Review

The Current State of the Art in Research on Predictive Maintenance in Smart Grid Distribution Network: Fault's Types, Causes, and Prediction Methods—A Systematic Review

Moamin A. Mahmoud [1],*, Naziffa Raha Md Nasir [2], Mathuri Gurunathan [2], Preveena Raj [3] and Salama A. Mostafa [4]

1   Institute of Informatics and Computing in Energy, Universiti Tenaga Nasional, Jalan Ikram-Uniten, Kajang 43000, Selangor, Malaysia
2   College of Computing and Informatics, Universiti Tenaga Nasional, Jalan Ikram-Uniten, Kajang 43000, Selangor, Malaysia; naziffa@uniten.edu.my (N.R.M.N.); mathuri_maths@yahoo.com (M.G.)
3   College of Engineering, Universiti Tenaga Nasional, Jalan Ikram-Uniten, Kajang 43000, Selangor, Malaysia; rajpreveena@yahoo.com
4   Faculty of Computer Science and Information Technology, Universiti Tun Hussein Onn Malaysia, Parit Raja 86400, Johor, Malaysia; salama@uthm.edu.my
*   Correspondence: moamin@uniten.edu.my; Tel.: +6-03-89213413

Abstract: With the exponential growth of science, Internet of Things (IoT) innovation, and expanding significance in renewable energy, Smart Grid has become an advanced innovative thought universally as a solution for the power demand increase around the world. The smart grid is the most practical trend of effective transmission of present-day power assets. The paper aims to survey the present literature concerning predictive maintenance and different types of faults that could be detected within the smart grid. Four databases (Scopus, ScienceDirect, IEEE Xplore, and Web of Science) were searched between 2012 and 2020. Sixty-five (n = 65) were chosen based on specified exclusion and inclusion criteria. Fifty-seven percent (n = 37/65) of the studies analyzed the issues from predictive maintenance perspectives, while about 18% (n = 12/65) focused on factors-related review studies on the smart grid and about 15% (n = 10/65) focused on factors related to the experimental study. The remaining 9% (n = 6/65) concentrated on fields related to the challenges and benefits of the study. The significance of predictive maintenance has been developing over time in connection with Industry 4.0 revolution. The paper's fundamental commitment is the outline and overview of faults in the smart grid such as fault location and detection. Therefore, advanced methods of applying Artificial Intelligence (AI) techniques can enhance and improve the reliability and resilience of smart grid systems. For future direction, we aim to supply a deep understanding of Smart meters to detect or monitor faults in the smart grid as it is the primary IoT sensor in an AMI.

Keywords: faults detection; predictive maintenance; smart grid; systematic review

1. Introduction

Smart Power grids are currently viewed as one of the significant segments of a system on which a cutting-edge society depends. The main essential goal of power system activity is to supply continuous power to the users [1]. With that said huge scope issues and unsettling influences (disturbance) within the grid frequently because power blackouts and this has impacts on the system dependability and customer satisfaction. In power grids, four crucial sorts of issue can happen in a distribution network, and these are a line-to-line fault (LLF), a three-phase-to-ground fault (LLLGF), a single line-to-ground fault (SLGF), and a double line-to-ground fault (DLGF) [1,2]. Hence, the single-line-to-ground fault is the most common fault detected in distribution system networks [3].

A single line-to-ground issue happens when one of the three-phase conductors of a distribution network reaches the ground because of creature contact, a line falling on the

ground, or wind [1]. SLGF (single line-to-ground) happens as frequently as 70% from the distribution system. Line-to-line faults happen when the high wind causes one stage to make contact with another stage, whereas 15% of deficiency in the distribution network is a result of a line-to-line shortcoming [3]. In DLGF, two lines will be required as opposed to one phase as in the SLGF circumstance, where 10% of the inadequacy in the distribution system is the direct result of a double line-to-ground fault. A three-phase-to-ground fault may be achieved by equipment breakdown, a conductor reaching different phases, or a tower falling on the ground [1]. Overall, this sort of issue is not ordinary and is the least perpetual at the speed of 5% in the distribution network [2]. Despite the way that the issue is not ordinary, the occasion of LLLGF is dangerous with an incredibly large fault current.

With the improvement of ingenious innovation and the commencement of smart grids, Condition-Based Maintenance is the strategy adopted by future smart grids. Condition-Based Maintenance innovation includes the failure-prediction rate of electrical power equipment [4]. The Phasor Measurement Unit (PMU) is a gadget that measures the electrical waves on a power grid utilizing a basic time derivation for synchronization. PMUs give us a tremendous measure of information [1] and checking such immense information physically is an infeasible assignment. The usage of distributed generators in the power system has expanded in recent years as they can fulfill the expanding power need locally. This can likewise decrease the ecological issues made by the conventional fossil fuel-based power generations methods [5]. A fault diagnosis approach dependent on quantitative models is applied. Through a scientific excess relationship, the model and the cycle are analyzed in each testing period. At the point when abnormalities are distinguished between the two signals, residuals are produced [6]. On account of no faults, residuals should be zero. By and by, this reality is unnoticed because of the noise and vulnerability properties of the model. Accordingly, a past investigation of residuals is required to distinguish faults correctly. Then again, residuals may not infer thinking about the faults that have happened [6].

Studies were produced using numerous prior years with respect to building a miniature unit that is connectable with the introduced distribution system, which can recognize the careful location of the fault event. The fault location ID can limit the working weight on the lineman and, in this way, can guarantee the unwavering quality of the stock by limiting the blackout time. With the improvements of the micro-controller and the (Global System For Mobile) GSM and Arduino empowered correspondence strategies, there is a clear route towards greater freedom in finding the fault location [3]. Thus, we utilize a real-time clock. The signals created are time-stepped with flags. Preparing and dissecting the obtained signal gives a proviso towards recognizing the fault location. Afterward, the fault location distinguishing proof dependent on estimating the nodal voltages and flows in the distribution system was created. The innovation is creating step by step, and consequently, new progressed modern gadgets with the least time reaction and precise outcomes should be acquired all together so that a distribution system stay solid and responsive [7].

High Impedance faults (HIFs) are those that have been characterized as faults with new qualities in the reach from 0 to 75 A adequately grounded distribution systems. Nonetheless, they are hard to recognize utilizing ordinary fuses or overcurrent relays [8]. From the study, the paper aims to survey the current literature concerning predictive maintenance and different sorts of faults that might show up within the smart grid, and Table 1 presents a comparison of different research papers.

Table 1. Comparison of different research review papers.

Research Papers	[9]	[10]	[11]	[12]	This Paper
Power Failure In The Smart Grid	✓	✗	✓	✓	✓
Type Of Faults Statistics	✗	✗	✓	✗	✓
Fault Detection And Fault Location	✓	✗	✗	✗	✓
Prediction Methods	✗	✓	✗	✗	✓
Challenges	✗	✓	✗	✓	✓
Motivation	✗	✗	✗	✗	✓
Opportunities	✗	✗	✓	✗	✓

The main goals of this study are to review previous research, summarize their findings related to predictive maintenance in grid distribution, identify fault types and causes, determine the prediction methods and techniques, and suggest taxonomic literature concerning failure prediction. The remaining parts of this work are as follows: The study's introduction is provided in Section 1, while Section 2 introduces the systematic review protocol description. Taxonomy is presented in Section 3 while prediction methods are presented in Section 4, and Section 5 presents a discussion that involves challenges, motivations, and opportunities. A comparison of this review with another review is presented in Section 5. Lastly, Section 6 provides the study conclusions.

2. Systematic Review Protocol

A systematic literature review is ordinarily used to sum up and decipher the applicable pieces of research [13]. It gives a comprehensive, clear, and repeatable inquiry of literature through a thorough and logical hunt of distributed and unpublished examinations while restricting inclinations in the review cycle. This strategy is significantly distinguished for its productivity and its ability to oblige various types of studies [14].

To direct an SLR, first, it is imperative to delimit the research zone and set up a convention to identify, select, review, and orchestrate relevant literature. This paper follows the four stages for an SLR proposed by the Denyer and Tranfield [14] methodology: (i) Data source, (ii) search strategy, (iii) determination of study, and (iv) qualification criteria. The accompanying Section gives a concise depiction of these four stages and demonstrates how they have been completed in the particular structure of this research. The research methodology is composed of the following four steps: (a) Information source, (b) search strategy, (c) selection of study, and (d) eligibility. To give an outline of the existing research in smart grid predictive maintenance, a bibliometric investigation was conducted utilizing the well-established and recognized databases from Google Scholar, IEEE, and ScienceDirect [15,16]. The phrases utilized in this paper were the combination of the following words ("Power Grid" OR, "Smart Grid") AND (Distribution) AND (Fault Prediction OR Predictive Maintenance) AND (Fault Location). All the articles from different sources were analyzed in-depth to allow readers a comprehensive outline of the subject [17].

The protocol portrayed in the previous segment was utilized to search, select, and evaluate preliminary papers. The following search was constrained to the title, abstract, and keywords. At first, 3146 studies were collected from three databases. In the first place, duplicates were excluded, i.e., studies accessible in more than one database, eliminating 2103 duplicates. Out of the 1043 remaining studies, 873 were firstly screened based on inclusion and exclusion criteria applied to the title, abstract, and keywords. These papers were stamped to be downloaded, and references that may not be retrieved were discarded. A while later, these studies were evaluated utilizing quality criteria obtaining 105 studies. These studies were utilized to extract the information defined. At last, 65 primary studies were chosen based on their quality for the final conduction stage and were utilized to extract the approaches displayed in others areas.

3. Taxonomy

This Section elaborates on the summary of the search process of the relevant papers. The first step started by carrying out a search, filter, and scan, and reading full-text relevant papers. After completing the first phase of the search process, all the research articles were categorized into two main categories, followed by sub-categories. Faults are the primary classification and are related to various kinds of studies with dataset or data-collection approaches including observation and full-text reads of different aspects. The second classification was the methods used to identify fault techniques. Figure 1 shows the taxonomy of smart grid predictive maintenance.
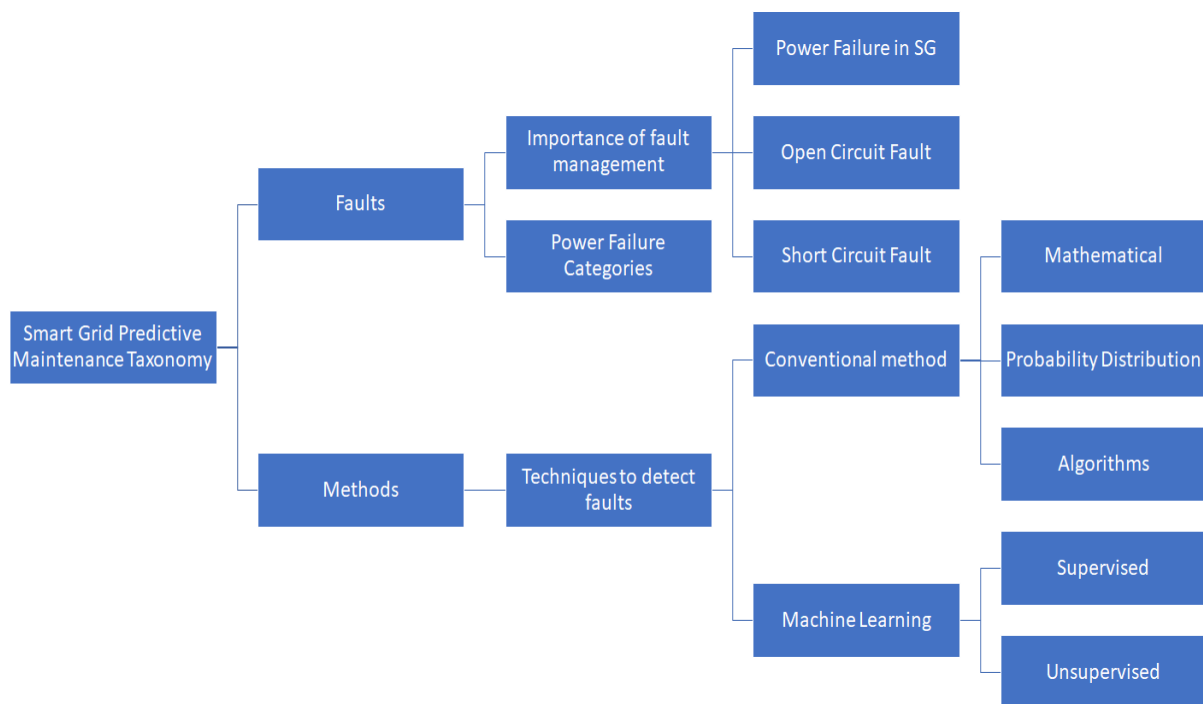

Figure 1. Smart grid predictive maintenance taxonomy.

3.1. Importance of Fault Management—Predictive Maintenance

Power faults in the smart grid should be managed and analyzed quickly enough to secure framework parts and keep up with normal operation. Predictive maintenance improves the smart grid financially and decreases synchronization issues. Indeed, predictive maintenance is a method that utilizes data analysis tools and methods to detect abnormalities in activity and potential deformities in gear and cycles that can be fixed before they bring about failure. Likewise, it is critical to distinguish, detect, and find the deficiency in the smart grid before a total breakdown occurs. Checking current signals and voltage given by smart devices in the smart grid is one technique to analyze faults in the system [18]. Analyzing shortcomings should be possible utilizing the most recent detecting information provided by wavelet examination or utilizing Markov model investigation [19–21].

In this manner, the smart grid system ought to give prompt analytic data to identify fault conditions in the system. Along these lines, the smart grid ought to give quick symptomatic data and reasons for fault conditions in the framework. Moreover, in the event of short circuits or high impedance faults, the system ought to work in an independent mode to secure the power network. Moreover, computerized transfers are utilized for appropriate line security in the power framework with the participation of the worldwide framework to detach fault lines.

3.1.1. Power Failures

There are a large number of issues that cause failure in smart grid systems such as flying items, lightning, blizzards, high-speed wind, pollution of insulators, actual contact by creatures, human mistakes, falling trees, terrible protection, over-burdens, insurance failure, etc. Additionally, the equilibrium three-stage smart grid system has the most power failures as reported. As stated in [22], power failure is characterized as an abnormal electric flow in the system and can be categorized into two types. The main kind is characterized as the outside deficiency, for example, phase to phase, or phase to ground fault. The subsequent category is the inward shortcoming, which happens at the air-conditioner side of the converter, DC transport, or energy storage system. However, power network faults of the system can happen at the generation side (sending end), transmission lines, or at the distribution side (receiving end) [23]. Hence, there are different areas that a failure can happen in within the smart grid system because of various factors.

3.1.2. Common Faults—Open Circuits

In common faults or open-circuit faults, the current streams in a circuit in a consistent way (or diverse ways) from and back to the source of EMF. Any break in the circuit, like an open switch, a break in the wiring, or a segment, such as a resistor that has changed its resistance from an unimaginably high value, will cause the current to be interrupted. The EMF will, in any case, be accessible; however, voltages and current around the circuit will have changed or halted. The open switch or the shortcoming causes what is usually called an OPEN CIRCUIT.

Open-circuit faults happen due to the failure of one or many conductors. The open circuit depicts the open-circuit faults for single, two, and three stages (or conductors) in open conditions [24]. The foremost broadly recognized reasons for these faults incorporate joint failures of links and overhead lines, failure of one or more period of a circuit breaker, and softening of a wire or conductor in one or many stages.

3.1.3. Short-Circuit Fault

Short-circuit faults can be characterized as an abnormal affiliation of low impedance between two places of diverse potential, regardless of whether it occurs intentionally or inadvertently. The chances that these issues are allowed to persevere in any event, for a short period, prompt widespread harm to the gear.

In the case these faults are permitted to continue, indeed for a brief period, it leads to extensive harm to the equipment. Low resistance affiliation occurs between two conductors that give electrical control to a circuit. This would deliver an abundance of voltage spilling and cause the best progression of current within the power source. The electrical power will cause a short circuit and course through a short course. Figure 2 shows an understanding of different types of phases. These faults are due to security failure between stage conductors or among stage and soil conductors, or both together.
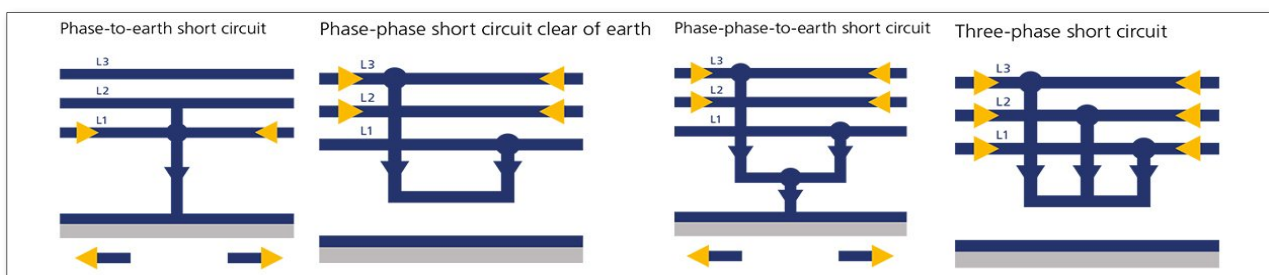

Figure 2. Short-circuit fault types.

The short circuit includes the inner impacts, including the breakdown of transmission lines or electrical equipment, weakening of the separator in a generator, aging of the

insulation, transformer, and other electrical equipment, inadequate design, and faulty installations [25]. However, external impacts incorporate over-loading of different types of instruments, insulation failure due to lighting surges, and mechanical harm by the public.

3.2. Statistics Faults—Power Failure

There are many fault causes that could prompt smart grid faults in the power system. The different kinds of fault causes are comparable, yet the extents are diverse in various nations, under various climate conditions, etc. The smart grid system fault contains outer components, normal variables, and a portion of the improper support factors. This paper is centered on the review of fault causes in smart grid systems. It is noted that a few insights in the paper are about transmission line fault causes, and although the fault causes are comparative, the rates of the causes of the fault are different.

3.2.1. Grid Statistical Analysis of Fault

Figure 3 illustrates the percentage representation of the causes of smart grid faults from the overall collection of research papers, and the pie chart is based on the occurrence of repeated failures in each research paper. The highest failure contributors are fault resistance, large-scale blackouts, and single-phase grounding (SPG) faults. Those are the most common faults from the study. A brief explanation of each fault according to the percentage is explained below.
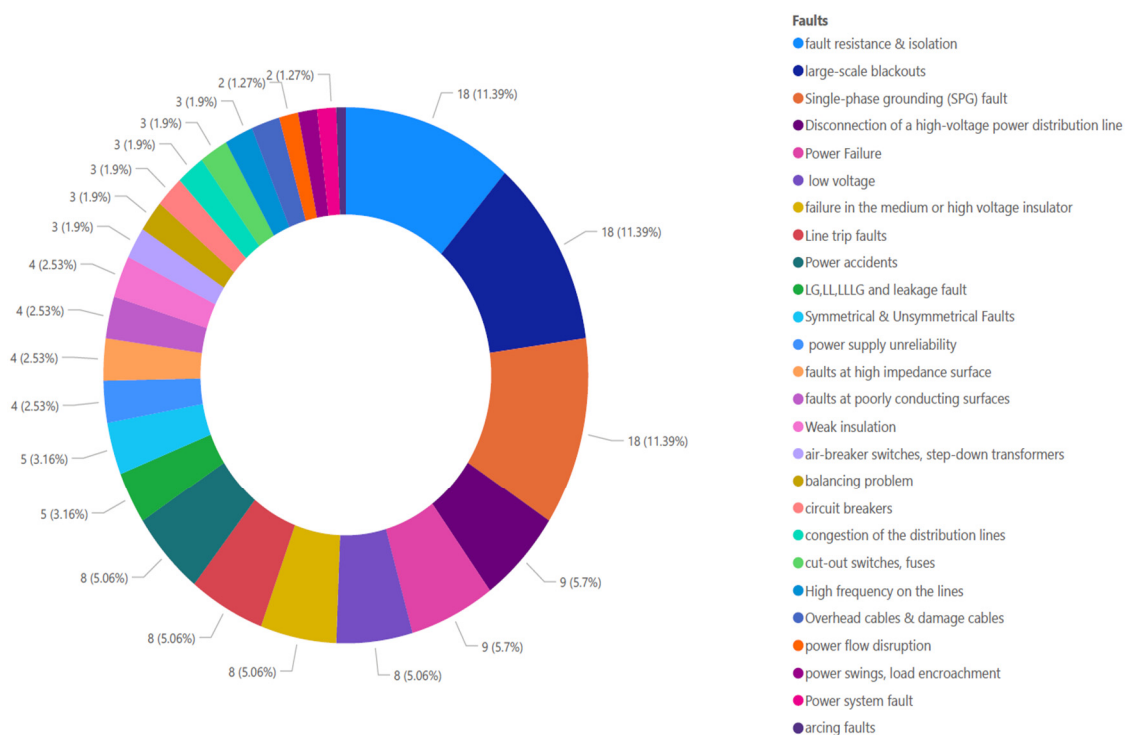

Figure 3. Causes of faults.

11.39%—Single-Phase Grounding (SPG) Fault, Large-Scale Blackouts, Fault Resistance, and Isolation

A few statistics show that single-phase-to-ground (SPG) faults, large-scale blackouts, fault resistance, and isolation faults establish a higher level of faults in a smart grid distribution network. SPG faults can become phase-to-phase faults, which trip the electrical switch, causing power interference and influencing the dependability of the power supply. Single-phase-to-ground (SPG) faults present a few disadvantages, and existing fault feeder choice strategies show low, unwavering quality in the field [26,27].

In a large-scale interconnected power network, when a power system failure happens, the system will reallocate the power flow, and if not treated, the over-loaded lines or transformers will be eliminated, which may cause a progression of chain responses, or even system breakdown, bringing about a power-grid power outage. A power grid blackout is regularly a chain response measure, and above all else, a single segment failure or various failures collected due to an ill-advised or not ideal crisis, leading to a weakening of the fault, becoming incapable to control. In the end, there is a blackout [26,28]. A blackout is generally the aftereffect of a progression of mishaps instead of simple failures. This advancement cycle is identified by a variety of factors, for example, mishap type, activity mode, power network structure, etc. It is hard to precisely foresee ahead of time due to the ever-changing process. Notwithstanding, it has an overall standard that is brought about by the unplanned disappointment, and afterward develops into a cycle of blackouts [29].

5.7%—Disconnection of High-Voltage Power and Power Failure in the Distribution Line

This is the percentage of faults brought about by power failure and the separation of a high-voltage power distribution line. A power failure (otherwise called a power cut, power blackout/power shock, power misfortune, or blackout) is a short- or long-term loss of the electric power to a zone [30,31]. There are many reasons for power failures in a power organization. Instances of these causes incorporate harm to electric transmission lines, faults at power stations, substations, or other different pieces of the circulation system, a short out, cascading wire, or electrical switch activity [32–34].

5.06%—Power Accidents, Line Trip Faults, Failure in Medium or High Voltage

From the statistics in this paper, these faults happen as a result of power accident faults, electric strings that run under a covering, combustible material that are left too close to uncovered electrical wiring in the working environment, and free connectors. Helpless wiring is unacceptable wiring that can prompt electrical flames and electric stun. Human blunders can happen in any circumstances that include individuals, for example, power system activity, electrical gear support, and power system dispatching. However, in a low-voltage system, these for the most part have no repetitive power supply [35]. Perhaps the most well-known reason for low voltage is the over-burden of the system. Various times, like early evening, are ordinarily popular times. The condition of the wiring in a territory is a typical reason for voltage issues. Age and erosion are typical reasons for low voltage, as are messy associations and helpless protection [36,37]. Poor or harmed grafting work can likewise be a reason. Line-to-line faults happen when two conductors connect for the most part but swinging of lines occurs due to winds, and 5–10 percent of the faults are of this sort [38]. These are additionally called unequal faults since their event causes unbalance in the system.

3.16%—Symmetrical and Unsymmetrical Faults, LG, LL, LLLG, and Leakage Fault

A symmetrical fault includes each one of the phases while an unsymmetrical fault includes just a couple of phases [1]. A symmetrical fault, including every one of the phases, is short-circuited to one another and regularly to the earth. Such a fault is adjusted for as the systems stay symmetrical, or it can be determined that the lines were dislodged at an equivalent point (for example 120° in a three-phase line). This is the most serious sort of fault including the largest current, yet it seldom happens [5]. Hence, adjusted short-out computation is performed to decide these large flows. However, unsymmetrical faults include just a couple of phases, and in unsymmetrical faults, the three-phase lines become uneven. Such faults happen between line-to-ground or lines. An unsymmetrical arrangement fault is between phases or between phase-to-ground, while an unsymmetrical shunt fault is unequal in the line impedances [6,39].

2.53%—Power Supply Unreliability and Weak Insulation

High-impedance faults come about because of conductors being brought down that create some fault current. For example, when the ground surface is wet verdant land or concrete, the fault current can be, in any case, not exactly the same as the system load, which unbalances the system and the conventional ground overcurrent protection, cannot separate the collapsed conductor faults from single-phase loads. Albeit, a high-impedance fault may not intrude on typical dissemination system tasks because of its low fault current, but it very well may be a significant public hazard [40]. High-impedance faults that come about because of collapsed conductors or vegetation touching stimulated conductors are additional potential wellsprings of rapidly spreading fire [23].

Power supply unreliability refers to those high flows that are additionally called inrush currents, and in power supplies, the fundamental justification for them is the charge of the bulk cap(s). High voltage and current floods can be the reasons for various segment failures, including wires, connect rectifiers, diodes, and FETs. [41,42].

Regarding weak insulation, most short circuits in power systems happen as a result of protection failure. The breakdown of the protection relies upon the voltage stress incorporated after some time.

1.9%—Congestion of the Distribution Lines and Circuit Breakers

A circuit breaker will trip on account of an electrical flow over-burden, yet an electrical short-out can be more serious. This issue is, in all probability, in the electrical wiring and ought to be amended promptly to forestall harm or more hazardous circumstance. An over-burden circuit is the most well-known justification for a circuit breaker stumbling [43]. It happens when a circuit is endeavoring to draw a more prominent electrical burden than it is expected to convey. At the point when too many machines or light apparatuses are working simultaneously, the inward-detecting instrument in the circuit breaker warms up, and the breaker trips, generally by methods for a spring-loaded segment within the breaker [44]. Figure 4 demonstrates a few causes of power system failures. A power transformer, like numerous electronic gadgets, faces numerous failures. Faults may happen in various parts and segments of the transformer because of mechanical, electrical, or thermal stress caused by various conditions [40]. The most frequent failures of the transformer and their causes are recorded below.
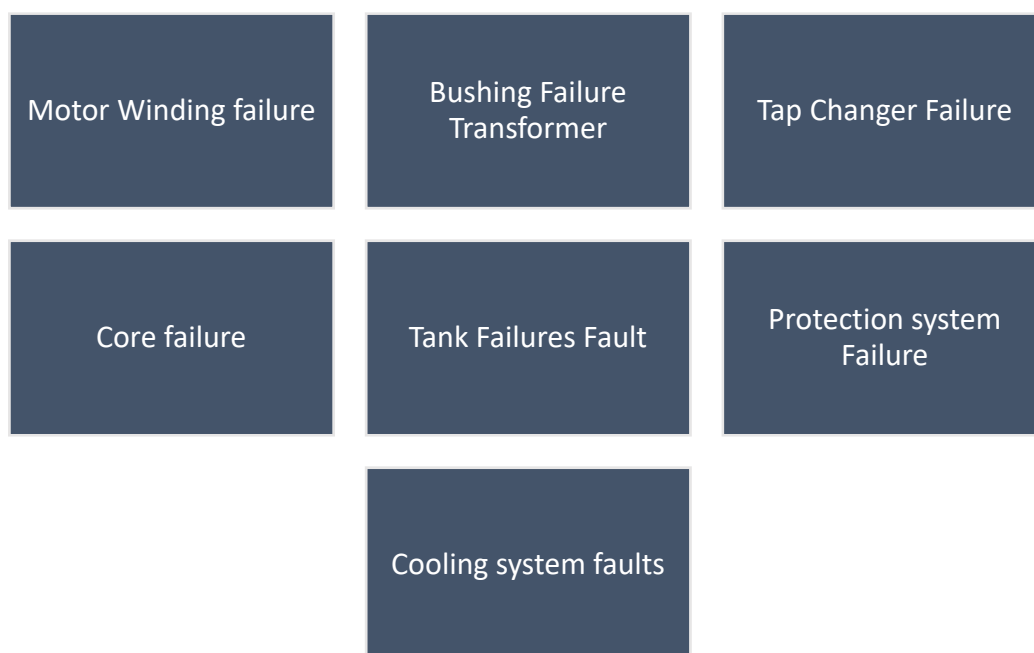

Figure 4. Power system failures.

The most common reasons for cable issues can be tracked back to mistakes in planning (weakening of the insulation properties caused by unsatisfactory overheating of stack streams due to low levels of cross-Sections of cable cores) [45]. Besides this, there is also harm caused in emergency modes due to dishonorable choices of defensive gear and the abandoning of manufacturing (breaks or gaps within the cable sheath, coordination of a few paper tapes, burrs on wires of current-carrying centers, etc.), abandoning of cable-laying (sharp twists of cables at turning points of a direct line), mechanical harm (pits, cuts, turns of cables), and overlooking systems separate to offices, which can influence cable execution (heat transport system, electric railroads, etc.).

1.27%—Power System Fault

Load encroachment happens when the impedance crosses the load ability at the furthest reaches of the working trademark. This implies that load infringement is characterized as the deliberate impedance due to the of burden current and voltage, surpassing the impedance controlled by the load ability at the furthest reaches of an impedance hand-off at a particular power factory [46]. Regarding a power system fault, electrical failure is an irregular condition, caused by gear disappointments such as transformers and pivoting machines, natural conditions, and human errors [8]. These faults are caused by interference to electric streams, hardware harms, winged creatures, animals, and indeed the passing of humans [47]. In Figure 5, the diagram describes the main three factors of faults, that is nature, external, and human error.
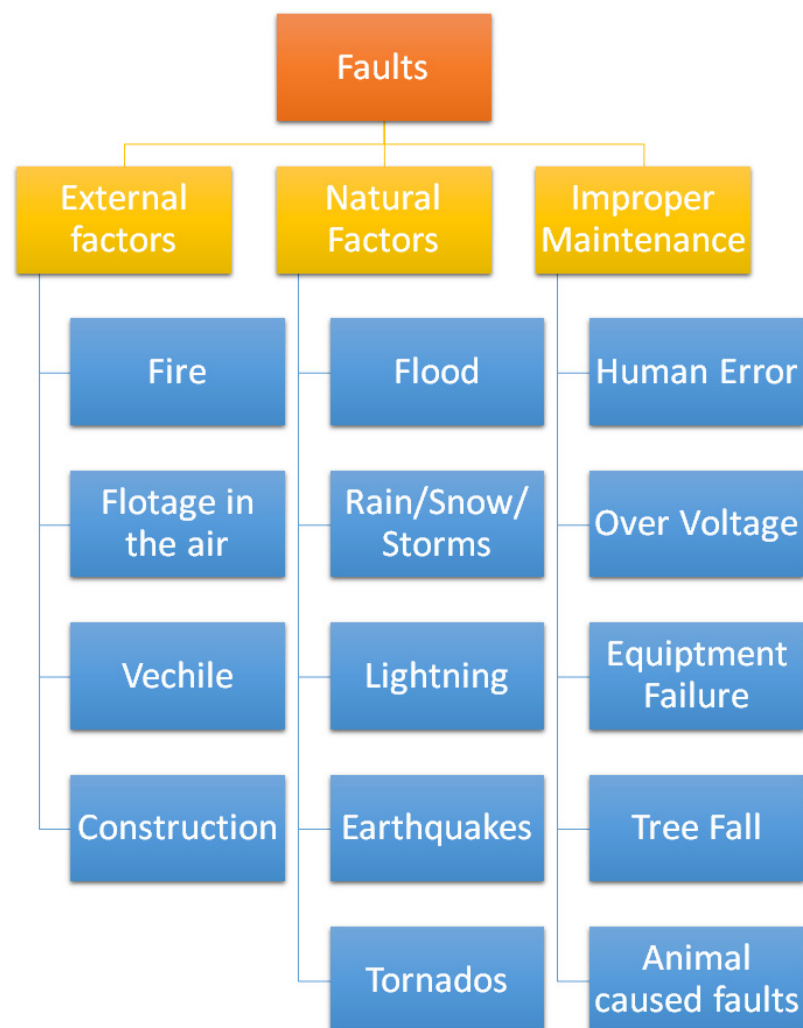

Figure 5. Fault categorization.

4. Prediction Methods

In early years, a fault was detected manually by a human at the site and cleared or isolated. With the tremendous growth of technology and depth of power systems, many methods have been analyzed and are still being researched to ensure the stability of power systems and the quality of utility service to its customer. However, faults in power systems are inevitable, but they can be minimized. This study discussed several methods and apparatuses that will help to improve the reliability of a smart grid for users.

4.1. Conventional Methods

4.1.1. Infrared Thermography-Based Technique with Multilayered Perceptron (MLP)

Subsequently, this technique encompasses non-destructive fault investigation and avoidance in a control substation, utilizing the computer vision approach and AI to distinguish the issue in the beginning phases of hardware equipment breakdown by misusing and exploiting the infrared thermal pictures. Hence, this methodology and the commitment to it result in a non-destructive way to deal with deformity examination in electrical force gear by utilizing AI and computer vision, and in this way, shows the viability of the methodology. For recognition, the methodology utilizes the MLP (multilayered perceptron) to arrange the thermal state of power substation components into "non-defect" and "defect" classes, accomplishing precision of 79.7%. The heat created in electrical components can be detected by infrared thermography (IRT). However, IRT catches the thermal profile of various electrical components utilizing an infrared camera. The thermal profile contains the heat picture and estimations of the temperature size of the gear. With the thermal profile, the heat images can be broken down by the thermograph, which classifies the status of imperfect parts by the direness level of support of the electrical gear [48]. At long last, the concerned offices can analyze the hot segment, fixing the hardware as per the matter of need. Over time, thermography has become a significant technique for foreseeing and forestalling the surface deformities of various materials because of its non-meddlesome, protected, and reasonable arrangement. As an electrical gadget weakens, its opposition rises and along these lines, it creates more warmth. The warm energy created from an electrical segment corresponds to the square of the flow and its obstruction (IR misfortune) [49]. The expansion in warmth can trigger the failure of an electrical segment and set the gear ablaze. Normally, whenever the IRT procedures are applied, the warm electrical defects and the status of the imperfection are perceived by review of its delta T (ΔT) standards. This method is usually known as a subjective-based temperature assessment framework. The delta T rules of any piece of the segment are clarified as an expansion in the estimation of the temperature over the temperature of the reference system, which is typically the encompassing temperature—the temperature of a comparative portion of the electrical segment under a comparable condition, or the most limit-worthy temperature of the part [49]. Various guidelines for the ΔT rules [49] are characterized by NFPA, NETA, NFPA 70-B, ASTM-E, and many more.

4.1.2. Traveling Wave Fault Location

Traveling wave techniques depend on the standard of reflection and transmission of the traveling waves between the fault location and line terminal. Figure 6 demonstrates the traveling wave method diagram.
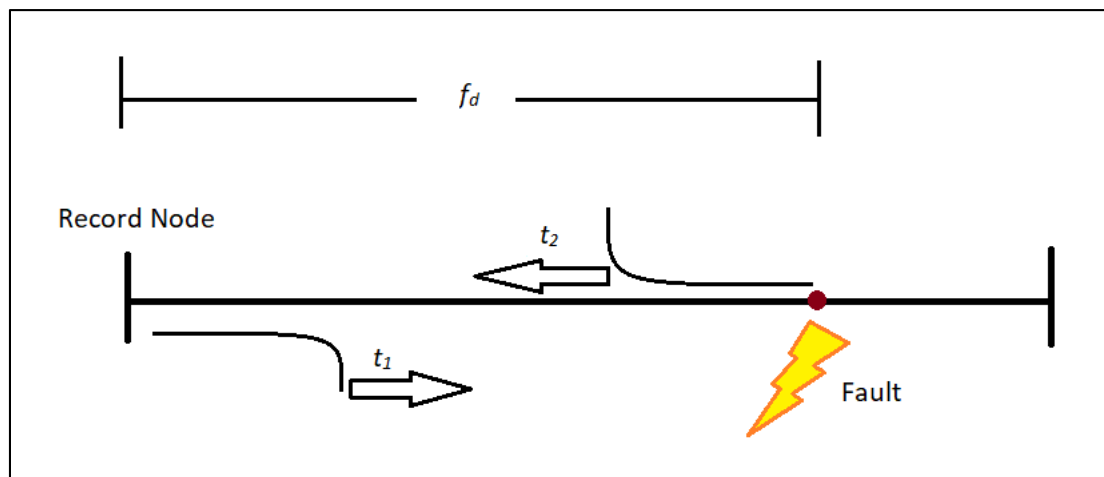
Figure 6. Travelling wave method.

This technique appears in Figure 6, where t_1 is the time used for the traveling wave from the estimation node to the fault location, t_2 is the time used for the reflected wave from the fault location to the estimation node, and f_d is the fault distance that needs to be identified. The fault distance is identified utilizing

$$f_d = \frac{v * (t_2 - t_1)}{2} \tag{1}$$

The traveling wave method requires fast information-obtaining gadgets, sensors, transient fault indicators, and a Global Positioning Framework (GPS) to catch the transient wave form for the fault area. In [49], an examination of the easing-up-related fault was dissected. The hour of appearance of the created traveling wave fault was identified utilizing GPS. The exactness of the technique relies upon the precision of the assessed estimations of line boundaries, for example, line inductance and capacitance. The benefit of this technique is that it is not affected by the heap difference, high establishing resistance, or arrangement capacitor bank. Traveling waves dependent on faultfinders for overhead lines are classified into a single terminal and two terminal zones. These two types were broken down and analyzed in [6], which depicted the legitimacy and bad marks of every technique. It shows that the two-terminal area method has wider possibilities than the single-terminal technique. Hence, the proposed traveling wave fault area method is quick and gives an exact fault area and can diminish the force misfortune. A solitary terminal fault area method utilizing the time–space and recurrence area attributes of the fault is proposed in [3] for transmission lines. The technique ascertains that the fault distance dependent on the decided time and speed. It shows that the traveling wave method is not affected by resistance, origin points, distances, and fault type.

Another technique that does not utilize GPS timing was recommended in [39], which recorded the transient wave at the bus bars utilizing wavelet de-noising. However, the transient wave has data about the fault and its measurable boundaries, which are used to find the fault. Notwithstanding, this technique yields higher mistakes contrasted with the fault area utilizing GPS, albeit the expense was decreased by precluding a GPS collector. A constant traveling wave-based fault area technique was proposed in [49]. The technique depends on two-terminal traveling waves and connects both ends of a transmission line by a correspondence framework. The upside of this technique is that it tends to be utilized in either synchronized or unsynchronized two-terminal information. A double-terminal fault area technique was proposed in [8]. This method utilizes a mix of traveling wave rules with wavelet chance to find faults. The technique finds the distance to the fault point by determining the hour that the introductory traveling wave arrived at the two stopping

points. The recreation results show that the technique finds fault points effectively and definitively.

From the audit, it can be seen that the traveling wave method is more broadly utilized in transmission lines rather than in distribution lines. The explanation for this is the sub-branches in the distribution system and the presence of lateral branches. The benefit of this method is that it is autonomous of the organization's configuration and gadgets introduced in the organization. The detriment of this technique is that it requires gadgets like GPS and sensors to catch transient waveforms, which means the technique is expensive in its execution.

4.1.3. Impedance-Based Method

The impedance-based method is one of the most commonly used techniques in power systems to locate faults because of its simplicity and economic efficiency compared to the traveling wave method. The basis of this technique is utilizing impedance estimates seen from the estimation node for the fault location. Figure 7 shows a straightforward diagram of the impedance-based method, and the basis of this technique is utilizing impedance estimates seen from the estimation node for the fault location.
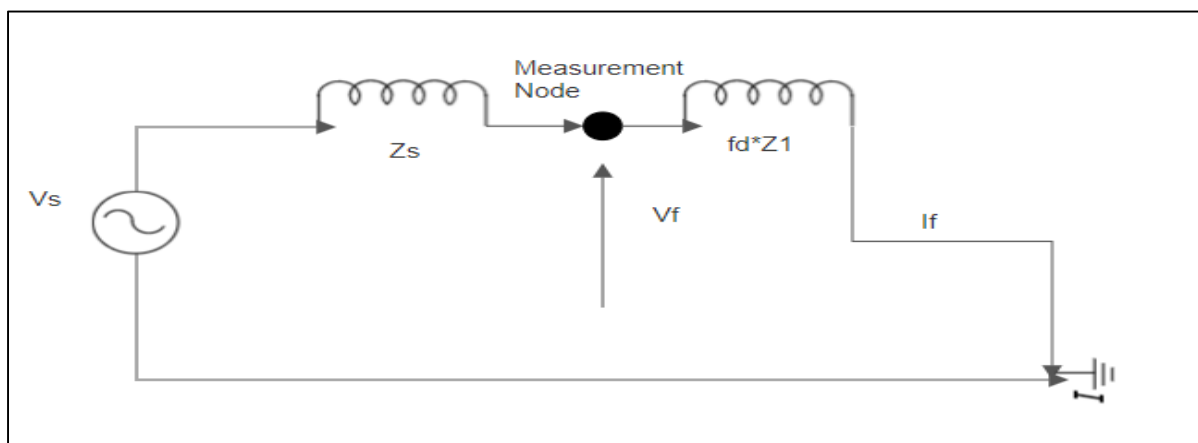

Figure 7. Impedance-based method.

This method utilizes voltage and current worth to discover the fault impedance. This strategy is advanced, classified as either a one-end strategy or two-end strategy. The one-end strategy utilizes the substation voltage and current for the fault area [50]. The two-end strategy utilizes the voltage and current at the two closures of the dispersion framework for fault area identification. Different approaches are taken for finding the fault distance, thinking about the wide extent of faults such as LLF, SLGF, DLGF, and LLLGF and different fault resistances. Different methods like the receptive segment method, the Takagi calculation, and Girgis techniques have been created previously. The goal of these methods is to gauge the area of the fault on outspread appropriation frameworks. The responsive part of the method appraises the obvious reactance of the line from the estimation hub to the fault and, afterward, changes the determined reactance to remove. Previous research [49] has determined the proportion of the receptive segment of the clear impedance to the reactance of the line for fault area. This likewise considered the effect of line capacitances on the fault area. Notwithstanding, the impediment of this method is that the fault resistance was not thought of. Thus, the technique is not legitimate for commonsense cases and will likely have considerable mistakes. The Takagi calculation utilizes the principal recurrence of current and voltage previous to and during a fault [49]. The method utilizes Thevenin theorem, utilizing the current and voltage of a faulty line to find a fault. In any case, the fault distance was identified utilizing the supposition that the staging point of the line current and the fault current is equivalent. Consequently, the

condition works for homogenous frameworks. The technique was applied in a pragmatic transmission line framework and was observed to work sufficiently.

4.1.4. Current Measurement and Synchronize Voltage

A fault location strategy for the distribution system to multi-source lopsided frameworks utilizing synchronized voltage and current estimation was accounted for in [49]. This technique utilizes synchronized voltage and current estimations at the interconnection of DG units, of which the Thevenin counterparts of positive arrangement, negative grouping, and zero succession for each source sort were utilized [51]. Tests on a 60-transport distribution framework for all fault types with different fault protections on each segment of the framework show great outcomes. The technique was likewise ready to adjust to changes within the framework organization.

4.1.5. Relay Protection System

The relay protection system can be further broken down into relays, transducers, trip circuits, and auxiliary power. To identify a fault, the condition of the power system should be noted and furthermore broken down. The most widely recognized signs utilized for fault discovery are voltages and current [52]. Moreover, light can be utilized to identify an open arc fault inside encased switchgear, but this is not addressed here. Hence, a pressure gauge measure can be utilized in a transformer to recognize pressure waves produced by a fault. Instrument transformers have been used since the late 19th century. These are usually condensed as VT for voltage transformers (or PT for potential transformers), CT for current transformers, and CVT for capacitive voltage transformers. Besides, instrument transformers comprise, on a fundamental level, two windings wound around an iron core. The association of a VT and CT is distinctive since the CT is associated in an arrangement with the principle current way and the VT is associated as a shunt-gadget to earth (if phase-to-earth voltages are estimated) or between phases (if phase-to-phase voltages are estimated). Over the years, CTs and VTs have been incredibly solid segments (for their precision of repeating the essential current or voltage at the auxiliary terminals) and their conduct comes with a couple of exemptions well known to power system engineers [53]. In a distribution framework, the transducers are normally found near the hand-off with the goal that the measure of wiring is restricted.

4.1.6. Monitoring and Sensors Infrastructure

Sensors permit the grids to be "smarter" and play a basic role in the constant checking and control of distribution systems and power transmission. In addition, sensors are fundamental for looking after grid stability and strength [54]. Grid control depends on the estimation and checking of electrical boundaries in distribution and transmission networks. Sensors measure a few classes of actual boundaries at the distinctive framework-level utilization, including energy storage, power age, distribution line, substations, transmission lines, client profile, and utilization. Among those sensors, Voltage Transformers (VTs) and Current Transformers (CTs) keep an enormous segment among inheritance and smart power system establishments [55]. The quantity of estimating gadgets and sensors within the power grid has expanded rapidly, as well as inside Smart Meters (SMs) and PMU. Moreover, AMI is understood as the most developed gadgets requiring consideration for future research.

Smart Sensors (SS) are sensors with working knowledge that is sent in power grid networks, which incorporate pressure sensors, current sensors, temperature sensors, climate sensors, voltage sensors, and humidity sensors, among others [55]. Smart sensors are detection gadgets with digitalization limits, and furthermore, advanced data preparing functionalities. SSs may utilize normalized correspondence conventions, like the IEEE 1815 Standard for Electric Power Systems Communications [56], DNP3, IEEE C37.238 PTP Power Profile, IEEE 1451 group of Smart Transducer Interface Standards, and others.

4.2. Machine Learning (ML) Methods

ML applications provide a few benefits that incorporate a maintenance cost decrease, a fix stop decrease, a machine deficiency decrease, spare-part life increments, a stock decrease, administrator safety improvement, increased production, fix check, an increment in general benefit, and others. They could be sorted as administered or unaided, contingent upon how they gain the information. Furthermore, fault detection is one of the basic parts of prescient maintenance; it is often required for enterprises to identify faults at the start phase [57]. The point is to show how complex the design can be and the regularly utilized accessible learning methods.

In unsupervised machine learning, there is no input from an outer educator or proficient master. It is based on preparing an information sample from an information source with the correct classification already allotted. The primary point in supervised learning is deciding the obscure classes of things by grouping, while characterization is for supervised learning. It refers to the capacity to learn and organize data without giving an error flag to evaluate the potential arrangement [58]. Hence, unsupervised ML fundamentally characterizes any machine-learning strategy that endeavors to learn structure without either feedback (like support learning (RL) or recognized yield (like supervised ML).

As of late, ML strategies have been generally applied in different fields of study. Choosing the most proper, basic, and productive could be of incredible concern. ML algorithms generally require gathering immense measures of information on failure status situations and health-issue situations for model preparation. ML algorithm improvement covers chronicled information determination, pre-preparing information, model choice, model preparation, model approval, and maintenance [59]. The means engaged with ML algorithm improvement can be indicated as information, including extraction and determination, traditional ML methods, and outputs. Predictive maintenance has been broadly connected in businesses such as manufacturing businesses using deep learning and ML strategies.

4.2.1. Support Vector Machine (SVM)

Support vector machines are understood as supervised learning that is utilized for both classification and relapse issues. In any case, for the most part, it is utilized in classification issues. SVM looks for the closest means, which it calls, bolster vectors; once it has found the closest means, it draws a line in order to interface them. SVM could be a well-known ML strategy that is widely utilized for both classification and relapse investigation, due to its high precision. SVM is characterized as a real learning concept with an adaptive computational learning procedure. SVM can be a directed ML procedure that can perform design acknowledgment, classification, and relapse analysis [60]. Within the predictive maintenance of industrial equipment, support vector machines have been broadly connected for distinguishing a particular status based on the obtained flag. In machine learning, ANN and SVM calculations are connected by creating gage corruption estimations forecast for two sorts of rail tracks, counting straight and bent portions. Furthermore, cruel squared blunders and coefficients of assurance are utilized within the execution evaluation of the proposed models. Support vector machines have a noteworthy coefficient of assurance esteem of 0.75. Figure 8 presents a basic drawing of support vector machines.
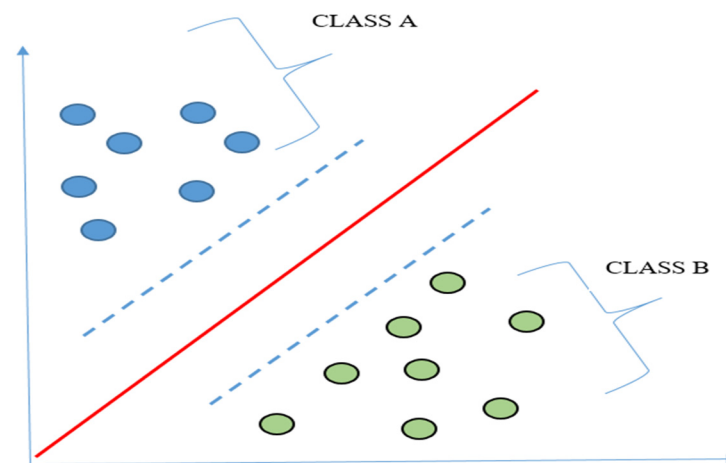
Figure 8. Support vector machine (SVM).

4.2.2. Artificial Neural Network (ANN)

In comparison to the other conventional machine-learning algorithms, ANN algorithms have recognizable preferences in tending to random information, fuzzy information, and nonlinear information. Artificial Neural Networks are essentially fitting systems with complex, unclear data and a large-scale structure. ANNs are broadly connected, and they are the most common ML algorithms. ANN indicators use factors such as temperature, dew point, mugginess, wind speed, wind heading, visibility, barometric pressure, and day of the week [61]. To extend the exactness of the ANN model, all the information was normalized so that all numbers were represented by a decimal beneath 1. The most advantage of this approach is its capacity for arbitrary flexibility in vitality and the result of widespread pertinence in numerous utilization designs [62].

4.2.3. Random Forest

Random Forest is suitable for a high-dimensional information model since it can handle lost values and can handle continuous, categorical, and binary information. Like its name, random forest consists of a huge number of individual decision trees that work as an ensemble [63]. Each tree within the random forest spits out a class prediction and the class with the most votes gets to be the model's expectation. Hence, it can be created effectively, and the combination of huge sets of random trees, for the most part, leads to precise models.

4.2.4. Recurrent Neural Networks (RNN)

Recurrent Neural Networks (RNN) display statistical properties of distinctive classes of time arrangement. Consequently, this structure can be utilized for power utilization classification. Thus, RNN is one of the foremost effective and cutting-edge neural lessons that can hold data. However, it endures the issue of vanishing slopes due to brief memory. Gradients are the qualities in neural systems that are utilized to update their weights [64]. At the point when RNN back multiplies through time, the gradient shrink recoils, and if the esteem of slope turns out to be excessively small by then, it will not be able to contribute as much within the learning. These strategies are connected for a single private buyer on a reference dataset of power utilization. Figure 9 shows a brief view of all machine-learning methods that have been explained in Section 4.2.
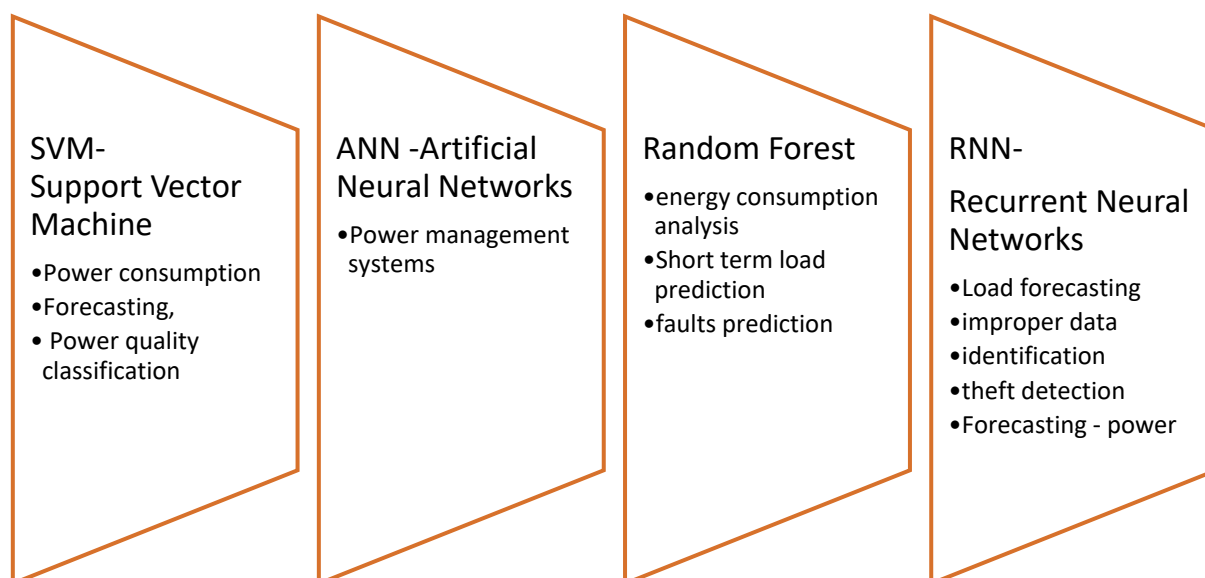
Figure 9. Machine-learning model.

4.3. Statistical Faults and Techniques—Formatting

Table 2 is a collection of related papers for smart grid fault prediction or fault location in the distribution and transmission grid, with references. The collection of papers is from three main databases, ScienceDirect, IEEE, and google scholar, from the year 2012 to 2020. This paper focuses on distribution faults in smart grids; however, research ontransmission faults provides perspective on how to view and analyze fault occurrences in distribution systems, and a few research papers focus on the overall smart grid faults whereby they cover both distribution and transmission.

Table 2. List of statistical faults and techniques.

Causes	Faults	Faults Covered	Location of Fault in a Grid System	Techniques	Ref
Equipment breakdown at a substation	- Arresters - air-breaker switches - step-down transformers - distribution, - cut-out switches - fuses - circuit breakers	- overall	Distribution	- infrared thermography-based technique with Multilayered Perceptron (MLP) - Improved Drosophila Optimization Algorithm - prediction-based maintenance (PBM)	[4,7,48]
large scale faults and small disturbances in the grid	- Symmetrical Faults - Unsymmetrical faults - 3-bus fault - Branch Trip fault - LL fault - LG fault	- LG, LL, LLG and LLLG - LG, LL, LLLG and leakage fault	Distribution	- machine-learning techniques like recurrent neural networks—SVM, LSTM - fuzzy inference system - Model Predictive Control (MPC) - Inter-area fault location algorithm - Decentralized fault detection of single-phase to ground fault using grounding resonant	[1,3,5,6,39]
Weather impacts - Lightning - Freezing - Wind - High & Low Temperature	- High-frequency transients are produced on the lines - Overhead cables & damage cables - Current stream between the burned off cables (short circuits) - High-impedance fault detection (HIFD)	- Overhead - Underground	Distribution	- Novel fuzzy logic approach - novel detection algorithm - predictive model-SVM	[8,46,47]
Electrical Power system faults	- Power accidents - line trip faults include aging and damage of the distribution equipment - failure in the medium or high voltage insulator - line fault	- Overall	Distribution	- artificial Neural networks (ANNs) with LSTM & SVM - Wavelet Energy Coefficient (WEC) - Group Method of Data - Handling (GMDH) - Long Short-Term Memory (LSTM) and Adaptive Neuro-Fuzzy Inference System (ANFIS) - Thevenin parameters - intelligent distributed agent-based scheme - one-class classification approach (fuzzy) - Nonrecurring protection scheme - SVM - Stockwell transform	[2,35–38,65–67]

Table 2. *Cont.*

Causes	Faults	Faults Covered	Location of Fault in a Grid System	Techniques	Ref
Power swing in the series compensated line.	- Circuit of the capacitor. - power swings, load encroachment,			- support vector machine (SVM) - robust fault detection and discrimination (RFDD)	[68,69]
- High-resistance faults on meshed low voltage - Power outages	- pole-to-pole (PP) or pole-to ground (PG) - single-phase-to-ground and three-phase faults in low voltage - faults in low-voltage - Disconnection of a high-voltage power distribution line - Power Failure			- hybrid passive over current relay - gradient boosting trees - Deep neural networks (DNNs) - superconducting fault current limiter (SFCL) - Petri net based protection monitoring - Machine Learning	[30–34,70–72]
Electrical wires are damaged or connections are defective or loose.	- arcing faults			- discrete wavelet transform (DWT)	[73]
distribution lines	- balancing problem - congestion of the distribution lines - faults corresponding to low and high impedance values		Distribution	- Model predictive control (MPC) - power line communication (PLC) devices - predictive control algorithm (Nash equilibrium)	[43,44,74]
Incipient faults in power distribution systems potentially	- power supply unreliability - Weak insulation causes more faults - recurrent faults	For underground cables, insulation aging presented as water tree electrical	Distribution	- human-level concept learning (HLCL) - Long short-term memory neural networks - Smart Sensors and Symlet Wavelet Function - Multidirectional Long Short-Term Memory (MLSTM)	[23,40–42]

Table 2. *Cont.*

Causes	Faults	Faults Covered	Location of Fault in a Grid System	Techniques	Ref
fault-location	- Outage detection and precise fault Location - Single-phase grounding (SPG) fault - detect the locations of faults - large-scale blackouts - fault resistance - Fault isolation	- Overall	Distribution & Transmission	- An efficient genetic algorithm-based (GA-based) technique - Discrete Wavelet Transform (DWT) and Support - Vector Machine (SVM) - Wavelet transform and deep neural networks - Multiended Approach - learning-based fault locator (LBFL) &SVM - RF-algorithm - Kalman filtering algorithm - Markov Decision Process - Quick Distributed Feeder Automation - Fault Localization Algorithm - traveling-wave fault location (TWFL - SMOTE—random forest algorithm - Calman filtering algorithm - Multiagent-based protection scheme like distributed algorithm for location/isolation and system restoration based IEC61850 GOOSE messaging standard - Decentralized IEC61499-based automation approach	[26–29,75–88]
Transmission line	- Power system fault - location of fault proportional to impedance - power flow disruption		Transmission	- Discrete wavelet	[89,90]
High impedance fault detection	- fault current magnitude is much lower than the nominal current - faults occur when the conductor touches a high impedance surface or poorly conducting surfaces		Distribution	- support vector machines - Low Impedance Faults (LIFs) with Matlab - wavelet packet transform & ML	[91–94]

5. Discussion

To progress the comprehensive analysis of the smart grid and its future challenges, it is principal to combine the research of the current smart grids and the range of long-term research to develop a more progressive and staged progression trend of the smart grid.

5.1. Challenges

The segment presented in Figure 10 describes the challenges in the smart grid. It is one of the challenging components blocking the longer-term advancement of the smart grid. Security will be the main concern in smart grid systems as anything that is smart must be connected to the cyber network. Smart grids inexorably play a significant part in power supply, and connecting the grid to the network triggers various vulnerabilities in the system. Cyber-security is one of the general issues for operation, since any single proviso has the possibility to transform danger into a disaster for utilities and the people involved with the grid. Secondly, the next issue to address will be grid straightening, as previously built electric control lines will be unable to deal with the advanced smart grid and the related renewable vitality sources. In addition, communication issues are ranked third as the protocols are not yet well defined in smart grid systems and there is a lack in data rates. The fourth ranked issue is the cost, as developing a smart grid is expensive. Last but not least, the Universal Popularity of Sensing Framework will be the last challenge of the smart grid due to the now limited AMI.
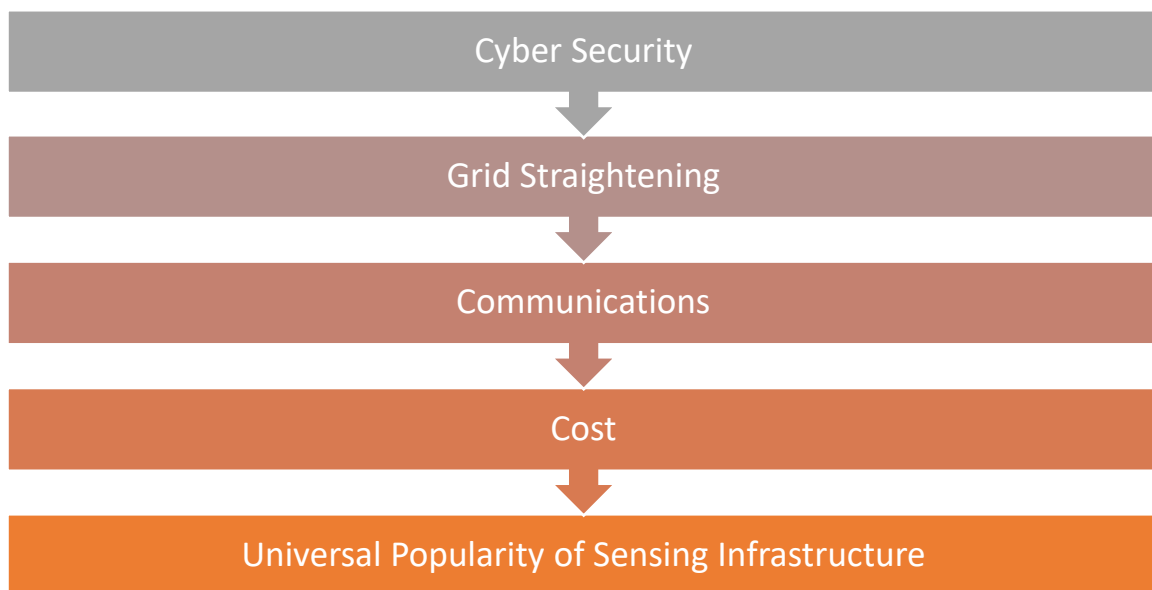

Figure 10. Challenges overview.

5.1.1. Cyber Security

In distribution systems and power generation, the integration of real-time checking, communication for analytics, advanced detecting, and communications for the analytics and control broadly increases the chances of assault, which can be viewed as cyber-attacks in control systems. As the cyberinfrastructure network increases, computerization and control take over the electric grid [94]. Therefore, cyber-attacks are capable of driving a framework to fail by displaying the wrong information, and can moreover suppress error messages and warnings from being shown—in this way, driving a system to collapse. The usual methods of attacking a smart grid system can be through computers, network cables and equipment, a master terminal unit, and remote terminal unit stages. In such systems, resiliency is required not as it were to manage cyber-attacks, but moreover to overcome the disturbances caused by physical harms to the equipment caused by normal disasters or any form of physical attack to the system.

5.1.2. Grid Straightening

The previously built electric control lines will be unable to deal with advanced smart grids and the related renewable energy sources. Hence, the interconnection guidelines may also need to be expanded to address more prominent levels of control calculation, such as low-voltage control (LVRT) [95]. With passing time, both electrical and mechanical parameters of grid infrastructure and transmission lines are altered. Execution of the components also breaks down over time as they ought to withstand push from mechanical, electrical, and normal strengths (dust, snow, wind, etc.) [15]—causing pressure, corrosion, and friction. Due to its immensity, complexity, and the fact that is constantly connected to human development and involvement, it is to be named an ecosystem on its own.

5.1.3. Communications

The smart grid will coordinate all the components of a power system to upgrade the execution of the grid. Much of the integration of components relates to communication systems, IT frameworks, and commerce forms. Persistent accessibility of two-way, high-speed digital communications is compulsory for current-day advanced systems. It is obscure to suppose a present-day grid without technology in this time. Interoperability and integration of all devices are not conceivable without it. Hence, the request for high-speed unlimited internet has gotten to be an urgent requirement for utility networks [16]. All the connected movement of a grid, including communicating with the client, will need to be carried out through the internet soon. The internet will not exist without power, but now power will also not be able to be maintained without the internet.

5.1.4. Cost

As the system is getting to be more modern and complex advances are being presented, the expense of power generation is growing simultaneously. Both fixed and variable expenses are expanding with complexity at both the distribution and buyer sides. Weak development means increased cost. Furthermore, as the expenses increase, energy efficiency and distributed generation (DG) [15] end up more alluring, this in turn decreases deals. Next, lower deals can also prompt the degradation of issued utilities, which can increase their expenses of the capital.

5.1.5. Universal Popularity of Sensing System

Smart grid systems in many areas intensely depend on the wide-area information collected by the sensing infrastructure. As of now, AMI has been comprehensively deployed in many nations. In a few nations, particularly in developing countries, for example, India, China, and South Africa, the ubiquity of AMI is limited. For a few detecting devices, for example, the phasor estimation units (PMUs), their present deployments are too constrained due to the high venture costs [10]. Hence, the limited deployments of detecting foundations are a challenge for the practical plan of smart grid networks.

5.1.6. Real-Time Estimation

The principal parts of future smart cities are SM and AMI. Its far-reaching sanctioning prompts a critical effect on the productive working of smart cities. The effect is identified as limitless investment funds as well as more noteworthy usability for buyers at all pay levels and providers of utilities, by giving real-time data assortment and client utilization designs. The improvement of smart cities relies upon the remote network guidelines, which should guarantee utility requests at lower costs, more transmission capacity, and the nature of administration. Besides, system backgrounds identified by remote organization and existing IoT ideas and execution are crucial to accomplish a completely interconnected city [56]. Real-time assessment ought to consider anticipating plans into distribution organizations, considering powerfully evolving conditions, and comparing time conditions.

5.2. Motivations

This segment briefly highlights the key motivations of communication systems in smart grid systems. As outlined in Figure 11, the motivations are related to the system in developing a smart grid.

Figure 11. Motivation overview.

5.2.1. Improve Use Experience

Communication infrastructures' key objectives in a smart grid system are to move forward quality and service reliability to clients, which incorporate decreased blackout times when a control system is hindered and improved notice of power network issues, as well as to give clients appropriate alternatives and devices and optimize their energy utilization to abridge the peak-hour utilization in order to maintain a strategic distance from control quality debasement or power outage.

5.2.2. Expanded Efficiency

Intelligent execution data and instruments will permit utilities to attempt their current obligations more productively, with longer-term benefits coming from mechanizing the smart grid. These increases in efficiency will offer assistance to diminish sending costs and operational costs in overseeing the smart grid system.

5.2.3. Improved Usage

In a smart grid, the communication infrastructure will give definite constant information on electrical transmission, distributed energy, power utilization, and market cost. These data permit the utility administrators to improve their dynamic cycles by recognizing which components are likely to fall flat and the substitution methodology online.

5.2.4. Greenhouse

A smart grid could lessen power misfortunes in the network and cutoff development in demand, due to embedded observation of the low-, medium-, and high-voltage systems through communication infrastructures, subsequently lowering carbon fuel utilization and greenhouse gas outflow [17]. However, a smart grid will empower choices for the renewable era and give clients the awareness and capabilities to decrease their energy utilization on carbon fuel-based control.

5.3. Opportunities

Fault prediction and location methods have been widely addressed in distribution systems over the years due to the concerns associated with the power grid that raise the importance of developing an intelligent model for failure monitoring able to identify and locate various kinds of faults. With the concepts associated with the power grid attracting growing concern among researchers, the importance of building an intelligent fault monitoring and diagnosis system capable of classifying and locating different types of faults cannot be overstated. Thus, there is the development of an analytics model for fault prediction and location in the power distribution grids, utilizing modern methods and technologies. Furthermore, it will predict faults and critical events that can pave the way for better asset performance management and planning. We identify the following potential opportunities from adopting predictive maintenance in a smart grid distribution network:

- Network operation sustainability.
- Optimize the grid operation and maximize the productivity.
- Smarter network operation and maintenance.
- Avoid/minimize sudden/unexpected fault and outage.
- Smarter and proactive maintenance strategies.
- Better asset performance management and planning.
- Predict faults and critical events.
- Automatic fault and outage management systems.
- Speed-up the fault location, reconfiguration, and restoration processes.
- Proactive and efficient maintenance.
- Reduce total maintenance costs.
- Proactive Maintenance scheduling methodology.
- Evaluating predictive maintenance options for optimal response.
- Fault prediction and location tool.
- Self-healing smart grid.
- Auto tracking network maintenance system.

6. Conclusions

The smart grid is an endless, interconnected framework, with many new and rising components and applications, which also needs intensive investigation into interoperability issues as well. As an outline, the significance of predictive maintenance is also developing due to the growing number of robots, digitization, and machine learning and AL insights presented into generation lines to automate routine activities. This literature review uncovers a clear drift towards more automated and real-time choice-making algorithms due to the development of Industry 4.0—the smart grid. A collection of papers has discussed the key terms of smart grid and predictive maintenance in the past few years, such as predictive maintenance in the smart grid, together with topics mainly related to the Internet of Things (IoT) and deep machine learning of artificial intelligence. The paper mainly discussed failures within the smart grid system from distinctive aspects. Then, power faults in the smart grid, including the reasons for an event, fault management, the type of failures, and protection are outlined in this paper. Fault management study includes, locating, detecting, and isolating faulty lines. To sum it up, this paper is centered on outlining the diverse types of power failures that are liable to happen in a smart grid system as a result of these sorts of faults. Developments in this research area are expected to enable a more strong and effective utilization of the grid within the move towards a smarter network grid. In conclusion, predictive maintenance algorithms can essentially benefit from the further exploitation of data frameworks engineered with the execution of big data innovations and algorithms.

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