Review

Planning and Optimizing the Replacement Strategies of Power Transformers: Literature Review

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Abstract: The power transformer is one of the most critical assets in power systems; therefore, planning and optimizing the economic investment for its replacement is crucial for the financial efficiency of the utility. A compilation of the main approaches reported in the literature for the replacement of oil-immersed power transformers is presented in this article. A chronological description of procedures presented in the literature for the determination of risk index, useful life evaluation, and transformer replacements is provided. Methodologies that use the theoretical basis of the degree of polymerization of the solid insulation of the units through the oxidation aging process to estimate their condition bring together the best tools currently available to achieve this objective. However, it is important and pertinent to complement these methodologies by considering the aging processes by pyrolysis and hydrolysis together and by incorporating economic analyses for appropriate replacement and management of these aged units.

Keywords: asset management; optimization; power transformer; risk index; useful life

1. Introduction

The power system infrastructure consists of critical and capital-intensive electrical assets, among which the power transformer (PT) is one of the costliest for power generation and transmission. These assets increase the voltage level at generation centers, allowing the transportation of energy over long distances, thus reducing Joule effect losses. Furthermore, PTs located in substations reduce the voltage to levels suitable for distribution in both industrial and residential areas.

An important and costly decision to be made during the PT lifecycle is its replacement to avoid a final failure and resulting consequences related to unacceptable economic, environmental, and social losses. Therefore, replacement must be optimally planned in order to avoid a hasty decision.

The international standard ISO 55000 [1] recommends that such decisions be made on the basis of risk assessments. The risk index for power transformers is performed through the evaluation of technical aspects that include both the probability of occurrence of a failure that compromises the availability of the unit, and the consequences caused by unavailability [2]. In effect, the final disposition of a PT can be decided based on a risk index that provides a broad overview of the transformer's condition and the consequences of its failure.

Transmission and sub-transmission transformers have nominal ratings ranging from tens to hundreds of MVA [3] and operate in medium and high voltage networks. Distribution and transmission companies manage PT fleets that can include hundreds of units, each of which costs about 60% of a transformation bay price [4].

Although the average PT service life is approximately 40 years under normal operating conditions [5], it is critical to know its health status.

This is because if the PT needs to be replaced, the production, installation, and commissioning time can range from one to two years, depending on the manufacturer's availability, time, and production capacity.

Long production and installation times, high acquisition costs, the strategic importance of the transformers within the fleet, maintenance schedules, and the overload of risks PTs can be exposed to mean it is essential to count on these methodologies for asset management. To develop such methodologies, the information available of each unit must be integrated to estimate its current and future condition within certain scenarios. In addition, such an analysis is useful to prevent major system failures or outages by detecting risky situations in timely manner, thereby reducing the likelihood of impacts on services, people, and nearby equipment.

In this context, this article presents a literature review of useful methods for planning PT replacement where the parameters and tests used to determine the PT health index, the risk index, the different methods used over the years to assess the condition of these important assets, and the replacement investments made are known. Figure 1 illustrates how the literature review was approached to understand how the replacement of aging equipment has occurred over the past decade. The remainder of this paper is organized as follows. Section 2 presents the adopted approach to structure the literature review. The methods for determining risk factors are described in Section 3. In Section 4, methods for calculating a transformer's useful life are outlined, and Section 5 describes the index to schedule the PT replacement. Finally, conclusions and a synthesis are presented in Section 6.
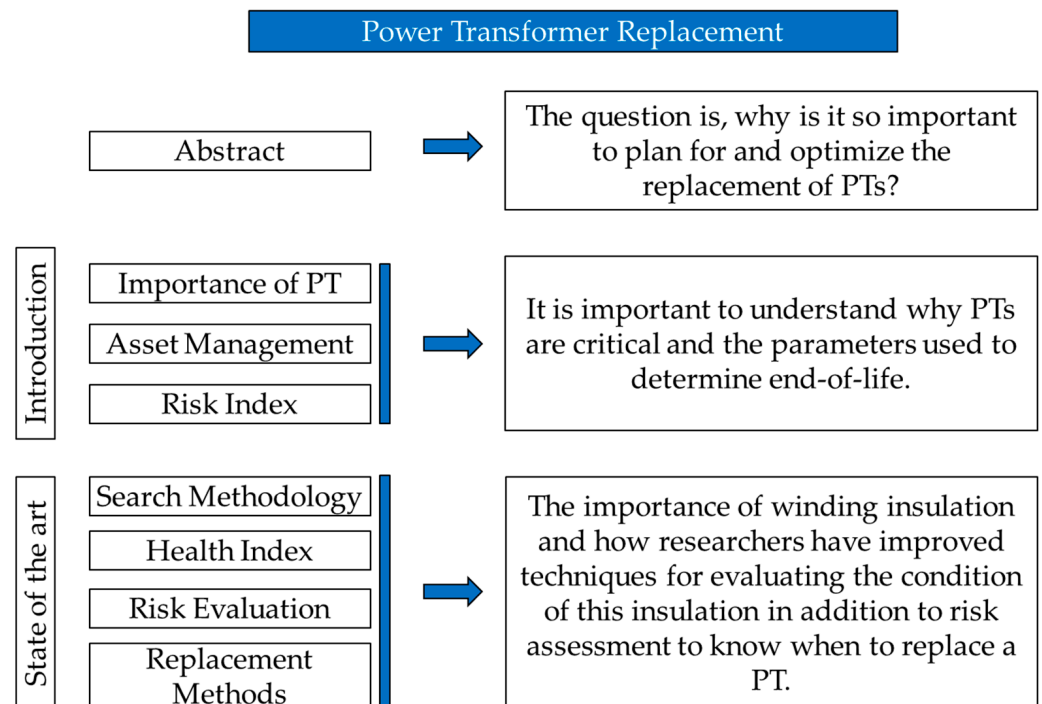
Figure 1. Paper logic structure.

2. Method to Structure the Literature Review

Within the first phase of elaboration of the state of art, the issues necessary to develop a long-term transformer replacement and management scheme were identified: (1) PT risk index, (2) PT status prediction or life index, and (3) investment scenarios in a PT fleet. These are related, as shown in Figure 2, according to their hierarchy. All areas are working in synergy to reach the desired objective, which is an investment scenario, including both the risk and the status of each area related to the PTs fleet.
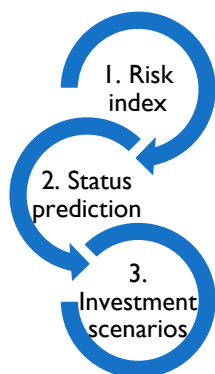
Figure 2. Topics to carry out a long-term transformer management scheme.

As performed in [6], each topic was searched using the following search rules, which were applied to titles, abstracts, keywords, and field of academic study as structured in the search catalog in Lens [7]:

1. Power transformers risk index = Risk index AND power transformer;
2. Power transformers status prediction = Status, power transformer, AND health;
3. Investment scenarios in power transformer fleets = Investment AND power transformer;
4. Investment scenarios in power transformer fleets considering the risk index = Risk index, power transformer, AND investment.

To apply the aforementioned search rules, each term was defined by a set of synonyms and related concepts, as follows:

(a) Risk index: "risk index" OR "risk assessment";
(b) Power transformer: "power transformer" OR "power system" OR "power network";
(c) Status: "life assessment" OR "status";
(d) Health: "life assessment" OR "health index";
(e) Investment: "investment" OR "improvement" OR "replacement" OR "economic assessment".

After applying the above rules, a "subject matter" filter was used to consider only those documents related to the electrical engineering field. The references found are reported in Table 1.

Table 1. References obtained with Lens searching rules.

Search Rule	Document Type				Total
	Book	**Journal Article**	**Conference Article**	**Other**	
PT. Risk Index-	8	178	110	37	333
PT. State-	12	667	5	0	684
P T.-Investment	21	321	259	167	768
PT Risk Index Investment–	0	3	1	1	5

Date of survey: 12 March 2021. Other: Indefinite, report, report summary, review, conference review.

The search for risk index in power transformers returned 333 results, which indicates that it is a recent issue because there are few articles about it (see Figure 3). Conversely, the search rule for investment scenarios in PT fleets based on the risk index only returned five results; among them, only three correspond to journal articles.

For this review, journal articles were prioritized because the peer review process guarantees the quality of the research. However, some conference articles were considered because these represent important pieces of information.
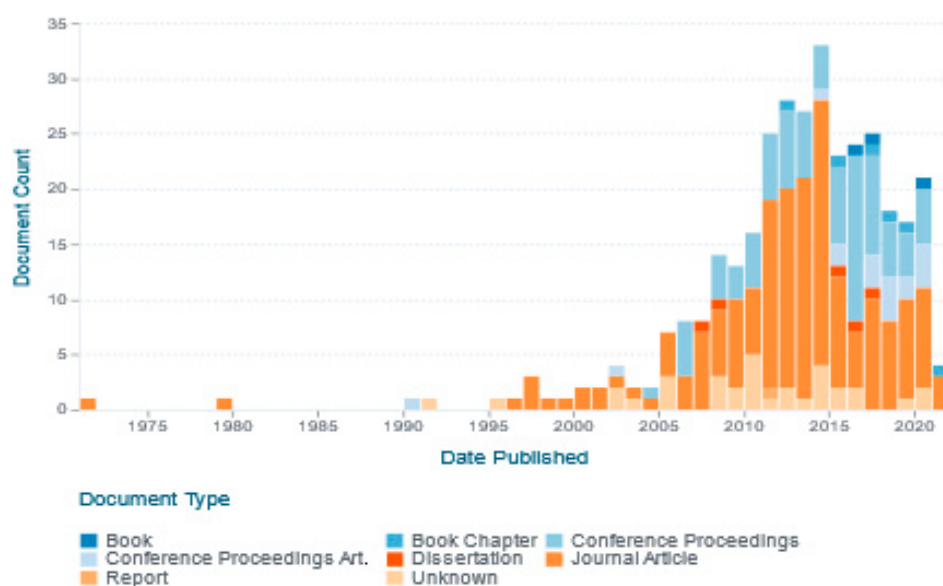
Figure 3. Risk index works over time.

A network was created with the bibliographic information of articles on each topic described in the search rules from Lens. The abstracts of the available articles were analyzed, and those with a strong connection to the topic were identified as the primary articles. The co-occurrence method (semantic proximity indicator or two terms interdependence) was used with the WOS viewer [8]. Based on relevance and citation analysis, this method identifies journal articles with several common themes associated with the search rules. The relevance represents the number of quotes the author receives from recognized journals, whereas the citation analysis system provides tools to identify patterns in scientific literatures based on bibliographic data, allowing us to track the evolution of the research over time [9]. The number of citations reflects the document's impact in the scientific field, while the network of citations reveals the relationships between investigations.

Each network article is discussed in the following sections; their relationships are analyzed, and their contributions are highlighted.

3. Risk Index Methodologies

Researchers have tried a variety of methods to calculate the risk index for PT. Fuzzy logic systems, whose input variables and membership functions can be modified according to the needs of the user, are the most commonly used. Rankings and weights, Markov chains, cluster analysis (k-means), and risk matrices have also been used.

PT diagnosis can be a complex task as there are several parameters to be considered [10,11].

Authors in [12] simulated a series of single-phase and three-phase short circuits to determine the transformer risk index. As the main source of deterioration of the evaluated assets, the authors focused on the damage caused to the winding insulating paper, which is appropriate because this kind of insulation cannot be regenerated. This paper is a pioneer for calculating the risk index using neural networks and fuzzy logic combined with transformed paper condition. The risk index is derived using hierarchical analytical processes of fuzzy logic, such as the speed of response and the minimal information required for operation, in addition to the advantages of neural networks, such as the distributed information storage, parallel processing, and self-learning [13]. The development of these models employs several entry criteria. c, resulting in a numerical value indicating the transformer's risk. Sun and Wang [14] present a method based on a tree-failure analysis and an improved fuzzy analytical hierarchy process to convert the fuzzy coherence rating into optimization problems, adopting a genetic algorithm to calculate the weight of the failure cause, given as a result of the reliability value of the transformer's components. The

methodology used in [15] integrates the calculation of the oil health index, the paper health index, and the severity and/or type of incipient failure to obtain the total asset health index using fuzzy logic. As a complement to the abovementioned methods, a neuro fuzzy scheme based on DGA which mainly evaluates the carbon ratio (CO_2/CO) is presented in [16]. Comparing the results, it is determined that the presented scheme has a better response speed than the fuzzy logic or former propagation of neural network methods.

In [17], the authors suggest adding the prioritization of risk to different modes of potential failures in the existing methodologies and weighing each factor differently because faults were given the same importance. Initially, the potential failure modes and damaging effects were identified, and then the risk value was defined based on operational impact, environmental, human, and economic losses, and influence in the power system. Finally, according to the probability of occurrence, identification, and severity, the risk index and a potential failure sequence are obtained. Later, Suwanasri et al. [18] add the assessment of the risk index associated with critical loads, its impact on the stability of the system, possibility and consequence of failure, possible damage to nearby properties, and socio-environmental impact. An importance matrix is created where it is classified from lowest to highest risk compared to the actual condition; this is calculated with oil data to decide which equipment to repair and/or change.

The proposal to separately evaluate the health index and the failure consequence factor to obtain the risk index from a technical point of view is presented in [19]. A risk matrix is created whose indices are the consequence versus the probability of occurrence. The numerical calculation of the risk index is carried out with the product between the probability of failure (PF) and the consequence factor (CF), or by evaluating the Euclidean distance between the origin of the risk surface and the point formed by PF and CF in the matrix. The recommendations according to the index obtained are: acquire a new asset, use it normally, perform maintenance, relocate, reduce its working regime, refurbish, repower, or perform the final disposal of the transformer. Lin and Xu [20] propose the use of the Markov approximation principle with the historical operation and maintenance data considering a failure's influence on the network economy and reliability. For high-risk index transformers, a load reduction is proposed to ensure the safety and availability of the network. This load reduction is calculated by analyzing the power flow, seeking the optimal value where the system is not affected, and minimizing the interruption probability. This is interesting because most companies want to guarantee the quality of the power supply to the user, which means keeping the most critical assets in the fleet in top condition.

On the other hand, Khuntia and Rueda [21] develop a risk optimization model that consists of two assessments: the condition of the transformer, and the criticality of the network to which it belongs. The condition is evaluated with respect to live parts, the oil insulation, the tap changer condition, the bushings, and the surge arrester. Meanwhile, the network is evaluated in terms of load factor, load shedding, expert criterial, and bushings creepage distance. By combining these assessments, a matrix is created where the transformer located at the furthest point, i.e., the one with the highest index in both criteria, requires priority maintenance or repair actions.

Up to this point, several methods disagree with each other and do not use the latest technologies to assess the health of the PT. However, [22] gather the best attributes found in the literature and use a grouping technique of units with similar characteristics, relying on the k-means algorithm to decide what to do with the assets. This demonstrates greater effectiveness compared to a ranking classification.

The authors compare two methodologies to obtain the health index, and large differences are evident because each one uses different weights for the input factor. Using the proposed methodology, similar results are obtained, demonstrating its usefulness for PT fleet management.

In his doctoral thesis, [2] shows a very good approximation of the PT condition by using tools, such as neural networks, differential equations, probability theories and stochastic processes, Monte Carlo approximations, and fuzzy logic. The report first presents

the results from the calculation of the degree of polymerization of four transformers under sample to obtain the health index of each unit using the fuzzy integration method. As a second step, it evaluates the consequence factor for the failure of each unit to obtain a risk index individually. Finally, it integrates the two previous factors (health index and the consequence factor) to propose a transformer fleet ranking aimed at providing information for the optimization process of these important assets. These steps are optimized by Cerón [23] in his doctoral thesis, where, in addition to the factors described in [2], he evaluates the future state of the units through a load and temperature forecast to analyze investment alternatives in a transformer fleet. As a result, he presents a methodology for the replacement of these assets, considering technical, economic, safety, environmental, and performance parameters. Using a real example of 102 transformer units, he demonstrates a long-term replacement strategy.

Finally, in [24], the proposed method combines three basic models: the physical degradation of the winding, the health index model, and the statistical model based on the end of the useful life of the asset. First, the individual breakage and the condition-dependent probabilities are obtained to calculate the expected remaining lifetime. As a result, a key decision is obtained for transformer managers to decide whether to perform maintenance or to replace the PT. The model is based on a set of 18 transformers only, and the probability of failure is calculated using active parts that are considered non-repairable, excluding measurements on bushings or tap changers where important failure frequencies must be taken into account for this type of study. However, oil segment replacements are included in the calculations, making the information obtained reliable over time.

Table 2 presents the synthesis of the methodologies described. It presents the input data found in the literature for the calculation of risk indices most commonly used by companies that own fleets of power transformers, showing that each author uses those they consider important or those they have in their test history, confirming that there is no standard for finding the risk index.

Table 2. Input data to obtain the risk index.

Input Data	Reference													
	[12]	[13]	[17]	[14]	[16]	[18]	[21]	[15]	[19]	[20]	[22]	[2]	[23]	[24]
History of single-phase and three-phase faults	√			√								√		
Element failure history		√										√		
Mechanical tests			√	√		√								
Physicochemical tests				√		√	√	√	√	√	√	√	√	√
Electrical tests			√	√		√		√		√	√	√		√
Visual inspection			√			√								√
Insulation characteristics				√					√				√	√
Maintenance and operation				√							√	√		√
Other components	√	√				√			√		√	√	√	√
Moisture content				√				√	√	√			√	√
External influences				√					√		√	√		
DGA analysis					√			√	√	√	√	√	√	√
Asset age						√			√		√	√	√	√
Load history						√			√		√	√	√	√
Power factor						√								
Network criticality							√		√		√	√	√	
Load Factor						√								

Table 2. *Cont.*

Input Data	Reference													
	[12]	[13]	[17]	[14]	[16]	[18]	[21]	[15]	[19]	[20]	[22]	[2]	[23]	[24]
Load shedding						√		√					√	√
Furans or degree of polymerization (DP)							√	√	√		√		√	√
Cost and repair time											√	√		√
Environmental impact											√		√	√
Penalty								√					√	
Paper degradation (hydrolysis, pyrolysis, and oxidation)								√					√	
Oil volume								√						
Risk to nearby buildings								√						

Source: Authors.

4. Methodologies for Evaluating the Useful Life of Power Transformers

In recent years, the methods for predicting the useful life of PTs have improved as new technologies have been introduced to monitor these important assets. Initial calculations were based on temperature, but alternatives, such as fuzzy logic, neural networks, Bayesian networks, and data mining, have been used to evaluate the parameters derived from insulating paper and oil measurements. Some of the major methods implemented are presented below.

In [25], a first approximation of the transformer's useful life calculation is presented, mainly using temperature as an indicator of insulation degradation. Guidelines for transformers' life management are defined, and it is recommended to consider a maintenance strategy, an aging mechanism (insulation degradation), and the condition assessment by technical diagnostics during asset monitoring. One year later, Qian and Yan [26] apply fuzzy logic to a set of oil dissolve gas data to determine whether the transformer is aging normally or rapidly. As a result, the applied methodology indicates the possible cause of the failure. In 2006, Pradhan [27] develops prototype transformers to evaluate aging by increasing the temperature at different scales and performing daily physicochemical tests. At the end of the studies, it is determined that some furans tests, such as "5-Hydroxymethyl 2 Furfural" and "2-Furfuryl alcohol," are unstable, while "2-Furaldehyde" behavior correlates with the insulation deterioration and the "2-Acetylfuran" helps to determine the assets' aging. Furthermore, the study concludes that the best insulation aging indicator is the degree of polymerization (DP); however, as it is a destructive test (because samples must be taken from the insulating paper), it must be correlated with DGA, furans, and other diagnostic tests. Based on this information, a team of researchers compared paper degradation tests with the temperature and chargeability data from a decommissioned transformer from 2001 to 2007 and found that the maximum paper degradation can be roughly estimated by using the Arrhenius equation [28].

In [29,30], Yang compares different PT aging methods and comes to the following important conclusions: (i) The carbon ratio analysis CO_2/CO considers a transformer to be aged when the radius of the gas content is greater than seven and, in some cases, greater than ten. (ii) The thermal method evaluates the hot spots of the transformer to estimate its aging. (iii) The methodology based on electrical parameters uses tangent delta tests and defines a maximum value of 0.6% for transformers between 330 kV and 500 kV at 20 °C and, in general, the tangent delta radius and its historical value should not exceed 30% for an unaged transformer. (iv) The solid insulation degree of polymerization method considers a transformer to be aged when it has the value of 150 to 200 ppm. (v) The methodology based on the furan content in transformer oil has a correlation coefficient of 0.9657 with the DP test value.

Knowing all these data, it is not appropriate to calculate the aging of PTs based only on the temperature. The main criteria for determining this parameter is a fusion between the DP, the results of electrical and physicochemical tests, and the asset's operating history. Lastly, the author recommends taking the first insulation paper sample after 15 years of operation and then at 5-year intervals. However, [31] propose a transformer thermal model in a fault-free operating environment based on a fuzzy neural network, which gives an early indication of any deviation of the transformer from normal operating conditions. The model considers internal measurements at different locations to predict future temperature hot spots. Meanwhile, in [32], the authors perform a method to find a PT's life index using DGA and temperature data. It is proposed to use DGA instead of furans because the data of the latter are scarce and have a higher probability of sampling errors. The method is divided into three parts: calculation of the reliability of the transformer's oil–paper insulation during normal operation, calculation while updating during the fault events, and calculation after reparation. Compared with a practical case, the asset's remaining life increases after proper maintenance is carried out. The "gray target" theory is used for data fitting and calculation of main function parameters.

Li et al. [33] present a self-learning method to estimate the DP value of the transformer insulation using oil parameters. Fuzzy clustering and linear regression are used. The calculations are then compared with actual values obtained from laboratory tests performed every 24 days on paper samples placed in glass bottles filled with different types of oil and exposed to different temperatures for 240 days. The proposed equation is compared with different authors' calculations and shows a better prediction of the real Partial Discharge (PD) value measured in the laboratory. Hence, this proposal can be used to automate monitoring equipment that shows the PTs' real-time solid insulation condition. Continuing this research topic, [34] present a Bayesian statistical learning-based methodology that calculates the health index to determine the PTs' status. This index is compared with a company's maintenance budget to predict the feasibility of performing maintenance or, conversely, waiting for a signal alarm to intervene in the asset.

Because not all utilities have a complete history of transformer tests, or some of these tests are missing, in [35], a time-updated health index is proposed, which performs the calculation of an asset's initial state through Markov chains, thereby estimating certain parameters and obtaining acceptable results.

Finally, [36] analyze a PT's life from an economic point of view, considering maintenance costs and failure penalties. It is concluded that the economic asset life is shorter than the operational life because, after a certain time, the maintenance and failure costs are so expensive that it would be feasible to opt for the transformer's replacement.

A summary of the methods found in this section is presented in Table 3. Both the input data and the calculation method used to estimate transformer health vary from author to author. Therefore, it is advisable to treat these methods as estimates because there is no standard that defines their general calculation.

Table 3. Methods used to calculate the useful life of PTs.

Method Used	Reference										
	[25]	[26]	[27]	[28]	[29]	[31]	[32]	[33]	[35]	[34]	[36]
Thermal aging	√			√	√						
Fuzzy logic		√					√	√			
Lab tests				√							
Carbon analysis (CO_2/CO)					√						
Empirical formulas				√	√						√
Neural networks						√					

Table 3. *Cont.*

Method Used	Reference										
	[25]	[26]	[27]	[28]	[29]	[31]	[32]	[33]	[35]	[34]	[36]
Weibull distribution							√				
"Gray target" theory							√				
Linear regression								√			
Greedy algorithm								√			
Markov chains									√		
Dempster–Shafer Theory									√		
Bayesian networks										√	
Lambert W function											√

Source: Authors.

5. Assessment Indexes for Power Transformer Replacement

In order to estimate the time when a PT should be replaced, several proposals have been discussed. In [37], the authors present a model that predicts the PT's remaining lifetime based on the paper insulation degradation to know its replacement time. Data were taken from test equipment at two-hour intervals for two years. Ambient temperature information was reconstructed according to IEC 60076-6 [38], assuming a load increase of 2% per year. The results are considered speculative as not all the necessary input parameters were available. It is noted that redistributing the load in the transformers is disadvantageous because it reduces their useful lifetime. Meanwhile, [39] recommends PT replacement using service classes (condition) and risk of disconnection as criteria. Gas analysis tests are used to determine the asset's condition through fuzzy logic rules, and the number of disconnected customers in a blackout is used to determine the equipment replacement or maintenance sequence. The data were tested in 10 transformers, resulting in the replacement sequence.

In [40], it was found that PT replacement alternatives could be evaluated using a probabilistic approach to paper insulation thermal degradation. Two scenarios are compared: one where the units are hypothetically replaced, and a second where input data are used, including the asset's loading history. As a result, by equalizing loads in different transformers, the waiting time for a first failure may be extended, but the unit's useful life will be considerably reduced. In addition, monitoring it is ideal to avoid calculation errors due to input parameters, as happens in the first scenario. After two years, in [41], gray incidence analysis is used to select a PT replacement based on the lifecycle cost of the asset. This model is good for dealing with uncertain, scarce, or only few data information problems. It uses fuzzy logic to adapt qualitative indices into quantitative ones and the entropy method to determine the weight of each of them. This method is used to select a transformer between two options, showing the best scheme. However, the authors recommend that further research be conducted to address conflicting evidence problems when using evidential reasoning.

Trappey et. al. [42] identify the key factors that influence the PT's normal operation to predict life expectancy, applying logistic regression based on the Weibull distribution. On the other hand, [43] presents a methodical decision-making system to determine the optimal replacement time for a PT. Two studies are performed: the first considers maintenance effects, and the second does not. Using the bathtub curve as a reference to represent the transformer's lifetime, the focus is on the spot where the stable zone ends to decide whether to replace or maintain the asset. The authors conclude that to extend a transformer's useful life, it has been shown to be cost-effective to perform at least one maintenance operation before replacing. The decision is based on an algorithm rather than on the condition of the equipment, which ignores several important factors.

The effect of changing the PT's oil on the measurement of furan content is evaluated in [44], because it is one of the most important parameters for determining the asset's age and whether it needs to be replaced. The oil change reduced the furan content, causing an error in the aging assessment. In order to compensate for this effect, the authors introduce a correction factor. Experimental examples in the laboratory are used to verify the functions with the correction factor, and the results are corroborated by data collected from 44 in-service transformers. This is an important milestone to consider when assessing the aging of insulation paper, as many of the operating transformers have had their oil changed during service.

In [45], the authors use the Monte Carlo method to predict load profiles in different scenarios (constant load, load increase, and load reduction). According to the results of the study, the cost of energy and the regulatory structure are responsible for the decision to replace a transformer. Using other parameters, such as humidity, temperature, transformer capacity, oxygen content, breakdown voltage, and the current age of the asset, a mathematical model is proposed to estimate the PT's remaining lifetime because these data can be easily and cheaply collected [46]. The authors use the de Pablo equation [47] to calculate DP, replacing the furan content due to its relationship with the above. Linear regression is used for furan content below 0.6 and non-linear regression is used for furan levels above 0.6 because the linear regression produces errors exceeding 160 parts per million (ppm) of DP after this value. The Monte Carlo method is also used in [48] to calculate the power delivered in case of failure, the penalty costs in case of failure, and to estimate the retirement year of aging units. This methodology analyzes the cost–benefit of replacing the PT, considering the system risk under several load steps.

Martin et al. [49] obtained failure and retirement data for 98% of the PTs in Australia in 2016. In this paper, failure cause data for different voltage ranges are presented, and the authors conclude that windings, on-load tap changers (OLTCs), and bushings are the main failure causes. In total, 46% of the withdrawals are attributed to changes or repowering of the network, while only 9% are attributed to insulation problems. It is also confirmed that utilities remove transformers mainly when the cost of maintenance or repair exceeds their budget. Data, such as these, are extremely helpful in the development of a risk-based methodology, such as that presented in [50], which also considers the lifetime of the ventilation and pumping systems and the risk of failure of the unit. This is important for equipment operating close to its load limit or in areas with extreme temperatures.

In [51], a methodology for the classification and replacement of PTs in substations is presented. Furthermore, among the health index classifications widely studied in the literature, the authors present an Operational Vulnerability Indicator (OVI) supported by parallelism (units working together or supporting each other), which identifies the percentage of load insured by the asset in case of a contingency. In this paper, 39 PTs from seven substations are compared to determine the next transformer to be replaced based on its health index, and also due to the risk of not having a backup load in the event of a power outage. The radius of the transformer is another parameter considered by the OVI, because the greater the difference between the primary and secondary voltages, the longer it takes to build the asset. It is concluded that it is possible to postpone the replacement of a transformer if it has a backup transformer prepared for its load.

In the latest development, Cerón [23] provides an optimal methodology for the replacement of transformers, which is achieved by using the risk matrix, whose axes consist of the estimated lifetime and the failure consequences. Key factors, including oil and paper moisture, hot spot temperature, chargeability, and DP, are considered when estimating the life used. Furthermore, Non-Linear Principal Component Analysis (NLPCA) is used to extrapolate the future state of the asset. The consequence of failure is quantified using a methodology that classifies the costs associated with equipment failure into four categories: financial, safety, environmental, and network performance. In addition, the optimization model and risk matrix can be used to determine the order of asset replacement in the future, taking into account both the annual budget and the assets' CAPEX amounts. This was one

of the most complete contributions, although it did not include equipment maintenance in its methodology.

There are other methodologies, such as those found in [24,52], that use the health index to predict the need to replace a PT.

Presented in Table 4 are the advantages and disadvantages of the most common replacement methodologies. The literature indicates that the end of transformer life is directly related to the end of life of the insulation paper. It is not possible to perform direct maintenance on this insulation (except in the case of a complete rebuild of the transformer), so it is considered a primary element in determining the condition of the asset. This is mainly assessed by the DP and is used in conjunction with the failure consequence factor to evaluate the risk of the asset and thus plan for replacement.

Table 4. A review of PT replacement methodologies.

Ref.	Development	Advantage	Disadvantage
[37]	A model predicting the remaining life of an insulating paper based on the degradation process.	Despite the lack of load data, a good estimate can still be made.	Because several input parameters are missing, the results are considered speculative. The proposed load redistribution can reduce asset lifetimes.
[39]	PT replacement model based on the condition and risk of disconnection to users.	By using data from samples in the oil, calculations are based on the actual condition of the equipment.	Data input is not always complete. Assets that are in different states of health can be weighed similarly using fuzzy logic.
[40]	Assessment of substitution alternatives based on probabilistic analysis of thermal degradation of paper.	With redistribution, it takes longer for a failure to occur. Having a fixed number of assets to replace each year makes management easier. Computing is reduced when similar units are grouped together.	Load balancing affects the remaining life of assets. Good monitoring is required to avoid errors in calculations. PD calculations show a significant deviation.
[41]	A model for evaluating investments based on lifecycle costs.	Based on lifecycle cost, it also considers reliability and maintenance. Deals effectively with scarce information issues.	Calculations are based purely on economics and not on asset operation.
[42]	Remote assessment of the PT's service life.	Calculates the transformer lifetime using data from both real-time and historical sources.	There are technical evaluations, but no economic evaluations for unit replacement.
[43]	Methodical decision-making system to determine the optimal replacement time for the asset.	An emphasis is placed on the characteristics of equipment operation at the point of instability. The effect of maintenance is considered. It combines both the economic and the reliability components.	All calculations are performed using an algorithm that ignores several critical parameters that should be monitored, including the actual condition of the asset.
[45]	An economic study of the replacement of the PT according to current regulations.	Predicts future equipment load scenarios.	In addition to power, it does not consider other parameters that can affect asset life.
[46]	A mathematical model for estimating a PT's remaining life.	By calculating other parameters, the degree of polymerization is calculated, thus avoiding the degradation of insulation during sampling.	Because it is not possible to make a fully reliable decision on asset replacement using linear or non-linear regression, the uncertainty of the calculated parameter is high.
[48]	A cost–benefit analysis method for replacing a PT.	It considers the risks associated with each loading stage, including penalties for not providing the service.	It focuses primarily on loads and hot spots while ignoring other important parameters that determine the condition of assets.
[51]	Methodology for classifying and replacing PTs in substations.	In addition to the risk index, it also takes into account whether other equipment is supporting the transformer load. Calculates the risk by considering the manufacturing time of the unit.	When data or measurements are not available, values are assumed, such as the level of furans. Economic factors, such as environmental damage, corporate budgets, penalties, etc., are not considered.

Table 4. *Cont.*

Ref.	Development	Advantage	Disadvantage
[50]	Methodology for predicting PT replacement using risk.	To make more accurate calculations, separates the detectability from the severity of a failure. Defining the type of failure that will occur next helps the operator take corrective action in a timely manner.	Only equipment parameters are considered, not economic or external factors.
[23]	Economic quantifications and risk matrix applied to transformer substitution.	Considers physical, economic, and external risks. Predicts future behavior and makes better long-term decisions. Optimizes replacement costs according to the company's budget.	The results are not affected by maintenance events on the asset that add uncertainty to the results. Maintenance can extend the life of the unit or change the inputs used to calculate of the asset health index.

Source: Authors.

6. Conclusions

The techniques for evaluating PT life have been refined over the past few years. The process began with estimates of failures, then moved to temperature and hot spot analysis, and finally arrived at its current stage of evaluating insulation of the paper by taking measurements in both the oil and in the insulating paper.

According to the literature, the life of a transformer is directly correlated to the lifespan of the insulating paper. This insulation is extremely difficult to maintain, so it is an essential element in determining the asset's condition. It is generally assessed by measuring or calculating the degree of polymerization.

Each author uses different input data and calculations to estimate transformer health. The same is true for the probability of failure and the consequence factor. This type of methodology should be treated as an expert opinion due to the lack of standardization of the calculation required.

In the absence of clearly defined asset management policies, utilities could not track the history of tests or data to assess the health of assets. Therefore, it is necessary to develop methods to estimate missing data.

Statistical models were first used to estimate transformer health, then fuzzy logic, then Markov chains and Bayesian networks, and then, finally, neural networks. On the other hand, training neural networks can identify normal operating conditions of transformers and detect changes in input signals that may indicate an early warning.

To present PT replacement models, recent studies have integrated issues, such as risk index, consequence factor, and economic impact. However, there is a lack of a more comprehensive methodology that considers these factors and, at the same time, integrates the maintenance of these assets, as good and scheduled maintenance can significantly affect the health of transformers.

In order to make the best decisions about which assets to replace or maintain, it is necessary to have a methodology for estimating future data. Thus, utility budgets can be estimated to be consistent with a good asset management system.

Table 5 shows the main aspects considered by each methodology.

Table 5. Main aspects considered by each methodology.

Reference	Risk Index					Life Evaluation								Economic Analysis			
	Life Based on DP	Health Index or Probability of Failure	Consequences of Failure	Evaluations and Weights	Fuzzy Logic	Statistical Analysis	Empirical Formulas	Neural Networks	Theories and Theorems	Algorithms	Bayesian Networks	Stochastic Processes	Future Prediction	Penalty	Maintenance	Replacement	Optimization
[12]			✓	✓	✓			✓		✓							
[15]		✓			✓												
[13]			✓	✓	✓					✓							
[14]			✓	✓	✓	✓				✓							
[2]		✓	✓			✓	✓		✓			✓					
[23]	✓		✓	✓		✓		✓		✓		✓	✓			✓	✓
[16]		✓	✓	✓	✓	✓		✓									
[17]			✓	✓		✓	✓										
[18]		✓	✓	✓													
[19]		✓	✓	✓													
[20]	✓	✓	✓	✓		✓			✓								✓
[50]			✓	✓													
[24]	✓	✓		✓		✓						✓			✓	✓	✓
[26]			✓		✓	✓											
[27]	✓						✓										
[28]	✓			✓		✓	✓										
[31]			✓	✓	✓	✓		✓		✓			✓				
[32]	✓		✓			✓			✓								
[33]	✓				✓					✓							
[35]		✓		✓		✓			✓	✓							
[34]		✓		✓					✓	✓	✓			✓	✓		✓
[36]			✓				✓								✓		✓
[37]	✓		✓			✓							✓				
[39]			✓	✓	✓					✓							
[40]	✓		✓			✓											
[41]			✓	✓	✓	✓	✓									✓	
[42]		✓	✓			✓				✓			✓				
[43]				✓											✓	✓	
[45]						✓								✓			✓
[46]	✓						✓			✓							
[48]				✓		✓				✓				✓	✓		✓

Source: Authors.

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