Bolted Fault (distribution primary)	Dual Line to Ground (DLG)	The currents on affected lines display a DC offset that gradually decreases over time. On affected lines, the currents downstream of the fault drop to zero.

		Meters located downstream on affected lines send out PONs. After the protection system trips, all meters on affected lines issue PONs if they have not already done so. There is a shift in the impedance phasors. The voltages on all three lines become equal. Upstream of the fault, currents on all three lines surge until the protection system trips. The currents on affected lines display a DC offset that gradually decreases over time. Downstream of the fault, currents on all three lines drop to zero. Meters downstream on all three lines send out PONs. After the protection system trips, all meters on all three lines issue PONs if they have not already done so. There is a shift in the impedance phasors. Affected line voltages become equal (or nearly equal). The voltage phases on affected lines become equal, and the line voltage phases become equal.
Bolted Fault (distribution primary)	Phase to Phase (P-P) (wire sway contact) (momentary)	Upstream voltages on the affected lines drop. Current increases significantly upstream in the affected phases. Current decreases significantly downstream in the affected phases. Voltages and currents at the delivery point drop significantly, and meters may issue PONs. There is a shift in impedance phasors.
Bolted Fault (distribution primary)	Secondary hot-to-hot short	In single transformers, half voltages or split phases can decrease to zero or become equal at certain times. The secondary current in a single transformer can go up, even if the load currents to users drop to zero. Impedance phasors may also shift. Affected meters may send PONs. If the transformer fuse opens, the secondary voltages and current will drop to zero.
Bolted Fault (distribution primary distribution secondary)	Fault on one phase causes a delayed trip on another phase; Fuse overload outages – unbalanced phases, for example	• Overvoltage on the distribution conductor • If the distribution interrupter operates, the full transformer voltage appears on the distribution conductor. • Power may flow backward on the distribution conductor. • Faults that occur farther from the distribution substation cause higher over voltages.
Bolted Fault (distribution secondary)	Dispatch may mistakenly send out crews; correct response is to bring loads back online in sections to avoid the pickup trip	A current surge on one phase and the neutral causes the system to trip. After a brief delay, a current surge happens on a different phase and the neutral. This issue may be related to motor loads.
Underbuilt fault to transmission circuit	Blown fuse or dropped primary line, no back feed	• A fault leads to a system trip. As power is restored, the load increases over several seconds or minutes, which can cause another trip.
Sympathetic Trip	Blown transformer fuse or dropped secondary line, no back-feed	Voltage and current on the affected line drop to zero after the fault. Current before the fault on the affected line decreases. Voltage before the fault on the affected line increases slightly.

		Meters affected by the fault send PONs.
Cold load pickup trip	Blown fuse or dropped primary line, back-feed from 3P delta load	If the fuse blows or the jumper breaks, secondary voltage and current drop to zero, and the meters on this transformer send PONs. If the secondary half-phase breaks, half the voltage drops to zero at some or all delivery points, and the related meters send PONs. There is a shift in upstream impedance phasors. The current upstream on the affected line decreases, while the upstream voltage rises slightly. The voltage phase on the affected line may reverse or become similar to that of another line. The downstream current might decrease. Currently, the other two phases might increase. If load protection trips open, voltage and current at the fault and downstream on the faulted line may drop to zero.
Open Phase (distribution primary)	Blown fuse or dropped line, back feed present from ungrounded capacitor bank	The current upstream on the affected line drops, while the upstream voltage rises slightly. There is a change in the upstream impedance phasors. The voltage phase on the affected line may reverse or become similar to that of another line. The downstream current might decrease. The current in the other two phases can increase. If the capacitor fuse blows, the voltage and current at the fault and downstream on the faulted line may drop to zero. A shift occurs in the upstream impedance phasors.
Open Phase (distribution secondary)	Blown fuse or dropped line, back feed from DG	The current upstream on the affected line drops, while the upstream voltage rises slightly. There is a change in the upstream impedance phasors. The voltage phase on the affected line may reverse or become similar to that of another line. The downstream current might decrease. The current on the other two phases could increase. If load protection trips open, the voltage and current on the faulted line may drop to zero.
Open Phase (distribution primary)	Open line connected to another phase	Current upstream on the affected line decreases, and voltage upstream rises slightly. There is a change in the upstream impedance phasors. The voltage on the affected line becomes similar in both magnitude and phase to the connected line. The current downstream may go down. The current on the other two phases might increase. If load protection trips open, the voltage and current at the fault and downstream on the faulted line may drop to zero.
Open Phase (distribution primary)	Open line connected to Neutral/Gnd; no backfeed	The current upstream on the affected line decreases, and the voltage rises a little. There is a shift in the upstream. The voltage on other lines may also rise a little. The voltage and current at the fault and downstream on the affected line drop to zero. Downstream meters issue PONs

Open Phase (distribution primary)	Downed energized primary line, arcin	The voltage and current waveforms are distorted near the fault. If the circuit has a heavy load and a fault occurs on the affected line, the current drops upstream and the voltage rises slightly. A voltage drop happens unless there is backfeed, which causes current to flow downstream from the fault. Downstream meters may show PONs. The voltage may rise on the other lines.
Open Phase (distribution primary)	Downed energized primary line, non-arcing	If the circuit is heavily loaded and a fault occurs in the affected line, a slight increase in voltage upstream as a result The impedance phasors upstream will shift. There will be a voltage drop unless there is backfeed and current flowing downstream from the fault. Downstream meters may show PONs. Other lines may experience voltage rises.
Open Phase (distribution primary)	Defective grid device, arcing	Voltage and current waveforms may become distorted near the fault. Impedance phasors may show jitter near the fault. Characteristic signals become weaker as the distance from the fault increases in both directions.
High Z (distribution primary)	SLG, arcing	Voltage and current waveforms become distorted close to the fault. Impedance phasors show jitter near the fault. Characteristic signals get weaker as you move away from the fault in either direction.
High Z (distribution primary)	SLG, non-arcing	• Subtle increase in current on both affected lines; may be fluctuating or steady • Shift in impedance phasor
High Z (distribution primary)	Phase to phase, arcing	• Voltage and current waveform distortion near the fault on both affected lines • Jitter in impedance phasors near fault • Subtle increase in current on both affected lines; will fluctuate randomly
High Z (distribution primary)	Phase to phase, non-arcing	Subtle increase in current on both affected lines; may be fluctuating or steady • Shift in impedance phasor

4. Traditional Fault Detection and Protection Methods

Traditional fault detection, which relies on basic overcurrent detection, uses measurements mostly taken at the substation [33] and, sometimes, from pole-top devices such as smart switches and reclosers. This approach can provide some useful results, but many faults, especially high-impedance faults, often go undetected or cannot be classified because their waveforms are too weak by the time they reach the substation. As the grid modernizes, we now have more data sources, including line sensors with Remote Terminal Units (RTUs), meters, and substation microprocessor relays, along with their potential and current transformers. By combining data from sensors along a feeder, from other feeders, and even from other substations, we can perform more advanced fault analytics. Clearly defining fault types and their effects on the grid will help us set requirements for RTU, feeder, and substation analytics, as well as for control center analytics, data collection, and processing.

5. Role of Artificial Intelligence in Smart Power Grids

The power grid is changing to meet the demand for more reliable, efficient, and sustainable energy [34]. Traditional grids use centralized energy generation and one-way power flow [35], but smart grids now use advanced communication, automation, and information technologies. These updates enable two-way energy exchange, real-time monitoring, and self-healing features. As a result, smart grids are important for adding renewable energy and supporting decentralized power generation. Still, these improvements introduce new challenges, especially in fault detection and diagnosis (FDD), which are key to maintaining power system stability and reliability.

Power system faults, such as short circuits, transformer failures, line outages, and load imbalances, can cause widespread blackouts and financial losses [36]. Traditional fault detection methods rely on set rules and manual checks, but these are less effective for today's complex smart grids. As a result, Artificial Intelligence (AI), including machine learning (ML), deep learning (DL), and data analytics, is now used to improve fault detection and diagnosis. AI methods can quickly process large amounts of real-time data, find complex patterns, and predict faults with high speed and accuracy.

This study examines how AI supports fault detection and diagnosis in smart grids, focusing on its impact on power system reliability. It covers the theory, real-world uses, and challenges of using AI-based FDD systems. By combining AI with advanced signal processing, statistical analysis, and IoT devices, this research aims to create a framework for real-time fault monitoring and diagnosis in smart grids.

5.1. Evolution from conventional grids to AI-enabled smart grids

Moving from traditional power grids to smart grids is a major change in how electricity is generated, delivered, and used. Smart grids use new technologies like Phasor Measurement Units (PMUs), Advanced Metering Infrastructure (AMI), and IoT sensors to monitor and control the power system in real time. These tools generate large amounts of data, which help improve grid management and enable early detection of problems.

Artificial Intelligence (AI) has changed how faults are found and diagnosed in smart grids by using machine learning, deep learning, and data analysis [37]. These AI systems can handle large amounts of data, spot unusual patterns, and accurately predict faults. This section examines various AI methods for fault detection and diagnosis in modern smart grids. Machine learning is important for finding faults and uses both supervised and unsupervised learning. Supervised models like Support Vector Machines (SVMs) and Random Forests use labeled data to identify known fault types. Unsupervised methods, such as k-means clustering and Principal Component Analysis (PCA), can be used with unlabeled data to identify new or unexpected patterns. Deep learning models, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), are also useful for diagnosing faults [38]. CNNs are good at analyzing images from thermal sensors or electrical signal spectrograms, which helps spot visual signs of faults[39]. RNNs are designed for sequential data and are effective at finding patterns in time-series data from the grid [40].

5.2. Comparative Evaluation of AI Techniques

Table 2 Performance Comparison of AI Techniques [5]

AI Technique	Detection Accuracy	False Positive Rate	Computational Efficiency	Applications
Supervised Learning	95%	3%	High	Fault Classification
Unsupervised Learning	85%	10%	Medium	Anomaly Detection
Convolutional Neural Networks (CNNs)	92%	5%	Low	Image-based Fault Detection
Recurrent Neural Networks (RNNs)	90%	7%	Medium	Time-series Data Analysis
Federated Learning	88%	6%	High	Distributed Fault Detection
Explainable AI (XAI)	91%	4%	Medium	Interpretable Fault Diagnosis

This study compared several AI methods to evaluate how well AI-based FDD systems work. The analysis examined detection accuracy, false alarm rates, and computational efficiency to highlight the strengths and weaknesses of each method. The results suggest that AI-driven fault detection can help stabilize power grids, reduce failures, and improve power system reliability.

Adding AI to smart grids greatly improves fault detection and system diagnostics. Using machine learning, deep learning, and data analytics, AI-based FDD systems can handle large amounts of data, find complex patterns, and predict faults more accurately. Still, it is important to address challenges like data privacy, model interpretability, and cybersecurity to use AI solutions effectively. This study examines how AI is used in smart grids and offers useful insights for power utilities, grid operators, and researchers. The results show that AI can strengthen grids and help create a more flexible, efficient power system.

6. Conclusion

The reliability of future power grids depends on how well planners handle new technologies, extreme weather, and unpredictable demand from electrification and data centers. Faults are always a concern for electric utilities, so they work hard to design protective systems that limit damage when faults occur. Traditional ways of detecting and locating faults have drawbacks because the grid is not fully observable. As observability improves, we gather more raw data that can help manage faults, but automated analytics are needed to process this information. By learning how faults behave, we can create distributed systems that share analytics tasks among smart sensors, substations, and control centers. This leads to better fault analysis and management. Using AI in smart grid fault detection and diagnosis has greatly improved power system stability and efficiency. This study shows that AI-driven FDD frameworks can handle the growing complexity of modern electrical grids. By using advanced machine learning, deep learning, and data analytics, the proposed framework detects and diagnoses faults with high accuracy, reduces false positives, and improves response times.

These findings have important real-world effects. AI-driven FDD systems make operations more reliable by reducing grid downtime and preventing large-scale failures, both of which are key to maintaining a steady power supply. Predictive maintenance with AI helps utilities spot potential faults early, lowering maintenance costs and extending the lifespan of electrical infrastructure. Real-time monitoring also improves how energy is distributed and helps bring renewable energy sources into smart grids more smoothly.

There are still some challenges to overcome before AI-driven FDD systems can be widely used. Collecting and processing large amounts of grid data raises privacy concerns, so privacy-preserving methods such as federated learning are needed. Cybersecurity is also a major concern, as smart grids face more cyber threats. The findings from this research can help guide those working in the power sector. Utility companies could see greater efficiency, lower costs, and better customer service by using AI-driven FDD solutions. Grid operators can use improved situational awareness and predictive analytics to respond to faults more quickly and maintain grid stability. For researchers, this study offers a starting point for exploring new AI methods, improving how these systems are deployed, and developing solutions to meet the evolving needs of smart grids. Overall, this research highlights how AI can transform fault detection and diagnosis in smart grids. The AI-driven framework presented here is a significant step toward making power systems more resilient, adaptable, and sustainable. As the energy sector evolves, AI-driven FDD technologies will help optimize grid operations, reduce outages, and support a shift toward a more sustainable and secure energy future.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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