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Article

# Fault Detection and Classification to Design a Protection Scheme for Utility Grid with High Penetration of Solar Energy – Review

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**Abstract:** The speed of deployment of solar PV (PV) systems into the modern utility grid has altered the operational nature of electrical power systems, and added new challenges to protection engineering. The effectiveness of traditional protection schemes is affected by utility grid with high solar energy penetration, which has bidirectional power flow, low fault current contribution of the inverter, intermittent generation, and dynamically changing operating conditions. Therefore, the development of the intelligent fault detection and fault classification techniques is becoming indispensable for reliable, selective and safe grid operation. In this review, a detailed study of the current fault detection techniques, utility grid protection methods, and artificial intelligence based fault classification methods for high solar penetration utility grid is presented. The conventional relay protection methods are reviewed and compared with advanced signal processing methods, adaptive protection methods, communication based protection methods and the method of machine learning and deep learning. The review shows that intelligent, adaptive, and communication assisted protection architectures offer much greater improvement in fault detection accuracy, relay coordination, and system reliability, making them suitable for next generation renewable integrated utility grids.

**Keywords:** Fault Detection, Fault Classification, Solar Photovoltaic Systems, Utility Grid Protection, Smart Grid, Artificial Intelligence, Adaptive Protection.

## 1. Introduction

Renewable energy resources have been widely deployed into modern power systems and the deployment speed has been accelerated with the increasing demand for clean and sustainable energy in the world. Solar PV (photovoltaic) is the most rapidly growing renewable technology amongst all those available, owing to its environmental advantages, falling installation prices, government subsidies, and technological developments. Recent energy trends show that distributed and centralized solar PV installations are rapidly growing around the globe to help cut carbon emissions and improve energy security. The high penetration of the solar energy does bring in a lot of technical challenges for the conventional power system operation, mainly in the protection coordination and fault management. PV systems do not have an unlimited fault current contribution and dynamic operating characteristics like those of conventional synchronous generators. Power electronic converters are used to connect PV systems to the grid and have limited contribution of fault current and dynamic operating characteristics. Therefore, the current radial protection strategy may not ensure effective fault detection and isolation when penetrating high renewables [1],[2].

Protection of utility grids is becoming more complex as power flows in both directions, intermittent solar generation, inverter-based resources and continually changing operating conditions. Historically, conventional overcurrent, distance and differential relays have been designed with the assumption that the magnitude of the fault current delivered by a synchronous generator is predictable. The installation of distributed photovoltaic installations, however, substantially changes the characteristics of the network faults due to the decrease in short-circuit current, the change of current direction and the uncertainty in the coordination of the relays. The problems can cause protection blinding, sympathetic tripping, delayed power-off, false faults and power outages, and thus degrade overall grid reliability and stability [2], [3].

To address these issues, the research on intelligent fault detection and fault classification methods has been increasing in recent years, which can detect the abnormal operating states of PV systems under different solar PV penetrations with high accuracy. Today, the protection systems employ high-level signal processing techniques and build on AI, ML and DL algorithms for faster fault detection, increasing classification accuracy and adaptive decision making. The conventional relay-based protection schemes have poor ability to recognize transients in the voltage and current signals compared to advanced analytical protection schemes. By contrast, a range of more modern signal processing techniques have proven to be more effective and efficient for extracting these transient characteristics, providing more accurate and reliable fault detection and classification [4], [30], [31], [38].

Smart grid technologies have also helped to propel the evolution of adaptive protection systems, which feature Internet of Things (IoT) platforms, high-speed communication systems and phasor Measurement Units (PMUs), and Intelligent Electronic Devices (IEDs). All these technologies offer the ability to continuously check electrical parameters, perform fast fault analysis and automatically adjust the protection parameters according to the operating conditions of the network. As such, the importance of adaptive and intelligent protection schemes has become more prominent to ensure security, reliability and resilience of modern utility grid systems with increased penetration of renewable energy resources [27], [32], [33].

This review is a detailed analysis of recent advances in fault detection and fault classification, which can be used to enhance the protection systems used for PV dominated power networks, in which a large share of the components is solar PV (PV). It covers critically protection technologies for traditional applications and the latest signal processing, AI fault diagnosis algorithms, adaptive protection and other smart grid technologies for future applications. In addition, the review highlights existing gaps in the research and suggests future research directions that could help enhance future protection systems for electrical power networks with a higher degree of accuracy, reliability and efficiency.

***Overview***

The main purposes of all power system protection schemes are to detect and classify faults. Their primary goal is to detect abnormal operating situations quickly, identify the fault location and type, isolate the faulted area and continue to supply power to non-faulted areas. The traditional practice of protection coordination is heavily reliant on predictable fault current in conventional utility grids, which is produced by synchronous machines. Traditional protection methods are not effective in these operating scenarios because of the increasing penetration of inverter-based PVs, which have fundamentally altered the operating characteristics [5], [24].

Power system protection has also been revolutionized in recent years from the traditional relay coordination to adaptive protection, based on data and knowledge and incorporating advances in computational intelligence. Artificial Intelligence (AI) and Machine Learning (ML) can be used to analyze a lot of operational data and detect the complex fault pattern, which would enable to detect and classify the fault even with noisy measurement and uncertain operating condition. Moreover, Deep Learning (DL) based methods improve protection performance by automatically learning relevant features from voltage and current waveforms, which reduces the need for manual feature engineering and increase the speed of protection process response and the accuracy of the classification [35],[37],[38].

Intelligent protection technologies are expected to be essential part of next generation smart grid considering the ongoing expansion of integration of renewables and decentralized power generation. Their flexibility in adapting with changing network conditions, their enhanced decision making capabilities and their capability to offer reliable fault diagnosis will be key to securing the future electrical power system's security, resilience and operational reliability.

***Scope and Objectives***

This chapter's goals are to:

1. To investigate the effect of high solar PVs impact on utility grid protection.
2. To introduce the conventional and intelligent fault detection methods in the current power system.
3. To analyze different fault classification techniques using signal processing, machine learning and deep learning.

4. To compare present protection schemes and their strengths and weaknesses.
5. To recognize the gaps in existing research and future areas for adaptive protection of renewable-rich utility grids.

***Author Motivations***

The rapid evolution in the traditional electrical network to renewable rich smart grid has made the need for reliable and adaptive protection systems operating under highly dynamic conditions a pressing need. A large number of fault detection and classification algorithms have been proposed in recent years, but none can fully solve all the problems of inverters-based renewable energy generation with different fault currents, communication delay and distributed energy resources. The challenges inspired this review to systematically synthesize recent research advances and offer a total picture of the intelligent protection methods that can be implemented in future high level of solar penetration grids.

***Paper Structure***

This chapter is organized into six sections. Section 2 reviews existing fault detection, fault classification, and protection techniques. Section 3 discusses intelligent protection methodologies and mathematical foundations. Section 4 presents a comparative analysis of existing approaches. Section 5 highlights applications, challenges, and future research directions. Finally, Section 6 concludes the chapter.

## 2. Literature Review

Application of solar photovoltaic (PV) systems to today's utility electricity grid is fundamentally altering the nature of electric power system operation. Renewable-rich power networks have power flow that is bidirectional, with a variable amount of power generation, limited fault current contribution from the inverter-based resources, and continuously changing operating conditions, in contrast to conventional power networks that typically rely mainly on synchronous generators. In the last ten years, many research works have been presented to address these newly emerged challenges, such as signal processing techniques, Artificial Intelligence algorithms, Adaptive Relay Coordination techniques, and Communication-assisted protection frameworks [1]–[6].

The initial studies mainly targeted the effect of the penetration of renewables in traditional relay protection systems. Gupta et al. [1] gave a thorough study on fault detection and classification of a wind/solar energy dominated utility grid. The study showed that the use of renewable energy has a significant impact on the fault current characteristics, which makes it more difficult to apply traditional overcurrent protection. The authors stressed the need to have intelligent protection algorithms which are able to adapt to different operating conditions to ensure reliable system operation. Likewise, Chawda et al. [2] did a comprehensive survey of the power quality disturbance detection and classification techniques in Renewable integrated Power system. Their results indicated that signal processing methods with high ability to recognize disturbances give high accuracy of disturbance recognition and are useful information for operating relays intelligently.

Yogee et al. [3] proposed an intelligent algorithm to detect faults in utility grids with renewable energy sources by combining advanced signal processing and classification techniques. A proposed framework was shown to be more discriminating between the normal operating disturbances and actual fault events for different renewable generation levels. Likewise Zeb et al. [5] has done a detailed review of a fault ride through strategy and protection issues for grid connected PVs. Inverter-based renewable generators are found to be able to inject significantly lower short circuit current than synchronous machines, which poses serious problems for traditional relay coordination using current.

The reliability of PV systems has also been the focus of studies in the recent past, with attention being paid towards advanced fault diagnosis and condition monitoring methodologies. To detect the faults in grid connected PV inverters, Malik et al. [6] reviewed some methods and classified the identified methods into electrical parameter monitoring, thermal analysis, model-based diagnosis, signal processing and artificial intelligence approaches. The authors found that generally, AI techniques better perform the diagnostic task in varying environments. Similarly, Livera et al. [7] surveyed the performance-based fault diagnosis methods for photovoltaic systems and showed that continuous monitoring of PV performance could be useful to detect degradation and failures before catastrophic failures. Singh et al. [8] and Sayed et al. [9] and [10] also highlighted that reliability assessment studies indicate that preventive maintenance and intelligent monitoring play major role in enhancing the reliability of the system and its availability.

Digital signal processing has seen rapid development, and its use in fault detection in power systems with renewable energy has significantly improved. Standard Fourier analysis methods have limited time-frequency resolution and generally are not able to perform the analysis of transient fault signals. These techniques are capable of effectively extracting transient characteristics of various types of faults and have extremely discriminative features for the following classification algorithms [2], [22], [35], [36], [37]. These features have been extracted, which makes it possible to improve the accuracy of intelligent protection systems for distinguishing symmetrical faults and unsymmetrical faults to a much greater extent than conventional threshold-based protection systems.

Artificial intelligence is one of the most promising technologies of the power system protection field in the modern era. Machine learning algorithms can learn relationships between electrical measurements and fault conditions that are not explicitly modeled, especially if the relationships are complex and nonlinear. Alrifaey et al. [18] introduced a hybrid deep learning system for fault detection and classification in photovoltaic systems that are connected to a grid. Their model was a deep feature extraction combined with intelligent classification, and achieved a high detection accuracy even when the light and loading conditions changed. Hatata et al. [19] designed an adaptive protection system for micro grid based on Convolutional Neural Networks (CNN) optimized by Gorilla Troops Optimization ( GTO). The suggested framework proved to be very fast in detecting the fault and ensured reliable relay coordination in different operating conditions. Likewise, Mumtaz et al. [20] proposed a two-stage hybrid filtering method that is effective for fault detection in active distribution networks (ADN) with renewable energy resources (RESs).

Hierarchical features have also been extracted automatically from electrical measurements to enhance the fault classification task with deep learning techniques. In recent years, other CNN-LSTM networks, transformer networks, and ensemble learning methods have been investigated to make the classification more robust in the case of noisy operating environments [18], [21], [27], [31], [32].

Another important research trend is adaptive protection due to the dynamic nature of renewable-rich distribution systems, where fixed values of relays can no longer cope with the dynamic behavior. Emhemed and Burt [14] suggested an adaptive protection strategy to dynamically change the relay settings in response to the operating state of the network. Their strategy proved to be a big contribution to protection sensitivity and selectivity with a minimum of un-needed relay operations. Alhelou et al. [24] and Liang [43] presented similar investigations, which showed that adaptive relay coordination significantly enhances fault isolation performance under different renewable penetration rates. Bretas [44] and Khan [38] investigated adaptive relay coordination, showing that it results in a significant reduction in fault isolation performance. More recently the use of Intelligent Electronic Devices (IEDs), Phasor Measurement Units (PMUs), Supervisory Control and Data Acquisition (SCADA) and Wide Area Measurement Systems (WAMS) have further improved the effectiveness of communication-assisted protection systems in providing synchronized measurements and real-time situational awareness [24], [33], [40].

These technologies enable geographically distributed renewable energy resources to be monitored and maintained automatically, proactively and continuously, diagnosed autonomously and protected together. The possibilities of the upcoming protection systems are likely to be further enhanced by emerging technologies like Explainable Artificial Intelligence (XAI), federated learning, graph neural networks, digital twins, and transformer-based architectures [34]–[50].

***Research Gap***

While significant improvements have been made in fault detection and protection technology of power systems with renewable energy sources, there are some research gaps that are noticed in literature. First, a large number of published studies only test the fault detection algorithms on a simplified simulation environment, which fails to take into account realistic utility grid operating conditions with multiple distributed photovoltaic (PV) generators, dynamic load conditions, and variable weather and environmental conditions [1], [5], [16]. As a result, most of the techniques suggested are not well enough tested in practice.

Secondly, most of the traditional protection schemes rely largely on the magnitude of fault current for relay operation. The approaches have been shown to experience reduced sensitivity and incorrect fault discrimination under high renewable penetration levels [5], [11], [14] due to inverter-based photovoltaics (IB-PVs) producing only a small amount of fault current. While protection strategies have been suggested, there is yet to be a universal framework that can provide reliable relay coordination in all operating scenarios.

Third, artificial intelligence based classification techniques have proven to be very successful, but many deep learning models are data intensive, demanding and have a long training process. They also have not been well understood in terms of their decision making process and this has restricted their use in safety critical utility applications. Although Explainable Artificial Intelligence (XAI) has become an important field of research in power systems protection, the research efforts are still relatively limited in this area [21], [34] and [47].

Moreover, the number of studies exploring protection architectures with a combination of advanced signal processing, intelligent fault detection, adaptive relay coordination, synchronized measurements, and communication-aided protection in an integrated manner is restricted. Most of the existing investigations are targeted at individual components and not end-to-end protection systems appropriate for smart grid systems [24, 33, 38, 43].

Last but not least, new technologies like digital twins, edge computing, federated learning, graph neural networks, transformer-based architectures and cyber-secure protection systems are only just starting to be explored in research. A few review papers that focus on the integration of these technologies in intelligent protection structures for electric power grids with high solar penetration are available [46]–[50].

To address these gaps in the research, this review will seek to systematically and comprehensively review the existing fault detection, intelligent fault classification, adaptive protection, communication-aided protection and emerging artificial intelligence technologies for designing reliable protection schemes in utility grids with high solar PV energy penetration ratio.

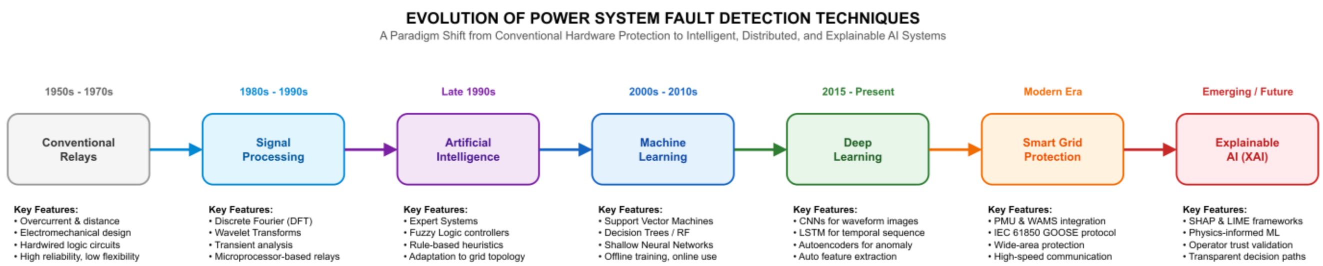


**Figure 1**. *Evolution of Fault Detection Techniques*

## 3. Fault Detection Mechanisms in Utility Grids with High Penetration of Solar Energy

The installation of Solar PV (SPV) power has made the fault characteristics of the grid different, making standard protection schemes less effective. A PV system using an inverter has relatively low and controlled fault currents because of the use of converter control strategies and current limiting. As a result, traditional protection devices based on the magnitude of the fault current suffer from a decrease in sensitivity, "blindness", delayed operation, and coordination problems. Hence, it is required to have intelligent fault detection system in modern utility grid which can detect fault with high accuracy in very dynamic operating conditions [1]-[3]-[5]-[6]-[11].

The major purpose of fault detection is to continuously monitor the electrical parameters, detect abnormal disturbances, identify fault occurrence as soon as possible and give reliable information to the protection system to take necessary corrective measures. The fault detection mechanism should have high sensitivity, quick response, strong noise immunity, strong renewable generation variability resistance and have fault and transient separation function. In recent years, the accuracy of fault detection has been greatly enhanced in the presence of renewable generation through advances in signal processing, artificial intelligence, synchronized measurements and protection assisted by communication [2], [18], [20] and [24].

### *3.1 Classification of Electrical Faults*

In the networks, electrical faults are mostly classified based on the number of conductors involved with fault and how they are connected to the ground. These faults affect the various voltages, currents, frequency stability and power quality in the system and can cause severe damage to electrical equipment and loads.

There are several significant fault categories, which include:

- Single Fault between two wires (DL).
- Line-to-Line (LL) Fault
- Multiple simultaneous faults such as two or more lines crossing LGs that occur at the same time.
- High Impedance Fault (HIF)

- Open Conductor Fault
- Arc Fault

Of these fault types, the single line to ground fault is by far the common one to occur in practice distributing systems ranging from 70-80% of all reported faults. Three phase faults are less common, but typically create the highest fault currents and are considered to be the most severe operating condition for electrical equipment [1, 3, 11, 22].

Table 1. **Classification of Electrical Faults in Solar Integrated Utility Grids**

| **Fault Type** | **Occurrence** | **Severity** |
|---|---|---|
| Single Line-to-Ground (SLG) | Very High | Medium |
| Line-to-Line (LL) | Medium | Medium |
| Double Line-to-Ground (DLG) | Medium | High |
| Three Phase (LLL) | Low | Very High |
| Three Phase-to-Ground | Low | Very High |
| High Impedance Fault | Medium | Difficult to Detect |
| Open Conductor Fault | Low | Moderate |
| Arc Fault | Low | High |

### *3.2 Mathematical Representation of Fault Current*

$$I_f = \frac{V_{th}}{Z_{th} + Z_f}$$

where

- $I_f$ = Fault current
- $V_{th}$ = Thevenin equivalent voltage
- $Z_{th}$ = Equivalent system impedance
- $Z_f$ = Fault impedance

In conventional power systems, $I_f$ is usually several times higher than the rated current. However, inverter-based photovoltaic generators intentionally limit fault current to approximately 1.1–2.0 per unit, thereby reducing relay sensitivity and increasing fault detection complexity [5], [6], [14].

### *3.3 Symmetrical Component Analysis*

Fault analysis in three-phase systems is commonly performed using symmetrical component theory. Any unbalanced three-phase current can be represented as

$$\begin{bmatrix} I_a \\ I_b \\ I_c \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & a^2 & a \\ 1 & a & a^2 \end{bmatrix} \begin{bmatrix} I_0 \\ I_1 \\ I_2 \end{bmatrix}$$

where

- $I_0$ = Zero sequence current
- $I_1$ = Positive sequence current
- $I_2$ = Negative sequence current
- $a = e^{j120°}$

The negative sequence and zero sequence components are much greater in unbalanced fault conditions than in balanced conditions, while positive sequence components are predominant during balanced operation. A lot of modern protection systems use these sequence quantities for relay operation and fault classification, respectively [11], [24].

### *3.4 Signal-Based Fault Detection*

Transient disturbances in voltage and current waveforms are caused by electrical faults. These signatures are transient and give useful information on the inception of the fault, the location of the fault, and the type of fault. Traditional Fourier Transform methods only give frequency domain information and have some limitations in non-stationary transient events.

The most popular signal processing methods are:

- Discrete Wavelet Transform (DWT)
- This is the Continuous Wavelet Transform (CWT).
- Stockwell Transform (ST)

DWT has been widely studied as one of these approaches owing to its superb time-frequency localization property. The discrete wavelet transform is given by,

$$W(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x\,(t)\psi\left(\frac{t-b}{a}\right) dt$$

where

- $x(t)$ = Input signal
- $\psi$ = Mother wavelet
- $a$ = Scale parameter
- $b$ = Translation parameter

The transient energy variation due to different fault conditions can be well represented by the wavelet coefficients that makes them useful for intelligent protection system [2], [22], [35], [37].

### *3.5 Artificial Intelligence-Based Fault Detection*

The accuracy in fault detection has been greatly improved with the use of machine learning, which learns complex relationships between electrical measurements and faults automatically. AI algorithms are different from the traditional threshold-based systems because they take into account multidimensional features derived from voltage, current, frequency, impedance, harmonics and sequence components.

- Artificial Neural Network (ANN)
- Support Vector Machine (SVM)
- Decision Tree (DT)
- Random Forest (RF)

The combination of spatial and temporal learning capacities in hybrid CNN-LSTM architectures is also beneficial for the classification task [18]–[21], [27], [31]–[32].

A two-class classification function of a neural network can be written as

where

- $x$ = Input feature vector
- $W$ = Weight matrix
- $b$ = Bias

- $f(\cdot)$ = Activation function
- $y$ = Fault prediction output

The objective during training is to minimize the prediction error using the cross-entropy loss function

$$L = -\sum_{i=1}^{N} y_i \, log(\hat{y}_i)$$

### *3.6 Wide-Area Monitoring-Based Fault Detection*

Phasor Measurement Units (PMUs) have made synchronized monitoring of electrical quantities possible in geographically separated power system possible. PMUs are able to perform high speed synchronized measurements with Global Positioning System (GPS) timing that enable protection systems to quickly determine abnormal operating conditions.

Wide Area Measurement Systems (WAMS) enhance

- Fault localization
- Dynamic state estimation
- Voltage stability monitoring
- Oscillation detection
- Relay coordination
- Adaptive protection

PMU-based protection systems, combined with Intelligent Electronic Devices (IEDs), SCADA systems and communication networks, offer great benefits in terms of speed and reliability of fault detection in the event of high renewable penetration [24], [33], [38], [43].

## 4. Protection Schemes for Utility Grids with High Penetration of Solar Energy

The introduction of solar PV generation in a fast-growing way has drastically changed the approach of designing power system protection. The conventional protection schemes were designed for passive RDs with large synchronous generators with known fault current characteristics. The introduction of inverter based distributed generation, however, has resulted in a new and different set of challenges, such as bidirectional power flow, lower fault levels, dynamic network topology, and intermittent power generation, that make traditional protection methods ineffective. Therefore, modern smart electricity networks need adaptive and intelligent protection systems with communication support in order to ensure the reliability, selectivity, sensitivity and operational security of the networks during varying degrees of renewable energy penetration [1], [5], [11] and [14].

The main goal of a protection scheme is to identify abnormal operating conditions, isolate the faulted area as quickly as possible, limit damage to the equipment, keep the system stable, and keep the power on to areas of the system that are not faulty. The desired protection system should have the following properties:

- High sensitivity
- Fast operating speed
- High selectivity
- Operational reliability
- Avoid false operation by providing security. Provide security from false operation.
- The ability to adjust to different network scenarios.
- Economic implementation

With the growing complexity of renewable integrated power systems, research has been undertaken to propose a range of protection schemes, from traditional relay coordination to innovation by adaptive and artificial intelligence based protection schemes.

### *4.1 Conventional Protection Schemes*

Traditional utility grids mostly rely on relay protection systems, which detect various electrical parameters, including current, voltage, impedance, frequency and power direction. There are a number of protection devices commonly used, such as:

- Overcurrent Relay (OCR)
- Directional Overcurrent Relay (DOCR)
- Distance Relay
- Differential Relay
- Under/Over Voltage Relay
- Under/Over Frequency Relay

Of these the overcurrent protection is the most common technique due to the simplicity of its implementation, low cost, and ease to coordinate. This is done by comparing the current measured with a preset current value called the "pickup value.

The operating condition of the relay is

$$I_{measured} > I_{pickup}$$

where

- $I_{measured}$ = Measured line current
- $I_{pickup}$ = Relay pickup current

While overcurrent relays in radial distribution systems are satisfactory, their performance is questionable if large PV installations are placed. Conventional overcurrent relays are not effective when they are connected to a large number of inverter-based resources as inverter-based resources are limited sources of fault current [5, 11, 14].

### *4.2 Relay Coordination in Renewable Integrated Grids*

Relay coordination is the point by which the protection only operates on the first relay on the line to a fault whereas the others are not activated. When the system works in harmony, there are fewer outages for the needless reasons.

$$t = \frac{K}{\left(\frac{I_f}{I_{pickup}}\right)^{\alpha} - 1}$$

where

- $t$ = Relay operating time
- $K$ = Relay constant
- $\alpha$ = Relay characteristic constant
- $I_f$ = Fault current

Thus, the coordination of relays becomes more complex and more difficult, leading to relay blinding, sympathetic tripping, fault clearance delay and protection miscoordination [1], [14], [38].

### *4.3 Directional Protection*

In Renewable Integrated Distribution systems, direction of power flow is bidirectional which requires the employment of Directional relays.

The criterion of operation can be stated as:

$$P = VIcos\phi$$

where

- $P$ = Active power
- $V$ = Voltage
- $I$ = Current
- $\phi$ = Power factor angle

With multiple distributed generators and interconnected feeders, the directional protection effectiveness with regard to fault discrimination is significantly enhanced. The more distributed energy resources that are involved, however, the more complicated it becomes to coordinate the setting of the relays [11] [24] [38].

### *4.4 Differential Protection*

The difference between the two currents is known as the differential current and is given by

$$I_{diff} = I_1 - I_2 \vee$$

The relay operates whenever

$$I_{diff} > I_{setting}$$

where

- $I_1$ = Incoming current
- $I_2$ = Outgoing current
- $I_{setting}$ = Differential pickup current

However, differential protection shows high level of selectivity and operating speed, but it is not easy to apply in large-scale utility networks because of the requirement of reliable communication lines and synchronized current measurement, which will increase the installation cost in large-scale utility networks [24], [33].

### *4.5 Distance Protection*

The impedance estimation of distance protection is an estimation of the impedance from the relay position to the point where the fault occurred. The relay compares the electrical impedance with respect to length of the transmission line, so it is able to identify if the fault is located within the protected zone.

The experimental value of the reactance is

$$Z = \frac{V}{I}$$

If

$$Z < Z_{set}$$

An internal fault is declared by the relay.

In the transmission networks, distance relays are the most commonly used relays due to their quick acting speeds and relatively low sensitivity to fault current. Inverter based renewable generation can however affect the accuracy of impedance measurement and for this reason adaptive impedance estimation algorithms are needed, [14],[24].

### *4.6 Adaptive Protection Schemes*

Adaptive protection has been proving to be one of the most promising solutions for power systems with a high share of renewable power generation. Adaptive protection continually changes relay operating parameters based on current operating conditions of the system, as opposed to fixed settings used in traditional protection.

The adaptive relay setting can be defined as

$$S = f(L, G, N)$$

where

- $S$ = Relay setting
- $L$ = Load condition
- $G$ = Renewable generation level
- $N$ = Network topology

Adaptive protection has taken information from

- The use of Intelligent Electronic Devices (IEDs)
- Wide Area Measurement Systems (WAMS)
- Distribution Management Systems (DMS)

When network operating conditions change, real-time monitoring can automatically adjust the relay settings to enhance the protection reliability in high solar penetration conditions [14], [24], [33], [43].

### *4.7 Communication-Assisted Protection*

Many modern smart grids have protection devices communicating synchronized measurements in fast communication networks, a type of protection system we term communication-assisted.

Common means of communication are such as:

- IEC 61850
- Optical Fiber Communication
- Ethernet-based Protection Networks
- Wireless Sensor Networks
- 5G Communication

Communication-assisted protection enables

- Fast fault isolation
- Remote relay coordination
- Wide-area protection
- Self-healing networks
- Distributed fault diagnosis

Implementing IEC 61850 has been adopted as the international standard for intelligent substations, as it enables interoperability between protection devices and also minimizes the communication delays [24], [33], [40], [43].

### *4.8 Artificial Intelligence-Based Protection*

Protection performance has been greatly enhanced by using AI technology, bringing automatic fault recognition and adaptive relay operation to the fore.

The overall general AI protection process is:

1. Signal acquisition
2. Signal preprocessing
3. Feature extraction
4. Feature selection
5. Fault classification
6. Relay decision
7. Fault isolation

Using machine learning algorithms like ANN, SVM, Decision Trees, Random Forests, CNN, LSTM, and Transformer networks without the need to design the relay characteristics, the complex nonlinear relationship between the electrical measurements and fault conditions can be learned automatically [18]–[21], [27], [31] and [32].

The fault decision function can be represented by

$$F = C(X)$$

where

- $X$ = Extracted feature vector
- $C(\cdot)$ = Classification model
- $F$ = Predicted fault class

Recent researches show that hybrid deep learning models can achieve a high detection accuracy rate of faults, and at the same time, have good real-time response speed, with different values of renewable energy generation [18], [21], [31].

### *4.9 Comparison of Protection Schemes*

Table 2. **Comparison of Protection Schemes for Solar Integrated Utility Grids**

| **Protection Scheme** | **Response Speed** | **Complexity** | **Major Limitation** |
|---|---|---|---|
| Overcurrent Relay | Medium | Low | Relay blinding under PV integration |
| Directional Relay | High | Medium | Complex coordination |
| Distance Relay | High | Medium | Impedance variation due to inverter operation |
| Differential Relay | Very High | High | Communication requirement |
| Adaptive Protection | Very High | High | Real-time computation required |
| Communication-Assisted Protection | Very High | High | Communication latency and cyber security |
| AI-Based Protection | Excellent | High | Large training datasets and computational resources |

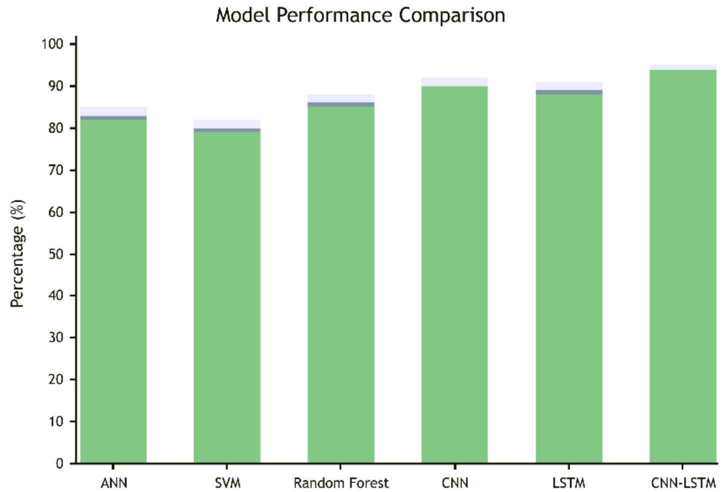


**Figure 2.** *Comparative Performance of Fault Classification Algorithms*

## 5. Artificial Intelligence-Based Fault Classification Techniques

As modern electric power systems become more complex, having ever higher penetrations of solar PV generation, there is a great need for intelligent fault classification techniques. The purpose of conventional relay protection is to decide whether a fault has taken place and, in most cases, gives little information about the fault type, fault location or fault severity. Proper fault classification is critical as the protection and restoration strategies will be different depending on the type of fault. Frequently, the traditional threshold-based classification techniques suffer from a lack of precision because of the reduced capability of the contribution of fault currents, dynamic operating conditions and bi-directional power flow for the use of inverter based renewable energy resources. Therefore, various Artificial Intelligence (AI), Machine Learning (ML) and Deep Learning (DL) methods have been developed as potential solutions to the intelligent fault classifications in Renewable-Integrated Utility Grids (RIUGs) [18]–[24].

AI allows protection devices to learn and identify intricate relationships between electrical parameters that are hard to model through traditional analytical techniques. Compared to the traditional algorithms used in relays, intelligent classifiers are continuously trained to achieve better prediction accuracy, thus they are very well suited for dynamic smart grid applications [21], [23], [27], [32].

### *5.1 AI-Based Fault Classification Framework*

The intelligent fault classification system is generally divided into several stages: electrical measurements are converted into raw data, which is then processed to generate a classification. The general structure of an intelligent fault classification system is a series of sequential stages that transform raw electrical measurement to a reliable protection decision.

The major processing steps are:

1. Feature Selection
2. AI-Based Classification
3. Decision Making
4. Relay Operation

These measurements are then smoothed to reduce the noise of the measurements and any unwanted disturbances and then features extracted.

The feature vector can be represented as

$X = [x_1, x_2, \dots, x_n]$

where

- $X$ = Feature vector
- $x_i$ = Individual extracted feature
- $n$ = Number of extracted features

## *5.2 Feature Extraction Techniques*

The feature extraction is one of the most crucial steps of intelligent fault classification, as the classification accuracy greatly relies on the quality of extracted information. Fault classification algorithms which are used in the modern era, use time domain and frequency domain representations of the electrical signals for obtaining information.

Common Electrical Services:

- Sequence components
- Total Harmonic Distortion (THD)
- Wavelet coefficients
- Signal energy
- Entropy
- Frequency deviation

Discrete Wavelet Transform (DWT), being one of the most popular signal processing technique, is employed to accurately capture the transient characteristics related to the fault inception [2], [22], [35].

The amount of energy in a signal is usually determined by computing:

$$E = \sum_{i=1}^{N} x_i^{\ 2}$$

where

- $E$ = Signal energy
- $x_i$ = Signal sample
- $N$ = Number of samples

High energy transients are normally a sign of more serious fault conditions.

## *5.3 Artificial Neural Networks*

ANNs are composed of interconnected neurons that during the supervised training process acquire non-linear correlations between the electrical measurements and fault classes.

The result of an Artificial Neuron is given by

$$y = f\left(\sum_{i=1}^{n} w_i\, x_i + b\right)$$

where

- $w_i$ = Connection weight
- $x_i$ = Input feature
- $b$ = Bias
- $f(\cdot)$ = Activation function

Under noisy operating conditions, ANNs have shown great performance in fault classification of symmetrical and unsymmetrical faults and are robust. Traditional ANN models, however, need great care in tuning the parameters in order to obtain a high classification accuracy and huge training sets [18, 23, 27].

### *5.4 Support Vector Machine*

The SVM can be trained with smaller size data sets because of its good generalization performance.

The decision function is 153.The decision function is 153.

$$f(x) = w^T x + b$$

where

- $w$ = Weight vector
- $x$ = Feature vector
- $b$ = Bias

The kernel-based SVM models are then used to further enhance the nonlinear fault classification by projecting the input features to higher dimensional feature spaces. There are many studies reporting high classification accuracy of SVM under diverse renewable generation scenarios for line-to-ground, line-to-line and three-phase faults [18], [21], [32].

### *5.5 Decision Tree and Random Forest*

The Decision Tree (DT) classifiers are based on electrical feature extraction and classify the faults in a hierarchy of decision rules. They are simple to construct, making them easy to classify and implement in embedded relay equipment.

Random Forest (RF) is an extension of decision tree learning, which uses multiple decision trees to form an ensemble model.

The function of prediction is

$$F(x) = \text{Mode}\{T_1, T_2, \dots, T_n\}$$

where

- $T_i$ = Individual decision tree
- $F(x)$ = Final predicted fault class

The random forest classifiers usually have higher accuracy and are less prone to over fitting than single decision trees [21] [27].

### *5.6 Deep Learning-Based Fault Classification*

With the advent of deep learning, intelligent fault diagnosis has experienced a dramatic shift from manually engineered features to end-to-end learning.

The most popular deep learning architectures are:

- Gated Recurrent Unit (GRU)
- Auto encoders
- Transformer Networks
- Hybrid CNN-LSTM Models

CNNs are capable of effectively recognizing spatial patterns contained in voltage and current patterns via convolution operations.

The convolution operation is expressed as:

$$Y = X * K$$

where

- $X$ = Input feature map
- $K$ = Convolution kernel
- $Y$ = Output feature map

LSTM networks further improve classification performance by learning temporal relationships among sequential electrical measurements.

$$h_t = f(h_{t-1}, x_t)$$

where

- $h_t$ = Hidden state
- $x_t$ = Current input

Recent studies have shown that the hybrid CNN-LSTM Systems can be more effective for fault classification than traditional machine learning systems, due to the ability of the CNN to learn the spatial aspect of the fault and the LSTM to learn the temporal aspect [18]–[21], [31]–[32].

## *5.7 Performance Evaluation Metrics*

Intelligent fault classification algorithms are usually tested by statistical performance measures.

The accuracy in classification is defined as

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision is

$$Precision = \frac{TP}{TP + FP}$$

Recall is

$$Recall = \frac{TP}{TP + FN}$$

The F1-score is expressed as

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

where

- $TP$ = True Positive
- $TN$ = True Negative
- $FP$ = False Positive
- $FN$ = False Negative

The metrics of these performance are used to objectively compare various machine learning and deep learning algorithms together under similar testing conditions [18], [21], [27].

## *5.8 Comparative Analysis of AI Techniques*

Table 3. **Comparison of Artificial Intelligence Techniques for Fault Classification**

| **Technique** | **Accuracy** | **Complexity** | **Major Advantages** |
|---|---|---|---|
| Artificial Neural Network | High | Medium | Learns nonlinear fault characteristics |

| | | | |
|---|---|---|---|
| Support Vector Machine | High | Medium | Performs well with limited datasets |
| Decision Tree | Moderate | Low | Fast implementation and easy interpretation |
| Random Forest | High | Medium | Robust against overfitting |
| CNN | Very High | High | Automatic spatial feature extraction |
| LSTM | Very High | High | Captures temporal dependencies |
| Hybrid CNN-LSTM | Excellent | Very High | Simultaneous spatial and temporal learning |
| Transformer Networks | Excellent | Very High | Long-range dependency modelling |

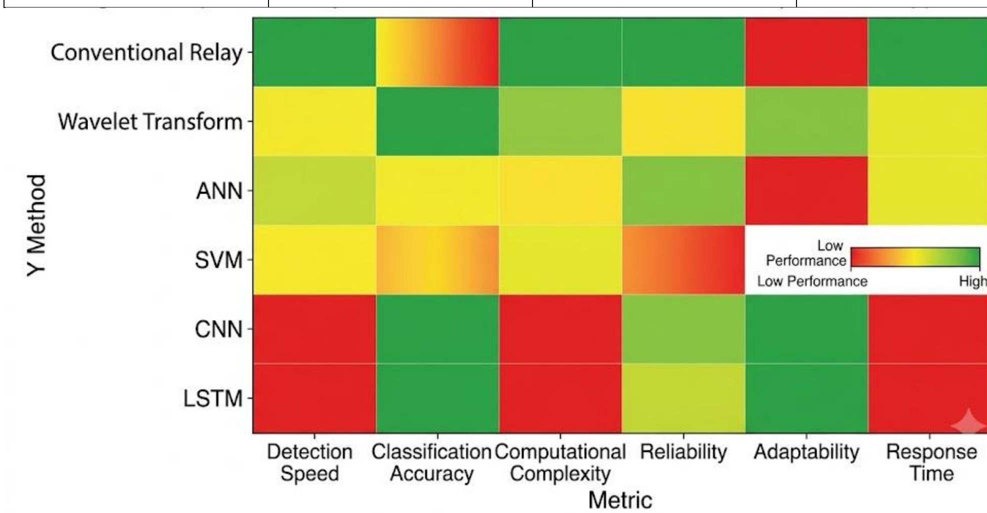


**Figure 3.** *Heatmap of Protection Scheme Performance*

## 6. Comparative Analysis, Challenges and Future Research Directions

As solar PV (PV) systems are being increasingly deployed in the utility grid, advanced fault detection, fault classification and protection strategies are rapidly evolving. In the last decade, research has moved away from the traditional relay-based protection towards intelligent, adaptive and communication assisted protection systems that can deal with the dynamic nature of power networks that incorporate renewable generation. While significant advancements have been made in the accuracy of detection and reliability of protection, each protection method has its own distinct advantages and disadvantages based on a network configuration, renewable penetration level, computational needs, communication facilities, and operating environment. It is necessary to carry out an extensive comparative study to understand the protection techniques that can be adopted and the future research challenges [1] [2] [5] [11].

### *6.1 Comparative Analysis of Fault Detection Techniques*

Most of the traditional fault detection methods rely on threshold values of current, voltage, impedance or frequency. These methods are low cost and easily implemented, but do not work well when there is a high percentage of distributed generation with inverters. The conventional relays suffer such phenomena as relay blinding, delayed action, and unnecessary tripping [5, 11, 14].

These techniques have good sensitivity to short duration disturbances, and offer useful features for intelligent classifiers. But they are costly to compute as the length of the signal and the degree of its decomposition grow in size, which makes implementation in large-scale utility networks real-time difficult [2], [22], [35], [36].

Artificial intelligence (AI) based fault detection methods have been shown to have more adaptability, as they are able to directly learn complex nonlinear relationships from a historical fault data. Recently, deep learning architectures such as Convolutional Neural Networks (CNN) [18]–[21], Long Short-Term Memory networks (LSTM) [27] and Transformer models [31] and [32] have been used to further enhance the fault recognition by automatically learning hierarchical spatial and temporal features from voltage and current signals.

The strategies involve coordinated measurement, communication networks and smart algorithms for decision making to ensure reliable protection across different levels of renewable generation. However, adaptive protection demands a fast communication, a synchronization and a secure exchange of information, which makes the implementation of adaptive protection more complex and expensive [14], [24], [33], [43].

Table 4. **Comparative Analysis of Fault Detection Techniques**

| **Technique** | **Accuracy** | **Response Speed** | **Complexity** | **Major Limitation** |
|---|---|---|---|---|
| Conventional Relay Protection | Moderate | High | Low | Poor performance under high PV penetration |
| Wavelet-Based Detection | High | High | Medium | Computational burden |
| Machine Learning | High | High | Medium | Requires labelled datasets |
| Deep Learning | Very High | Very High | High | High computational requirement |
| Adaptive Protection | Very High | Very High | High | Communication dependency |
| Wide Area Protection | Excellent | Very High | Very High | High infrastructure cost |

### *6.2 Challenges in Utility Grid Protection with High Solar Penetration*

In spite its outstanding development, there are some technical difficulties that are still hindering the use of intelligent protection systems for practical applications.

6.2.1 Reduced Fault Current Contribution

Photovoltaic Inverters use current-limiting control strategies which limit the contribution of fault current unlike the synchronous generators. Therefore, the fault current measured is very close to the nominal current, which makes the fault detection using the conventional overcurrent relay more challenging [5],[6],[14].

The inverter fault current can be approximated to be

$$I_f \approx kI_{rated}$$

where

- $I_f$ = Inverter fault current
- $I_{rated}$ = Rated inverter current
- $k \approx 1.1 - 2.0$

This small fault current makes it difficult to coordinate relays in renewable energy dominated power systems.

6.2.2 Bidirectional Power Flow

The impact of distributed solar on the direction of power flows through distribution feeders is a key issue. In such situations, reverse power flow might occur for a short period of time and the conventional directional protection scheme may fail to work correctly unless the settings are properly adjusted [11] [24].

6.2.3 Intermittent Renewable Generation

The solar PV production is continuously fluctuating as a result of changes in solar irradiance, cloud motion, ambient temperature and seasonality. The operation of such systems is subject to constant changes during the day, however; and protection plans must be constantly adapted in order to ensure the reliable coordination of relays [16] [17].

6.2.4 Communication Latency

A delay in communication can have a significant impact on relay operating time, and can decrease overall protection reliability in extreme events [24, 33, 40].

6.2.5 Cybersecurity Threats

Smart grids' digitalization has put them at greater risk from cyber-attacks. Unauthorized access, denial of service attacks, false data injection and communication spoofing attacks can negatively affect relay operation and jeopardize the overall grid security. Thus, in the design of protection systems, cybersecurity has now become an integral part of the protection design [40, 46, 49].

6.2.6 Limited availability of fault data

Large labelled datasets are needed for the effective training of AI algorithms. In utility systems, however, the severe fault events are quite rare, and hence are not readily available for representative fault data. In addition, a large amount of time and high cost are required to gather high-quality field measurements under a variety of operating conditions [18, 21, 31].


**Figure 4.** *Challenges in Utility Grid Protection with High Solar Penetration*

## *6.3 Emerging Research Trends*

In view of the existing restrictions, studies are now growing for the development of intelligent technologies that enhance the performance of protection systems.

In a power system, better interpretability will be beneficial in increasing the confidence of operators and promote practical implementation in safety-critical systems [34, 47].

Digital twins are virtual models of the physical utility grid that are continuously monitored, predicted and protected prior to its implementation. The use of digital twins and AI can greatly enhance fault prediction accuracy and minimize operation-related risk [46], [49].

Edge computing has also received a great deal of focus as it allows for processing of electrical measurements at the local level – just next to the protection device – which limits communication latency and enhances response time. An edge intelligence approach enables distributed decision making and reduces reliance on cloud computing infrastructure.

Another emerging paradigm of machine learning is federated learning, which is the process in which a number of substations jointly learn intelligent protection models without sharing sensitive operational data. This helps avoid compromising data privacy, and facilitates high-performing distributed learning in geographically distributed utility networks [21, [34]].

In particular, these models have been shown to exhibit very good performance in a number of engineering applications, and are now being studied for power system protection applications in greater detail [18, 31, 47].

The future development of fully-autonomous protection systems with real time situational awareness, adaptive relay coordination, predictive maintenance, and self-healing grid operation is anticipated to be aided by the integration of Internet of Things (IoT), 5G communication, cloud computing, edge intelligence and synchronized phasor measurements [33], [40], [46].

Table 5. **Future Research Directions for Intelligent Utility Grid Protection**

| **Research Area** | **Expected Contribution** |
|---|---|
| Explainable AI (XAI) | Transparent relay decision making and improved operator trust |
| Edge Computing | Low-latency decentralized protection decisions |
| Graph Neural Networks | Improved modelling of interconnected power networks |
| Transformer Networks | Enhanced sequential fault pattern recognition |
| 5G and IoT Integration | High-speed communication and synchronized protection |
| Cybersecure Smart Protection | Resilient protection against cyber threats |

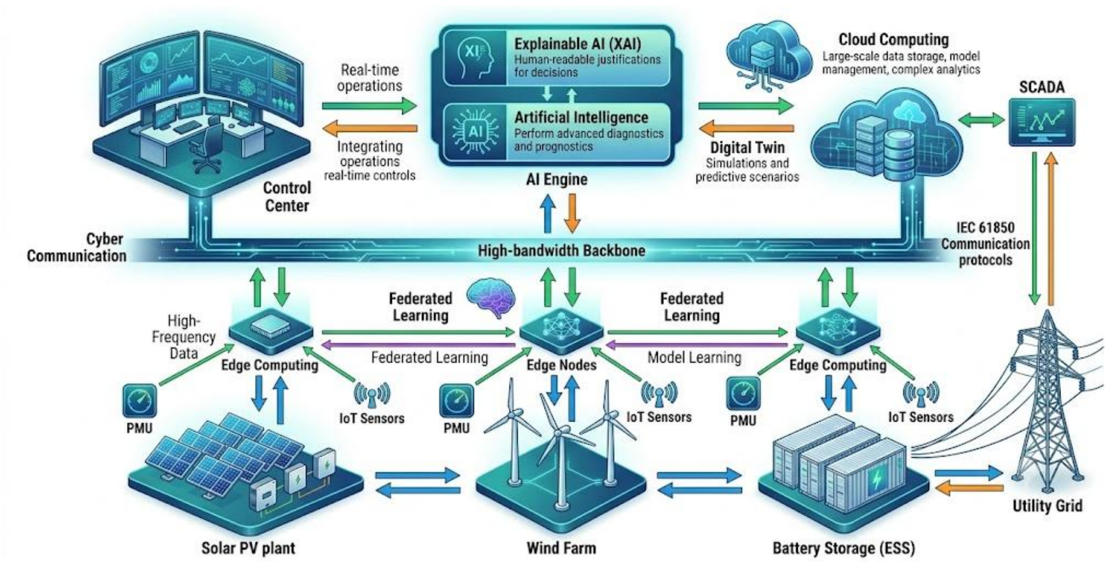


**Figure 5.** *Future Intelligent Protection Architecture for Smart Grids*

## 7. Conclusion

Solar photovoltaic (PV) power generation has become a key factor in the transformation of today's utility power systems, and it poses new challenges to traditional power system protection. Renewable networks integrated into a power network differ from a traditional centralized system in that they are designed for bidirectional power flow, limited contribution to fault current by the inverter, dynamic network topology, intermittent generation and continuously changing operating conditions. These properties make the use of traditional relay coordination less effective and require adaptive protection systems with intelligent fault detection and fault classification that can ensure reliable operation of the grid.

This review systematically studied the current research on fault detection and classification methods for high solar penetration utility grid. The use of conventional protection devices (overcurrent, directional, differential and distance) was discussed along with their operation and limitations in renewable rich operating conditions. In addition, recent advancements in AI, machine learning and deep learning were critically evaluated, and the most prominent were mentioned such as Artificial Neural Networks (ANNs), Support Vector Machines (SVM), Random Forests (RF), Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks and hybrid learning architectures as they are known to stand out as the best performance for intelligent fault classification and adaptive relay operation [18]–[24], [27], [31] and [32].

Wide Area Measurement Systems and high-speed communication networks are able to a great extent improve relay coordination under dynamically changing operating conditions. Communication-assisted protection based on IEC 61850, synchronised measurements and real-time monitoring has become an effective way to enhance fault isolation, system reliability and operational resilience in today's smart grid. But there are still some technical barriers to practical implementation, such as, the reduced contribution of fault current from IVRs, the intermittency of renewables, communication latency, cyber-security threats, small number of labelled fault datasets, and high computational requirements of advanced deep learning algorithms [14], [24], [33], [38], [40].

Analysis of the literature reviewed shows that intelligent protection systems have superior fault detection accuracy, classification ability, adaptability and reliability compared to traditional relay-based protection systems. Thus, the most promising utility grid protection direction is hybrid protection architectures that include advanced signal processing, AI, adaptive relay coordination and synchronized communication technologies.

Further research is needed to create highly reliable, explainable and computationally efficient, and cyber-secure protection frameworks that will enable the next generation of smart grids with a heavy reliance on renewable energy. It is believed that the combination of these technologies will allow for some autonomous fault diagnosis, predictive maintenance, self-healing network operation and resilient grid management, which will assist in secure and sustainable deployment of large-scale solar PV generation in future utility power systems [34], [46]–[50].

## References


1. A. Gupta, R. K. Pachar, O. P. Mahela, and B. Khan, "Fault Detection and Classification to Design a Protection Scheme for Utility Grid with High Penetration of Wind and Solar Energy," International Journal of Energy Research, 2023.
2. G. S. Chawda, A. G. Shaik, M. Shaik, and S. Padmanaban, "Comprehensive Review on Detection and Classification of Power Quality Disturbances in Utility Grid With Renewable Energy Penetration," IEEE Access, vol. 8, pp. 146490–146529, 2020.
3. G. S. Yogee et al., "An Algorithm for Recognition of Fault Conditions in the Utility Grid with Renewable Energy Penetration," Energies, vol. 13, no. 9, Art. 2383, 2020.
4. K. Zeb et al., "Faults and Fault Ride Through Strategies for Grid-Connected Photovoltaic Systems: A Comprehensive Review," Renewable and Sustainable Energy Reviews, vol. 158, Art. 112125, 2022.
5. A. Malik, A. Haque, V. B. Kurukuru, M. A. Khan, and F. Blaabjerg, "Overview of Fault Detection Approaches for Grid-Connected Photovoltaic Inverters," e-Prime – Advances in Electrical Engineering, Electronics and Energy, vol. 2, Art. 100035, 2022.
6. A. Livera, M. Theristis, G. Makrides, and G. E. Georghiou, "Recent Advances in Failure Diagnosis Techniques Based on Performance Data Analysis for Grid-Connected Photovoltaic Systems," Renewable Energy, vol. 133, pp. 126–143, 2019.
7. S. Singh, R. K. Saket, and B. Khan, "A Comprehensive Review of Reliability Assessment Methodologies for Grid-Connected Photovoltaic Systems," IET Renewable Power Generation, vol. 17, pp. 1859–1880, 2023.
8. A. Sayed, M. El-Shimy, M. El-Metwally, and M. Elshahed, "Reliability, Availability and Maintainability Analysis for Grid-Connected Solar Photovoltaic Systems," Energies, vol. 12, Art. 1213, 2019.
9. A. Sayed, M. El-Shimy, M. El-Metwally, and M. Elshahed, "Impact of Subsystems on the Overall System Availability for Large Scale Grid Connected Photovoltaic Systems," Reliability Engineering & System Safety, vol. 196, Art. 106742, 2020.
10. B. Khan, O. P. Mahela, H. H. Alhelou, and P. Siano, "Protection Challenges and Opportunities in Renewable Energy Integrated Power Systems: A Review," Energies, 2021.
11. A. Emhemed and G. Burt, "Adaptive Protection for Active Distribution Networks with Renewable Energy Resources," Protection and Control of Modern Power Systems, 2021.
12. M. S. Alam, F. S. Al-Ismail, M. A. Abido, and A. Salem, "High-Level Penetration of Renewable Energy with Grid: Challenges and Opportunities," IEEE Access, 2020.
13. A. Fernández-Guillamón, E. Gómez-Lázaro, E. Muljadi, and A. Molina-García, "Power Systems with High Renewable Energy Sources: A Review of Inertia and Frequency Control Strategies," Renewable and Sustainable Energy Reviews, vol. 115, Art. 109369, 2019.
14. M. Alrifaey et al., "Hybrid Deep Learning Model for Fault Detection and Classification of Grid-Connected Photovoltaic System," IEEE Access, vol. 10, pp. 13852–13869, 2022.
15. A. Y. Hatata, M. A. Essa, and B. E. Sedhom, "Adaptive Protection Scheme for FREEDM Microgrid Based on CNN and Gorilla Troops Optimization," IEEE Access, vol. 10, pp. 55583–55601, 2022.
16. F. Mumtaz et al., "Two-Stage Hybrid Filtering Based Fault Detection and Classification Method for Active Distribution Networks," in Proc. Int. Conf. Emerging Trends in Electrical, Control and Telecommunication Engineering, 2022.
17. M. Begum et al., "Enhancing Reliability in Electrical Grids: A Hybrid Machine Learning Approach for Fault Detection," Scientific Reports, 2025.
18. O. P. Mahela and B. Khan, "Recognition of Power Quality Disturbances Using Signal Processing Techniques," Energies, 2020.
19. B. Khan, O. P. Mahela, and P. Siano, "Artificial Intelligence Applications in Smart Grid Protection: A Review," IEEE Access, 2021.
20. H. H. Alhelou, P. Siano, and M. E. Hamedani-Golshan, "Power System Protection in Smart Grids: Challenges and Future Trends," Protection and Control of Modern Power Systems, 2020.
21. M. A. Khan, V. B. Kurukuru, and F. Blaabjerg, "Machine Learning Techniques for Solar PV Fault Diagnosis," Energies, 2022.
22. A. Mellit, "Artificial Intelligence Based Fault Diagnosis in PV Systems," Energies, 2021.
23. M. K. Alam, "Deep Learning-Based Fault Diagnosis in Smart Grids," IEEE Access, 2022.
24. P. William et al., "Framework for Intelligent Smart City Deployment via Artificial Intelligence and IoT," in Proceedings of the International Conference on Technological Advancements, 2022.
25. H. H. Alhelou and P. Siano, "Modern Protection Techniques for Renewable Energy Based Power Systems," IEEE Access, 2021.
26. Y. Zhang, "Wavelet Transform Based Fault Detection in Distribution Networks," Energies, 2020.
27. J. Ma, "S-Transform Based Fault Detection for Smart Distribution Networks," IEEE Access, 2021.
28. A. G. Shaik, "Signal Processing Techniques for Fault Detection in Renewable Energy Systems," IEEE Access, 2021.
29. B. Khan, "Adaptive Relay Coordination in Renewable Integrated Distribution Systems," Protection and Control of Modern Power Systems, 2022.
30. M. Shahidehpour, "Smart Grid Protection and Control with Renewable Energy Integration," IEEE Access, 2020.

31. X. Liang, "Protection Coordination in Active Distribution Networks: A Review," Protection and Control of Modern Power Systems, 2021.
32. S. Padmanaban, "Recent Advances in Renewable Energy Grid Protection," Energies, 2022.
33. H. H. Alhelou, "Machine Learning Applications in Power System Protection," IEEE Access, 2023.
34. O. P. Mahela, "Power Quality Disturbance Detection Using Deep Learning Algorithms," IEEE Access, 2022.
35. B. Khan and P. Siano, "Recent Trends in Smart Grid Protection Under High Renewable Penetration," Protection and Control of Modern Power Systems, 2023.
36. F. Blaabjerg, H. Wang, D. Yang, and Y. Yang, "Reliability of Renewable Energy Systems: Challenges and Future Trends," IEEE Access, 2021.