Received: 21 February 2023 | Revised: 25 April 2023 | Accepted: 1 June 2023

IET Generation, Transmission & Distribution

DOI: 10.1049/gtd2.12893

The Institution of Engineering and Technology WILEY

ORIGINAL RESEARCH

Methodology for scheduling long-term replacement of aging power transformers, considering risk

Andrés Felipe Cerón Piamba[1] | **Andrés Arturo Romero Quete**[2] | **Guillermo Aponte Mayor**[1]

[1]Research Group GRALTA of the School of Electrical and Electronic Engineering, Universidad del Valle, Ciudad Universitaria – Meléndez, Cali, Colombia

[2]Instituto de Energía Eléctrica, Universidad Nacional de San Juan - CONICET, San Juan, J5400ARL, Argentina

Correspondence
Andrés Felipe Cerón Piamba, 760036. Carrera 44 #13–38, Cali – Valle del Cauca, Colombia.
Email: andres.ceron@correounivalle.edu.co

Funding information
Ministry of Science, Technology and Innovation of Colombia, Grant/Award Number: BPIN 2021000100223

Abstract

This article presents an optimization methodology to schedule the replacement of power transformers (PT) into a fleet. The objective is the minimization of the summation of the risk indices of the PT. Each PT risk index is calculated from the estimation of the life used and the strategic importance of the unit. The PT life used is estimated as a relationship of the solid insulation polymerization degree, where aging processes due to oxidation, hydrolysis, and pyrolysis are considered from the calendar date when the unit starts its operation until different future scenarios. For the calculation of the PT strategic importance, financial, security, environmental, and network performance aspects are considered. Then, using the optimization model, together with the CAPEX and the available budget over a planning time, a strategy for optimally replacing the critical units is determined. The model was applied for a group of 102 units, demonstrating its applicability and effectiveness. The developed methodology serves to support the manager of these assets in making decisions in the long term.

1 | INTRODUCTION

Power transformers (PT) are generally considered to be the most crucial and expensive asset within an electrical transmission system [1]. As a result of the current worldwide increasing demand for electricity, the load on transformers is also increasing and yet most transmission systems currently have large fleets of aged transformers [2]. The failure of a power transformer can have great technical and economic impact [3]. Therefore, it is necessary to optimize the transformer replacement strategies, ensuring maximum utilization of assets and minimizing system risks [4].

The risk index is a useful indicator for making strategic decisions regarding the replacement of an asset [5], and it is determined from the consequence factor and the probability of failure. The consequence factor is obtained by analysis based on the assumption that all assets will fail in the future and the consequences of such a failure can be estimated. These consequences can be approached from different perspectives such as equipment safety, personnel safety, environmental safety, corporate image, consequences for production, and delays in the achievement of goals [6]. The probability of failure is a concept that merges the condition of the particular transformer unit and the external events that can trigger a final failure. Such external events can be of different nature, such as atmospheric discharges, sabotage, and other events such as short circuits or overloads [7]. Once, the transformer risk index is estimated. the management of the fleet can be performed by prioritizing the units with high risk index values. This hierarchy allows adequate management of resources. Reference [8] proposes a practical method for risk analysis of the power transformer fleets that appropriately considers the best attributes of the methods reported in the literature to calculate the failure probability factor and the consequence factor. Moreover, such a paper contributes to the risk analysis field by including risk matrices and clustering techniques to support the decision-making process. Nevertheless, this method fails to determine when the units must be replaced.

Reference [9] presents a model that supports transformer fleet management efforts by optimizing the acquisition and the deployment of high-voltage transformers dynamically over time. Nevertheless, this dynamic model only considers the possibility of replacing transformers that have already failed.

Reference [10] describes optimal scheduling that is achieved through an algorithm that selects high-revenue investments. Although this solution employs the risk index, it only considers the age calendar for the health index and facilities located in a grid area with flexibility for the consequence factor.

Reference [11] proposes a Dempster-Schafer's theory of evidence for fault diagnosis to decide on condition-based maintenance. Such a method was developed to analyze faults in individual assets, but not to make decisions over a large power transformer fleet.

Reference [12] uses the transformer failure rate as a replacement decision criterion. Initially, a first-order model of transformer degradation is proposed. Then, the Weibull distribution is used in a Monte Carlo simulation to generate the variations of degree of polymerization along with time based on the historical data, and the transformer failure rate is determined. Nevertheless, the paper degradation model presented in this work does not consider all degradation processes (oxidation, hydrolysis, and pyrolysis), nor does it consider the influence of the dynamics on paper moisture.

Reference [13] proposes a hybrid method based on the Pareto distribution and Monte Carlo search algorithm to estimate the transformer end of life. In this approach, economic valuation of the old transformer and new transformer is compared in time, but as in [12], the paper degradation model used in this work does not take into account all degradation processes.

The novelty of this paper is to present a useful methodology that integrates different pieces of evidence reported in the literature, which have not been connected up to now, specifically, a method for the evaluation of the estimated life based on the aging of solid insulation using the degree of polymerization, a method for calculating the consequences of failure, the acquisition costs of the equipment, and the budget available for PT replacement. The core of the proposed methodology is the formulation of a novel optimization problem that integrates the above models to determine the replacement priority of risky assets in a large PT fleet. The proposed methodology is tested in a case study, and the obtained results are presented and analyzed in detail.

The rest of the article is organized as follows. Section 2 describes the aging of cellulose and polymerization degree (DP) useful life (UL). Section 3 describes the research problem and the proposed methodology. Section 4 presents the results obtained from 102 units currently in operation. Finally, conclusions are given in Section 5.

2 | THEORICAL FRAMEWORK

The aging of PT is mainly caused by the degradation of insulation materials (mainly mineral oil and insulation paper) that is due to long-term joint action of multiple stresses including electrical, thermal, mechanical, and environmental factors [14]. Although oil degradation can be managed by treatment methods such as dehumidification, purification, and filtration, or even by oil replacement, no paper refurbishment methods are currently available.

The paper used as solid insulation in transformers is obtained from vegetable cellulose, that is a polysaccharide, which forms long chains of linked monomers. The length of these chains is called the DP, which is an indicator related with the mechanical strength of the paper and thus with the condition of the power transformer. At the beginning of its UL the insulating paper has a DP of around 1000, as it degrades, this value decreases; when the DP is less than 200 it is considered that the unit has reached the end of its reliable life.

The DP value can be determined by taking a sample of the insulating paper directly from inside the unit which is then subjected to the viscosity method. This test requires a major maintenance operation which in many cases is impractical and very risky, since in general the worst condition paper sample is located in the inaccessible areas of the winding. There are indirect methods to estimate the DP value, the first one consists of using the concentration of furans in oil. The second alternative consists of using loading guides, which analyze the depolymerization process as a function of the thermal degradation of the paper. This second method is the one employed in this article, and it is reported in [15]. In addition, it is noted that it is more feasible to forecast depolymerization through the analysis of transformer load evolution, than from the analysis of furans in the oil, due to the availability of historical data. In effect, usually, there is enough data about supplied load, but few about the furans in oil evolution. In conclusion, to our knowledge, the degree of polymerization seems to be the best indicator for forecasting the aging of the insulating paper in the long term.

2.1 | Hot spot temperature

For PT in use, thermal and electrical phenomena interact with each other, thermal phenomenon being the result of dynamic loading and variable environmental conditions [16, 17]. Thermal stress is the main cause of deterioration of the transformer insulation system, especially solid insulation. However, the deterioration of solid insulation does not occur uniformly in the windings of PT, but is concentrated in specific areas called 'Hot Spot', where the greatest aging of solid insulation occurs due to thermal degradation [18]. Therefore, estimating the Hot Spot Temperature is very useful to estimate the aging of solid insulation due to the thermal effect, given the criticality it has on it.

In the literature, there are different methodologies to obtain the Hot Spot Temperature, the most recognized being the Susa thermodynamic model reported in [19–21], the equation model exponential and differential equations from IEC 60076–7 [22], and the exponential equation model from IEEE Std. C57.91 [23].

IEC 60076-7 [22] presents the thermodynamic model developed by Susa in [19–21] as a further development, which considers the influence of temperature on oil viscosity and has been physically verified. Additionally, the Susa model allows estimating the Hot Spot Temperature profile, considering the dynamics of the insulation system as a function of time, based on the operating history (attended load, ambient

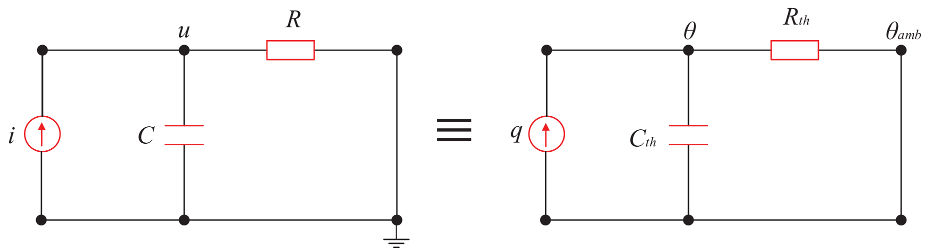

FIGURE 1 Basic diagram of the thermoelectric equivalent [21].

TABLE 1 Equivalent variables of the thermoelectric analogy.

Electrical equivalent			**Thermal equivalent**		
Parameters	**Symbol**	**Unit**	**Parameters**	**Symbol**	**Unit**
Current	i	A	Generated heat	q	W
Voltage	u	V	Temperature	θ	°C
Resistance	R	Ω	Resistance	R_{th}	°C/W
Capacitance	C	F	Capacitance	C_{th}	J/°C
Reference node	Gnd	V	Room temperature	θ_{amb}	°C

temperature), data from the characteristics plate, and few heat run test protocol parameters [16].

The thermodynamic model is based on the analogy of two conventional theories: heat transfer through fluids and electrical circuits. In addition, the model establishes that it is possible to mathematically relate the interaction of thermal and electrical phenomena. In Figure 1 the electrical circuit and its thermal equivalent of the model are presented in a simplified diagram. Table 1 lists the symbols used in the diagram of Figure 1.

From Figure 1, the electrical equivalent parameters are: i is current, C is capacitance, R is resistance, and u is voltage; the thermal equivalent parameters are: q is the heat generated, C_{th} is the thermal capacitance, θ is the temperature, R_{th} is the thermal resistance, and θ_{amb} is the ambient temperature [21]. R_{th} and C_{th} represent the capacity of the material to resist and store heat, respectively [21]. The electrical phenomenon is defined mathematically by the theory of RC circuits based on Ohm's law and Kirchhoff's rules, and the thermal phenomenon, by the energy balance equation [21].

The estimation of the Hot Spot is achieved by solving the differential Equations (1) and (2) [15, 19–21, 24]. The first represents the temperature of the oil at the top of the transformer θ_{TO} and the second, the temperature of the hottest spot θ_{HS}.

$$\left[\left(\frac{1+R\cdot K^2}{1+R}\right)\cdot\mu_{\mathrm{PU}}^{n}\cdot\Delta`_{\mathrm{TO,R}}\right] = \left[\mu_{\mathrm{PU}}^{n}\cdot\tau_{\mathrm{TO,R}}\cdot\frac{\mathrm{d}`_{\mathrm{oil}}}{\mathrm{d}t}+\frac{(\theta_{\mathrm{TO}}-\theta_{\mathrm{amb}})^{n+1}}{\Delta`^{n}_{\mathrm{TO,R}}}\right] \tag{1}$$

$$\left[K^2\cdot\mu_{\mathrm{PU}}^{m}\cdot\Delta`_{\mathrm{HS,R}}\right] = \left[\mu_{\mathrm{PU}}^{m}\cdot\tau_{\mathrm{W,R}}\cdot\frac{\mathrm{d}`_{\mathrm{HS}}}{\mathrm{d}t}+\frac{(\theta_{\mathrm{HS}}-\theta_{\mathrm{TO}})^{m+1}}{\Delta`^{m}_{\mathrm{HS,R}}}\right] \tag{2}$$

where K is the load factor described by the quotient between load and nominal load, R is the ratio between load and no-load losses, θ_{amb} is the ambient temperature, $\Delta\theta_{\mathrm{TO,R}}$ is the temperature increase of the top oil over θ_{amb}, $\Delta\theta_{\mathrm{HS,R}}$ is the hottest spot temperature rise over θ_{amb}, $\tau_{\mathrm{TO\text{-}R}}$ is the thermodynamic time constant of the top oil, $\tau_{\mathrm{W\text{-}R}}$ is the thermodynamic time constant of the winding, μ_{PU} is the viscosity of the oil in per unit, n is an empirical constant that depends on the type of oil circulation, and m is an empirical constant that models the non-linear thermal behaviour of the unit windings. For ONAN cooling mode, constants values are $n = 0.25$ and $m = 0.25$. For the ONAF and OFAF cooling modes, in PT with external cooling these values are $n = 0.5$ and $m = 0.1$ [21].

2.2 | Aging of cellulose

The Arrhenius relation in (3) is widely accepted to model the aging of paper [25].

$$\frac{1}{DP\,(t)}-\frac{1}{DP\,(t_0)} = A\cdot e^{\frac{E_a}{R\cdot\theta_{HS}(t)}}\cdot\Delta t \tag{3}$$

where $DP(t_0)$ and $DP(t)$ are the DP values at the start time t_0, and at the end time t of the time interval Δt, A is the pre-exponential factor that depends on the chemical environment, $R = 8.314$ (J/mol K) is the gas constant, E_a is the activation energy of the aging reaction given in J/mol, and θ_{HS} is the temperature in K of the paper hot spot where the highest paper degradation of the windings occurs.

In [26], the general Arrhenius relation was disaggregated to consider hydrolysis, oxidation, and pyrolysis, as shown in (4) and (5):

$$\frac{1}{DP\,(t)}-\frac{1}{DP\,(t_0)} = \sum_{t_0}^{t} k(t)\cdot\Delta t \tag{4}$$

$$k(t) = A_{oxi}(t)\cdot e^{\frac{-E_{a,oxi}}{R\cdot(273+\theta_{HS}(t))}} + A_{hyd}(t)\cdot e^{\frac{-E_{a,hyd}}{R\cdot(273+\theta_{HS}(t))}} + A_{pyr}(t)\cdot e^{\frac{-E_{a,pyr}}{R\cdot(273+\theta_{HS}(t))}} \tag{5}$$

where $k(t)$ is the degradation rate and oxi, hyd, and pyr subscripts correspond to oxidation, hydrolysis, and pyrolysis, respectively.

Reference [15] proposes a holistic methodology for solid insulation aging assessment based on all thermal degradation process and the influence of dynamics on paper moisture. Paper moisture is estimated using as input external variables such as the load, ambient temperature, transformer technical data, and measurements for oil moisture.

2.3 | DP-based useful life

In [27], Equation (6) is proposed to describe the dependence of the UL on the degree of polymerization during accelerated degradation experiments for Thermally Upgraded Paper (TUP).

$$UL_{TUP}(DP) = \begin{cases} 1 & if \quad DP \le 200 \\ -0.881 \cdot \ln\left(\dfrac{DP}{622}\right) & if \quad 200 < DP < 622 \\ 0 & if \quad DP \ge 622 \end{cases} \tag{6}$$

Likewise, (7) is proposed in [28] as an alternative method for Not Thermally Upgraded Paper (No-TUP).

$$UL_{No-TUP}(DP) = \begin{cases} 1 & if \quad DP \le 200 \\ \dfrac{\log_{10}(DP) - 2.903}{-0.006021} & if \quad 200 < DP < 800 \\ 0 & if \quad DP \ge 800 \end{cases} \tag{7}$$

3 | PROBLEM DESCRIPTION AND PROPOSED METHODOLOGY

3.1 | Problem description

There is a lack of methodologies to help the asset managers to decide the best long-term replacement strategy for risky units belonging to a large power transformer fleet. In particular, the power transformer risk must be considered in an appropriate asset management framework.

3.2 | Future forecasting risk index values

To make successful future replacement decisions using risk index values, it is necessary to apply forecasting techniques to the values of ambient temperature, load, and humidity in the oil.

3.2.1 | Load and temperature values

The Non-linear Principal Component Analysis (NLPCA) enables time dimension data to be converted into a new space by searching for the linear dependences between the data. Generally, this space is obtained through the application of the correlation matrix to the data, giving rise to linear subspaces defined by the eigenvectors. NLPCA analysis allows for finding a better representation of the data by defining the new space using curved or polynomial subspaces. Works such as [29–32] have demonstrated the application of NLPCA in the recovery or estimation of data and its application in predictive models.

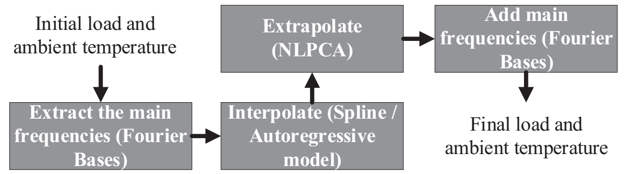

FIGURE 2 Block diagram of the method to interpolate and extrapolate the ambient temperature and load profiles.

The method used to estimate the missing data (interpolation) and the prediction of future data (extrapolation) for load and ambient temperature is illustrated in Figure 2.

The initial step is to obtain the load and ambient temperature profiles from which the outliers, zero data, or erroneous readings due to failures or sensor malfunctions are filtered out.

Then, the repetitive or harmonic contents of the load and the ambient temperature are estimated by adjusting the Fourier base functions [33]. Once the adjustment of the based functions has been carried out, it is subtracted from the load or temperature to start the interpolation process.

The next step is to estimate the missing values of the load or the ambient temperature by interpolation. The duration of the missing segments is established, and they are divided into two segments: less than or equal to 2.5 h and greater than 2.5 h. An interpolation is applied to the first group of segments using the spline or cubic interpolation method, while an autoregressive model is applied to the second group due to the amount of missing data. An autoregressive model in (8) uses the linear combination of its past values and a stochastic term to represent a certain process [34].

$$X(n) = \sum_{i=1}^{M} a_m X(n-m) + a_0 + \varepsilon(n) \tag{8}$$

where a_m is the coefficient that represents the contribution of the previous data to the new data, a_0 is the value of the constant or baseline of the process, and $\varepsilon(n)$ is the variability of the process represented stochastically. Autoregressive models have been successfully applied in the electricity sector to forecasting tasks such as wind power generation [35] or the prediction of energy market load and prices [36].

Once the signal becomes continuous through interpolation, the future values are estimated by applying the NLPCA. The load and temperature information were divided into days, that is segments of 48 data were reduced to 24 by applying a first encoder. Subsequently, the training of the inverse NLPCA model reduces the 24 data to 12 and performs the estimation of the data to be extrapolated, which then are decoded to end the process.

TABLE 2 Characterization of the optimization problem.

Feature	Qualitative item	Qualitative system	Quantitative unit
Effective	Intervention's urgency	Used life and consequence of failure	Risk index
Efficient	Investment needed	Budget	Capex (USD)

The reverse NLPCA model uses an intermediate layer of 20 neurons that provides a good number of degrees of freedom for the curved surfaces that describe the dynamics of the system.

Finally, the main frequencies of the extracted Fourier functions are added again to obtain the results for the load or temperature. Since the information is in the form of a function, it is possible to find its values at the interpolated and extrapolated points of the signal. Statistical performance metrics were implemented to obtain a measure that demonstrates its effectiveness. These are: mean square error (MSE), roots mean square error (RMSE), coefficient of determination (R^2), average percentage absolute error (MAPE), and concordance correlation coefficient (CCC).

3.2.2 | Oil moisture values

Oil humidity variations inside PT satisfy the following conditions: stochasticity, continuity, temporal independence, self-similarity and, is a memoryless process. Therefore, oil humidity content can be estimated using the generalized Wiener Process, also known as Arithmetic Brownian Motion (ABM) as described in [15].

3.3 | Optimal risk-based replacement

The method for scheduling PT replacement must be efficient and effective [10]. Therefore, it must prioritize the replacement of assets that are a threat to reliability through risk index management. Additionally, budget limitation must be considered. Thus, a replacement wave is averted, ensuring future financial sustainability of the transmission system operators.

To translate the above-described properties into a mathematical formulation, quantitative and qualitative evaluations are needed. These are shown in Table 2.

The Capex is an investment figure that has a monetary value. For the complete formulation of the problem, an objective function must be provided to find a suitable optimization algorithm. Based on this, it is expected that an optimal replacement calendar can be generated.

3.4 | Formulation of the optimization problem

The first step to define the objective function is to understand how the objective variable x is represented. In this work, the objective is to know whether a transformer is replaced, and in what year. This means that the decision variable is binary. Then, if T transformers are considered to be replaced during an analysis horizon of P periods, the decision variable becomes a vector with $T{\cdot}(P{+}1)$ entries. Here, each of these represents a route or option, as shown in Figure 3.

In Figure 3, the first option is to replace the transformer in period 1. The second option is to keep the transformer in service and then replace it in period 2. The third option involves keeping the transformer in service until its replacement in period 3. The fourth option is like the previous one, but its replacement is carried out in period 4. Finally, the option named $P{+}1$ means that the transformer continued in operation during the study period and was never replaced. The scheme shown in Figure 2 must be considered for each one of the T transformers to be considered for replacement into the analyzed period.

Each option presented in Figure 3 has an associated risk and an implementation cost, for example, the first option implies a capital expense in period 1 but is the best option to minimize the risk index. In contrast, the $P{+}1$ option does not generate capital expenditure but increases the risk index.

The objective of the optimization is to minimize the risk of the power transformer fleet to be renovated. Therefore, replacement should be assigned as soon as possible. Considering this description and the indivisibility of the project between years, it is reasonable to use annual optimization. Mathematically, the risk-based optimization is expressed by (9).

$$\min_{i\in T, j\in P} \sum_{j=1}^{P+1} \sum_{i=1}^{T} UL_{i,j} \cdot CoF_i \cdot x_{i,j} \tag{9}$$

subject to

$$\sum_{i=1}^{T} CAPEX_{i,j} \cdot x_{i,j} \le B_J \, where$$

$$B_J = B_j + \left(B_{j-1} - \sum_{i=1}^{T} CAPEX_{i,j-1} \cdot x_{i,j-1} \right), \forall j \in P+1 \tag{10}$$

$$\sum_{j=1}^{P+1} x_{i,j} = 1, \forall i \in T \tag{11}$$

$$x_{i,j} = \{0,1\} \in N^+ \tag{12}$$

$$\begin{aligned} i &= \{1, T\} \in N^+ \\ j &= \{1, P\} \in N^+ \end{aligned} \tag{13}$$

In (9), UL is the Useful Life, CoF is the Consequence of Failure, x is a decision binary variable, which equals one if the transformer i must be replaced in the period j and zero, 0, if not. The restriction (10) limits the investment according to the total available budget, B_J, which results from the summation of the budget available for each period j, that is, B_j with the

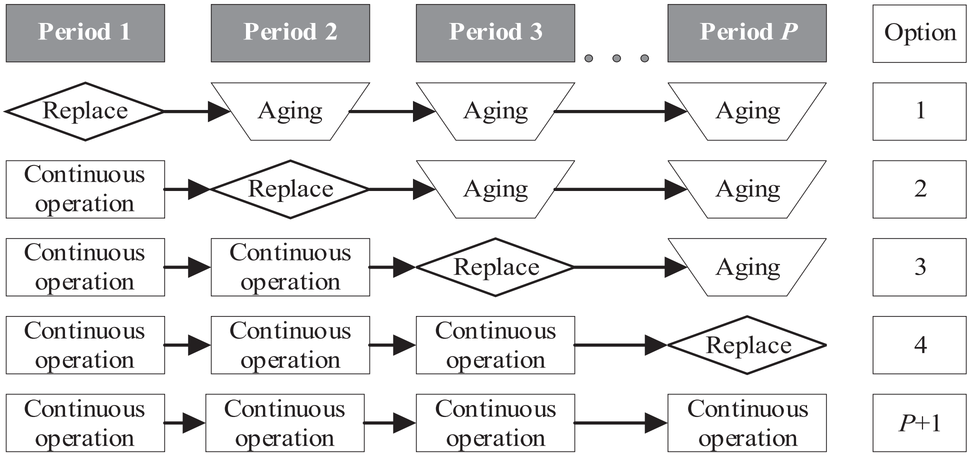

FIGURE 3 Possible replacement options for a power transformer.

remained budget, not executed in previous periods. Restriction (11) ensures that an option can only be executed once during the planning period, P+1. Restriction (12) limits the target variable to take binary values. In fact, restriction (13) specifies the domain for the periods and possible PT replacements in which this expression is valid.

3.5 | Optimization algorithm

Once the problem is defined mathematically, the next step is to provide an algorithm that offers a solution, achieving the minimization of the risk while considering the budget limitations.

Because the problem is combinatorial which means that the variable x in (9) can only take integer values, to achieve the desired solution, the problem can be modelled by Mixed Integer Linear Programming (MILP), so that the Branch and Bound algorithm is readily applicable. Therefore, an optimization algorithm called intlinprog of the MATLAB optimization toolbox was used.

3.6 | New multi-period replacement optimization methodology

Figure 4 shows a conceptual methodology to schedule in the long term the replacement PT into a large fleet. It is important to highlight that because power transformer fleets typically have tens or even hundreds of units, it can result necessary to identify in a cluster those risky transformers, approaching their final life, to then apply the optimization problem, in Section 3.5, only over those identified units. For this purpose, steps one to four in Figure 4 are proposed to obtain an initial risk matrix, and a cluster of aged units. However, because of space limitation, those four steps are considered out from the scope of this paper, but it is recommended to apply a methodology like the reported in [8] or [37], for this former classification in clusters.

In what follows, each numbered step in Figure 4 is briefly described:

Step 1. Compilation and filtering of test results. At the same time, the data necessary for the calculation of the consequence of failure (CoF) is acquired.

Step 2. Power transformer health indices are computed for each power transformer in the fleet. For this purpose, a methodology like the one described in [37] can be used.

Step 3. Consequences of power transformer failure are computed for the whole fleet, according to the methodology presented in [37] or [38].

Step 4. Critical units into the fleet are selected from the initial risk matrix. Thus, the analysis is focused on the highest risk transformers. Such a filtering can be carried out using a clustering technique (e.g. k-means), like that proposed in [8] and [37].

Step 5. Acquisition, filtering and organization of the input data to estimate the UL of the critical units selected in the previous step.

Step 6. Interpolation and extrapolation of the load and ambient temperature profiles, completing the information for the future analysis period by using NLPCA.

Step 7. Estimation of the hot spot temperature profile from the profiles obtained in the previous step using the methodology described in [15, 24] based on (1) and (2).

Step 8. Estimation of the oil moisture profile for the analysis period defined in step 6. This is achieved using the Brownian Bridges and the Arithmetic Brownian Movement defined in [15].

Step 9. Estimation of the paper humidity profile from the humidity profile in the oil according to [15].

Step 10. Obtaining the degradation profile of the solid insulation based on (4) and (5).

Step 11. Tabulation of the values of the degree of polymerization obtained in the previous step for each year of the analysis period.

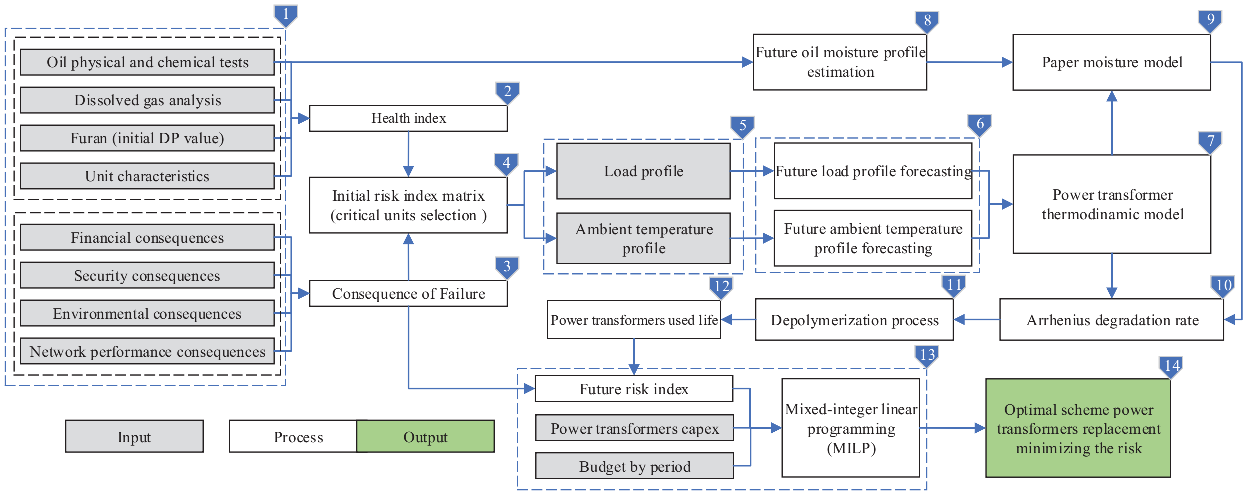

FIGURE 4 Multiperiod replacement optimization method in the long term for power transformers considering the risk index.

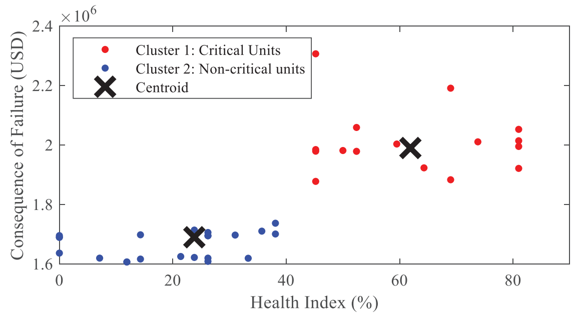

FIGURE 5 Risk matrix for 110 kV. Selection of the critical units.

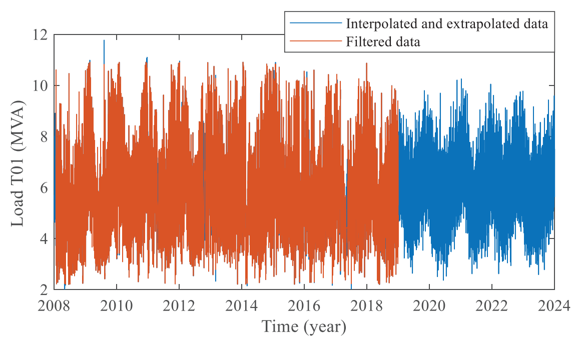

FIGURE 6 Load profile for T01.

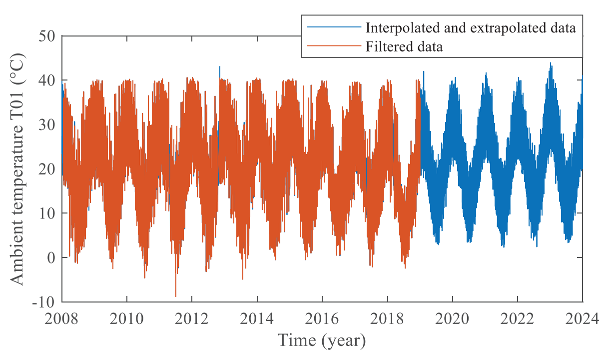

FIGURE 7 Ambient temperature profile of substation 1.

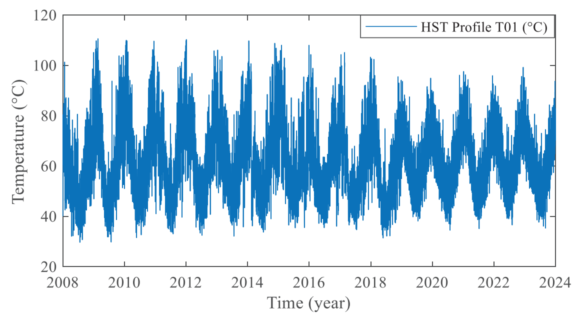

FIGURE 8 Hot spot temperature profile for T01.

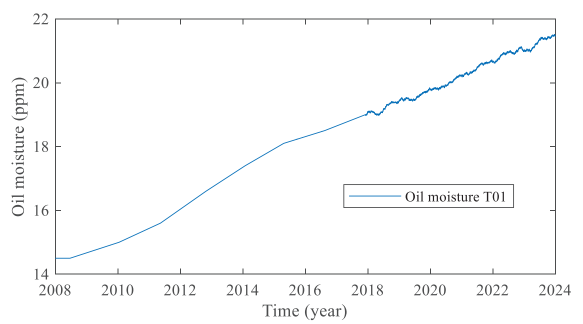

FIGURE 9 Oil moisture values interpolated and extrapolated for T01.

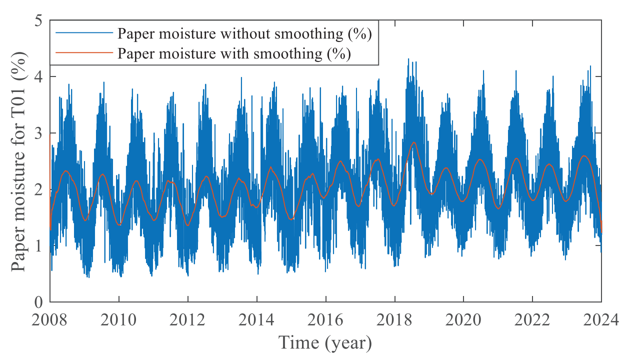

FIGURE 10 Paper moisture profile for T01.

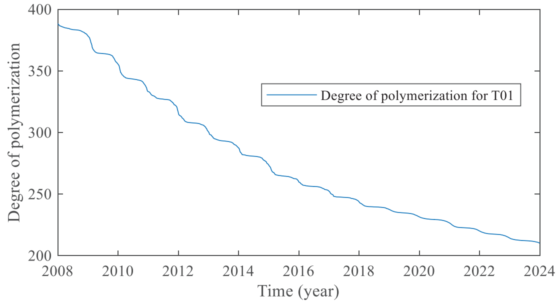

FIGURE 11 Arrhenius degradation for T01.

Step 12. Estimation of the UL of each unit under study, and entering the data obtained in the previous step following (6) and (7).

Step 13. Risk matrix uses the UL and the consequences of failure as the axes. The capex of the units and the budget of the company are also entered for the analysis period. With this information, the developed optimization model (9) is executed with the restrictions (10) to (13).

Step 14. The output information indicates the optimal long-term replacement strategy.

4 | CASE STUDY

4.1 | Case description

The methodology was applied to a power transformer fleet consisting of 102 units, of which 39 units have a nominal primary voltage of 110 kV and the remaining 63 have a nominal voltage of 34.5 kV. The results of the physicochemical tests, and the data for dissolved gases and furans, were collected from steps 1 to 4 in Figure 4. Then, the health index was calculated based on [37]. In parallel, its consequence factor was calculated and subsequently the risk matrix of the 102 units was plotted. The obtained values were grouped using MATLAB *k*-means, identifying that the group with the highest risk corresponds to the equipment with a nominal voltage of 110 kV. Therefore, *k*-means was applied again only for the 110-kV equipment, obtaining a total of 16 transformers with the highest risk index as shown in Figure 5. These were named as T01–T16.

Applying step 5, for each of the 16 critical transformers, the load and ambient temperature profiles were acquired for the period from 20 January 2008 to 01 January 2019 (approximately 11 years).

Next, from step 6, the load and ambient temperature profiles of the 16 transformers were interpolated and extrapolated based on Figure 2. For extrapolation, a future time of 5 years was considered, that is, the profiles were extrapolated until 01 January 2024 as it is shown for T01 in Figures 6 and 7.

After applying step 7, the hot spot temperature profile was estimated for each of the 16 critical transformers, obtaining the profile shown in Figure 8. In step 8, the moisture values of the oil were interpolated and extrapolated for each of the 16 units, obtaining the profile presented in Figure 9. Subsequently, in step 9, the moisture profiles of the paper were estimated, obtaining the profiles shown in Figure 10.

In step 10, the degradation of the solid insulation was estimated for each one of the 16 transformers under study with the information of the initial DP and using (4) and

TABLE 3 Useful life values.

	Date					
Unit	**1 January 2019**	**1 January 2020**	**1 January 2021**	**1 January 2022**	**1 January 2023**	**1 January 2024**
T01	0.82	0.83	0.85	0.86	0.87	0.88
T02	0.67	0.67	0.68	0.69	0.71	0.72
T03	0.83	0.89	0.91	0.92	0.94	0.95
T04	0.67	0.68	0.69	0.70	0.71	0.72
T05	0.84	0.87	0.89	0.92	0.95	0.97
T06	0.69	0.70	0.71	0.73	0.75	0.78
T07	0.66	0.68	0.70	0.71	0.73	0.75
T08	0.76	0.77	0.78	0.79	0.80	0.82
T09	0.72	0.73	0.74	0.75	0.77	0.78
T10	0.70	0.71	0.72	0.73	0.74	0.75
T11	0.70	0.71	0.72	0.74	0.76	0.77
T12	0.71	0.72	0.73	0.75	0.76	0.77
T13	0.71	0.72	0.73	0.75	0.76	0.78
T14	0.99	1.00	1.00	1.00	1.00	1.00
T15	0.74	0.76	0.77	0.80	0.82	0.84
T16	0.85	0.87	0.89	0.92	0.94	0.96

TABLE 4 Budget available for renovation of critical units.

Year	Increase (%)	Budget (USD)
2020	–	500,000
2021	2	510,000
2022	2	520,200
2023	2	530,604
2024	2	541,216

TABLE 5 Characteristics of critical units, Capex, and consequence of failure values.

Unit	Nominal voltage (kV)	Rated power (MVA)		Capex (USD)	*CoF* (USD)
		ONAN	ONAF		
T01	110/13.2	10	12.5	342,365	2,014,650
T02	110/34.5/13.8	21	30	708,357	2,003,712
T03	110/34.5	21	30	600,559	1,995,509
T04	110/34.5/13.8	21	30	708,357	2,011,004
T05	110/34.5/5.84	50	60	936,235	2,059,357
T06	110/34.5/5.84	50	60	936,235	2,052,976
T07	110/34.5/13.2	40	50	881,343	1,921,729
T08	110/34.5/13.2	40	58	908,156	1,923,552
T09	110/34.5/13.2	22.5	30	708,357	1,981,837
T10	110/34.5/13.2	22.5	30	708,357	1,985,027
T11	110/34.5	22.5	30	600,559	1,979,558
T12	110/13.2	20	25	511,925	1,883,533
T13	110/13.8	20	26/33	578,356	1,878,064
T14	110/34.5/13.2	20	25	602,299	1,979,103
T15	110/34.5	10	–	315,603	2,307,019
T16	110/34.5/13.8	21	30	708,357	2,191,442

(5). Figure 11 shows an example of the degradation obtained for T01.

In step 11, the annual values of the degree of DP were tabulated from 01 January 2019 to 01 January 2024, using the extrapolated values.

In step 12, (6) was applied for TUP or (7) for No-TUP, obtaining Table 3 that presents the tabulated useful life values for the extrapolated period.

Step 13 corresponds to the preparation of the input data required to run the optimization model. Therefore, in addition to the values of CoF calculated as indicated in [11] and UL per year (UL), the cost of the units and the budget of the company are necessary. This information is presented in Tables 4 and 5. Capex values were obtained based on [39].

CoF, consequence of failure.

Finally, the optimization results obtained in step 14 are presented in Table 6. It must be considered that the results are binary, that is, 0 represents that no action is performed and 1 implies performing the action presented by each option, according to Figure 12.

TABLE 6 Optimization results.

Unit	Option 1	Option 2	Option 3	Option 4	Option 5	Option 6
T01	1	0	0	0	0	0
T02	0	0	0	0	0	1
T03	0	0	0	1	0	0
T04	0	0	0	0	0	1
T05	0	0	0	0	0	1
T06	0	0	0	0	0	1
T07	0	0	0	0	0	1
T08	0	0	0	0	0	1
T09	0	0	0	0	0	1
T10	0	0	0	0	0	1
T11	0	0	0	0	0	1
T12	0	0	0	0	0	1
T13	0	0	0	0	0	1
T14	0	1	0	0	0	0
T15	0	0	1	0	0	0
T16	0	0	0	0	1	0

4.2 | Results and discussion

Table 7 shows the replacements that should be made and the evolution of the budget over time for each period.

Examination of the obtained results shows that the optimal replacement scheme is to first replace T01 in 2020. Then, T14 should be replaced in 2021. Subsequently, T15 should be replaced in 2022. Then, T03 should be replaced in 2023. Subsequently, the last equipment replacement should be carried out for T16 in 2024.

Finally, based on the optimization, the units T02, T04, T05, T06, T07, T08, T09, T10, T11, T12, and T13 shall not be replaced. This substitution scheme represents the lowest total risk index of the fleet for the case study with an IR value of 1.012×10^8.

5 | CONCLUSIONS

The UL estimation methodology allowed the estimation of the evolution of the degradation of the solid insulation as a function of time under the operating conditions of the PT.

Filtering of the load and ambient temperature profiles is a key step for obtaining an efficient method because the noise and the abnormal or zero values that are not filtered out decrease the performance of the proposed extrapolation model.

The NLPCA model can correctly extrapolate the shape of the signals in the future.

The optimization model allows for a technical and economic evaluation of the units of a power transformer fleet, supporting the asset manager in the design of investment strategies for future replacement through the analysis of the evolution of aging in long-term scenarios that consider the solid insulation,

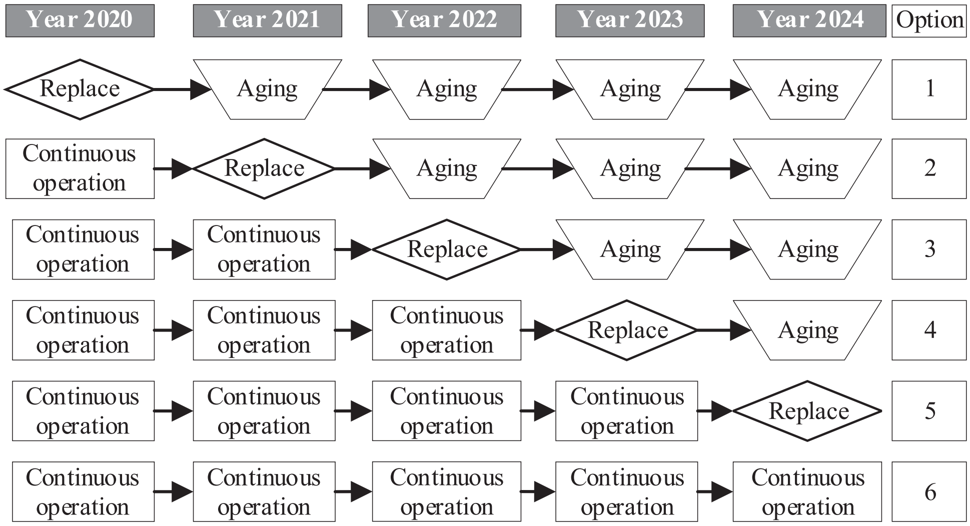

FIGURE 12 Replacement options scheme for each critical unit.

TABLE 7 Budget and execution of replacements for the case study.

Year	Initial budget (USD)	Replaced unit	Execution (USD)	Budget available after execution (USD)
2020	500,000	T01	342,365	157,635
2021	510,000	T14	602,299	65,336
2022	520,200	T15	315,603	269,933
2023	530,604	T03	600,559	199,978
2024	541,216	T16	708,357	32,837

the strategic importance of each unit, the cost of replacing equipment, and the available budget in order to minimize the total risk of the fleet.

AUTHOR CONTRIBUTIONS

Andrés Felipe Cerón Piamba: Formal analysis, investigation, methodology and writing—original draft. Andrés Arturo Romero Quete: Conceptualization, investigation, project administration, supervision and writing—review & editing. Guillermo Aponte Mayor: Conceptualization, investigation, project administration, supervision and writing—review & editing.

ACKNOWLEDGEMENTS

This work was supported by the Ministry of Science, Technology and Innovation of Colombia (MINCIENCIAS), under grant: BPIN 2021000100223—'Implementation of a digital platform to realize the value of the assets that belong to the electrical network of the archipelago of San Andres and Providencia'.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

ORCID

Andrés Felipe Cerón Piamba https://orcid.org/0000-0002-4820-776X

REFERENCES

1. Zhou, L., Hu, T.: Multifactorial condition assessment for power transformers. IET Gener. Transm. Distrib. 14(9), 1607–1615 (2020). https://doi.org/10.1049/iet-gtd.2019.0727
2. Duval, M., Pablo, A.D., Atanasova-Hoehlein, I., Grisaru, M.: Significance and detection of very low degree of polymerization of paper in transformers. IEEE Electr. Insul. Mag. 33(1), 31–38 (2017). https://doi.org/10.1109/MEI.2017.7804314
3. Martin, D., Watson, N.R.: Statistical analysis of Australian and New Zealand Power Transformer Catastrophic Fires. In: 2018 Condition Monitoring and Diagnosis (CMD) 2018 Proceedings, vol. (240 V), pp. 1–5 (2018). https://doi.org/10.1109/CMD.2018.8535670
4. Wijnia, Y.C.: Processing risk in asset management: exploring the boundaries of risk based optimization under uncertainty for an energy infrastructure asset manager. Eng. Syst. Serv. Sect. Energy Ind. Dr. Thesis, TUDelft, The Netherlands 240 (2016). https://doi.org/10.4233/uuid:e7fcf310-749f-4e4e-bbab-78eef99d0342
5. International Organization for Standardization (ISO): ISO 55000: Asset management — Overview, principles and terminology. www.iso.org, pp. 25 (2014)
6. Cerón Piamba, A.F., Orduña, I.F., Mayor, G.A., Romero Quete, A.A.: Panorama de la gestión de activos para transformadores de potencia. Inf. Tecnológica 26(3), 99–110 (2015). https://doi.org/10.4067/S0718-07642015000300014
7. Medina, R.D., Zaldivar, D.A., Romero, A.A., Zuñiga, J., Mombello, E.E.: A fuzzy inference-based approach for estimating power transformers risk index. Electr. Power Syst. Res. 209, 108004 (2022). https://doi.org/10.1016/j.epsr.2022.108004
8. Romero Quete, A.A., David, H., David, J., Moreno, G.: A practical method for risk assessment in power transformer fleets. DYNA 84(200), 11–18 (2017). https://doi.org/10.15446/dyna.v84n200.54364
9. Enders, J., Powell, W.B., Egan, D.: A dynamic model for the failure replacement of aging high-voltage transformers. Energy Syst. 1(1), 31–59 (2010). https://doi.org/10.1007/s12667-009-0006-5

10. Brandão, M.B.: Otimização de Investimentos para a Modernização da Rede Nacional de Transporte de Eletricidade. Diss. grau mestre em Eng. Eletrotécnica e Comput. Técnico Lisboa. Lisboa, Port. (2016)
11. Xu, Y., Li, Y., Wang, Y., Wang, C., Zhang, G.: Integrated decision-making method for power transformer fault diagnosis via rough set and DS evidence theories. IET Gener. Transm. Distrib. 14(24), 5774–5781 (2020). https://doi.org/10.1049/iet-gtd.2020.0552
12. Liang, G., Li, S., Qi, Y., Cao, J., Hao, Y., Chen, W.: A transformer replacement decision method based on probability assessment of failure rate. Energy Power Eng. 09(04), 748–755 (2017). https://doi.org/10.4236/epe.2017.94B080
13. Zareian Jahromi, M., Mehrabanjahromi, M.H., Tajdinian, M., Allahbakhshi, M.: A novel method to estimate economic replacing time of transformer using Monte Carlo algorithm and ANN. IIUM Eng. J. 19(2), 54–67 (2018). https://doi.org/10.31436/iiumej.v19i2.793
14. Ye, Z., Wu, K., Cheng, C., Song, W.: Replacement of aging power transformers considering system risks under multi-level load. In: IEEE Power Energy Soc. Gen. Meeting January 2018, pp. 1–5 (2018). https://doi.org/10.1109/PESGM.2017.8274472
15. Medina, R.D., Romero, A.A., Mombello, E.E., Rattá, G.: Assessing degradation of power transformer solid insulation considering thermal stress and moisture variation. Electr. Power Syst. Res. 151, 1–11 (2017). https://doi.org/10.1016/j.epsr.2017.04.006
16. Romero Quete, A.A., Mombello, E.E., Rattá, G.: Assessing the loss-of-insulation life of power transformers by estimating their historical loads and ambient temperature profiles using ANNs and Monte Carlo simulations. Dyna 83(197), 104 (2016). https://doi.org/10.15446/dyna.v83n197.48134
17. Mharakurwa, E.T., Nyakoe, G.N., Akumu, A.O.: Power transformer hot spot temperatures estimation based on multi-attributes. Int. J. Appl. Eng. Res. 14(7), 1584–1592, (2019)
18. Medina, R.D., Romero, A.A., Mombello, E.E., Ratta, G.: Comparative study of two thermal aging estimating methods for power transformers. IEEE Lat. Am. Trans. 13(10), 3287–3293 (2015). https://doi.org/10.1109/TLA.2015.7387233
19. Susa, D., Lehtonen, M.: Dynamic thermal modeling of power transformers: Further development - Part I. IEEE Trans. Power Deliv. 21(4), 1961–1970 (2006). https://doi.org/10.1109/TPWRD.2005.864069
20. Susa, D., Lehtonen, M.: Dynamic thermal modeling of power transformers: Further development — Part II. IEEE Trans. Power Deliv. 21(4), 1971–1980 (2006). https://doi.org/10.1109/TPWRD.2005.864068
21. Susa, D.: Dynamic thermal modelling of power transformers. Dr. Diss. Dep. Electr. Commun. Eng. Helsinki Univ. Technol. (2005)
22. International Electrotechnical Commission (IEC): IEC 60076–7 Power transformers - Part 7: Loading guide for mineral-oil-immersed power transformers (2018)
23. Institute of Electrical and Electronics Engineers (IEEE): IEEE C57.91 Guide for loading mineral-oil-immersed transformers and step-voltage regulators. IEEE Std C57.91-2011 (Revision of IEEE Std C57.91-1995), pp. 1–123 (2011). https://doi.org/10.1109/IEEESTD.2012.6166928
24. Cerón, A.F., Lozano, R.A., Aponte, G., Romero, A.A.: Hot spot temperature estimation in mineral oil immersed power transformers using support vectors regression. Inf. Tecnol. 31(4), 35–44 (2020). https://doi.org/10.4067/S0718-07642020000400035
25. Stevens, G.C., Emsley, A.M.: Review of chemical indicators of degradation of cellulosic electrical paper insulation in oil-filled transformers. IEE Proc. Sci. Meas. Technol. 141(5), 324–334 (1994). https://doi.org/10.1049/ip-smt:19949957
26. International Council on Large Electric Systems (CIGRE): Brochure 323. Ageing of celluose in mineral-oil insulated transformers. Task Force D1.01.10, p. 87 (2007)
27. Sen, P.K., Pansuwan, S.P.S.: Overloading and loss-of-life assessment guidelines of oil-cooled transformers. In: 2001 Rural Electric Power Conference. Paper Presented at the 45th Annual Conference (Cat. No. 01CH37214), pp. 1–8 (2001). https://doi.org/10.1109/REPCON.2001.949516
28. Stebbins, R.D., Myers, D.S., Shkolnik, a.B.: Furanic compounds in dielectric liquid samples: Review and update of diagnostic interpretation and estimation of insulation ageing. In: Proceedings of the 7th International Conference on Properties and Applications of Dielectric Materials (Cat. No.03CH37417), vol. 3, pp. 921–926 (2003). https://doi.org/10.1109/ICPADM.2003.1218572
29. Scholz, M., Kaplan, F., Guy, C.L., Kopka, J., Selbig, J.: Non-linear PCA: A missing data approach. Bioinformatics 21(20), 3887–3895 (2005). https://doi.org/10.1093/bioinformatics/bti634
30. Carreira-Perpiñán, M.Á., Lu, Z.: Manifold learning and missing data recovery through unsupervised regression. In: Proceedings - IEEE International Conference on Data Mining, ICDM, pp. 1014–1019 (2011). https://doi.org/10.1109/ICDM.2011.97
31. Gashler, M.S., Smith, M.R., Morris, R., Martinez, T.: Missing value imputation with unsupervised backpropagation. Comput. Intell. 32(2), 196–215 (2016). https://doi.org/10.1111/coin.12048
32. Ping, X.-O., Lai, F., Tseng, Y.-J.: Evaluation of imputation methods for missing data and their effect on the reliability of predictive models. In: The Sixth International Conference on Bioinformatics, Biocomputational Systems and Biotechnologies, pp. 8–14 (2014)
33. Mallat, S.: Chapter 1 - Sparse Representations. A Wavelet Tour Signal Process. Third Ed. Sparse W., pp. 1–31 (2008). https://doi.org/10.1016/B978-0-12-374370-1/00005-7
34. Pires, A.J.: Short-term load forecasting based on ANN applied to electrical distribution substations. IEEE Electr. Power Energy Conf. (I), 427–432 (2004)
35. Wang, X., Guo, P., Huang, X.: A review of wind power forecasting models. Energy Procedia 12, 770–778 (2011). https://doi.org/10.1016/j.egypro.2011.10.103
36. Weron, R.: Electricity price forecasting: A review of the state-of-the-art with a look into the future. Int. J. Forecast. 30(4), 1030–1081 (2014). https://doi.org/10.1016/j.ijforecast.2014.08.008
37. Zaldivar, D.A., Romero, A.A., Rivera, S.R.: Risk assessment algorithm for power transformer fleets based on condition and strategic importance. Algorithms 14(11), 319 (2021). https://doi.org/10.3390/a14110319
38. OFGEM: DNO Common Network Asset Indices Methodology version 2.1. no. April, (2021). [Online]. https://www.ofgem.gov.uk/sites/default/files/docs/2021/04/dno_common_network_asset_indices_methodology_v2.1_final_01-04-2021.pdf
39. Comision de Regulación de Energía y Gas (CREG): Resolución CREG 015 de 2018 - Metodología para la remuneración de la actividad de distribución de energía eléctrica en el Sistema Interconectado Nacional. pp. 239 (2018). [Online]. http://apolo.creg.gov.co/Publicac.nsf/1c09d18d2d5ffb5b05256eee00709c02/48a0d6c822f31e7005257deb00491afa/$FILE/Creg179-2014.pdf

How to cite this article: Cerón Piamba, A.F., Romero Quete, A.A., Aponte Mayor, G.: Methodology for scheduling long-term replacement of aging power transformers, considering risk. IET Gener. Transm. Distrib. 1–11 (2023). https://doi.org/10.1049/gtd2.12893