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Fault detection and diagnosis in power transformers: a comprehensive review and classification of publications and methods

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ABSTRACT

A challenging problem in the protection of power transformers is the fault detection and diagnosis (FDD). FDD has an essential role in the reliability and safety of modern power systems; thus, it has been recently the center of attention in both industrial and academic studies. Due to unpredictable nature of fault, it should be located and isolated fast so that its impact on transformers is minimized. The main advantage of FDD is that it prevents costly repairs, costly downtimes, putting human into danger, and destruction of the equipment nearby. Thus, understanding failure modes, their cause and effects, and developing real-time automated devices for fault diagnosis with the ability to capture the early fault signs. Recently, various studies have been conducted on FDD in transformers using different views, methods, constraints, and objectives. There are good reviews in this context, but they are mainly focused on a specific area of this vast context. The purpose of this study is to classify the publications and make a systematic review of the FDD techniques and algorithms from different aspects and views from 1990 to 2020. This paper also summarizes the pros and cons of the existing methods. This paper provides a comprehensive background for future studies by evaluating the studies of this area and categorizing them.

1. Introduction

Power transformer is an essential device that serves as a vital link in a chain of other devices that provide electricity to consumers. If a transformer fails, the utilities will face significant economic consequences, including revenue loss and market backlash. Thus, end users may experience an electrical shortage, resulting in the shutdown of numerous industries, production being paralyzed and unemployment being exacerbated. In other words, the reliability of power network is contingent upon the transformer's reliability. Thus, keeping the transformer in good condition is essential for system reliability. Transformers are continuously exposed to fault occurrences due to various reasons, which all have different impacts on them. In this research some of the most commonly occurring failures are discussed with their causes and impacts. Automated fault detection is one method for increasing the reliability of transmission and distribution networks. These faults are immediately monitored to prevent their expansion. As a result, the network operators seek a precise and reliable monitoring procedure for fault detection and diagnosis (FDD**)**, which has become more essential for process monitoring as the demand for increased safety, reliability, and performance of power systems grows. If process faults are detected early enough while the system is operating in a controllable area, abnormal event development can be minimized. Thus, major system failure and catastrophes can be averted. FDD has garnered interest in both industry and academia. FDD aims to determine the type, size, location, and time of the fault based on system measurements.

Recently, several FDD methods for power transformers have been presented. However, no solution that both reliable and affordable, as well as scalable has been presented thus far. It is critical to identify the major impediments. Previous reviews in this context have concentrated on a single subject, such as frequency response analysis (FRA) [1,2], dissolved gas analysis (DGA) [3, 4], and computational intelligence methods (CI) [5]. The authors of [1] and [2] have comprehensively reviewed FRA methods and their applications for fault diagnosis and identification in power transformers. These studies examined the FRA theory and applications, as well as its challenges. The authors of [3, 4] reviewed the background and operating guidelines for DGA in order to address the origin of gas formation, detection methods and results interpretation via data analytics. DGA is widely accepted as a method for detecting transformers incipient faults. Reference [5] discusses computational intelligence (CI) methods to maintain an oil-filled power transformer by presenting state-of-the-art fault detection techniques and

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investigating the historical developments. The author of a recent study [6] reviewed the causes of transformer failures in substation and existing techniques, with particular emphasis on bushing-failure, as a major cause of transformer breakdown. While some reviews of the literature on transformer FDD have been published, there is still a dearth of comprehensive reviews on transformer fault detection and diagnosis methods. Thus, the purpose of this study is to present an organized, up-to-date, and comprehensive review on power transformers fault diagnosis and detection methods from 1990 to 2020, and summarize the pros and cons of the existing methods.

2. Complete review on power transformer publications and failure causes

A. Comprehensive review of publications

In the last three decades, the transformer FDD has attracted the attention of many authors. Recently, improvements and applications of transformer FDD have been reviewed [1–6]. However, some points of view were overlooked. As a result, this paper attempts to overcome the aforementioned pitfalls. The study reviews and categorizes failure causes, sources, and types. Additionally, the power transformer assessment and FDD methods, as well as their advantages and disadvantages are discussed. Fig. 1(a) and (b) show the distribution of studies on transformer FDD by country and decade (1990-2020). Between 1991 and 2000, the majority of research focused on mathematical models of the system's physical mechanism and structure [7–63]. Between 2001 and 2010, most studies have concentrated on accuracy and computational efficiency [64–170]. In this decade, some new data driven approaches have been presented due to the monitoring technologies, measured data, availability of physical models, and communication infrastructure.

From 2011-2020, most studies have tried to move FDD studies from offline to online methods and generalize the available solutions to enhance accuracy and computational efficiency [171–436]. These issues and other areas of power transformer are discussed in the following.

B. Comprehensive review of transformer failure causes

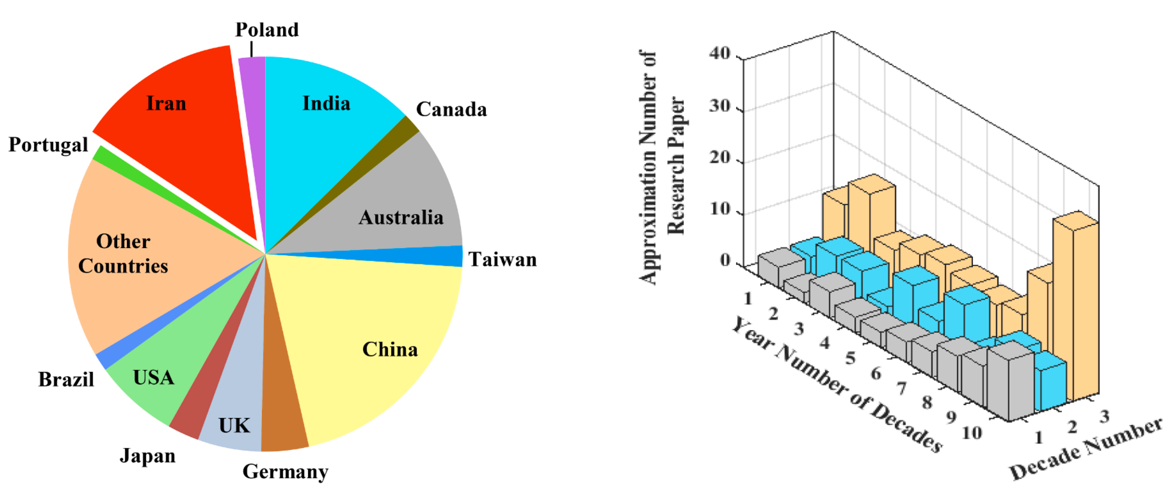
In this section, the causes of transformer failure are discussed in detail. As with all electrical devices, when a fault occurs in a transformer, the transformer fails [6]. Numerous issues may arise as a result of a failure. When a fault occurs at the distribution end, the power of the whole area might black-out. Because transformers contain a large volume of oil that is in direct contact with high-voltage components, a fault might be very hazardous. As a result, fire and explosions are possible. There are numerous causes of various faults, and each has a unique effect on the power system. The transformer is comprised of an electrical circuit (insulation and windings), a magnetic circuit (clamp structures, yoke, and core), oil, a tank, bushings, terminals, a conservator, a radiator, and a breather. Any of these components may develop a fault. Table 1 summarizes the classification of faults examined in Refs. [6, 8, 233], CIGRE, IEEE, and EPRI surveys.

Different fault types in transformer regarding various criteria are summarized in Fig. 2. The first criterion is based on the fault timing. If a fault occurs in several stages during the diagnosis process, it is called dynamic; otherwise, it is static. A fault might be physical, electrical, or thermal regarding its origin. A fault might be intentional or accidental regarding its nature. A fault might be transient, intermittent, or permanent regarding its persistence.

A transient fault needs no intervention and it disappears eventually. If a fault reoccurs constantly, it is said to be intermittent. To remove a permanent fault, an external intervention is required. A fault is considered to be internal or external regarding its location. The causes of these failures are listed in Fig. 3. The internal faults include magnetic, mechanical, electrical, chemical, and environmental faults. According to the statistics, internal faults constitute 70-80% of the power transformer damages [174].

Electrical disturbances, lightning, switching transients, insulation failures, moisture, overloads, line disturbances, stress or fatigue, careless transportation between installations and factories, earthquakes, and explosions into the transformer oil tank are the primary causes of internal and external faults in power transformers [175,176]. All of these events may cause thermal degradation of the paper and oil insulation, resulting in hot spots, overheating, partial discharges or arcing, as well as mechanical defects such as core movement, open or shorted turns, displacements between low- and high-voltage windings, winding deformation in both radial and axial directions, spiraling, and hoop buckling.

Fig. 4 shows the impact of failure mechanisms and their frequency of occurrence in power transformers discussed in [177] from 1991 to 2010. Transformers fail due to primarily as a result of a loose connection, a dielectric fault, moisture, lightning, electrical breakdown, excessive overloading, incorrect maintenance, and other causes [64].



(a) (b)

Fig. 1. Research on FDD in transformers

Table 1
Statistical survey results by CIGRE and other references for transformer components faults

Fault Type	CIGRE, %	Ref [6], %	Ref [8], %	Ref [233], %	IEEE survey-1986%	EPRI 1991survey%
Winding	37.69	34	30	45	41	21
Tap changer	31.16	26	40	26	-	13.8
Core	2.61	5	5	3	10	-
Tank	0.75	21	6	7	3	17.2
Bushing	17.16	20	14	17	13	30
Auxiliary	10.63	20	5	2	17	12

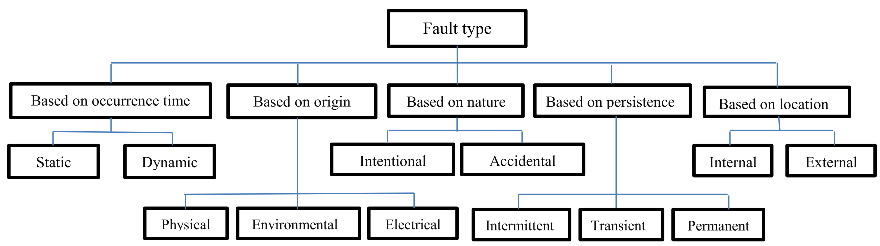


Fig. 2. Fault type classifications

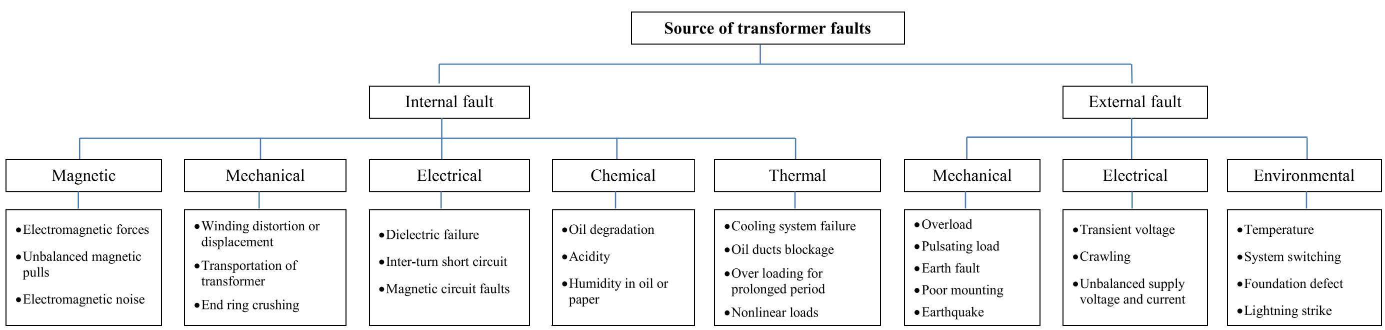


Fig. 3. Different types of faults caused by various operating conditions

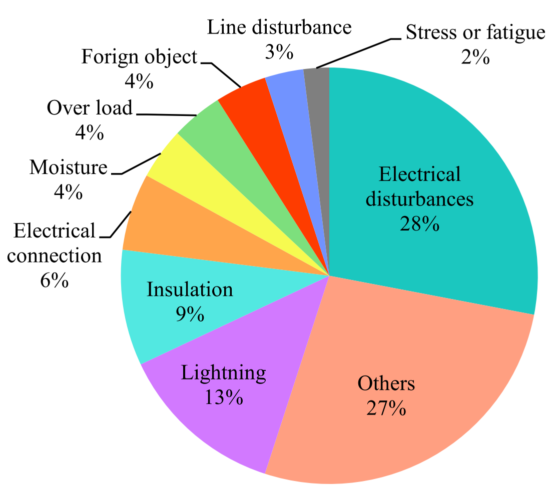


Fig. 4. Transformers failures causes between 1991 and 2010 [177].

3. Complete review on transformer Assessment and FDD Methods

A. Classifying transformer assessment methods

Condition monitoring of power transformers has become reality in recent years. To obtain information about the transformer's health status, the transformer condition can be determined using the incipient faults detected and monitoring data collected by the condition monitoring system. As shown in Fig. 5, there are twenty-two major categories of transformer condition monitoring. In follows, each assessment technique will be discussed separately in light of this figure.

Polarization and depolarization current (PDC) measurements: One of the most recent and non-destructive methods for determining the oil conductivity and moisture content of transformer homogeneous and composite insulations is the polarization and depolarization current (PDC) testing. To complement other methods, PDC has grown in popularity due to the ease with which it may be used to evaluate high-voltage insulation. As a result, PDC is able to measure the moisture content of the oil and paper insulation and evaluate its impact on the insulation's ageing [13]. During the rising current measurement phase of the polarization process, with a varied time constant and various insulating objects, the specimen's conductivity is measured, monitored, estimated, and characterized on the basis of the results of the PDC measurement. Then, the same test object is discharged with ground generating depolarization, and the charging and discharging currents are influenced by the dielectric property and insulating structure [86, 90, 334].

Power/Dielectric dissipation factor (PF/DDF): Using the dielectric dissipation factor (tan) test, transformer windings, bushings, and the oil tank can be inspected for insulation integrity. Reactive (capacitive) and resistive leakage currents flow when an alternating voltage is supplied across the insulator. Moisture, age, and conductive impurities in the oil all affect the resistive component's magnitude, whereas frequency determines the capacitive component's magnitude. The dissipation factor [180] is the quotient of resistive and capacitive current. The capacitive current's magnitude is nearly identical to the leakage current's at low

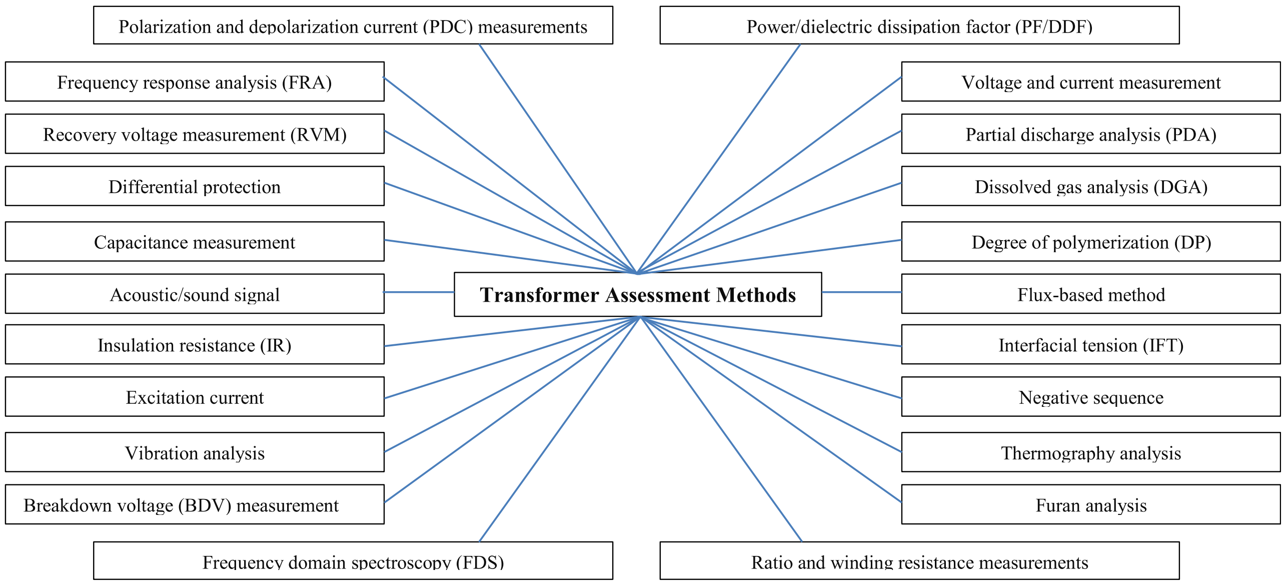


Fig. 5. The main categories of transformer assessment technique

frequency. It is hence known as a power factor test. According to IS-1866, the value of tan for new oil at 90 0C might vary from 0.010 to 0.015 depending on the transformer's rating [182].

Frequency response analysis (FRA): The FRA method is also known as the transfer function method. This method explains that changes due to the winding's deformation and displacement change the parameters of the transformer and modify its transfer function [15,35,87,96,119,179,192,194,223,260,265,266,280,287,292,295,318,422]. Because of the wide range of frequency regions in the complicated RLC link, a number of impedance values must be assigned to each frequency zone in order for the transfer function to vary. In the event of any structural damage, the RLC link is altered, which in turn alters the transfer function at different frequencies. The transformer may be malfunctioning in various frequency ranges based on these variances. CIGRE and IEEE try to develop tests, guidelines and standards for transfer function method on transformers [21,37,117]. Transfer function can detect the following mechanical and electrical faults [11,78,81,94,97,183,186,218,225,251,254,262,281,291,293,296,448,452]: short circuit (SC), radial deformation (RD), axial displacement (AD), disc-space variation (DSV).

Voltage and current measurement: In this technique, the correlation between the input current and the instantaneous output and input voltage difference (ΔV) of a particular phase is considered as a transformer fingerprint that can measure each cycle to detect any initial fault in the transformers [50,209,217,227,268,270,334]. In the healthy transformer, the ΔV-I locus can be used as the fingerprint for sinusoidal and non-sinusoidal operating conditions, which for internal faults detection can be compared constantly with the online measured locus [236,257]. Through simulations and experiments, the online detection approach is tested to see how different fault kinds and intensities, as well as different harmonic orders and magnitudes, have an impact on the ΔV-I locus [121, 174]. Load level and PF have little effect on the proposed ΔV-I locus [215].

Recovery voltage measurement (RVM): Another time-domain method for determining the oil and winding moisture content of a power transformer is to use the return voltage. When this method was first developed in the 1990s, many people were surprised to see that it is still an efficient way to determine the insulation's moisture content [187]. Measurement parameters such as maximum peak voltage, central time constant and initial slope of RV curve can be used to monitor insulation conditions [189, 190]. A DC voltage U_c is applied to the electrodes of a completely discharged test object in order to conduct an offline non-destructive diagnostic procedure. When testing an object, it is common practice to use an applied DC voltage of between 0.5 and 2 kV [137]. For this test, the high voltage source (T_c) is charged for T_c minutes, and then the test object (T_d) is disconnected from the high voltage source (T_c-T_d) for a predetermined amount of time (T_d-T_c). Using the given calibration curves, the moisture content may then be calculated from this time constant [196].

Partial discharge analysis (PD): It is the localized dielectric discharges in a partial area of a liquid or solid electrical dielectric insulation system subject to high-voltage field stress by IEC 60270. Presence of partial discharges indicates that the insulation material is degraded. Experiments have shown that one of the main reasons of insulation failure in power transformers is the partial discharges [74,237,316]. On the other hand, PD measurements have appeared as a non-destructive, powerful, sensitive, and indispensable diagnostic tool [128]. These include electromagnetic emission (radio wave, light and heat), acoustic emission (audible and ultrasonic), ozone production and the discharge of nitrous oxide gases. The PD phenomenon can be detected and localized using a variety of measurement techniques, including electrical, chemical, acoustic piezoelectric, ultra-high frequency (UHF) sensors, and optical.

Differential protection: Differential relays are the most frequent kind of transformer protection. This approach distinguishes the internal disturbances and faults using the weighting factors and differential current trajectory depending on the differential current locus in the relay characteristic [7,26,257,297]. To achieve this protection dependability, usually a differential-restraining characteristic with two operating and non-operating regions is modeled and the real differential restraint ratio is tracked during faults. Unbalanced primary and secondary circuit breakers can efficiently separate the primary and secondary currents of the power transformer by activating the differential relay [76,335]. Maintaining winding current on both sides is the basis of differential defense. The typical approach calls for measuring the primary and secondary phase currents, converting them to a standard base value, and then comparing the results to the observed differences [105]. The Disparity is a persistent indicator of malfunctioning situations. During normal operation, the fault current is quite low, but in an abnormal state it is much higher [35,158]. The internal flaws, on the other hand, are more advantageous because they are recognized as the criteria for winding inter-turn failure detection.

Dissolved gas analysis (DGA): Power transformer status monitoring with dissolved gas analysis (DGA) is a widely acknowledged and well-established technique. When the transformer has numerous internal problems, the rate of solid and liquid decomposition suggestively increases. This method appears to be a vital option for detecting the onset of a fault in oil-filled power transformers [19,45,49,51,58,68,100,125,205,285,288,289,298,309,310,270,271,311,318,320,321,324]. Cellulosic and glucose-based transformer paper insulation, pressboard and a variety of solid joints decompose to produce dissolved gases [107,109]. There is an improvement in the rate of decomposition of glucose, cellulose and oil when there is a defect in a large power transformer loaded with liquid mineral oil [336]. Dissolved gases have been used by some authors to classify these internal defects. In the past, several major gases were linked to the amount of gas production and the types of internal faults that existed [337,338]. Numerous approaches to dissolved gas analysis have been presented, including the Roger ratio, the Doernenburg ratio, the Key gas ratio, the IEC ratio Logarithmic Nomo graph, and the Duval triangle methods. Each technique is based on collecting information or gathering knowledge, by establishing alternate connections with multiple experts. As a result, they provide disparate diagnoses for the same oil sample. This technique can be used to discriminate between faults in a wide range of oil-filled equipment. A coded list of faults that can be detected by DGA is provided by IEC Publication 60599.

Capacitance measurement: Using capacitance measurements, bushings may be inspected and excessive winding movement can be detected. A transformer's bushings are analogous to a series of capacitors. The capacitance between a bushing's conductor and a dielectric dissipation factor (DDF) tap is often referred to as C1, whereas the capacitance between a DDF tap and ground is referred to as C2 [15]. About 30 years is the average lifespan of a bushing. When a bushing experiences difficulties like cracking or moisture intrusion, its capacitance rises and its service life shortens. It is thus possible to determine the state of the bushings by measuring capacitance. According to [35], moisture infiltration is the primary cause of bushing failure in 90 percent of cases. The test can also be performed to assess capacitance between specific windings and the main tank. Mechanical deformation of the windings and core can be detected using any deviation in the capacitance value [294].

Degree of polymerization (DP): Another reliable approach for determining the health of paper insulation is the DP. Since their existence is dependent on the polymeric and fibrous nature of cellulose and its byproducts, these materials have good mechanical properties [111]. Degree of polymerization is a term used to describe the number of monomer units in transformer solid insulation. One important metric for measuring the strength of a solid paper-insulation system is the DP (or degree of polymerization) [269]. Carbon, hydrogen, and oxygen C5H10O5 make up the transformer's paper insulation, which contains glucose monomer particles bonded together to create the cellulose. Molecular weight estimate procedures like viscometry or gel permeation chromatography (GPC) [272] are used to evaluate paper samples taken from the de-energized transformer. GPC uses molecular weight distribution to calculate a DP value for cellulose paper. When the cellulose is degraded, GPC is able to detect it through the chromatogram [127]. GPC's sampling and testing procedures are detailed in [127]. Furan analysis is more commonly utilized than DP because of the intrusive sampling technique.

Acoustic/sound signal: Acoustic machine signatures and signal analysis are also receiving attention [339]. Increasing the low signal-to-noise ratio (SNR) generated by a loud industrial environment is a major problem in audio fault diagnosis approaches [340]. For practical applications, denoising preprocessing procedures have been ruled out in favor of anechoic chamber approaches [341]. As the amplitude, attenuation, or phase delay of signals produced by PD are measured, it is possible to locate and identify the location of PD. Acoustic waves in the range of 20–350 kHz are used by the AE (acoustic emission)to identify Parkinson's disease (PD) [74,342]. An audible or non-audible AE signal is generated during PD by mechanical stress on materials near the place of origin. Several types of sensors, including as piezoelectric transducers, microphones, accelerometers, sound-resistance sensors, and fiber optic acoustic sensors, are often employed to detect the signal [425].

Flux-based method: The linkage and leakage flux can be analyzed and measured using the voltage induced in very simple air-core coils located at the transformer windings surface [59,115,130,320] [369,370,371]. When a transformer is in normal condition, equal flux passing through its core leg induces equal voltages in the related short circuits, or even a strong deformation. If the induced voltage changes, it indicates that a fault has occurred in that phase. In the other word, this symmetry is lost when an internal fault occurs, and the induced voltage measurement can be used to detect this fault. Short circuit currents cause compressive forces on inner windings, but tensional forces on outer windings that try to rupture the conductors [84,387]. Three phase equivalent test or per-phase test methods can be used to determine short circuit impedance. An input voltage must be provided sequentially to each of the HV windings, while keeping the matching LV winding shorted, in order to measure short circuit impedance.

Insulation resistance (IR): Insulation deterioration, dryness, or failures in windings or core earthing can all be detected using IR techniques. The test winding is subjected to a high DC voltage (often between 1 kV and 5 kV). The instrument measures the leakage current and calculates and displays the IR. IR measurements require a guard ring electrode in order to avoid the influence of leaks [132]. Voltage and current are often measured with the ammeter voltmeter technique, followed by resistance in the mega ohm range. The recommended method for measuring IR is based on shorting all the windings with terminals of bushings for better results and a precautionary standpoint, and grounding the tank and the core [383]. In light of the above configuration, it may be said that The PI is a ratio of the IR at the end of a 10-minute test to the IR at the end of a 1-minute test at a fixed voltage. Values 1 are dangerous, 1.1–1.25 are uncertain, 1.25–2.0 are reasonable, and $>$2.0 are respected according to industry standard practice [294]. As a result, PI is a critical factor in electrical design. The IR of the core to ground is measured by detaching the core grounding outside the tank. When a transformer is installed, moved, or DGA indicates an increase in the flammable gas levels, this test is frequently performed to ensure the core does not shift and make contact with the tank [163].

Interfacial tension (IFT): Insulating fluid's interfacial tension (IFT) can be measured to estimate the fluid's degradation. Non-polar saturated hydrocarbons make up the bulk of transformer insulating oil. In addition to the acid number, IFT is a significant chemical analysis test for detecting sludge and slurry buildup within the transformer tank [259]. However, hydrophilic carboxylic acids, which are formed during the oxidative decomposition of paper and oil, might alter the fluid's chemical and physical properties [220]. As hydrophilic components are added to the insulating oil in an IFT test, the oil's surface tension decreases. Premature degradation of oil can be predicted using neutralization number and IFT [368].

Excitation current: Testing for short circuits, ground faults, and core delamination; as well as for inadequate electrical connections and difficulties with the load tap changer (LTC) are all part of this process. In this test, the HV side is excited while the LV neutral and all other terminals are kept floating due to the lower magnitude of the magnetizing current in the HV winding. If there is a ground fault, a large amount of current with low excitation voltage will flow into the high-voltage side because of the grounded neutral. The single phase voltage and magnetizing current, as well as their phase angle, are measured during this test [132]. Faults are found by comparing the measured value to previous tests or other phases. In the case of an excitation current of 50 mA, a difference of more than 5% between the two phases indicates short circuited turns, ground faults, de-laminations of the core, shorts in the core laminations, and inadequate electrical connections [90]. This test must be performed before any direct current test since residual magnetism has an effect on the test results.

Negative sequence: It has become increasingly popular in recent years to use the negative sequence algorithm to protect power transformers, and numerous modifications have been presented [77,138,166]. However, it should be noted that the negative sequence approach is only an optional "add-on" to the classic differential relay scheme and its installation increases the protection system's complexity. As a result of inter-turn fault, the three-phase current system becomes asymmetric, demonstrating itself through appearance of a negative sequence component [171,245,308,332]. This negative sequence current component can be monitored to detect minor faults. Minor turn-to-turn faults can be detected by negative-sequence current using magnitude and phase information. The directed [77,138,151,171,212], and the differential percentage restrained [135,159,167] methods and the algorithm for negative sequence protection with internal/external fault discrimination are the two primary approaches to implementation.

Vibration analysis: The transformer vibration includes on-load tap changer vibration, winding vibrations, and core vibrations [72,79,82,174,183,231,232,277,306]. Internal faults in transformers can be detected through analysis of the changes in the transformer tank's vibration response. The tank vibration response changes if the mechanical properties of the core and windings change [129,209]. An accelerometer and other vibration analysis equipment can be used to monitor the transformer's core, shield, and moving elements from the outside. The most common mechanical damages (such as looseness, misalignment, unbalance, and other issues) can be detected and tracked using vibration analyzers [88]. Noise is produced as a common by mechanical vibration, which occurs as a result of deformation. Even if the equipment is online or activated, the accelerometer can be used to take vibration measurements.

Thermography analysis: Most faults change the thermal behavior of transformers [65]. Thermal behavior of transformers is affected by most defects. Thermal imagers, cameras that detect invisible infrared energy and turn that data into a pictorial image on a screen, are a typical way of contactless temperature analysis. Even when the equipment is operational, infrared cameras are the most commonly used tools for inspecting, as they can quickly and accurately identify the areas of high temperature [343]. Abnormal conditions can be detected using thermograph or hot spot temperature (HST) [65,66,67,255,305]. The effective life of the power transformer and its loading are affected by the HST. The HST represents the limiting temperature of the insulation system of a transformer [179]. With a temperature increase of 75 degrees Celsius, a transformer will fail instantaneously, according to [200]. Infrared thermography uses infrared light from a target surface to create color-coded pattern images that can be used to spot defects. The test is able to pinpoint the exact location of the hot spot and to show the temperature gradient at joints and other exposed areas. If the results don't match the historical data, a DGA on the same transformer can be used to verify them. In this way, this approach serves as an initial defect detector as well as an additional complement to DGA. Transformer tanks cannot have their internal temperature measured with a thermograph [106].

Breakdown voltage (BDV) measurement: According to the IEC 60156 standard, BDV measurements can be made at room temperature [18]. Oil samples with no particles larger than 100 nm are used for BDV measurements. With regard to each sample's class of particulates, the influence of the particles is deemed to be minimal. There is a problem with the IEC 60156 method because it is not sensitive enough to oil particle contamination [210,219]. Use of a cumulative Gaussian probabilities methodology is used to characterize the BDV findings. Typical BDVs for mineral oils, esters, and silicone fluids range from 50 to 70 kV for new, dry insulating oils, which can be lowered significantly when solid particles and free and/or dissolved water are present [252]. There are a number of standards for in-service transformers' BDV criteria, which demand that the space between the electrodes be no smaller than 2.5 mm [252]. It should be noted that a high rating does not necessarily mean that the fluid is free of contaminants [24].

Furan analysis: Another method used to protect the power transformer against catastrophic failure is the Furan analysis [226,237]. An integrated, non-periodic and post-diagnostic technique, furan analysis can assess the state of cellulose paper inside transformers without interrupting service. Measuring these furanics present in transformer oil, the paper insulation with a high degree of confidence can be found. The degradation degree is determined by the concentration and types of furans in oil sample [328]. Two primary methods used to detect the furfural or furan concentration in transformer oil are the confocal laser Raman spectroscopy (CLRS) and high-performance liquid chromatography (HPLC). The furan is very sensitive to the ageing of paper and comparatively stable than other furanoid compounds.

Frequency domain spectroscopy (FDS): The measurement technique is similar to capacitance and DDF/PF, but it is used at different frequencies, typically between 0.001 Hz and 1000 Hz. Dielectric material frequency response is commonly utilized to diagnose insulation systems [29,30]. Transformer insulation's DF and complex permittivity can be measured as a function of frequency to get an inside look at how well the components are insulated. A current flows through an insulating system when a sinusoidal voltage is put across it [31]. To determine DF and complex capacitance, the test sample is subjected to sinusoidal voltages over a wide frequency range using FDS techniques. The amplitude and phase of the response current flowing through the insulation are recorded as a result. In the recent decade, a huge number of studies have been published to fill in some of the gaps in our knowledge. Many studies have presented theoretical and experimental results to show the impact of temperature, electric field, aging, and paper and oil moisture content on FDS results (e.g., [32–37]).

Ratio and winding resistance measurements: The IEEE Std C57.12.90-2010 [27] specifies tests for liquid-immersed distribution, power, and regulating transformers, which includes these tests. It is possible to calculate the ratio of HV to LV winding turns by performing the ratio test [52]. A shorted turn or open winding circuit can be found by conducting this test. As stated on the transformer nameplate [52–54], the measured ratio is 5% of the rated voltage ratio between windings. The voltmeter method, the comparison method, and the ratio bridge method are all acceptable methods for conducting the ratio test [52]. Testing for winding resistance can be done as a type test or as a routine check. There are a number of things that can go wrong, such as broken conductors, shorted winding disks, shorted winding layers and improper bushing connections, which can affect the operation of the tap selector and the diverter switch. When comparing measurements, it is necessary to record the measurement temperature and convert the resistance to a standard temperature. Winding damage can be indicated by a deviation of greater than 5% [53]. A voltmeter-ampmeter approach or a bridge method can be used to measure transformer winding resistance [54].

Table 2 summarizes the typical problems of transformer components that may be detected with transformer assessment techniques. Meanwhile, their advantages and disadvantages are briefly listed in Table 3. To help the reader to have a more practical view of the topic, Fig. 6 shows the costs and complexity of implementing each assessment technique that could be simply classified into three categories (low, medium and high).

B. Classification of transformer FDD methods

Numerous fault diagnosis techniques have been proposed in the literature for various transformer components. These methods can be classified as knowledge-based, data-driven, or value-based methods. Fig. 7 illustrates the methods introduced in this article for identifying faults in various transformer components.

B.1. Knowledge-driven methods

When the information required developing the mathematical model is unavailable, prohibitively expensive, or time-consuming, knowledge-based methods are an excellent alternative approach for fault detection. These techniques are founded on physical principles, fault mechanisms, and specialized knowledge. Knowledge-driven methods are used to determine the system's essence and to implement real-time fault diagnosis. The results of these methods are identified by the accuracy of the

Table 2
Diagnostic matrix of transformer assessment techniques vs. transformer components

Type of problem/Assessment technique	Winding	Core	Tank and accessories	Dielectric	Tap changer	Cellulose paper	Bushing	Oil and paper impregnation
Polarization and depolarization current				●		●		●
Dissolved gas analysis	●	●	●		●		●	●
Recovery voltage measurement	●			●				●
Voltage and current measurement	●				●			
Frequency response analysis	●	●						
Partial discharge analysis	●	●	●				●	●
Furan analysis		●				●		
Differential protection	●	●	●		●		●	
Thermography analysis		●	●				●	
Excitation current	●	●			●			
Negative sequence	●							
Vibration analysis	●	●			●			
Frequency domain spectroscopy	●			●				●
Acoustic/sound signal	●		●	●	●		●	
Measurements of degree of polymerization				●		●		
Flux-based method	●	●						
Power/Dielectric dissipation factor		●		●			●	●
Capacitance measurement	●						●	●
Insulation resistance		●		●			●	
Interfacial tension					●	●		●
Breakdown voltage measurement				●			●	●
Ratio and winding resistance measurements	●				●			

experience richness and the mathematical model. These techniques are based on qualitative models and are typically accomplished through empirical and mechanism-based knowledge. Mechanism knowledge-driven methods should establish an accurate mathematical model based on the perception of the system structure and physical mechanism, which mainly include parameter estimation [17,422], state estimation [73,186], simultaneous parameter and state estimation [95,103, 449], and parity spaces [57]. System state estimation has been studied extensively by generation of state observers [195] using real measurement or data generated by model through comparison of the theoretical estimates and the measurements.

When all state parameters are not observable, the methods based on state-estimation are useful. State estimation methods are classified as Kalman filter based [124] and Observer Based [116]. First-principle mode [91], gray-box [204] and black-box [215] methods are among parameter estimation methods. The above methods depend on the residual analysis between the parameters of the nominal model and the estimated FDD model. However, extended Kalman filter [216] and two-stage Kalman filter [217] are among simultaneous state and parameter estimation methods. Typically, physical principle laws governing the system's behavior, such as energy and mass balance, are used to generate a first-principle model. While these methods are robust in terms of describing the dynamic behavior of the system and are accurate estimators, they are not suitable for real-time computation and require a good and fast-response controller to stabilize the system quickly enough to detect and diagnose sudden faults.

The steady state response is tracked and abrupt faults are detected using a gray-box model. These methods employ combined regression techniques to drive system characteristics or physical parameters from a static model. To reduce the computational complexity, and maintain the system performance, non-complex models can be used. Numerous studies have described transformers using gray-box models [228,229]. In contrast to physical properties, dynamic black-box models develop mathematical models using system identification techniques that are incapable of governing cannot govern system characteristics due to the estimated variables' physical insignificance. A black-box model may be appropriate for on-line FDD where parameters are estimated continuously via recursive identification techniques. Additionally, it is capable of executing unique faults via state-space equations. Parity relations are expressed as algebraic equations with state-space equations that are like observers but easier to design. Besides, it can ensure that the system's framework is consistent with the measurements. Thus, linear-algebraic framework can be used to solve most FDD problems. The parity-based FDD residual matrix is directly obtained using the instructions given in references [115,221].

Empirical knowledge-driven fault diagnosis mainly relies on domain specific expertise and long-term accumulation of experience. It makes use of empirical knowledge to design reasoning and decision-making mechanisms for qualitative diagnosis. They are further classified as graph theory [69,235] and expert systems (ES) [20,25,48,58,68,104, 198,198,278,319,320,440,441,442] based on their inference mechanism. Graph theory is a branch of mathematics and computer science that studies graphs. Graphs are mathematical structures that represent the conjugated relationships between objects in a set [235]. Graph theory can be used to model a wide variety of physical and abstract systems. Techniques for graph-based data storage and algorithm design are particularly advantageous when utilizing computers. ES is one of the most extensive and most active artificial intelligent methods that require a high level of expert knowledge in some domains. ES uses experience and knowledge obtained from one or more experts to estimate and judge and develops an intelligent computer program system to simulate the decision-making process of the human expert for solving complex problems [319,320]. ES is particularly suitable for the problems in which it is difficult to establish a mathematical model or expert experiences and knowledge are relied on.

Graph theory can be used to model a wide variety of physical and abstract systems. Techniques for graph-based data storage and algorithm design are particularly advantageous when utilizing computers.

B.2. Data-driven fault diagnosis methods

Data-driven methods model processes using the relation between fault classes and data patterns. These methods reduce dimensions based on rigorous multivariate statistics unlike pattern classification methods, which learn the fault performance pattern using entire data. Thus, it can convert high dimensional data into a lower dimension only for data domain of interest. As a result, this strategy is useful for large-scale modern engineering systems. They employ a variety of data mining techniques for extracting and classifying fault features from massive amount of acquired operating data [300]. Transformers employ three major data-driven method groups: quantitative artificial intelligence methods [246,291,308,320], statistical analysis [113,178,260,303,304, 316,437,438,445,453] and signal processing [84,96,197,221,256,325].

Table 3
Summary of the advantages and disadvantages related with transformer assessment methods

Transformer assessment method	Advantage	Disadvantage	Literature
Polarization and depolarization current	The oil-paper insulation's state may be reliably assessed using this method; Polarization and conduction are two distinct dielectric phenomena.	Design and insulation composition details are difficult to come in practice.	[114,151, 346]
Dissolved gas analysis	Preliminary signs of abnormality.	Expensive; uncertainty in study; Has some ambiguities in its analysis; Not useful for oil less transformer	[331,378, 421]
Recovery voltage measurement	Simplicity; non-destructiveness; and speed of usage right on the job site are the most appealing features of this tool.	Need experienced experts; RVM spectra can be difficult to disentangle from the effects of oil and paper.	[97,98, 317]
Voltage and current measurement	Models created for the sole purpose of verification.	Difficulty in detecting early signs of a problem; For unbalance load cannot be used.	[121,174, 215]
Frequency response analysis	Winding and core problems can be detected using this instrument; Can detect capacitive effects at high frequencies	Costly; needs to have the healthy condition data; needs expert's opinion; requires additional sophisticated instruments; it is difficult to find which part of the transformer has failed	[286,290, 299]
Partial discharge analysis	An approach that is well-established in the electric utility industry.	This method Impressive from tank and winding.	[332,418]
Furan analysis	is extremely susceptible to paper aging; can estimate the transformer's remaining life span.	Insulating oil can only adequately assess the quality of a transformer's solid insulation if it is replaced or reclaimed.	[125,328]
Differential protection	Robust and classical method.	Inability to identify interterm defect at inception level in instrument-sensitive transformer; precision of the current transformer is critical here; winding insulation breakdown might affect this method's sensitivity; Sensitive to the structure of transformer.	[211,213, 214]
Thermography analysis	Good in real-time monitoring.	Difficult to locate the fault point	[230,419]
Excitation current	A reliable transformer condition evaluation does not necessitate the use of a baseline value.	Affects the strength of the residual magnetic field; fault region cannot be detected on the defective phase.	[90,132, 224]
			[181,192]
Negative sequence	Turn-to-turn fault detection; The signal for fault detection is available.	Unable to detect the faults in no load conditions; the instrument transformer's inaccuracy impressed me; unbalanced load cannot be employed; measurement complexity.	
Vibration analysis	A mechanical or electrical fault can be detected using this technique.	A winding-mounted sensor is required; Vibration model is complicated.	[183,261]
Frequency domain spectroscopy	to accurately estimate the dryness state and ageing of transformer insulation system particularly in paper insulation more	is hard to distinguish between the dielectric response and the effects of geometry, aging, and moisture.	[102,160, 282]
Acoustic/sound signal	Demonstrates high resistance to electromagnetic interference (EMI).	Low sensitivity to damping of oil, conductors, core, and main tank due to measurement complexity and data processing.	[123,196]
Degree of polymerization	easy conduction; can be easily empirically related to insulation condition	There are no known mechanisms or rates of the process; oil pollution and uneven paper aging limit the applicability of this technology in the real world.	[111,122, 269]
Flux-based analysis	Good accurate; sensitive; identify the faulty phase; stable during energizing and over-flux in online conditions.	Details about transformer structure and sensors are required; impressed by the instrument transformers error; unable to detect the turn-turn faults located in the middle point of each winding	[125,322, 327,329]
Power/Dielectric dissipation factor (PF/ DDF)	It is extremely vulnerable to ageing products and polar pollutants; can determine the pollutants in the insulating oil's concentration.	Cannot locate discrete defects; to do the tests, the cable system must be taken out; no field data available for establishing criteria.	[182,273, 279]
Capacitance measurement	Measuring values are easily readable; has a wide range of frequencies; high accuracy; also, measurements may be performed in a high magnetic field.	May be affected by contaminants such as dust and moisture, both of which can lead to errors; Gives non-linear results.	[64,180]
Insulation resistance	Contamination such as excessive moisture or dirt is immediately apparent; equipment that is easy to use, economical, and readily available is just some of the advantages of conducting a thermal imaging test on a building's insulation.	Unable to locate the fault.	[23,182]

(*continued on next page*)

Table 3 (*continued*)

Transformer assessment method	Advantage	Disadvantage	Literature
Interfacial tension (IFT)	Can assess the level of oil deterioration.	The test is relatively expensive; needs an expert; takes a long time from the extraction of the oil sample to receiving the findings back from an external laboratory; are affected by oxidation and contamination.	[259,330,368]
Breakdown voltage (BDV)	is a relatively quick and easy way of determining the amount of contamination in insulating oil; On-site testing.	It needs periodic testing to ensure; unable to locate the fault.	[24,210]

Quantitative artificial intelligence methods are used to train different learning algorithms on collected data in order to identify complex faults automatically and intelligently and diagnose failures. Among artificial intelligence techniques, decision tree [246,247,248,249,439,444,446], Fuzzy Logic [9,19,27,28,29,125,177,289,291,297,301,326], support vector machine (SVM) [48,203,207,228,251,308,321,323,441], artificial neural network (ANN) [10,14,20,34,42,71,120,132,202,205,241,320,447], can be mentioned. Because intelligent methods require training prior to processing, which is time consuming, using them to locate faults would be difficult. Artificial neural network (ANN) can generate an output given previously unknown inputs. Because ANN calculations are performed in parallel; their speed is high, and programming can be accomplished through training rather than explicitly defining instructions. Support vector machines are used to solve problems involving regression and classification. SVM is a method for learning with a small sample size that results in excellent generalizability when used with a small training sample. Unlike neural network in which trial and error is used to determine the number of hidden layers, the SVM algorithm determines the number of support vectors. Hence, SVM is superior over ANN. Besides, in contrast to ANN, SVM achieves an excellent performance without training. In fuzzy set theory, instead of the probability concept, the possibility concept is used. Possibility is defined in the range of [1,0]; where 0 indicates totally impossible and one indicates completely possible. If statistical information is accessible, probability can be used as an appropriate uncertainty measure. When there are no statistics available as in uncommon situations, an expert should describe confidence degrees in various hypotheses. Decision tree learning forms a decision tree by the training data. A decision tree is a flowchart with tree structure; internal nodes represent tests on attributes, branches denote the test result, and the leaves hold a class label.

Signal processing aims to extract fault features in the frequency and time domains via various signal processing techniques, including (1) frequency domain methods (including sweep frequency response and low voltage impulse tests) [11,12,15,38,96,256,451]; (2) Time domain methods (including wavelet transformation and Fourier analysis) [13,37,75,84,89,99,101,274,325]; and (3) time frequency methods [16,31,197,234,242]. By using Fourier transforms, steady state signals can be analyzed spectrally. Also, they can be used to classify faults. On the other hand, Wavelet transforms maps the time-series signals into a 2D domain, which represents the information in different scales and time shifts. In the second category, two different methods are used to measure the frequency response: low-voltage impulse (LVI) and sweep frequency response analysis (SFRA). In LVI, a wideband frequency spectrum impulse signal excites the transformer windings and the response signal is measured in time domain. To generate a frequency response signature, both signals are converted to frequency domain. A sinusoidal signal with variable frequency and constant amplitude is applied to one end of the winding under test to carry out an SFRA measurement, and the response

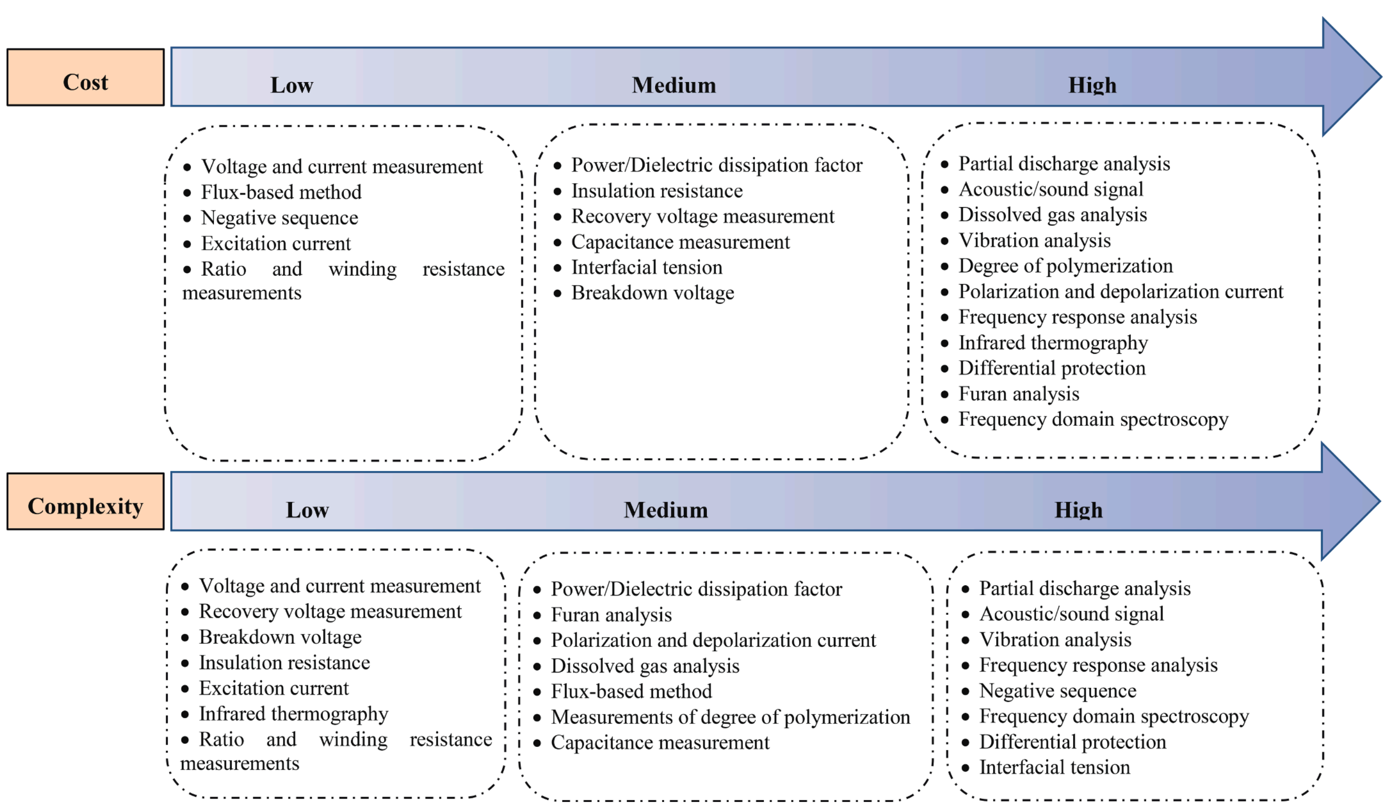


Fig. 6. Taxonomy of the cost and complexity of implementing each assessment technique

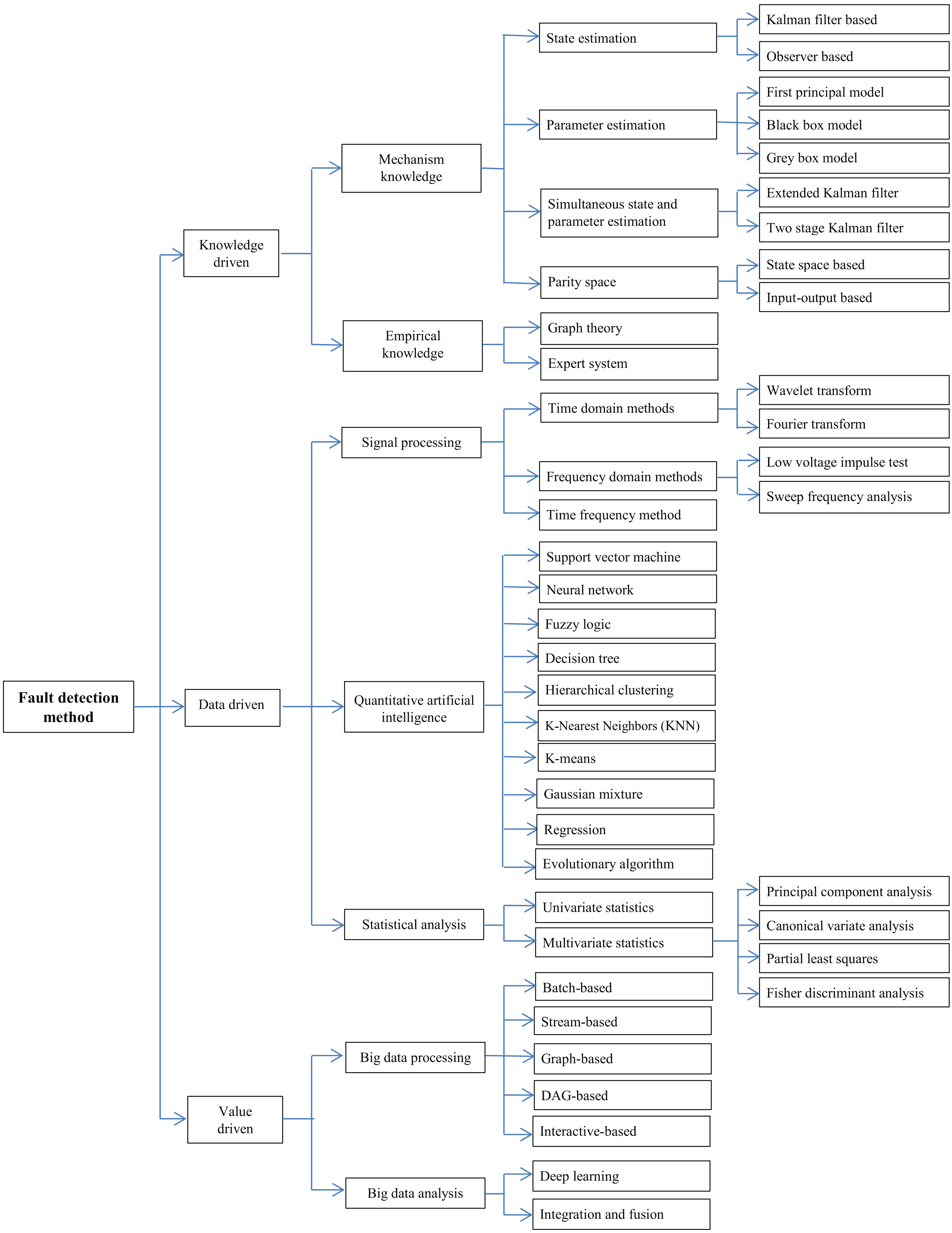


Fig. 7. Classification of transformer fault detection and diagnosis methods

on the other end of the winding is measured. Phase and amplitude of signals taken from selected terminals of the transformers are plotted vs. frequency.

Statistical analysis extracts fault features and describes the correlation between variables using statistical models or statistics descriptions [303]. Transformers are analyzed statistically using the following methods (1) univariate statistics [222,243,208,244,266]; (2) multivariate statistics (include principal component analysis [110,173,239,240], canonical variate analysis [172], partial least squares [250,271], and fisher discriminant analysis [80,283]).

Principal component analysis (PCA) is used to decompose multiple (possibly) correlated variables into multiple (smaller) uncorrelated variables referred to as principal components. A reduced set is easier to analyze and interpret. Canonical variate analysis (CVA) is very similar to principal component analysis (PCA); multivariate data is sent to a program that calculates new values and variables for each new variable and sample. Unlike in principal component analysis, where the new variables are principal components, in canonical variate analysis, the new variables are canonical variates. Their distinction is in how the new variables are chosen. PCA is not given any information about groups or group membership; it simply needs to calculate the new variables in such a way that the variability of the scores for the entire data set is maximized. However, CVA needs information about groups and group membership in order to minimize within-group variation and maximize between-group variation, respectively. Reduce/model spectral data using Partial Least Squares (PLS). It is comparable to principal component analysis in terms of extracting principal components from data.

The difference of PLS and PCA is that a model is built using both the spectral data and the property or assay data together iteratively. PLS models a system with fewer and more associated dimensions compared to PCA. Fisher discriminant analysis is also used to investigate the differences of two or more groups on several variables, or sets of variables, simultaneously. Particularly, discriminant analysis provides the possibility (a) to predict group membership based on a set of independent variables or (b) determine how predictors' best differentiate groups. In discriminant analysis, it is assumed that group membership is mutually exclusive and the predictor variables are independent.

B.3. Value driven fault diagnosis methods

As equipment's intelligence and automation levels increase, processing and analyzing collected big data becomes more critical in order to obtain a high diagnostic value[293,294]. However, difficulties in predicting fault types, a scarcity of fault samples, widespread uncertainty, and computational overload have precluded the use of previous fault diagnosis techniques. Thus, the majority of big data scientists are focused on delving deeper into massive monitoring data and performing rapid analysis. This section discusses and summarizes value-driven diagnosis in the context of big data processing systems and analytical methods for big data.

Big data processing is a term that refers to programming models or techniques that access large amounts of data in order to extract useful information that can be used to provide and support decisions. Using local high-performance computers and simple parallel operations, traditional processing methods increase computational power. The critical issues are overcoming the limitations of relational databases and serial algorithms, as well as developing new types of distributed processing systems for big data [425]. Big-data processing is classified as DAG-based (directed acyclic graph) [175,258], graph-based [426], stream-based [427], interactive-based [428], or batch-based [429] depending on the processing method.

A batch is a collection of data points from a specific time period. In other words, the batch processing model accumulates a collection of data over time and feeds it to an analytics system for processing. Streaming processing is key to turning big data into fast data and handles continuous data. The streaming model feeds data into analytics tools piece-by-piece in real time. Graph analytics is another commonly used term, particularly referring to data analysis in a graph format using data. Graphs are comprised of nodes, edges, and properties, which represent and store data in a way that relational databases are not equipped to do. Directed Acyclic Graph (DAG) is a directed graph without any cycles. DAGs are used to model various kinds of information. Also, DAGs can represent collections of events and how they affect each other. Data scientists employ interactive analytics as a set of approaches to explore data interactively, supporting exploration at the rate of human thought. Big data interactive is an interesting area of study. There are three main functions in interactive data processing: quantitation, integration and peak detection. During peak detection, the software determines starts and stops of the peaks. During integration that only occurs after peak detection, the areas under the peaks are determined.

Big data analysis extracts meaningful insights, such as customer preferences, market trends, unknown correlations, and hidden patterns. Historically, fault diagnosis techniques have relied on simple models for analyzing and processing single sample sets. These models performed poorly and were not generalizable. The requirements for fault diagnosis are difficult to meet when using big data. Thus, deep learning is widely used today for big data analysis in order to achieve hierarchical representations of fault features [195,450]. Additionally, integrated methodology and data fusion techniques are frequently used to obtain more reliable and comprehensive diagnostic data. Among the advantages of big data analytics, the followings can be mentioned: it can be used for preventing fraudulent activities and better decision making. Deep learning is an excellent technique for detecting complex structures in large amounts of data. It adaptively extracts fault features via sufficient conversions and combinations, with no manual intervention required to distill the physical significance of features [430]. Data fusion integrates multiple data sources to generate information with higher consistency, accuracy, and usefulness compared to the information provided by any individual data source [431,432]. Data integration brings together data from a variety of disparate sources and storage technologies to create a unified view of the data. While data integration is concerned with heterogeneous data, data fusion is concerned with homogeneous data.

To better understanding, which FDD is more related to which TAM, a direct link between TAM and FDD methods in transformers has been shown in Table 4.

C. Comparison between different fault detection and diagnosis methods

Knowledge-based, data-based and value-based driven diagnosis techniques have various pros and cons. Under specific situations, each method can exploit all of its advantages, but if the situation changes, the method may be not applicable. At small data volumes, knowledge-based detection performs best. Among its advantages are its simplicity and ease of inference, rapid diagnosis, and strong explanatory power. To obtain accurate fault features from small data sets, value- based and data-based methods cannot be used. As the volume and richness of the data increases, obtaining relevant knowledge and expert experience, hindering the applicability of knowledge-based methods, becomes more difficult [433]. Advantages and disadvantages of knowledge-driven and data-driven methods show in Table 5 [434]. Moreover, Table 6 illustrates comparison between knowledge-driven, data-driven and value-driven methods [423]. However, data-driven methods, which provide the possibility of diagnosis without modeling, are simple, helping the accurate exploitation of fault information from large data sets and excluding the uncertainty interference [435].

Value-driven methods are very similar to data driven methods from many points of view, including providing diagnosis through the processing of monitoring data. However, applying using value-driven methods to this volume of data is challenging, as it is computationally expensive and time-consuming. With the exponential growth of data volume, previous fault diagnosis methods become almost incapable, such as inability to produce a result, insufficient or inaccurate results, or

Table 4
A direct link between transformer assessment methods (TAM) and fault diagnosis and detection methods (FDD).

Transformer assessment method	Integrated with fault diagnosis and detection method	Most important features
Polarization and depolarization current	SVM [333], Statistical technique [344], ANN [345,346].	The quality index of the insulation tested. When the IR values are low, it is quite important [413,414].
Dissolved gas analysis	Kalman filter based [139], Black box model[140], Grey box model[141], Graph theory[267], Wavelet transform [142–144], Fourier transform [347], SVM[348-350], ANN [145, 351-353], Fuzzy logic [146, 354,355], Decision tree [349,357], KNN [358,359], K-means[360], Regression [361,362,443], Evolutionary algorithm [147-149,363-366], PCA [367].	Good diagnostic and detection ability based on laboratory chromatography [167]; The equivalent hydrogen method is a similar, but less expensive, alternative [415].
Recovery voltage measurement	Expert system [151]	A basic understanding of oil–paper insulation's water content and the aging process [414].
Voltage and current measurement	Input-output based [215]	Input current vs. differential voltage between input and output voltages shown on a locus diagram [356]
Frequency response analysis	Kalman filter based [369], Parameter estimation [370], Expert system [152]. Wavelet transform[153], Fourier transform [154], Black-box [385], Low voltage impulse [96], Sweep frequency analysis [96,191], Artificial intelligence [372], Statistical analysis [373], Deep learning[374]	Diagnoses turn to turn faults in the low frequency bands utilizing the LCR complex network variation and measuring the transformer frequency response [416]; Identifies electrical or mechanical faults in the windings, contacts or core of the power transformer [168]; There are just a few tests that can be done. Further detailed analysis on injection and signal collection is lacking [169,417].
Partial discharge analysis	Fuzzy logic [288], Kalman filter based [375], SVM [376], ANN [377], KNN [379], Evolutionary algorithm [380], Time frequency method [381], Fourier transform [382], Expert system [383].	Although traceable and accurate measurements may be made, there is a lack of robustness and confidence (interferences) [418]; Sensitivity is higher than in online tests. Ultra high frequency sensors can be used to monitor the liquid insulation within the transformer tank (UHF) [414].
Furan analysis	Fuzzy logic [384]	Laboratory analysis. Allows evaluating of the status of insulation aging [414].
Differential protection	Fuzzy logic [385], Wavelet-based [386,387], SVM [388,389], ANN [156, 157], Fourier transform [390], PCA [158,159], Deep learning [391], Statistical analysis [392], Decision Tree [393].	Primary protection for its certainty, reliability, and operation speed [112]; False operations caused by the magnetization current [113]. Primary protection for its certainty, reliability, and operation speed [63]; False operations caused by the magnetization current [170].
Infrared thermal image	FRA [394], Deep learning [395], SVM [396], ANN [397].	Easy interpretation [419]
Excitation current	Wavelet transform [398].	Evaluates the insulation between coils of the windings, the magnetic circuit of a transformer and the tap changer. Turn signal short circuit detection [352, 413,414].
Negative sequence	Fuzzy logic [62], ANN [157].	Operates by measuring the magnitude and the phase of negative sequence component of current in primary and secondary [278]; Comparing the ratio of the negative sequence components of the line currents with the transformer turns ratio [327].
Vibration analysis	State estimation [264], Time frequency method [161], SVM [399,400], Wavelet [401], fuzzy logic [162], Fourier transform [163], Deep learning [402].	Suitable for mechanical faults in on-load tap changer and transformer [149].
Frequency domain spectroscopy	SVM [404], Evolutionary algorithm [405].	Insulation degradation and moisture detection. When measuring at frequencies other than the grid's, the sensitivity is improved (some faults are more dominant at low frequencies and others at high frequency) [138].
Acoustic/sound signal	Wavelet transform [164, 165], SVM [406], ANN [407,408], KNN [409].	Suitable for mechanical faults in on-load tap changer and transformer [149].
Degree of polymerization	SVM [410], ANN [411], Decision tree [166], Statistical methods [412].	One of the significant methods for evaluating the strength of solid paper-insulation structure [343].

a too slow diagnostic speed. Value-based methods, which are excellent in big data value mining, demonstrate the best performance in this situation.

In Reference [436], the fault diagnosis process is made of data acquisition, feature extraction and fault decision sections, from the perspective of the workflow of diagnosis. Table 6 shows that every stage has its features and diagnostic tasks, which are different in knowledge-driven, data-driven and value-driven diagnosis methods.

4. Conclusion

Fault detection and diagnosis is a significant issue in both research and practice. The transformer FDD is crucial for the reliability of the power system. This study reviews transformer fault detection and diagnosis in detail, focusing on the most well-known methodologies proposed in the literature for transformer fault detection and diagnosis. This study evaluates power transformer fault detection and diagnosis comprehensively in two sections: a) Failure causes and fault types: reviewing the transformer failure sources and types presented in different studies, which have been conducted to identify the root causes and possible solutions. b) Transformer FDD methods and assessment methods, where FDD methods are classified according to their driving factors as knowledge-, data- or value-driven diagnosis. The methods presented here represent various approaches to resolving the fault diagnosis problem. However, depending on the measured data, the availability of physical models, the communication infrastructure, and monitoring technology, some solutions outperform the others. For example, the data-driven methods would perform better when an

Table 5
Advantage and disadvantage of knowledge-driven and data-driven methods

	Knowledge-driven	Data-driven
Advantages	• They are advantageous in resolving the incomplete information problem. Also, they can consider various types of diagnostic information that the data driven-based methods cannot employ. Also, they can apply domain knowledge and expert experience to the FDD process, particularly when information is not sufficient. • They can also be generalized. Fundamentally, they can extrapolate beyond the training data because the models are created based on the primary principles. They can operate correctly at any level of fault severity in a wide range of operating conditions. • Since the physical meaning of the whole FDD processes is evident, they are understandable. Technicians can understand the reasons or mechanisms of the results. When the monitoring data patterns change as a result of normal performance degradation, usual maintenance and component replacement, the knowledge driven-based methods can still work by adjusting model parameters. • A huge volume of labeled faulty data is not required. Domain knowledge based on a deep understanding of the systems can be used to obtain the qualitative and even quantitative relationships between faults and symptoms without labeled faulty data.	• A deep understanding of the causal relationships between faults and transformer symptoms, is not required. Since patterns are automatically learnt from data, they do not need physical models. Thus, implementation of the data driven-based methods is easy. • They are advantageous in resolving the uncertain information problem Uncertainties can be described in domain knowledge, expert experience, relationships among faults and symptoms, physical/regression models and measurements using algorithms like fuzzy logic. • In general, the accuracy of their fault detection and diagnosis is higher than the knowledge driven-based methods. Also, their sensitivity to patterns changes of monitoring data is high. • In case of missing crucial variables, they can still work. Because measurement patterns of limited variables could be distinguished for fault isolation. • They can employ artificial intelligence as a promising strategy. Most artificial intelligence algorithms are open sourced with a rich documented information.
Disadvantages	• A deep understanding of the causal relationships between faults and transformer symptoms is required. Hence, most technicians find implementation of the prior-knowledge methods challenging. • Generally, the accuracy of the data driven-based methods is higher than the knowledge driven-based methods. Because the accuracy of physical models is usually lower than data driven-based models. • If the sensors are installed different than required, comprehensive adjustments are always necessary. Usually, adjustments should be carried out by an expert to change equations and parameters.	• Training the diagnosis models required a huge volume of labeled faulty data. However, achieving faulty data is costly. Practically, it is not possible to conduct so many faults in a real transformer. • They are not able to extrapolate beyond the training data range. Most faults constitute a wide range of severity levels from slight to serious. Primarily, the same fault at various severity levels cannot be diagnosed by machine learning models, which are trained using faulty data of a certain severity level. • They can only provide fault detection and fault diagnosis results. Technicians cannot understand the reasons or mechanisms based on the results, which are essential for making further decisions. • It is doubtful if the data driven-based methods are reliable. The models are trained such that they achieve the best performance on training data set. No effective approaches have been presented to detect the over-fitting problems. Therefore, the performance of models is not guaranteed in practical applications.

Table 6
Comparison knowledge-driven, data-driven and value-driven methods [423]

	Previous fault diagnosis (knowledge-driven and data-driven)	Fault diagnosis based on value-driven (big data)
Data acquisition	Single data source Structured data	Distributed data sources Heterogeneous, multi-dimensional, uncertain, incomplete data
Feature extraction	Serial extraction based on prior knowledge Shallow structure Single model	Adaptive parallel extraction Deep structure Universal model
Fault detection	Direct diagnosis	Integrated decision making based on information fusion Visualization of diagnostic results

accurate model of the system is unavailable but real data measurements of the physical system are available. As volume and richness of data increases, value-driven methods would work better. Finally, model-based approaches would be better options when the system's detailed and reliable model is available. This review enables the user to determine the most effective method of fault diagnosis and alternative methods for enhancing the transformer's monitoring capability.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that cdocould have appeared to influence the work reported in this paper.

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