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Predictive Maintenance for Distribution System Operators in Increasing Transformers' Reliability

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Abstract: Power transformers' reliability is of the highest importance for distribution networks. A possible failure of them can interrupt the supply to consumers, which will cause inconvenience to them and loss of revenue for electricity companies. Additionally, depending on the type of damage, the recovery time can vary and intensify the problems of consumers. This paper estimates the maintenance required for distribution transformers using Artificial Intelligence (AI). This way the condition of the equipment that is currently in use is evaluated and the time that maintenance should be performed is known. Because actions are only carried out when necessary, this strategy promises cost reductions over routine or time-based preventative maintenance. The suggested methodology uses a classification predictive model to identify with high accuracy the number of transformers that are vulnerable to failure. This was confirmed by training, testing, and validating it with actual data in Colombia's Cauca Department. It is clear from this experimental method that Machine Learning (ML) methods for early detection of technical issues can help distribution system operators increase the number of selected transformers for predictive maintenance. Additionally, these methods can also be beneficial for customers' satisfaction with the performance of distribution transformers, which would enhance the highly reliable performance of such transformers. According to the prediction for 2021, 852 transformers will malfunction, 820 of which will be in rural Cauca, which is consistent with previous failure statistics. The 10 kVA transformers will be the most vulnerable, followed by the 5 kVA and 15 kVA transformers.

Keywords: distribution system; distribution transformers; k-means clustering; machine learning; maintenance planning; predictive maintenance

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1. Introduction

Power distribution transformers are crucial parts of power system equipment because they regulate the voltage to various levels on the system components from the generator to the final consumer [1]. Temporary or permanent failure of a transformer interrupts the power supply to end users, causing them problem in their work or everyday life activity. Additionally, the market value of the transformers is high enough, and any possible malfunction in them causes additional expenses to the Distribution System Operators (DSOs). It is essential to prevent potential failures and aid in the early detection of issues to prevent unplanned outages and maintain transformer operation reliability. These failures may cause extensive outages or even blackouts, affecting both the transmission [2] and distribution system [3]. Therefore, monitoring systems that consider the weather conditions with an energy management system must be integrated in the distribution system [4].

In recent research works, efficient allocation strategies have been proposed that can be also applied to power transformers. These strategies lead to the optimal target, according to the technical state of the art, allowing assignment of a failure rate target to different units and then to reach the desired reliability goals for the whole system. In [5], a guideline to determine the appropriate allocation method in relation to the chosen application, available resources, and needed accuracy is presented. In [6], a novel method is focused on the adequate distribution of maintenance budget to system units according to the primary variables impacting availability and maintenance of equipment. The manufacturing sector's decision-making procedures are being transformed by Industry 4.0 technology [7], where important maintenance policy trends include "remote maintenance" and the "autonomous maintenance".

Some reasons for insulation failure in transformers are overload conditions for long durations, overvoltages, overcurrents, and failure of cooling equipment [8]. Hence, power utilities consider the health assessment of transformers to be a crucial factor to have a dependable and effective operation [9]. Each unplanned power outage of a transformer results in financial losses for both the owner of the transformer and the energy consumers it supplies. Therefore, it is critical to identify any signals that could point to a potential transformer defect as soon as possible. No matter where the transformer installation is located, effective diagnostic procedure selection and accurate interpretation of the findings of various types of measurements are required.

In [10], a single-phase transformer's physical geometrical dimensions are modeled using 3D finite element analysis to mimic the operation of a real transformer. The paper in [11] describes the creation and use of a technology for the analysis of dissolved gases in oil for the identification of defects in power transformers. The work in [12] provides an expert system made to perform insulation diagnostics, and other researchers in [13] discuss the state and most recent developments in several power transformer diagnostic approaches. The purpose of [14] is to describe, analyze, and explain current physicochemical diagnostic procedures for evaluating the insulation state in old transformers. Under on-site operating settings, the proposed methodology in [15] enables quick, accurate, and secure partial discharge (PD) diagnostics in a power transformer. A Fourier transform infrared (FT-IR) spectrometer was used to construct an analytical instrument in [16], while [17] addresses the issue of on-line dissolved gas analysis (DGA) of a power transformer. Researchers in [18] investigate and contrast traditional and intelligent DGA interpretation techniques.

Data mining is one method used to develop fault prediction models. Data mining is a complex technique that includes both computer science and statistics to uncover hidden, undiscovered, and possibly important information from huge databases [19]. Data mining comprises several techniques that can be applied on varying datasets. Classification and regression are the two methods that are most frequently used in the development of predictive models, according to [20]. Classification classifies each item in a data set into one of the predefined classes or groups [21].

The major goal of maintenance is to minimize malfunctions and maintain the functionality of the system. Maintenance aims to cut down failures that may happen during regular equipment operation [22]. An unanticipated production delay, decreased efficiency, and occasionally other consequences might result from equipment failure. Reactive, preventive, predictive, and prescriptive maintenance procedures are all combined into effective maintenance [23]. Only when a functional failure is brought on by the function's deterioration are repairs or replacements considered reactive maintenance. The routine examination, alterations, cleaning, replacement of parts, and component repairs make up preventive maintenance. To evaluate the state of the equipment, predictive maintenance employs nonintrusive testing methods, visual inspection, performance data, and data analysis. Through better design, installation techniques, failure analysis, and scheduling, prescriptive maintenance improves equipment condition and rate of degradation [22]. All maintenance strategies are analytically presented in Figure 1.

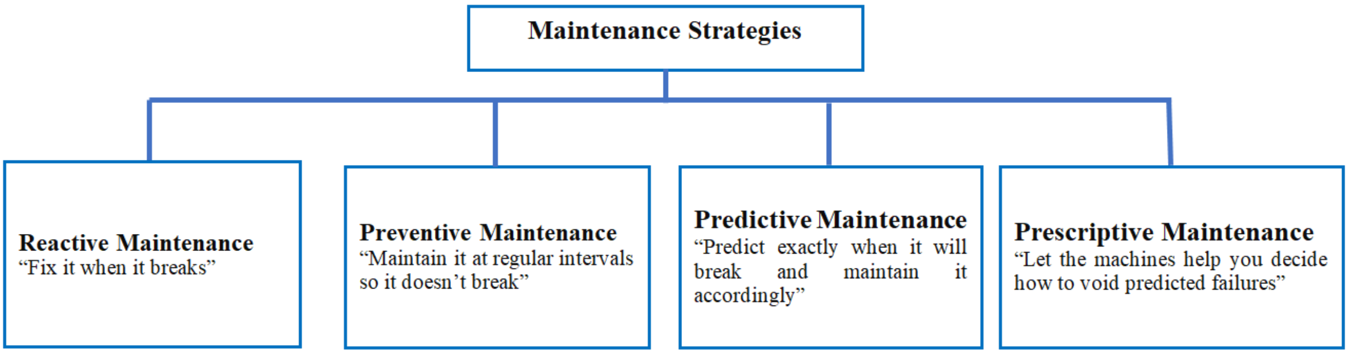


Figure 1. Maintenance strategies.

It is feasible to suggest cost reduction, machine failure and repair reduction, and inventory reduction methods through the treatment and analysis of these data [24]. Artificial Intelligence (AI)-based methods are some of the technologies used to examine the vast amount of data available [25]. In order to increase the power transformer's reliability, data communication, storage, and acquisition systems must be more reliable. Additionally, massive amounts of monitored data from intelligent devices must be analyzed. The ability of contemporary power systems to gather and retain enormous volumes of data from their constituent parts is advancing [26]. For the creation of scalable, adaptable, and pluggable data analysis and real-time self-monitoring systems for manufacturing environments, the suggested Intelligent Data Analysis and Real-Time Supervision (IDARTS) architecture is presented in [27].

Similar problems are tackled internationally using a variety of optimization strategies, including neural networks optimized by Genetic Algorithm (GA) and Fuzzy c-Means [28] or with self-adaptive strategies for diagnosing fault problems in transformers [29], with the drawback of requiring a heavier processing burden because of the deployed neural network. Fuzzy logic, developed by [30], is another tool for making decisions. According to [31], there are optimization techniques, such as linear programming, that use an objective function in order to maximize or reduce a result. Determining this objective function might be challenging in complicated systems, where it is unclear how the variables are related.

According to data from Compania Energetica de Occidente, 1297 transformers burned in 2016; replacement required substantial expenses and power supply disruptions [32,33]. There have been several recorded causes of burning, including atmospheric discharges, third-party manipulation, overload, and lack of secondary distribution line trimming. By eliminating superfluous repair tasks and fewer unexpected power outages, developing preventive maintenance plans can help cut costs. Due to the unpredictable nature of the dataset, this study suggests using ML methods as a classification strategy. Using these methods, it is possible to categorize and rank maintenance needs according to business requirements.

There have been plenty of research works on transformers predictive maintenance using various techniques. However, most of the research to date has been on the degradation of oil alone using dissolved gas analysis (DGA) for transformer health index assessment, whereas the integrated model for fault diagnosis using other diagnostic data has received little attention [9,10,12–14]. Major types of faults [18,20] include high- and low-energy arcing, partial discharge, and hot patches with a range of temperatures, but if negligent implementation is used, there is no region for a normal aging condition that might lead to a diagnostic of any of the faults. To avoid these issues, researchers collected different types of data than the insulating oil parameters for the power distribution transformers from the Compania Energetica de Occidente [32,33]. The variables were binary, continuous and categorical, such as the keraunic-level criticality or the earth discharge density. The authors proposed an AI technique for scheduling predictive maintenance of the power distribution transformers. The aim of this work is to propose a new methodology for the same prediction with higher prediction ability. With more accurate prediction of transformer failures, the reliability of the distribution system will be higher, providing more satisfied customers and fewer expenses for the DSO, both for maintenance or replacement of the power distribution transformers.

The motivation for this study comes from the need to improve the reliability of power transformers in distribution networks. Transformer failures can cause significant disruptions to the distribution network and result in costly outages and repairs. By enabling predictive maintenance through accurate failure prediction, distribution system operators can reduce the probability of transformer failures and minimize the impact of any failures that may occur. The research question of this paper was to investigate whether the proposed model can accurately predict transformer failures and thus enable distribution system operators to perform predictive maintenance increasing the reliability of their transformers.

The main contributions of this paper are as follows:

- Introducing a predictive maintenance approach for distribution system operators to increase the reliability of transformers;
- Proposing a novel model for predicting transformer failures that outperforms existing models;
- Demonstrating the effectiveness of the proposed approach through a case study on an existing distribution network.

The main advantages of using models to solve the problem of transformer failure prediction include:

- Increased accuracy: Models can often predict transformer failures with higher accuracy than traditional rule-based approaches.
- Early detection: Models can detect potential failures before they occur, enabling distribution system operators to perform preventive maintenance to avoid outages and costly repairs.
- Scalability: Models can be applied to large-scale distribution networks to identify potential failures across many transformers simultaneously.

The structure of this work is as follows. In Section 2, the most common transformer failures are discussed, while in Section 3 the model description is presented. The data collection and description of the data is reviewed in Section 4. Then, in Section 5, two different strategies for early MS detection are discussed: supervised learning using support vector machines (SVM) and non-supervised learning using k-means clustering. In Section 6, the proposed methodology estimates the predicted number of transformers that will present malfunction in the future. The concluding notes are provided in the two last sections.

2. Common Transformer Failures

The failure of a power distribution transformer may happen due to internal causes inside the transformer [34] or due to environmental conditions such as lightning. In [35], an effort was made to use an online overvoltage monitoring system to acquire the waveform characteristics of encroaching lightning impulses in power transformers. In another paper [36], a 35 kV distribution transformer that had been struck by lightning was used as the study object to determine the electromagnetic transient and the protective measures that should be taken for transformers when struck by lightning. In [37], the lightning protection of high-voltage transmission lines was approached as an optimization problem where optimal design parameters are calculated for the lines, relating their cost with the lightning failures' cost, aiming to reduce or even eliminate lightning failures. Another research team examines the developed overvoltages at the entrance of a distribution substation, due to lightning strike to the connected line, and computes them while considering various configurations [38]. Using the primary–secondary islanding technique for controlling the distributed generation units during grid-connected and islanding operation due to various causes, such as lightning, another work discusses the viability of planned islanding operation and looks into the impact of unplanned islanding [39].

Another factor that may affect a power transformer is extreme weather conditions. In [40], a risk assessment is performed, proving that incorporating load management in asset planning is a viable measure that would offset the probability of catastrophic failure of geomagnetic disturbances. Ref. [41] covers some of these impacts on the electric power system, specifically distribution transformers and underground cables, while [42] examines power quality issues in the distribution system. The primary components of the distribution transformer are the terminals of the magnetic and electrical circuits, the bushings, the tank, the oil, the radiator, the conservator, and the breather. Any of the components listed below that are failure-prone can cause the transformer to malfunction. Within the text each reference to the word "burned" is related to at least one of the malfunctions that are analytically described in 2.1 to 2.6. A typical power distribution transformer is depicted in Figure 2.

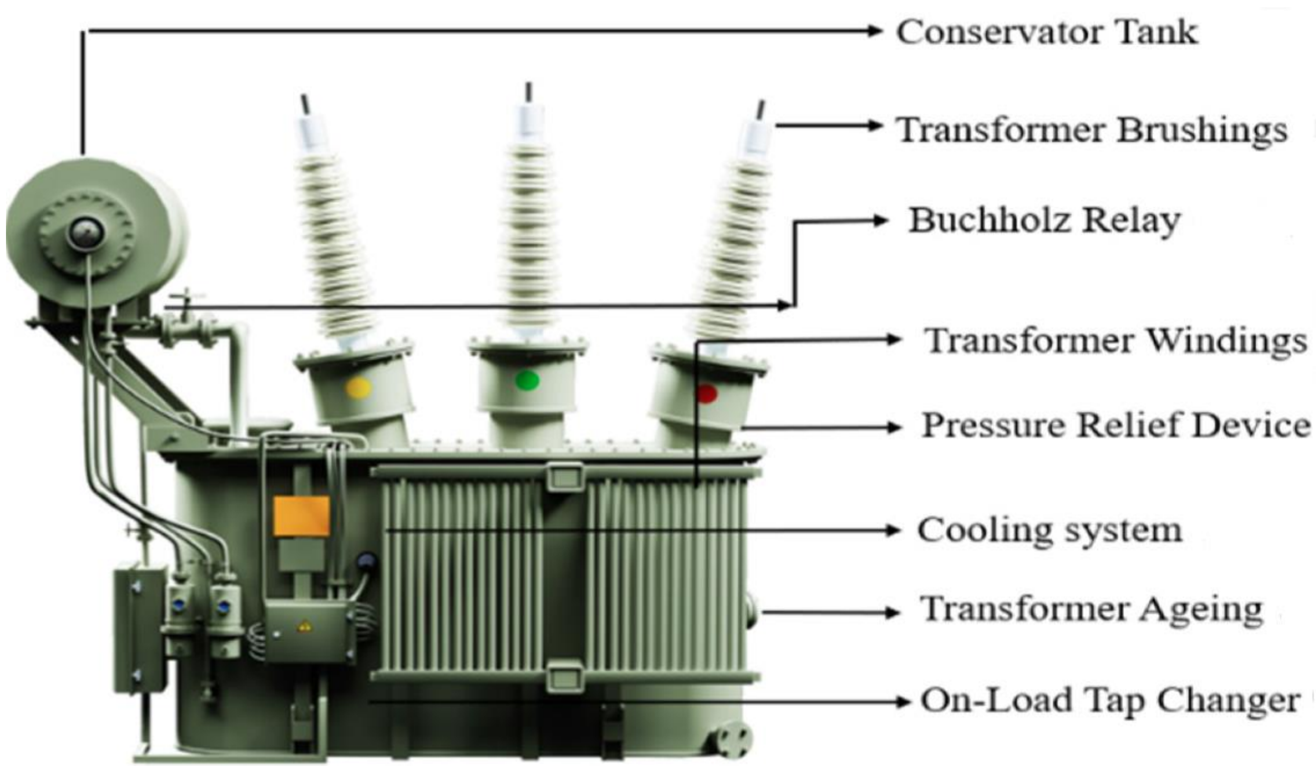


Figure 2. A typical power distribution transformer.

2.1. Core

The transformer's core both conducts magnetic flux and gives it mechanical strength. DC magnetization or displacement of the core steel during the transformer's construction are the two main causes of core failure.

2.2. Winding

The transformer's windings, which are positioned around the core limb as cylindrical shells, are responsible for carrying the current. Each strand of each winding is covered with paper insulation. The windings must be able to endure mechanical forces that can induce winding displacement in addition to dielectric stress and temperature requirements. These forces can manifest during lightning and short circuits. Most winding failures are caused by transient overvoltage or short circuit. The creation of hot spots, the production of copper sludge, low oil levels, or mechanical flaws in the windings during transformer construction are a few examples of the causes of winding short circuits. Transient overvoltage may be caused by lightning or improper transformer connection.

2.3. Tank

The tank physically protects the transformer core and windings and serves as a container for the cooling oil. It must be able to tolerate environmental pressures including solar rays, corrosive air, and high humidity. The tank is examined for leaks, corrosion, and other signs of abusive handling. A transformer's internal arcing can rapidly evaporate the surrounding oil, creating a high pressure inside the transformer that can cause the tank to break.

2.4. Solid Insulation

For electrical isolation, press board and paper formed of cellulose are employed as solid insulation between the windings. Long chains of glucose rings make up the structure of cellulose, which breaks down over time to form shorter chains. The average number of these rings in the chain, or degree of polymerization (DP), serves as a proxy for the condition of the paper [43].

The transformer insulation system's most vulnerable point is this sturdy insulation. Forces produced during short circuits or by the movement of the transformer can mechanically damage solid insulation. $CuSO_4$ production, hot spots produced by insufficient oil, or overloading of the transformer can all cause faults in insulating materials.

2.5. Insulation Oil

Insulation between the windings and the desired cooling of the transformer are both provided by the transformer oil [44]. There are two causes of cooling oil failure: either improper oil circulation or inadequate transfer of heat to the cooling circuit. As a result, the oil in the transformer becomes more viscous and the temperature in the cooling circuit becomes too high. The main factor for oil contamination and the production of conducting particles is moisture and oxygen combined with heat. As a result, the temperature inside the transformer will increase, and a short circuit will result from the oil insulation failing.

2.6. Bushings

To connect the transformer to the power system, bushings remove the winding terminals from the tank's outside and cover them with electrical insulation. Sliding bushings and capacitance graded bushings are the two main types of bushings employed. A center conductor and insulation made of porcelain or epoxy surround the solid bushing. Short circuit is the primary bushing failure mode. It can be a result of damage or insulation material flaws. Sabotage, shipment, or flying parts from other malfunctioning equipment can all cause damage. Damages, porcelain cracks, and faulty gaskets allow water to enter the bushing's insulation, which causes the bushing to fail.

3. Model Description

Computers are taught to learn from experience using ML, much as people do naturally. ML techniques do not rely on a mathematical model to describe the data; instead, they employ computational methods to learn information from the data. In general, AI has been applied in a great variety of technical problems. For example, the electromagnetic field prediction of electrostatic discharges can be conducted either by ML techniques [45] or by developing an ANN tool [46]. A heuristic technique for lowering the frequency of high-voltage substation outages caused by atmospheric overvoltages is presented in [47]. As the amount of data available for learning rises, they adaptively improve at performing their tasks. Optimized and predictive maintenance strategies are evolved to improve power availability for consumers [48]. Although SVM and k-means clustering are well-known techniques, their efficiency varies depending on the dataset and situation at hand. As a result, it is critical to assess their performance on an individual basis. We intended to compare the performance of these algorithms on a specific dataset and problem in this work, which we feel would be beneficial to people working in this area. Our findings show that our suggested model generation strategy based on k-means clustering outperformed the classic SVM method on our dataset in terms of classification accuracy [49]. Other researchers find that preventive maintenance has been proven effective in improving the continuity of service and reliability of customers [50]. The new method has higher accuracy and efficiency in predicting highlight dates' load rates and is used from [51].

To justify the use of numerical modeling in this study, several previous works have successfully employed this approach for analyzing transformer performance. For example, in one study [52], a numerical simulation was used to investigate the effects of different operating conditions on transformer oil temperature and winding hot spot temperature. Another study [53] utilized a finite element method to analyze the effect of thermal aging on the insulation properties of transformers. Additionally, a paper by [54] presented a numerical model for predicting the partial discharge inception voltage of power transformers. These previous works demonstrate the effectiveness and validity of using numerical modeling in transformer performance analysis, which justifies its use in this paper as well. Overall, the numerical modeling used in this study involves the development and training of an Artificial Neural Network (ANN) model using historical maintenance records and operational parameters, as well as the evaluation of the model's performance using various performance metrics.

There are several ML algorithms that can be used for predictive maintenance of transformers. Some examples include:

1. Regression algorithms: Linear and non-linear regression algorithms can be used to predict when a transformer component is likely to fail using multiclass classification [55] or ANN [56]. These algorithms can analyze historical data from sensors and other sources to identify patterns that indicate a component is nearing the end of its useful life.
2. Random Forest: Random Forest is an ensemble ML algorithm that can be used to predict the remaining useful life of transformer components [57]. It creates a set of decision trees and uses the majority vote of these decision trees to predict the outcome [58].
3. Gradient Boosting: The Gradient Boosting algorithm uses an ensemble of weak models, such as decision trees, to predict the remaining useful life of transformer components [59]. It works by iteratively adding new models to the ensemble and adjusting the weights of the previous models [60].
4. Deep Learning: Deep learning algorithms, such as convolutional neural networks and recurrent neural networks, can be used to analyze sensor data and predict when a transformer component is likely to fail [61]. These algorithms can learn to detect patterns in the data that are not visible to humans [62].
5. Anomaly Detection: Unsupervised ML algorithms such as One-Class SVM, Isolation Forest, and Autoencoder can be used to detect anomalies in the data, indicating a failure [63]. These algorithms can detect patterns in the data that are not visible to humans.
6. Predictive modeling: Predictive modeling algorithms such as the Markov Chain Monte Carlo (MCMC) [64] and Bayesian networks [65] can be used to predict the remaining useful life of transformer components. These algorithms use probabilistic models to estimate the likelihood of a failure occurring [66].

Overall, using ML algorithms for predictive maintenance of transformers can help to improve the efficiency, effectiveness, and reliability of the maintenance process. By analyzing data from sensors and other sources, ML algorithms can predict when maintenance is needed, optimize maintenance schedules, and identify the root cause of problems, thus improving the overall performance of the transformer model.

We have included these algorithms in the methodology section to provide a comprehensive overview of the different methods available for predictive maintenance of transformers. The inclusion of these methods may serve as a basis for future research and comparison with other approaches in the field.

In this paper, we used the k-means clustering algorithm to group transformers based on their behavior patterns and characteristics. We then used Support Vector Machine (SVM) as a machine learning algorithm to develop a predictive model to identify which transformers are at risk of failure. The SVM algorithm was trained on clustered data to predict the probability of failure for each transformer. We also evaluated the performance of the predictive model using metrics such as accuracy, precision, and recall. The results showed that the predictive model was able to identify the transformers at risk of failure with high accuracy and precision.

The use of machine learning algorithms such as k-means clustering and SVM can significantly improve the reliability and efficiency of transformer maintenance, reducing costs and minimizing outages.

k-means clustering is an unsupervised ML algorithm that can be used for the predictive maintenance of transformers. The general process for using k-means clustering for predictive transformer maintenance is as follows:

1. Data collection: Collect data from sensors and other sources that can be used to train the k-means clustering algorithm. This data could include information about the transformer's operating conditions, such as temperature, voltage, and current, as well as information about the transformer's components, such as the age and condition of the components. Additionally, these data could include the transformer's type, the location of its installation, the environmental conditions to which it is exposed, etc.
2. Data preprocessing: Prepare the data for use in the k-means clustering algorithm by cleaning and preprocessing them. This includes removing missing or duplicate data, normalizing the data, and transforming them into a format that can be used by the algorithm.
3. Feature selection: Select the features that will be used by the k-means clustering algorithm to group similar transformer components together. This includes selecting a subset of the available features or creating new features by combining or transforming existing features.
4. Clustering: Apply the k-means clustering algorithm to the preprocessed data to group similar transformer components together. The algorithm partitions the data into k clusters, where k is the number of clusters chosen.
5. Cluster evaluation: Evaluate the performance of the k-means clustering algorithm. This can be performed by measuring the quality of the clusters, such as by using the silhouette score, or by comparing the clusters to the labeled data if available.
6. Model deployment: Once the model has been trained and evaluated, it is deployed for use in the predictive maintenance process. This includes using the clusters to identify groups of similar transformer components that are likely to fail at the same time, and scheduling maintenance accordingly.
7. Model retraining: Retrain the model over time to account for new data and changes in the transformer's operating conditions. This helps to improve the accuracy of the predictions over time.

We used the k-means clustering algorithm in methodology for predictive transformer maintenance. The k-means clustering algorithm is used to group transformers based on their behavior patterns and characteristics. We used k-means clustering to identify groups of transformers that share similar characteristics, such as number of users, type of clients and electric power not supplied.

The k-means algorithm is an iterative process that involves the following steps:

- Initialization: Randomly select k data points as initial centroids.
- Assignment: Assign each data point to the nearest centroid.
- Recalculation: Recalculate the centroid of each cluster.
- Iteration: Repeat steps 2 and 3 until convergence.

In the case of our methodology, we initialized k (the number of clusters) based on the elbow method to find the optimal number of clusters. We then assigned each transformer to the nearest centroid and recalculated the centroid of each cluster. The process continued until the algorithm converged.

The k-means clustering algorithm helps us to identify which transformers are more likely to fail and which ones are performing well by grouping them based on their characteristics and behavior patterns. This information is then used to develop a predictive model that can identify which transformers are at risk of failure and require maintenance, allowing for proactive maintenance to prevent downtime and extend the life of the transformers.

Figure 3 displays the flowchart for the proposed model. For various values of K, Figure 3 depicts the average clustering accuracy of the suggested model creation technique utilizing k-means clustering (the number of clusters). The accuracy rose with rising K values, which is consistent with the iterative refining process of the k-means algorithm. Initial centroids are picked at random in stages 1–3 of the process, and data points are allocated to the nearest centroid. Steps 4–6 update the centroids to represent the mean of the data points allocated to each cluster. The method iterates through stages 4–6 until convergence is obtained in step 7. The findings in Figure 3 indicate that our suggested strategy of building models using k-means clustering can improve classification accuracy.

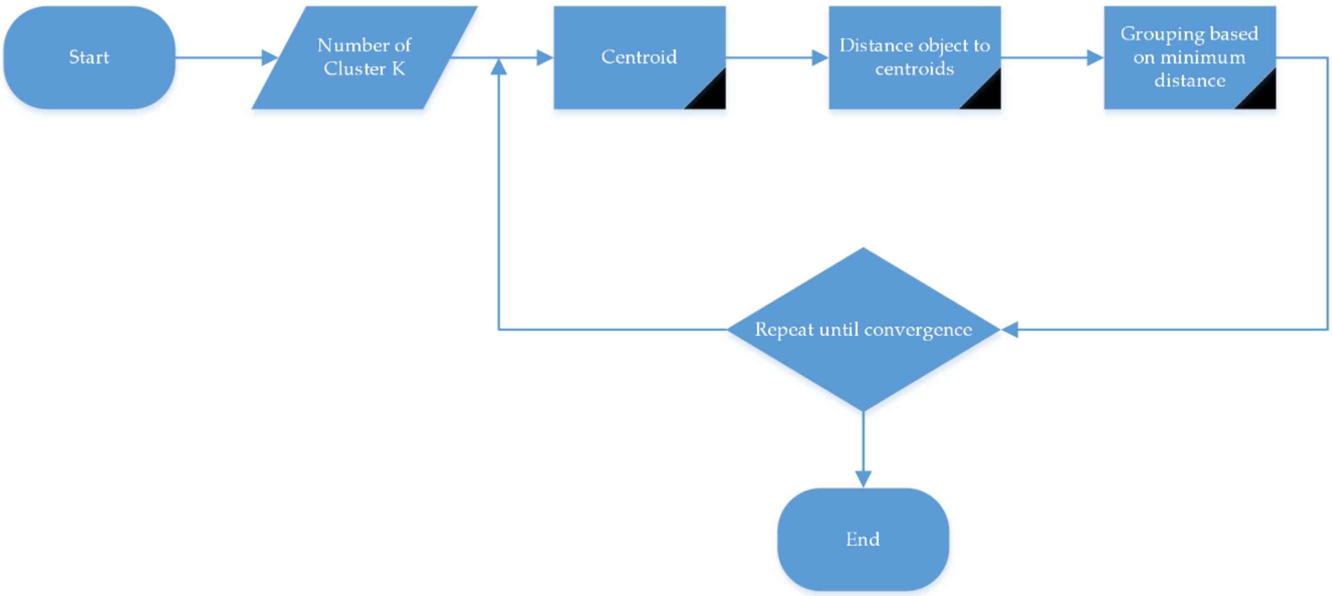


Figure 3. Flowchart of the proposed model.

Overall, using k-means clustering for predictive maintenance of transformers can help to improve the efficiency, effectiveness, and reliability of the maintenance process. By grouping similar transformer components together, the k-means clustering algorithm can help to identify groups of components that are likely to fail at the same time and schedule maintenance accordingly, thus improving the overall performance of the transformer model.

SVMs are a type of supervised ML algorithm used for classification and regression tasks. The goal of an SVM is to find a hyperplane that separates the data into different classes, or in the case of regression, to find the best hyperplane that fits the data.

The basic idea behind an SVM is to find a hyperplane that maximally separates the data into different classes. The equation of this hyperplane is represented as:

$$\mathrm{w} \cdot \mathrm{x} + \mathrm{b} = 0 \quad (1)$$

where w represents the weights of the features, x represents the input features, and b represents the bias term. The weights and bias are learned during the training process.

SVMs also have a concept of margin, which is the distance between the hyperplane and the closest data points from each class, called support vectors. The objective of an SVM is to find the hyperplane with the largest margin.

The optimization problem for an SVM can be represented as:

$$minimize\left(\frac{1}{2}\right)\cdot\|w\|^2 \tag{2}$$

Subject to:

$$\mathrm{y}\cdot(\mathrm{w}\cdot\mathrm{x}+\mathrm{b}) \geq 1 \text{ for } \mathrm{i}=1,2,\ \ldots,\mathrm{n} \tag{3}$$

where n is the number of data points, y is the class label (-1 or 1), and $\|w\|$ is the norm of the weights.

The above optimization problem is a quadratic programming problem and can be solved using optimization techniques such as Sequential Minimal Optimization (SMO).

In the case of non-linearly separable data, SVMs use the kernel trick to map the data into a higher dimensional space where the data become linearly separable. The kernel function is represented as:

$$\mathrm{K}(\mathrm{x},\mathrm{y}) = \varphi(\mathrm{x})\cdot\varphi(\mathrm{y}) \tag{4}$$

where φ is a mapping function that maps the input data into a higher dimensional space, and K(x, y) is the dot product of the mapped data. Some commonly used kernel functions are the linear, polynomial, and radial basis function (RBF) kernels.

k-means clustering is an unsupervised ML algorithm that is used to group similar data points together into clusters. The goal is to partition the data into k clusters, where k is the number of clusters chosen.

The basic idea behind k-means clustering is to find k cluster centroids, which are the mean value of the data points in each cluster. These centroids are used to define the boundaries of each cluster. The algorithm iteratively assigns each data point to the cluster whose centroid is closest to it, and then updates the centroids based on the new assignment of points.

The process of k-means can be formalized in the following steps:

1. Initialize k centroids randomly: The k centroids are initialized randomly from the data points.
2. Assign each data point to the nearest centroid: Each data point is assigned to the cluster whose centroid is closest to it. This can be completed by calculating the Euclidean distance between the data point and each centroid.
3. Update the centroids: The centroid of each cluster is updated by taking the mean of all the data points assigned to that cluster.
4. Repeat steps 2 and 3 until the centroids do not change anymore or a stopping criterion is reached.

The algorithm can be mathematically represented by the following:

1. Initially, k centroids are chosen randomly from the data points. Let the k centroids be represented by $c_1, c_2, \ldots, c_k$
2. Assign each data point x to the closest centroid, which can be represented by:

$$\operatorname{argmin}(1 \leq \mathrm{j} \leq \mathrm{k})\|\mathrm{x}-\mathrm{c_i}\|^2 \tag{5}$$

3. Update the centroids by taking the mean of all the data points assigned to that cluster.

$$\mathrm{c_j} = \left(\frac{1}{\mathrm{n_i}}\right)\cdot\sum_{\mathrm{j}}^{1}\mathrm{x}(\mathrm{j}) \tag{6}$$

4. Repeat steps 2 and 3 until the centroids do not change anymore or a stopping criterion is reached.

Figure 4 depicts a thorough block diagram presenting the suggested methodology's flow and the interconnections between its many components.

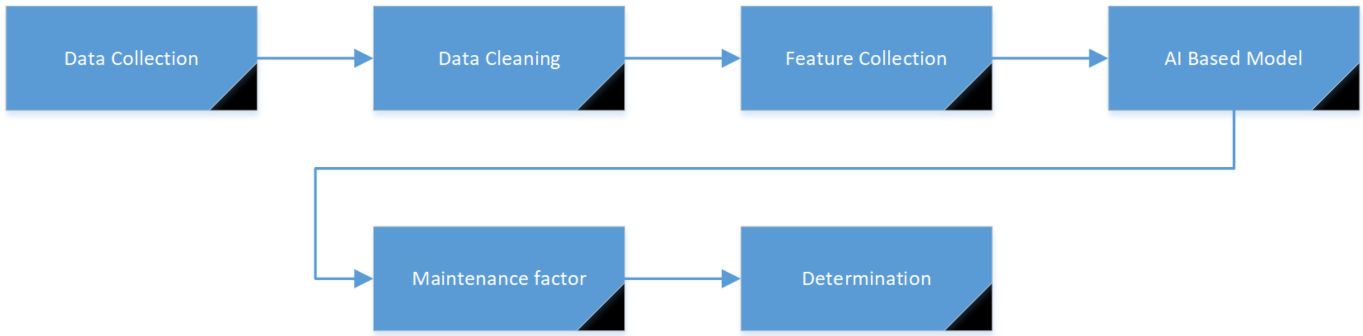


Figure 4. Block diagram of the proposed methodology.

As machine learning techniques become more prevalent in various fields, the evaluation and validation of these techniques have become increasingly important. Performance metrics such as root-mean-square error (RMSE), mean absolute error (MAE), and root-mean-square deviation (RMSD) are commonly used to evaluate the accuracy of machine learning models [67].

Furthermore, the use of machine learning techniques, such as ANNs, has been found to be effective in predicting the remaining useful life (RUL) of various engineering systems, including transformers [68]. In addition, previous studies have demonstrated the effectiveness of ANNs [69] in predicting transformer faults and estimating the remaining life of transformers [70]. Our proposed AI-based model is based on an ANN approach and is tailored to the specific problem of determining the maintenance factor for distribution transformers. The presented approach in this work is well-justified and will provide a significant improvement over existing methods.

This paper proposes a methodology that uses k-means clustering and Support Vector Machine (SVM) algorithms for predictive maintenance of transformers. Its main advantages are:

- Non-linear relationships: The SVM algorithm can capture non-linear relationships between the input features and the output labels, which is useful when dealing with complex systems like transformers.
- Scalability: k-means clustering is computationally efficient and can handle large datasets, making it suitable for industrial applications with large amounts of data.
- Interpretable results: k-means clustering provides interpretable results that can be visualized in the form of clusters, which can help engineers understand the underlying patterns in the data.

Despite the above-mentioned advantages, the proposed methodology also has some limitations compared to other methods. These main disadvantages are as follows:

- Feature engineering: The performance of the SVM algorithm is highly dependent on the quality and relevance of the input features. This requires significant effort and expertise in feature engineering, which may not be available in all applications.
- Sensitivity to hyperparameters: Both k-means clustering and SVM require tuning of hyperparameters, such as the number of clusters and regularization parameter, respectively. The performance of the model can be sensitive to these hyperparameters, and selecting optimal values requires careful experimentation.
- Limited to labeled data: The SVM algorithm is a supervised learning method and requires labeled data for training. This can be a limitation in applications where labeled data are scarce or expensive to obtain.

The specific needs for a custom initialization method depend on the specific characteristics of the proposed model, such as the number and type of layers, the activation functions used, and the size of the input and output layers. In addition, the specific data used to train the model also influence the choice of initialization method. For example, if a section of the data is highly unbalanced or noisy, a custom initialization method is designed to help address these issues. Ultimately, the specific needs for a custom initialization method depend on the details of the model and data used in the study.

Some potential disadvantages of using a customized initialization method include the increased complexity and time required to develop and implement the method, as well as the possibility that the customized method may not generalize well to other datasets or models. Additionally, if the customized method is not carefully designed or implemented, it may lead to over fitting or under fitting of the model, which can negatively impact its performance. It is also possible that the customized method may not result in significant improvements over standard initialization methods, in which case the additional effort and complexity may not be justified.

4. Distribution Transformers Data at Cauca Department of Colombia

In the current work, AI techniques have been applied on open access data [15] that other researchers have similarly used to predict future malfunctions of the distribution transformers, helping them to create their maintenance schedule. A total of 15,873 distribution transformers of the Cauca Departments of Colombia are included in the data chosen for the analysis presented in this work [71].

These distribution transformers located in the rural and urban areas of the 42 municipalities are connected to the operator's network at voltage levels of 13.2 kV and 34.5 kV. There are 13,112 transformers in the urban areas and 2761 in the rural areas. In Table 1, the names and classification of variables for the dataset of distribution transformers of the Cauca Departments of Colombia are presented. There are 16 variables (binary, continuous, and categorical), which pertain to the years 2019 and 2020. Next to each variable, a short description follows. Many variables, such as temperature during the transformer's operation, the level of oil, and overloads, could not be measured, but are nonetheless crucial for classification. Additionally, several transformers could malfunction for unknown reasons, such as electrical discharges or wrong connections.

The technical records of 15,873 transformers were used, out of which 2761 belong to urban areas, and 13,112 to residential customers. The raw data include history, containing the reported terms for the transformers and transformers' technical data: rated power, number of customers connecting, type of installation, etc. The analysis data used in this paper's ML classifiers (SVM and k-means clustering) include the following: the top 16 reported technical concerns for the problematic transformers population from the raw data, which are location, rated power, self-protection, average and maximum earth discharge density, burning rate, keraunic level criticality, detachable connectors, type of clients, number of users, electric power not supplied, type of installation, air network, circuit queue, length of network, and burned transformers.

The rated power of the transformers range is between 5 to 2000 kVA, as shown in Table 2. Also, in Figure 5, both the number of transformers for each rated power and the number of the burned transformers for the years 2019 and 202 are presented.

Table 1. Names and classification of variables for the dataset of distribution transformers of the Cauca Departments of Colombia.

Name of Variable	Type of Variable				Short Description
	Binary		Continuous	Cate-gorical	
	1	0			
Location	Urban area	Rural area	-	-	Location of the transformer
Power [kVA]	-	-	X	-	Transformer capacity
Self-protection	Self-protected	Not self-protected	-	-	Inbuilt switch for low voltage (LV) protection in the transformer or not
Average earth discharge density [Rays/km^2 year]	-	-	X	-	Typical annual rate of lightning strikes per km^2
Maximum earth discharge density [Rays/km^2 year]	-	-	X	-	The annual average for lightning strikes per km^2
Burning rate	-	-	X	-	The quantity of component failures per unit of recording time.
Keraunic level criticality	High risk	Low risk	-	-	Variable product of a prior study conducted by other parties on behalf of the distribution company
Detachable connectors	There are detachable connectors	No detachable connectors	-	-	Removable medium voltage connectors for easy repair of the transformer
Type of clients	-	-		X	Residential, commercial, or industrial consumers
Number of users	-	-	X	-	Number of clients the particular transformer is supplying
Electric power not supplied [kWh]	-	-	X	-	The energy that the DSO ceases to sell when the transformer is out of service.
Installation type	-	-		X	Indicates whether the installed transformer is in a cabin, in a H-type structure, if it has a macro with an anti-fraud net, if it is a pad mounted type, if it is in a simple pole-type structure, an anti-fraud net pole, a metal tower or others
Air network	Aerial type	Non aerial type	-	-	Identifies if the LV network of the transformers is of the aerial type or not
Circuit queue	Position in the terminal	Position in a passing point	-	-	Shows whether the transformer is situated at a circuit's terminal point within the medium voltage network
Length of network [km]	-	-	X	-	Length of the distribution lines that the transformer feeds
Burned transformers	Burned	Not burned	-	-	Shows whether the transformer has burned this year

Table 2. Transformer data and number of burned transformers for 2019 and 2020.

Rated Power [kVA]	Number of Transformers	Damaged Transformers in 2019	Damaged Transformers in 2020
5	1571	23	52
10	3511	423	296
15	3981	252	118
20	13	0	10
25	2651	58	87
30	322	4	6
37.5	1057	17	29
45	686	8	14
50	305	2	2
75	1134	1	11
100	4	0	0
112.5	576	1	4
125	4	3	0
150	27	0	0
200	2	0	0
225	14	0	0
250	1	0	0
300	5	0	0
400	1	0	0
500	1	0	0
630	3	0	0
1000	1	0	0
1125	1	0	0
1250	1	0	0
2000	1	0	0
Total	**15,873**	**792**	**629**

ML algorithms are divided into two categories: controlled training and uncontrolled training. A collection of training data is utilized to train the algorithm for controlled training, which enables it to identify the earliest indications of technical problems, follow their progression, and create a predictive model that can help identify whether the transformer is at risk of malfunction. An effort was made to cluster the data for unsupervised learning so that transformers at danger and transformers that are not at risk belong to different clusters.

The extracted data frequently contain gaps, omissions, confusing information, noise interruptions, and other issues that have an impact on how well the prediction models function. Therefore, to prevent complications in the future, they must be pre-processed and validated. It could take a while and be tedious to extract variables from the data of the transformers. However, the necessary variables from the raw data using statistical analysis software have been extracted, and then the data that will be the most useful for our needs have been formatted. Transformer values that were missing were handled by deleting the associated technical record. Each reported issue for the technical history has been made to constitute a separate column after the data have been transformed to one record per transformer. A value of "1" is used to indicate the presence of a documented technical issue for the technical history and "−1" to indicate its absence.

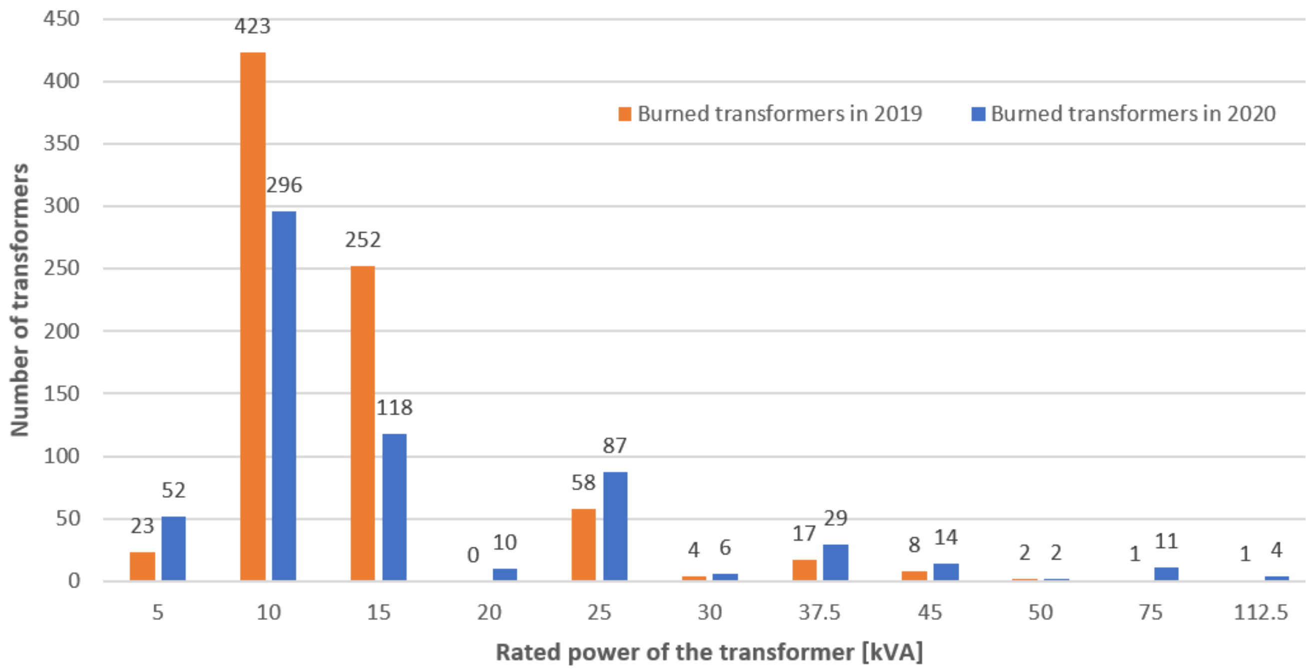


Figure 5. Transformer data and number of burned transformers for 2019 and 2020.

5. AI Methods for Early Transformer Issue Detection

In this study, we aim to investigate the use of AI methods, such as natural language processing (NLP) and ML, to automatically analyze technical trial eligibility databases and electronic technical data bases of DSOs, find matches between active technical trials and suitable transformers, and recommend these matches to DSOs and investigators for a particular prediction of transformer failure. We use the gathered dataset to apply two well-known techniques—SVM and k-means clustering—to analyze the data to enhance the maintenance process for transformers and ensure that customers have a reliable supply of energy.

The paper proposes a methodology for predictive maintenance of transformers using Support Vector Machine (SVM) algorithms and k-means clustering. The methodology consists of several steps. Firstly, we preprocess the data by selecting relevant features and normalizing the data. The relevant features include operational and environmental variables such as nominal power of the transformer, earth discharge density and type of network (aerial or non-aerial type), which have been found to affect the health of transformers. Normalization is performed to ensure that all variables have the same scale and range.

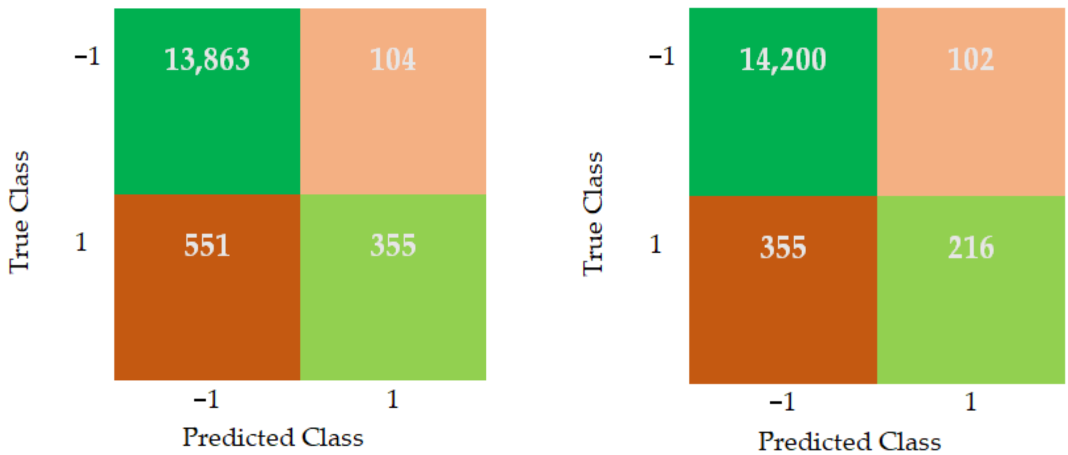
Then, k-means clustering is applied to group the data into clusters based on similarity in the feature space. The number of clusters is determined using the elbow method, which selects the number of clusters that minimizes the within-cluster sum of squares. The resulting clusters are labeled and used as input for the SVM algorithm. In the SVM step, a binary classification model is trained to predict the health state of each transformer based on the labeled clusters. The model is trained using a labeled dataset, which consists of historical data on transformer health and corresponding cluster labels. The SVM algorithm uses a non-linear kernel function to capture non-linear relationships between the input features and the output labels.

Finally, the performance of the proposed methodology is evaluated using various metrics such as accuracy, precision, recall. The evaluation is carried out on a test dataset that was not used during the training phase to ensure the generalizability of the model.

5.1. Support Vector Machines (SVMs)

SVM is a supervised learning method that analyzes the data used in regression and classification studies. A label, with numbers +1 belonging to the appropriate class and −1 not, is used when there are two classes being classified. In our study, we used two different methods to select the features for the SVM and k-means models. For the SVM model, we used a method called sequential forward feature selection, which selects the most informative features by iteratively adding one feature at a time based on their performance on a cross-validation set. This process continues until the desired number of features is reached. For the k-means model, we used a method called mutual information-based feature selection, which selects the features that have the highest mutual information with the target variable (in our case, the class label) while minimizing the redundancy among the selected features. So, even though the same dataset was used to train both models, the features used for each model were selected using different methods. Transformers in our situation are classified as either +1, meaning with technical issues, or −1, meaning without technical concerns.

The dataset is split into two subsets: 14,873 transformers for training and 1000 transformers for testing. The Matlab ML toolbox is used to produce the results. Figure 6 displays the training's outcomes for years 2019 and 2020, respectively. Although different supervised learning models are employed, the SVM provides the best accuracy of 95.60% and 96.93% for the years 2019 and 2020, respectively, as they are depicted in Figure 6. Successfully and unsuccessfully learned points are shown in Figure 6 as well. It is obvious that 104 (year 2019) and 102 (year 2020) transformers (points) are unsuccessfully taught for class −1, whereas 551 (year 2019) and 355 (year 2020) transformers (points) are poorly learned for class +1.



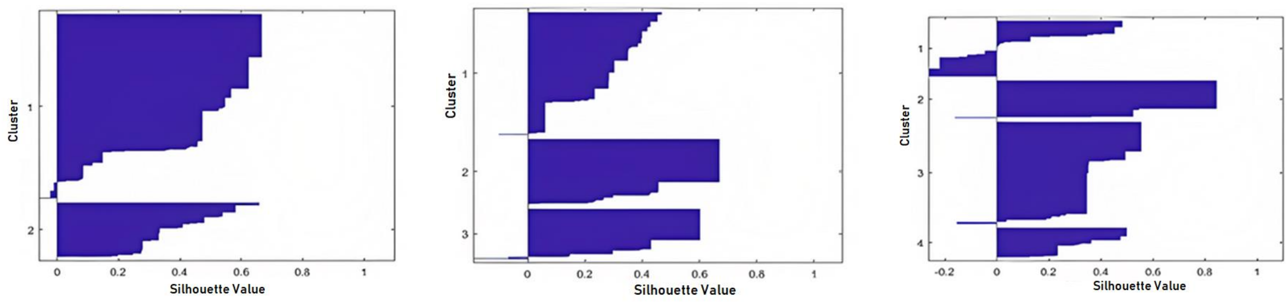
(**a**) (**b**)

Figure 6. (**a**) The percentages of successfully and unsuccessfully learned points for both classes (Year 2019). (**b**) The percentages of successfully and unsuccessfully learned points for both classes (Year 2020).

All 1000 transformers utilized for testing are appropriately categorized according to the obtained classifier. In addition, we tested the SVM learning while eliminating some features. The accuracy of learning increased to 96.74% and 97.25% for the years 2019 and 2020, respectively, when the following features were removed: location, power, removable connectors, electric power not supplied, air network, and circuit queue. We can infer from the foregoing that the reported terms under consideration should not have a significant impact on the transformers' technical problems. Additionally, the learning accuracy is higher than this presented in [33], in which it was 95.43% for 2019 and 90.62% for 2020.

5.2. k-Means Clustering

In unsupervised learning, a hidden structure in the data is found when the correct response is not known up front. A natural grouping of the data is produced by the clustering technique, and items from the same cluster have a higher degree of similarity than those from other clusters. In k-means clustering, a "prototype" data point serves as a representation for each cluster. Figure 7 depicts the clustering in clusters 2, 3, and 4. The clusters' average value indicates that two clusters are the ideal quantity. It is appropriate given that there are just two classes to which the transformers belong. The first one is for transformers that have technical problems, and the second one is for transformers that do not. The intention of this work is to explain that the performance of the proposed model construction method using k-means clustering was evaluated using the leave-one-out cross-validation method. In this method, each data point is left out in turn, and the model is trained using the remaining data points. The left-out data point is then classified using the trained model, and the process is repeated for each data point. The overall accuracy of the model is calculated as the proportion of correctly classified data points. This evaluation method allows us to assess the robustness and generalizability of the proposed model construction method.



(**a**) (**b**) (**c**)

Figure 7. Clustering in: (**a**) 2 clusters, (**b**) 3 clusters and (**c**) 4 clusters.

Our proposed approach is based on a customized initialization method for the parameters of the model. The main advantage of this method is that it takes into account the specific needs of our problem and optimizes the initial values of the parameters accordingly. To implement this method, we first analyze the characteristics of the data and the architecture of the model. We then design a customized initialization strategy that takes into account the specific needs of our problem. More specifically, we start by defining the activation functions and the number of hidden layers for the neural network. Next, we initialize the weight and bias parameters of each layer based on a customized initialization method. We then train the model using back propagation with a suitable loss function. Our customized initialization method is based on a combination of heuristics and domain knowledge.

The paper also discusses the practical implications of the proposed methodology for distribution system operators. By using predictive maintenance, operators can detect potential failures in transformers before they occur, allowing for timely maintenance and repair. This can lead to cost savings by reducing unplanned downtime and extending the lifespan of transformers.

In summary, our proposed approach is based on a customized initialization method that takes into account the specific needs of our problem. By analyzing the characteristics of the data and the architecture of the model, we design a customized initialization strategy that optimizes the initial values of the parameters. While our method requires significant domain expertise and experimentation, we believe that it offers several advantages over standard initialization methods for deep learning models. The proposed methodology offers a promising approach to predictive maintenance of transformers in the electrical power industry and has the potential to improve the reliability and efficiency of distribution systems.

6. Maintenance Scheduling for 2021

According to the prediction for 2021, using the previously presented methodology, there will be 852 transformers that will present malfunction, 820 of which will be in Cauca's rural areas, which is consistent with past failure statistics. From Figure 8 and the relevant Table 3, it is obvious that the 10 kVA transformers remain a priority at risk, with 5 kVA and 15 kVA following. Additionally, in Table 3, the percentage results of the failures in transformers, related to the total transformer number (on each rated power), are presented as well. It is obvious that the higher the absolute number of the installed transformers (per rated power) the higher the percentage failure for the specific rated power. The residential sector receives the majority of the transformers' (96.2%) energy, making its consumers the most exposed to and impacted by the frequency of unexpected power outages. For transformers with a rated power of 100 kVA and between 125 kVA and 2000 kVA, there is no predicted transformer that will present malfunction. The impact of failure in a high-rated power transformer in comparison to a low one has some significant differences. First of all, in a high-rated power transformer, the number of non-power-supplied customers is greater, and consequently, the profit losses of the power companies are also higher. Additionally, the maintenance cost and replacement cost of a high-rated power transformer are also higher than a low-rated one.

As can be seen in Figure 8 and Table 3, the proposed methodology is compared to the methodology proposed in [33]. The methodology proposed in the current work predicts in general in every transformer's power, rating a smaller number of transformers that may present problems in comparison to [33]. The total predicted burned transformers for the methodology presented in [33] is 910, while for the AI methodology presented in this work, the number is 852. This difference of 58 transformers is not negligible. Taking into consideration that the proposed methodology presents a higher accuracy rate than that in [33], it has a positive impact on the maintenance of these transformers. The maintenance of the transformers that may be burned is more expensive than periodic maintenance with fewer spare parts that must be replaced and with fewer working hours. Consequently, the proposed methodology saves a considerable amount of money to the DSO that may be used in investments.

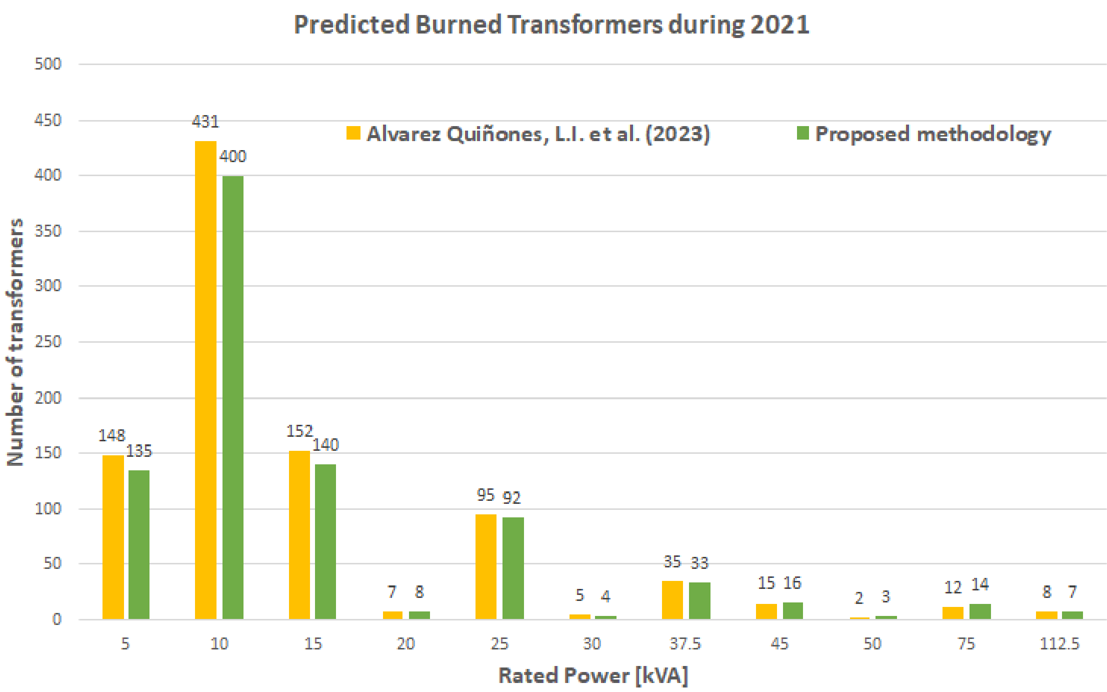


Figure 8. Predicted burned transformers during 2021 for both the methodology in [33] and the proposed methodology.

Table 3. Transformer data and predicted burned transformers during 2021 for both the methodology in [33] and the proposed methodology.

Rated Power [kVA]	Number of Transformers	Number of Predicted Burned Transformers			
		Methodology in [33]		Proposed Methodology	
			[%] *		[%] *
5	1571	148	0.93	135	0.85
10	3511	431	2.72	400	2.52
15	3981	152	0.96	140	0.88
20	13	7	0.04	8	0.05
25	2651	95	0.60	92	0.58
30	322	5	0.03	4	0.03
37.5	1057	35	0.22	33	0.21
45	686	15	0.09	16	0.10
50	305	2	0.01	3	0.02
75	1134	12	0.08	14	0.09
100	4	0	0.00	0	0.00
112.5	576	8	0.05	7	0.04
125	4	0	0.00	0	0.00
150	27	0	0.00	0	0.00
200	2	0	0.00	0	0.00
225	14	0	0.00	0	0.00
250	1	0	0.00	0	0.00
300	5	0	0.00	0	0.00
400	1	0	0.00	0	0.00
500	1	0	0.00	0	0.00
630	3	0	0.00	0	0.00
1000	1	0	0.00	0	0.00
1125	1	0	0.00	0	0.00
1250	1	0	0.00	0	0.00
2000	1	0	0.00	0	0.00
Total	**15,873**	**910**	5.73	**852**	5.37

*: Expresses the percentage of the transformer of the specific rated power to the total number of the installed transformers, which is 15,873.

7. Discussion and Limitations

Since power transformers are the foundation of the power system, which is a complex network, their efficient performance is essential to the system's dependable and secure operation. They are highly expensive and take a lot of time to maintain and replace if they are damaged because they are critical components. The biggest issues with power transformers are the various flaws that develop in them. These devices are subject to mechanical, thermal, and electrical stresses because of fluctuating loading and weather conditions. In the worst-case scenario, these shifting variables could cause several defects that would create abnormal circumstances and cascade failure. Transformers can be maintained in a variety of methods, including predictive, corrective, and preventative maintenance.

There are certain limitations in the proposed methodology. First of all, for the power transformers that break down, their related data are sparse, and traditional trained models perform poorly since there are not enough characteristics that can be learned. Additionally, the available data were for just two years (2019 and 2020). Although important for classification, several factors, such as the temperature during transformer operation, the oil level, and overloads, could not be measured and many transformers may also fail for unexplained reasons with no correlation with those mentioned in this work. Modern predictive maintenance tools should use a real-time monitoring system that analyzes gases using a variety of DGA techniques, collecting temperature from the transformer's winding and the environment, collecting data from the relays that protect the transformer for various threats (such as overvoltage, over frequency, overcurrent, etc.), and performing risk analysis by comparing measured data to historical databases. In the future, the use of such a system will help to improve prediction in transformer failure, saving costs for the DSOs.

From the current work, the following conclusions can be obtained:

(a) The majority of fault detection techniques focus on evaluating a single failure; however, many failures may occur simultaneously and are advised to be further studied.

(b) Other key and essential techniques for diagnosing transformer faults include acoustic signal processing and image identification, which have garnered considerable interest from power companies, academic institutions, and equipment operating units.

(c) The accuracy of prediction may be greatly increased by using the mined association rules between dissolved gas content and additional data (such as oil temperature, load, and winding temperature).

(d) As previously described, the suggested methodology uses a classification predictive model to identify the minimum distribution transformers that are vulnerable to failure. This methodology provides better accuracy than in [33] for the years 2019 and 2020 as they are depicted in Figure 6. Consequently, it will also present better prediction results for 2021 than the other researchers described in [33].

Consequently, (a), (b), and (c) need further study. Future work should collate these additional data, which must be gathered by a DSO on which the proposed methodology will be applied.

8. Conclusions

The recommended methodology employs a classification predictive model to identify with minimal error the number of transformers in the Cauca Department of Colombia that are very susceptible to failure. This was verified by training, testing, and validation using real data in Cauca. In accordance with prior failure statistics, the prognosis for 2021 states that 852 transformers would malfunction, 820 of which will be in rural Cauca. The 10 kVA transformers, and then the 5 kVA and 15 kVA transformers, will be the most at risk.

The reported results for application of ML methods to early detection of technical issues not only can help distribution system operator to increase the number of selected transformers for predictive maintenance but also can be beneficial for customer satisfaction to improve the amount of delivered energy. Early recognition and accurate diagnosis of technical issues are crucial to delay expensive problems as much as possible and improve the reliability of the network. Due to predictive maintenance, the mean time between failures improves the performance of distribution power transformers and it increases the expected lifetime of the transformers, a fact that both delays the transformer's replacement for some more years and saves funds for the distribution system operators.

The results illustrate that the use of ML on transformers' technical history data could speed up the process of technical maintenance of transformers and help find transformers for which major technical issues can occur. As future research, the proposed methodology could be applied to the Greek Distribution Network or/and the Greek Transmission System, taking into consideration the same parameters and some more (e.g., the dielectric strength of the transformer's insulation oil). A more cost-effective maintenance schedule for electric power distribution companies might be created with the help of a precise estimation of the usable life left in transformers.

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