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Review

A Review of Health Assessment Techniques for Distribution Transformers in Smart Distribution Grids

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Received: 7 October 2020; Accepted: 13 November 2020; Published: 16 November 2020

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Abstract: Due to the large number of distribution transformers in the distribution grid, the status of distribution transformers plays an important role in ensuring the safe and reliable operation of the these grids. To evaluate the distribution transformer health, many assessment techniques have been studied and developed. These tools will support the transformer operators in predicting the status of the distribution transformer and responding effectively. This paper will review the literature in the area, analyze the latest techniques as well as highlight the advantages and disadvantages of current methodologies.

Keywords: transformer health; transformer failures; distribution transformer; real-time assessment

1. Introduction

With the increase in peak demand and the need to improve grid infrastructure for the ease of operation and management with high reliability, the distribution smart grid is one of the most important elements to accelerate the modernization of the currently aging power system. The distribution grid is also the area that is affected significantly by smart technologies [1]. Automating and controlling the grid remotely will help reduce operating costs, increase information accuracy as well as quickly fix faulty areas in the electricity power system [2].

The distribution transformer is the last component for voltage transformation in the power grid. It is used to convert the medium voltage to the low voltage level that is used for households or for commercial use. Distribution transformers are thus one of the most important components of the distribution power system [3]. Moreover, for each HV/MV primary substation, there are tens of secondary substations. As a result, in a medium-sized city with 40 HV/MV primary stations, there is around one thousand distribution transformers. Many of them are damaged every year due to various reasons. Accelerated degradation and failure of distribution transformers can occur because of several conditions such as oil leakage, overloading, unbalanced loading and harmonics. However, the majority of failures are caused by a combination of these electrical, mechanical and thermal stresses acting upon the power transformer components over time [4]. Although the manufacturer generally establishes design and operational limits, the impact on service life is non-binary and multi-dimensional in nature. For example, exceeding a thermal limit to a moderate extent for a short amount of time will not cause immediate failure, but more severe overloading for an extended period will likely cause irreversible damage. If these impacts can be more fully characterized or impending issues can be detected in the field, it could help utilities reduce the rate of failures and degradation, increase the reliability of electric service and reduce the cost of utility operations and maintenance. Therefore, it is important to study and develop effective methods of monitoring the condition and health of distribution transformers.

There are many papers available on these individual diagnostic techniques for distribution transformers. However, a review of all these techniques is not available in recent times. In this paper, a brief introduction of different monitoring methods for distribution transformers is outlined and the different schemes based on different assessment methods is discussed. The main contributions of this paper are described in the following:

- The paper provides a special review of modern monitoring distribution transformers methods. A number of methodologies are presented, evaluated and discussed. The advantages and disadvantages of using individual methods are presented.
- The paper investigates different thoughts regarding the appropriate parameters for different online/real-time monitoring processes to evaluate the statement of distribution transformers.
- A number of failure modes are also discussed in this paper.

This paper has a practical value since it is a good reference work to help new transformer operators to establish a strategy for transformers maintenance and replacement. The paper is organized into the following sections: Section 2 covers distribution transformer failure modes and investigates the components that are most critical to distribution transformer health. Section 3 reviews the development of health assessment techniques. This section summarizes the advantages and disadvantages of different evaluation methods including basic health index calculation methods, fuzzy logic, machine learning algorithms and hybrid artificial intelligence approaches. Section 4 presents the advanced technologies for real-time transformer health assessment in smart distribution grids and Section 5 presents our conclusions.

2. Distribution Transformer Failure Modes

Different investigations and test analyses have been conducted to identify the root causes and to identify the preventive measures to avoid the breakdown of power transformers. In paper [4], the part that is indicated as the most critical to power transformer health is insulation with an incident rate of about 41%; then, components showing high failure rates are windings, 14%, bushings, 10%, and on-load tap changers at about 10%. Other components such as the cooling system, core, and operational errors do not have a significant impact. In papers [5–7], the statistical data of component failures are collected from 350 power transformers to establish a three-level model of failure mechanism, failure linkages, and failure modes. Even though power transformer and distribution transformer have the same main working principles and key components such as insulation, windings, core, etc, these transformers differ in complexity and size. In this Section, the author will reference failure modes that pertain to these common working principles and components, investigate the reasons for distribution transformer failure from literature to identify the components that are most critical to distribution transformer health.

Distribution transformers can be of two types: pole mounted and substation transformers. In each of the two cases, according to the norm EN 60076, different construction features can be identified. Some of these are more common for the first type, some for the second. In particular, insulation can be either dry or oil-based. In the first case, insulation can be either oil-based, polymeric or air. In the second, insulation is typically oil-based. The basic structure of a distribution transformer is shown in Figure 1 [8–10].

Figure 1. Structure of a distribution transformer.

From Figure 1, the main components of the distribution transformers are core, windings, tank, insulation and bushings.

- *Core*: The transformer's core is made of silicon steel. This core is used to transmit the power from the primary to the secondary coils of the transformer through electromagnetic induction. The core fails due to DC magnetization or displacement of the core steel during the construction of the transformer. The lamination of the core can also peel off and increase losses and heat due to eddy-current.
- *Windings*: Windings are the conductors wrapped around the core limb. A transformer consists of a primary winding and one or more secondary windings connected via an electromagnetic field. Windings generate magnetomotive force that is carried by the core to other windings for changing voltages. The most frequent fail in windings is due to short-circuits or transient over-voltages.
- *Tank*: The tank is the physical protection for the transformer core and windings as well as is an oil container for cooling the transformer. The failure of the transformer tank can occur anywhere due to oil leakage, insulation material loses insulation function, dents … Oil leakage leads to flashover and transformer breakdown.
- *Insulation*: The insulation between windings in transformers is usually provided by transformer oil. Oil contamination due to the oxidation processes and increasing size of the colloidal particles can generate conducting particles, raise the temperature inside the transformer and finally damage the oil insulation.
- *Bushings*: are used to provide insulation while routing the winding terminals through the tank for connection with the power system. The main failure mode of the bushing is short-circuit. It may be due to material faults in the insulation or due to damage. The damage can occur due to sabotage, during shipping or airborne parts from other failed equipment. Damages, cracks in the porcelain and bad gaskets provide ingress of water inside the insulation of the bushing leading to its failure.
- *Tap changer*: is used to regulate the output voltage of a transformer by changing the number of turns in one winding. For distribution transformers, tap-changer cannot be changed while the transformer is energized, it can only be changed after isolating the transformer from the circuit [11]. Therefore, the damage caused by a tap-changer fault rarely happens.

Based on the parameters used to evaluate the distribution transformer statement in the literature [12–21], the standard for overhead type distribution transformers [22] and investigation data from distribution transformers supervisors in utilities, authors have broadly categorized the component failures of service transformers, transformer failure rate and operation impact level as in Table 1.

Table 1. Overhead distribution transformer failure modes.

	Component	Failure Category	Failure Mode	Frequency of Occurence	Operation Impact Level
1	Insulation	Chemical/Mechanical	Water accumulation in the oil/paper	High	High
		Chemical/Thermal	Aging of oil/paper		
		Thermal	Thermal degradation of oil/paper		
2	Winding	Electrical/Mechanical	Short circuit between turns/strands	Medium	High
			Short-circuit to ground		
			Open circuit		
		Magnetic/Mechanical	Conductor tilting, conductor bending, clamping system failure, axial instability, and lead deformation		
			Winding bulk movement		
			Buckling		
3	Bushing	Electrical/Mechanical	Short circuit within capacitance graded layers	Medium	High
		Mechanical/Thermal	Bushing thermal expansion		
		Mechanical	Bushing failure due to porcelain damage		
4	Tank	Mechanical/Thermal	Internal rupture	Low	Low
			Leakage		
5	Core	Electrical/Mechanical	Multiple grounding	Low	Low
			Ungrounded core		
			Short circuit core laminations		
		Mechanical/Thermal	Core deformation		
6	Other	Unknown causes	Operational errors, lack of maintenance, and protection system trips/failures	Low	N/A

All of the above measurement techniques must comply with the specified standards. The standards and limits of various measurement techniques are given in Table 2. All these limits are derived from IEEE and IEC standards [23–25].

Table 2. Measurement techniques and limit levels as per standards.

Measurement Technique	Standard	Limit Level for Distribution Voltage Class		
		Normal	Suspect	Poor
Hot spot temperature (insulation class 150)	IEEE C57.91-1995, IEC 60076-7	<95 °C	95–105 °C	>105 °C
Power factor	IEC 60422	≤0.1%	0.1–0.5%	>0.5%
Voltage harmonic distortion	IEEE 519-2014	THD(Uf) ≤ 5%	5%	>5%
Noise level (for transformer of power 50 kVA)	IEC 60076-10 (2001), IEEE C57.12.90 (2006)	39–42 dB	42–45 dB	>45 dB
Humidity (saturation percentage)	IEEE 62-1995	0–20%	21–30%	>30%
Turns ratio	IEC 60076-3 2000, IEEE C57.12.90	≤0.1%	≥0.2% to ≤0.5%	≥0.5%
Winding resistance	IEC 60076-3 2000	<1%	≥ 1% to ≤4%	≥5%
Core resistance	IEC 60076-3 2000	≥1000 MΩ	≥100 MΩ	≤10 MΩ
Short circuit impedance	IEC 60076-5 2000	≤1%	1% ≤ 2%	≥5%
Dissolved gas analysis	IEEE C57-104-2008	0–1920	1920–4630	≥4360
CO_2/CO ratio test	IEC 60599 1999	≥3–10	≤3	≥10 and above
Dielectric Strength	IEC 60422-2005	≥50 kV/mm	≤50–40 kV/mm	≤40 kV/mm
Interfacial tension	IEC 60422	≥28 dyne/cm	28–22 dyne/cm	≤22 dyne/cm
Frequency domain spectroscopy	IEC 60422 2005	≤2.2% (Dry)	≥2.2 and ≤4.8% (Moderately wet)	≥4.8% Extremely wet

From Table 1, it can be seen that various electrical, mechanical, chemical, and thermal modes of failure may occur. These failure modes will generally produce symptoms that are electrical, mechanical, chemical, or thermal.

3. Transformer Health Assessment Techniques

In order to provide information about the transformer's state of health and detect incipient faults, the monitoring system must perform physical measurements and analyze the results in the context of given environmental conditions. Health Indices methods are practical tools to aggregate the results of multiple operating observations, field inspections, and site and laboratory testing into a single objective index that quantifies overall health [26,27]. They are important for asset management because they help to identify, prioritize, and schedule required investments into capital and maintenance programs. Effective methods of monitoring the condition and health of distribution transformers could help utilities to proactively mitigate failures and degradation. The objectives of the monitoring process are to:

- Determine the most appropriate measurement techniques to employ for low cost, accurate, and in-situ health monitoring of distribution service transformers
- Synthesize or create methods of determining transformer health from these measurements as well as contextual or environmental data as appropriate
- Implement the system for field validation. Algorithms will be implemented locally and/or centrally (on a server) to measure and analyze the operational characteristics of distribution service transformers and provide an overall health index encompassing the pertinent failure and degradation modes

Significant deviations or rapid changes in this index or its factors could be used to predict the need for maintenance, reconfiguration, upgrade, or replacement. Ultimately, this will improve reliability and reduce the cost of electric service. It is particularly important with the advent of higher penetrations of distributed PV, electric vehicles, and other energy resources that are rapidly changing the operation of the grid and have the potential to introduce added stress to service transformers. Several studies proposed various methods of establishing health indices for power transformers from the available measurement techniques [28–31]. Many of these methods can be applied to distribution transformers because the underlying working principles and key components are the same. However, the prioritization and acceptable operation range of these measurements or conditions must be carefully reassessed.

3.1. Health Index Calculation

Health index (HI) calculation is a useful technique, it is the most basic method that was used to create maintenance strategies for transformers [32]. This method uses the representative indexes of the transformer's operation and statement to convert them into a quantitative index and evaluate the general condition of the transformer. The structure of the health index calculation method is shown in Figure 2.

In [32,33], a health index calculation method is applied to assess the distribution transformer conditions comprehensively. The statement of the transformer is classified in a range from "perfect health" to "very poor condition". The overall health index is presented in the following equation:

$$\mathrm{HI} = \frac{\sum\limits_{ci=1}^{n} (S_{Pi}.W_{Pi})}{S_{max} \sum\limits_{ci=1}^{n} (W_{Pi})} \tag{1}$$

where:

- HI is the health index metric;
- S_{Pi} is the score of each assessment condition that is identified based on the measured data
- S_{max} is the maximum score of assessment condition
- W_{Pi} is the weight of each assessment condition;
- n is the number of the assessment condition.

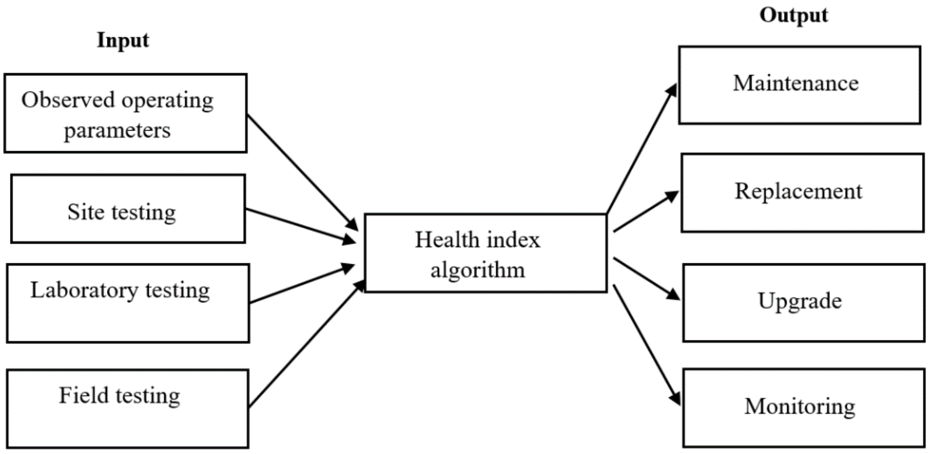

Figure 2. The structure of the health index calculation method.

The method was tested on a 3-phase 15 kVA distribution transformer. The monitored components are dissolved gases, oil, and furan. The results showed that this method could only diagnose the general conditions of transformers. It cannot indicate exactly the type of possible faults. To identify the failure components, additional analysis is required.

In [34], the data collection criterion was improved to estimate the transformer's health. This paper pointed out that the conventional health index calculation usually requires many investigation parameters that could raise the testing and operating costs. The paper proposed an improved health index table that requires only 15 testing parameters instead of 24 testing parameters in the conventional health index calculation. The new health index table was carried out on thirteen testing transformers. The achieved results were compared with the conventional health index calculation and only have 7% different. This will help the transformer evaluation process to be implemented faster and easier to apply in practical works. The drawback of the health index calculation method is that it requires many parameters to evaluate the transformer's conditions, therefore, the monitoring may be costly. The diagnostic system only reflects the preferences of the human-expert in interpreting results because the set of rules derives from heuristic experience. In this way, it is difficult to translate them into mathematical formulas.

3.2. Fuzzy Logic

To overcome the limitations of the health index calculation method, fuzzy logic has been proposed as a suitable approach. Fuzzy logic is supposed to be used for representing vague concepts and uncertain information, especially in cases in which conventional logic techniques couldn't be applied effectively [35,36]. The structure of a complete fuzzy control system includes three steps: fuzzification, inference and defuzzification. At the first step, fuzzification calculates fuzzy values from exact values at the input. The fuzzy inference applies all applicable fuzzy rules to calculate the fuzzy value for the output. The defuzzification determines the exact output value from the fuzzy result obtained in the fuzzy inference step [37]. The basic structure of fuzzy control system is shown in Figure 3.

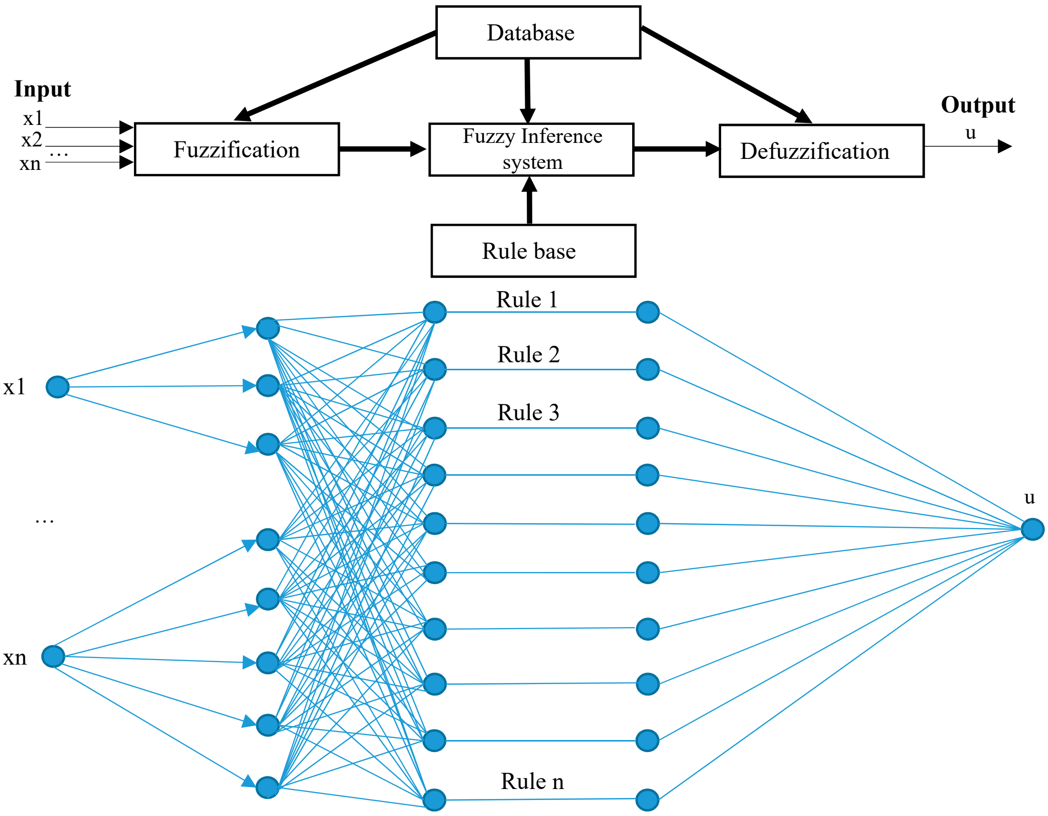

Figure 3. The basic structure of the fuzzy control system.

In recent years, the advantages of fuzzy logic and its related applications such as optimization, decision making and diagnosis have been put into evidence. In diagnostic applications, fuzzy systems are typically used. In [38], Fuzzy logic is applied to evaluate the possible effects of the health condition on the oil-immersed transformer. The five considered health indices are dissolved gas analysis (DGA), furans, load history, aging and humidity. The transformer's statement is assessed based on three cascade connection fuzzy subsystems including risk, maintenance and decision. This cascade model helps to evaluate the probabilities of an error occurring and its corresponding consequences. The maintenance subsystem model helps to estimate the level of the maintenance recommendations based on the output of the risk model, health index and failure rate. The overall decision model outputs the level of required maintenance actions. The proposed method is deployed on a 35 years-old transformer. The results show the estimation of the date in which the transformer may need a maintenance action, and the required actions to extend the transformer lifetime. Paper [39] uses a fuzzy knowledge-based expert system to assess the transformer's health. All the parameters can be analyzed individually. Because of the variation in operational and the effect of many factors controlling the transformer variables, the policies applied to manage transformers may differ even with the transformers that have the same rating and calendar age. Due to the inexact information and the complexity of the asset management model. The article pointed out that Fuzzy logic is an effective tool that can give a highly reliable assessment for solving this kind of problem.

Fuzzy logic is also applied for analyzing transformer data in paper [40] to diagnose the transformer faults. This method uses a multi-band infrared imager sensor and a discharge circuit detection sensor to set up the eight sensors detection platform. The fault diagnosis model is given based on the consistency of sensors and sensor's trust degree. The fuzzy model with a multi-sensors system can help to get accurate results and enhance the system operation. Through experiment and analysis, this fault diagnosis model can improve the fusion precision and diagnostic accuracy more effectively than the general fusion algorithm and arithmetic mean value algorithm and can scientifically diagnose the transformer equipment of power grid from multi-angles. Thereby, the feasibility and effectiveness of the method are verified. In [41], fuzzy logic was applied to predict the health index values. In this article, oil quality, furan and dissolved gas were used as assessment parameters. However, it is obvious that this assessment method has some limitations, the scoring and ranking values still depend on the opinion of operators in the utilities. The values of the health index will be inconsistent even if they use the same equation because of using different weighting factors and scoring methods.

3.3. Machine Learning Algorithms

Normally, the transformer HI can be computed from a parameter by the creation of a relationship rule and equation. To improve the accuracy and reliability, the HI needs to be determined from many parameters that might be not related to each other and hard to calculate. Several papers presented the method for predicting transformer health using artificial intelligence tools, such as machine learning (ML) [42–44]. ML is the algorithm that improves automatically through experience. ML can teach oneself and adapt non-linear mappings between input and output. Advanced ML techniques is used to build surrogate models that can be put in an application as low computational-cost approximations of more expensive calculations. All the ML-based HI methods need the database to learn the wanted correlations and make predictions or decisions without being explicitly programmed to implement the task. Transformer condition assessment programs using artificial intelligence algorithms may have the potential to apply to inexpensive sensor systems which helps to keep the overall system cost and complexity low. The basic structure of the machine learning method is shown in Figure 4.

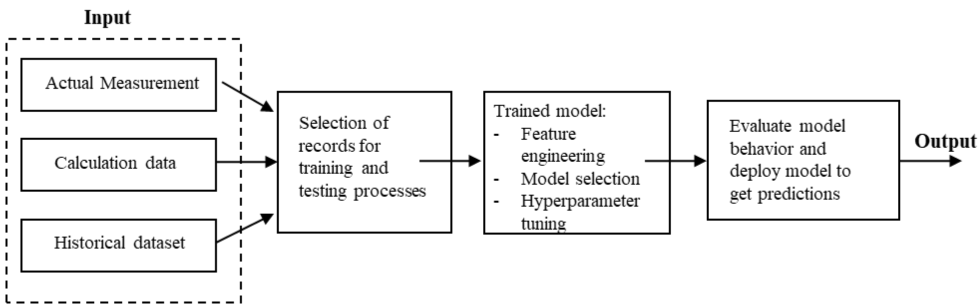

Figure 4. The basic structure of machine learning method.

The most common algorithm of ML used for transformer diagnosis is Artificial Neural Network (ANN). In [45], a four-layer ANN is utilized to evaluate the distribution transformer's health status. The ANN includes one input layer, one output layer, and two hidden layers. The data of 84 different patterns of distribution transformers was collected to train an artificial neural network. The experimental test results of the proposed ANN are 97.62% matched to the results provided by the utility. In [46], an ANN approach has been made to classify the condition of the transformer based on the predicted HI value. The model was a feed-forward ANN with two hidden layers (four and two neurons respectively) that was trained on real measurements of 59 working transformers. Based on the testing outcomes, 97% of the testing samples were correctly classified based on a three-class condition problem. It can be observed that ANN can provide a reliable result but this method requires lots of data, especially for architectures with many layers. The same approach was also applied in other related works [47,48].

The other powerful ML algorithms are random forest (RF) and support vector machine (SVM). RF is an ensemble learning method for classification and regression. In the training time, RF constructs a multitude of decision trees and then exports the class prediction [49]. The class prediction with the higher number of votes is the model's prediction of the individual trees. In [50], RF is used for fault diagnosis applied to transformers because of its strong model generalization ability. RF can produce a proximity matrix based on the similarity among patterns without preprocessing data. The model of the transformer's fault diagnosis was compared with some experiments on real transformers. The results show that the RF model has high accuracy and results are more stable than the other methods. Meanwhile, SVM is a supervised learning model with associated learning algorithms. It is more suitable for nonlinear problems with a small sampling. The SVM model represents the samples as points in space, the samples of the separate groups are divided by a wide clear gap. The new samples are mapped in the same space and its category will be predicted depending on the side of the gap where they fall. For example, in a set of training samples, each sample is marked as belonging to one or the other of two categories, the SVM model then assigns new samples to one category, making it a non-probabilistic binary linear classifier [51].

The ML algorithms have huge potential in practical applications with many outstanding advantages. There are still some remaining problems that need to be investigated such as how to deal with new datasets to avoid overfitting problems or how to increase the accuracy for learning algorithms. One of the weaknesses of the ANN approach is the tendency to find only a local minimum in its training due to improper initial value. In this case, the optimization algorithms can be deployed to optimize the initial value and thus increase the accuracy of the neural network training. More detail of this approach is presented in Section 3.4.

3.4. Hybrid Artificial Intelligence Approaches

In recent years, the searching algorithms have been interested in by researchers to find the best subset of features in the feature selection problems [32]. As mentioned above, the hybrid artificial intelligence approaches that use optimization algorithms to support leaning algorithms can overcome the weakness of single learning algorithms. Because the selection parameters of learning algorithms has a significant impact on its own usefulness and classification performance. Therefore, it is necessary to find the optimal value of these parameters to improve the accuracy of the prediction. The optimization algorithm can support the health index computation methods and fuzzy logic as well to optimize weighted parameters so the results for transformer health assessment will be more accurate. Figure 5 presented a general structure of hybrid artificial intelligence model.

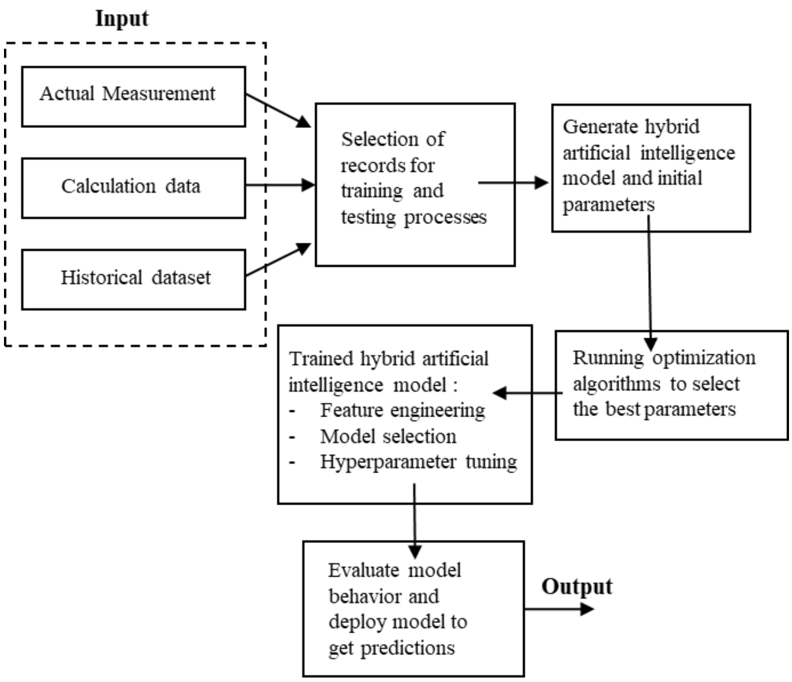

Figure 5. A general structure of the hybrid artificial intelligence model.

The genetic algorithm (GA) is a good computational tool in seeking optimum and supporting for multi-objective functions. It was the most advanced algorithm of artificial intelligence techniques and was widely used to solve optimization problems. In [32], a hybrid algorithm of transformer health index computation and GA is proposed. The health index of the transformer was identified based on weighted parameters. The genetic algorithm was used to support the conventional health index computation. It optimized these weighted parameters and then provided a better weight approach. A smart system is utilized to online supervise distribution transformers. The system integrates intelligent electronic devices to collect data from sensors that are installed on transformers. With the inclusion of a communication network, the results of transformer health assessment is transferred to the control room and cell phone of the transformer operator. In articles [52,53], the combination of genetic algorithm (GA) and support vector machine (SVM) was also presented.

Particle swarm optimization (PSO) is another optimization algorithm which is commonly applied in coordination with an artificial neural network. PSO can be utilized to problems which GA can be utilized to. The combination of PSO and SVM is presented in article [42]. In order to obtain the best classification model, the PSO was used to provide optimizing parameters for the SVM module. The transformer statement was classified by groups: excellent, good, normal, attention and fault, the fault statement was divided into five levels based on the temperature failure of overheating. The results proved that the proposed method can improve the accuracy of transformer health evaluation. The results showed the proposed method had the highest accuracy. Similar approaches can be found in the articles [54,55].

A comparison between transformer health assessment methodologies based on the dependency on the transformer monitoring parameters, number of samples, the accuracy, the complexity, implement cost and computation effort is presented in Table 3.

Table 3. Transformer health assessment methodologies comparison.

Methods	Dependency on the Datasets	Dependency on the Weighted Parameters	Number of Samples Required	Accuracy	Complexity	Implement Cost	Computation Effort
Health index calculation [33,34,56–60]		√	Small	Low	Low	High	High
Fuzzy logic [38–41,61–63]		√	Small	Low	Low	High	Low
Artificial neural networks effort [45,46,64,65]	√		Large	Good	Low	Low	Low
Machine learning algorithms using Random Forest [66,67]	√		Large	Good	Low	Low	Low
GA based health index determination [32]		√	Small	Good	High	High	High
Combination of GA and support vector machine [52,53]	√		Large	High	High	Low	High
PSO and Support Vector Machine SVM [68]	√		Large	High	High	Low	High

Table 4 summarizes the above analysis highlighting the advantages and disadvantages of the well-known approaches present in literature.

Table 4. Advantages and disadvantages of transformer's health assessment methodologies.

	Method	Advantages	Disadvantages
1	Health index calculation [33,34,56–60]	- Reliable - Can work with small number of samples - The weights can be regulated depending on the assets under investigation	- The accuracy depends heavily on weighted parameters - The condition monitoring may costly and the results only reflect the preferences of the human-expert - Low accuracy for the systems and devices are controlled linguistically, or have a contradictory condition
2	Fuzzy logic [38–41,61–63]	- Reliable - Easy to apply. - Provides a more effective solution to complex issues - Easily be modified to improve or alter system performance. - Inexpensive sensors can be used which helps you to keep the overall system cost and complexity low.	- The accuracy depends heavily on selected parameters. - Validation and Verification of a fuzzy knowledge-based system need extensive testing with hardware. - Need advanced power electronic control units
3	Artificial neural networks effort [45,46,64,65]	- Reliable - Ability to work with incomplete knowledge - Less computational effort - Fast	- Need lots of data, especially for architectures with many layers - When the difference between the training samples and the fault samples is very large, the reasoning used by ANN to conclude is questionable, additional training data were needed - Results depend on training data - Can not be applied to small sample data
4	Machine learning algorithms using Random Forest [66,67]	- Reliable - Less computational effort - Inexpensive sensors can be used which helps to keep the overall system cost and complexity low. - Can estimate missing data and maintains accuracy when large proportions of the data are missing.	- Cannot be applied to small sample data - When the difference between the training samples and the fault samples is very large, additional training data were needed. - The accuracy depends on selected parameters of learning algorithms and training data. - Need advanced power electronic control units
5	Genetic algorithm (GA) based health index determination [32]	- Reliable - Support for multi-objective functions. - It is a powerful computational tool in seeking optimum and also considered the most up-to-date product of artificial intelligence techniques. - It can get the best result by continuously replacing the current population with the new population.	- It always takes a long time-period. - Not applicable to problems with too many variables - It might not find the most optimal solution to the defined problem in all cases.
6	Combination of genetic algorithm (GA) and support vector machine (SVM) [52,53]	- Very useful for many diverse searching and optimization fields and achieved good progress. - Has a better global view of searching space and scalability and can avoid local optimal solutions due to effective exploitation and exploration searching. - Excellent performance on small samples, high dimension and nonlinear problems. - It can classify and predict unseen samples with the desired accuracy. - High-diagnostic accuracy	- Not suitable for large and unclear data set. - It is very difficult to select appropriate SVM parameters. Because the selection of SVM parameters has an important influence on the classification accuracy of SVM. - Over-fitting or under-fitting can occur during the SVM process.
7	Particle swarm optimization (PSO) and Support Vector Machine SVM [68]	- It has a better solution of the small sample, nonlinear, high dimension case of classification, and has strong generalization ability. - Can be able to find the optimal value of the global and can be improved to the global optimal value faster. - Requires fewer parameters, and has the advantages of rapid convergence.	- The parameters selection has a significant impact on its own usefulness, and classification performance. - The method is vulnerable to the shortcomings of a local minimum. - Cannot work with scattering problems.

It is necessary to consider the dependency of the studied methods on the load condition, temperature and the effect of transformer aging over time. It is investigated that the root causes of these failures on distribution transformers are mainly due to the overloading and unbalanced loading [69,70]. The transformer loading effects directly on the current in the winding and hence, raise the temperature in the winding and the oil of the transformer which results in accelerating the transformer aging, reduce the service life of the distribution transformers [71,72]. This represents the relationship bound tightly between transformer loading parameters, transformer's temperature and aging to the distribution transformer health. To the best of our knowledge, there is no limit to include the parameters into the studied model. However, in the studies that were implemented to assess distribution transformer health, transformer loading and transformer temperature (winding temperature, top oil temperature, etc.) are usually selected as the most important parameters determining the transformer health [73]. The transformer aging index is also an important parameter, but this parameter can only be calculated through other parameters [74]. The estimation of transformer aging parameters is complex and non-deterministic because the heat transfer process is distributed over different surfaces in the winding and insulation structures and there may be measurement errors. It requires a high-quality sensor to provide high accuracy data. Transformer aging is normally included in the evaluation models that use Health index calculation or Fuzzy logic [38] methodologies. Artificial intelligence approaches are often applied based on actual measurement parameters to enhance accuracy. Further research will be investigated in the future to evaluate the importance of the indicators on the distribution transformer, thereby improving the accuracy and reliability of the assessment models.

4. Advanced Technologies for Real-Time Monitoring Transformer Condition in a Smart Distribution Grid

Due to some economic aspects, the online condition monitoring system has not been directly implemented in distribution transformers in past times [75,76]. However, with the new generation of the smart distribution grid, the internet of things (IoT), cloud computing, and advanced metering infrastructure are often combined in the electric power systems. This complex system can gather huge data and information, assisted by an array of new approaches, technologies and applications. The real-time data collection, transmission, data access, and rapid analysis of huge amounts of multivariate data are becoming the basis for sustaining the reliable operation of power systems. The development of these advanced technologies aims to optimize the operation of the distribution network, simplify the distribution transformer monitoring process but still ensure high accuracy. While the Internet of Things can help to track, monitor and manage electric equipment through connecting with the internet for information exchange, improve the communication platform of the smart grid. Cloud computing provides a solution to store huge amounts of data and process heavy computational work for transformer monitoring activities of the distribution grid. Many research studies have been implemented to take advantage of this smart management system.

Because distribution transformers are critical assets and the load of a distribution transformer is governed by the end-user, which therefore makes it an uncontrollable load [58,65], further uncertainty comes from PV integration at the distribution level as well as EV recharging facilities. Thus extensive and continuous monitoring is required. Most conventional diagnosis methods for distribution transformers were traditionally carried out off-line when the transformer was taken out of service. With the development of the information technology and smart sensors devices, the reliability of the transformer status assessment system can be carried out on line. The monitoring process is carried out online, in real-time, and thus the accuracy of the condition analysis for the transformer can be greatly improved. Real-time monitoring of transformers can help to find out the potential risks of failure for distribution transformers. For this reason, further analysis can be implemented to identify the development trend of the risks easily and help giving necessary decisions in time in order to avoid unexpected and catastrophic equipment shut-downs. Monitoring data is also stored on the cloud system and analyzed to assist in making decisions on the replacement and maintenance of distribution transformers in the future.

In [77], an online transformer health monitoring system is proposed by using the global mobile service (GSM). A mobile-embedded system including a single-chip microcontroller and sensors is designed to monitor load currents, over-voltage, transformer oil level and oil temperature. If there is any abnormality in the system, the GSM module will send short message service (SMS) messages to designated mobile telephones containing information about the abnormality. After the fault clearing, the total system again starts to monitor the condition of the transformer. As it is a wireless communicating system, there is no need for high-cost large cables. In paper [78], GSM is also used to monitor distribution transformers' parameters such as current, temperature, oil level, vibration and humidity in every fifteen seconds. The monitoring process is implemented pretty the same with the described system in [79]. The microcontroller is the core of RTU that collects data from sensors nearby the transformer and sends data to monitoring nodes via GSM/GPRS module. GPRS has high efficiency, convenience and low cost and provides a good solution to meet the need of distribution transformer monitoring systems. Figure 6 presents the general flowchart of the monitoring systems.

The investment cost of a distribution transformer is much lower than that of a power transformer. In order to get quality evaluation results, high-quality sensors are required. This means that the monitoring system will be very expensive, not consistent with the actual ability of the utilities. Therefore, the corresponding monitoring system for distribution transformers should be designed to be acceptable. To save installation costs, the monitoring parameters are usually voltage, current or ambient temperature that can get easily from electrical measurement systems. These parameters also contribute significantly in identifying the potential risks of transformers in operation, thereby making initial assessments of transformer status before making more thorough inspection decisions. Real-time monitoring transformers using advanced metering infrastructure (AMI) is an effective low-cost solution for managing smart transformers as well as smart grids. In [80], an AMI system is proposed to supervise transformer operation under fire hazards. The main parts of the detection system are sensors, valve systems and the control box. The control box will receive measured data from sensors and send commands to control the system. This smart monitoring system not only provides fast fault detection but also improves the overall health of transformers as well as the distribution system. In [81], the AMI systems are used to collect data in real-time including transformer loading, transformer aging, estimated ambient temperature, computed the hottest temperature from oil-immersed distribution transformers. The gathering information can be used indirectly to determine the priority candidate transformer for replacement before failure. The meter measurements can be utilized to develop temporally high-resolution views of transformer loading indirectly to determine each operational transformer's aging acceleration. In [49,82], the papers provided a methodology that was used to predict the outage and congestion for distribution transformers. This paper uses the hourly usage data collected from Ameren Illinois' AMI meters to determine distribution transformer outage, failure, and overload. The proposed methodology not only detects and visualizes outage and congested areas in near real-time but also detects transformers and distribution areas with a long history of outage and congestion.

More recently, portable systems allow diagnosing the dielectric part of many electrical apparatus including oil-insulated transformers [82–84]. The portable system uses a sensor which is a special wideband antenna. It allows to detect both partial discharges pulses and the signal of AC supply voltage remotely from the tested component; in this way, the need for direct connection or component turn-off is avoided.

Table 5 compares the considered monitoring parameters, the advantages and disadvantages of real-time monitoring techniques in the literature.

It can be seen that the advanced techniques are good solutions and have the potential to provide a low-cost health assessment system based on existing sensors, energy monitoring meters and the existing communication networks. These solutions can support utilities to monitor distribution transformers continuously and set up suitable transformer management strategies. However, low-cost does not directly translate into a short lifetime or lack of robustness. A good design practice may achieve higher quality and lifetime from lower-cost components (e.g., design for manufacturability, good weatherization, good thermal design, etc.). Point out the distinction between number and cost of power and distribution transformers: power transformers more expensive but fewer of them.

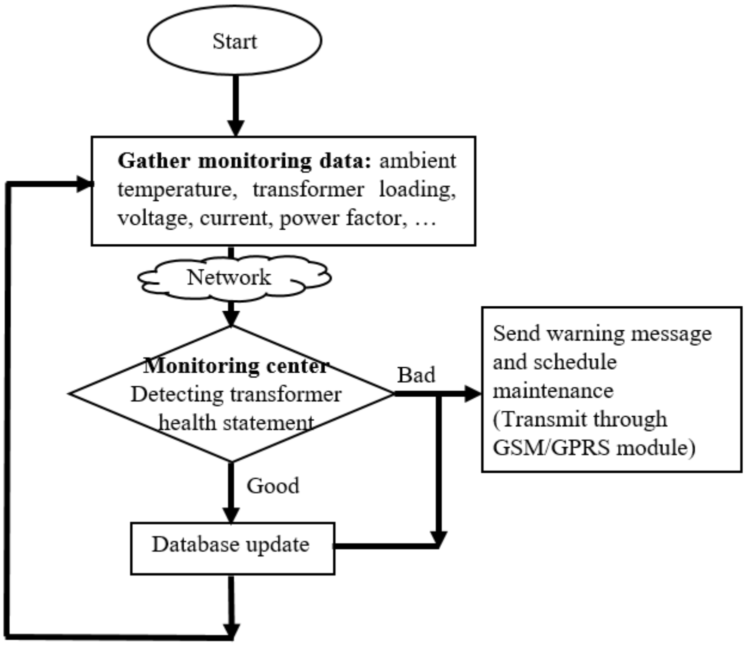

Figure 6. The flowchart of the monitoring systems.

Table 5. Literature comparison.

	Monitoring Techniques	Monitoring Parameters	Advantage	Disadvantage
1	Health condition monitoring using IoT (GSM/GPRS) [78,79]	1. Current 2. Voltage 3. Oil level 4. Oil temperature	Reliable Low cost Time resolution: 1 min	Need to add sensors on transformers: Oil level indicator
2	Online condition monitoring system for substation and service transformer [85]	1.Age 2. Loading history 3. Inspection and maintenance 4. Type of transformer 5. Location 6. Unbalanced voltage 7. Harmonic load current and power factor 8. Efficiency deviation due to internal fault 9. Winding temperature 10. Top oil temperature 11. Oil level	High accuracy Low cost: 2% of transformer cost (15 kVA three-phase) Time resolution: 30 min	Need to add sensors: Oil level indicator Energy meter
3	Studies to Utilize Loading Guides and ANN for Oil-Immersed Distribution Transformer Condition Monitoring [65]	1. Three-phase loading values (current); 2. Ambient temperature; 3. Calculated top oil temperature 4. Calculated hot spot temperature	Reliable Low cost, only use Energy meter Time resolution (1 h) No need to add sensors	Further studies needed to improve the precision
4	A real time study on condition monitoring of distribution transformer using thermal imager [86]	1. Thermal imager	High accuracy Time resolution (1 h)	High initial cost
5	Remote Condition Monitoring System using public network [87]	1. Temperature 2. Oil level 3. Loading 4. Humming noise	Saving cost Easy to extend to the other monitoring parameters	The accuracy will have significant changes when some imbalance occurs in the mechanical forces

Table 5. *Cont.*

	Monitoring Techniques	Monitoring Parameters	Advantage	Disadvantage
6	Online distribution service transformer health assessment using real-time grid energy monitor [88]	1. Top oil temperature 2. Vibration 3. Transformer loading 4. Power factor	Reliable Low cost, only use Energy meter High time resolution (1 s) No need to add sensors	Further studies needed to improve the precision
7	Multi-source information analysis (statistical data, text mining) [89]	1. Voltage deviation 2. Load rate 3. Unbalance factor 4. Harmonic voltage distortion	Higher accuracy Low cost, only use Energy meter Good time resolution (15 min) No need to add sensors	Need conventional test data (Unbalance and Harmonic distortion)
8	Transformer Fault Diagnosis based on Multi-source Information Fusion [90]	1. DGA 2. SCADA real-time data 3. Special sensor real-time data 4. Related electrical test data 5. Operation and repair records	Very high accuracy Can predicting the location, type and property of transformer faults.	Need to use many parameters for information fusion methods that they match to each other for high accuracy and they need to use many types of historical transformer fault data.
9	Leveraging advanced metering infrastructure (AMI) [91]	1. Transformer loading 2. Transformer Aging 3. Estimated Ambient temperature 4. Computed hottest temperature	Comfortable for utility to monitor and set up suitable asset management plans. Time resolution (1 h)	Need to install many of smart meters that be installed at customer locations for each of distribution transformers
10	Advanced Metering Infrastructure (AMI) [49]	1. Customer Information System 2. Transformer loading 3. Weather data	Can collect the loading data of all areas.	Need to install many of smart meters at customer side Need to collect many information from customer side
11	Smart Transformer using Advanced MeteringInfrastructure (AMI) and Advance SensorInfrastructure (ASI) [80]	1. DGA 2. Temperature 3. ambient temperature 4. Real-time loading 5. Electrical parameters	Comfortable for utility to monitor and set up suitable asset management plans.	Need to install many of smart meters that be installed at customer locations for each of distribution transformers
12	Wireless Partial Discharges diagnosis [84]	1. Voltage pulses	Wireless Small physical dimension Portable High accuracy No sensors needed	Devoted to dielectric health only Further studies needed to improve the precision concerning noise

The low-cost health assessment system is also relative to the cost of the considered transformer. The US market for distribution transformers is currently standing at about 650,000–750,000 units per year. The price of a distribution transformer ranges from $700 to $12,000, depending on order quantity and kVA ratings [1]. Therefore, health assessment solutions for distribution transformers must be lower cost but sophisticated and precise solutions may not be as important. Because the number of distribution transformers in the electric power system is huge, any reasonably reliable health assessment solution for distribution transformers may be helpful to reduce the cost of maintenance, replacement, and outages—better than "nothing".

5. Conclusions

The paper presented a study to determine the most significant influencing indicators on distribution transformer operation and service life. The health assessment techniques were reviewed based on up-to-date literature. This is to provide more information to transformer operators about the important parameters of distribution transformers that need to be considered. This also gives the other researchers an overview of the development process of transformer condition assessment technologies, thereby continuing to develop new effective evaluation techniques.

Real-time monitoring has become a very important technology in the field of distribution transformer maintenance and has attracted more and more attention worldwide, especially with high penetration of PV systems in the distribution power grid. The potential functions of failure prediction, defection identification, and life estimation bring a series of advantages for utility companies: reducing maintenance cost, lengthening the transformer's life, enhancing the safety of operators, minimizing accidents and the severity of destruction, as well as improving power quality. Due to these benefits and the pressure utilizing the existing assets under a competitive environment, real-time monitoring is now a hot topic to power system managers and engineers as well as researchers.

Research in recent years clearly shows that advanced signal processing techniques and artificial intelligence techniques are indispensable in developing novel real-time monitoring systems. Benefiting from the development of computer techniques and communication techniques, signal processing and AI have become the most powerful tools to make next-generation real-time monitoring equipped with high levels of sensitivity, reliability, intelligence, and cheapness.

Author Contributions: Conceptualization, Q.T.T.; writing—original draft preparation: Q.T.T., P.W., J.J.; writing—review and editing, Q.T.T., P.W., J.J., K.D., L.R., E.R.S. and G.Z.; supervision, L.R.; project administration, L.R. and K.D. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Asia Pacific Regional Energy System Analysis (APRESA) project supported by the Office of Naval Research (ONR) under Federal Award identification number (FAIN) N000141712923.

Conflicts of Interest: The authors declare no conflict of interest.

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