International
Journal
Of Advanced Research in Engineering & Management (IJAREM)
ISSN: 2456-2033 || PP. 39-53

Design and Simulation of Machine Learning Based Predictive Maintenance Model for a 60MVA Power Transformer

Enitan O. Onatoye, Godwin O. Igbinosa, Owomano N. Imarhiagbe, Opeyemi A. Ajibola*, Maaji Yusuf, Ayodeji Bakare, Olawale S. Yekini
Department of Electrical, Electronic and Telecommunication Engineering,
Bells University of Technology, Ota 112104, Nigeria

Abstract: This study addressed the challenges associated with routine power transformer (PT) maintenance strategies by using Random Forest (RF) model to predict PT maintenance. The goal was to reduce unexpected failures and unnecessary costs associated with both breakdown and preventive maintenance scenarios. Utilizing a dataset from several diagnostic tests conducted during breakdown and preventive maintenance, specifically the 3-phase and short circuit tests, the study aimed to predict the maintenance interval rate for proper scheduling of PT maintenance. The methodology formulated transformer maintenance as a supervised binary classification task, distinguishing between good operating conditions (Class 0) and conditions needing maintenance (Class 1). The RF model achieved an impressive 97% accuracy, demonstrating outstanding performance in predicting the maintenance needs of power transformers. The system architecture involved stages of collecting data, data preprocessing, feature selection, training of model, and maintenance prediction. The F1-score, precision, and recall metrics of the RF model illustrates very high performance, particularly in identifying transformers in good operating conditions. While plotting maintenance predictions against current dates, it was observed that regular maintenance check was required twice within a month, with a 14-day interval between these events. However, the usual annual preventive maintenance can still be done just to ensure proper working condition of all components of the power transformer. Additionally, comparative analysis revealed that the RF model is simpler to implement, requires minimal hyperparameter tuning, trains faster, and is more computationally efficient compared to other tree-based machine learning (ML) models like XGBoost, Light GBM, AdaBoost, and ANN. These advantages make RF a practical and reliable choice for real-world predictive maintenance applications.

Keywords: Machine learning (ML), Power transformer, *Predictive maintenance, Random Forest (RF) classifier model, Transmission sub-station*

1. Introduction

Power transformers (PTs) are critical components in the electrical power transmission and distribution networks. PTs do voltage step up and step down in long range transmission to ensure transmission efficiency and safe delivery to end users. Owing to their important role in power systems, dependable power transformations, and efficient operation are needed. The relative maintenance of power transformers has mainly been carried out as a reactive and time-based approach [1]. Usually, it means reactive maintenance, in which the problems are solved only after a failure occurs, leading to long downtimes, expensive repairs, and unpredicted blackouts. While time-based approach is a form of preventative maintenance, most of the maintenance activities are conducted after a set number of operational hours not considering the actual equipment state. This leads to unnecessary maintenance operations, and higher operating costs, and it does not minimize the possibility of breakdown incidences [2]. A predictive maintenance model seems to be a plausible way of addressing some of the issues arising out of conventional maintenance plans. Using data analytics and machine learning to enable prediction, PM can predict future failures of the equipment. Through this approach, there is early scheduling of maintenance, the chances of having a long downtime, high cost of maintenance, and improvement of the reliability of power transformers is enhanced. The advances in sensor technology and data acquisition systems have brought the predictive maintenance models to be used a reality. It is possible to wonder how sensors can be useful in transformers, but there are several opportunities to measure the temperature, the level of oil, load, and vibration parameters of the transformers. The data gathered from these sensors can in particular be subjected to machine learning techniques in order to find out patterns for failures in imminent processes [3]. As for power transformers, its dependability and durability are important to the stable and effective delivery of electrical power supply. Their performance, therefore, has to be enhanced through proper maintenance practices. It concerns the development and simulation of a model for scheduling maintenance of power transformers at the Akangba transmission sub-station, with the view to optimizing the maintenance and increasing the operational dependability of the transformers [4].

The first and foremost of these aims is to create an extensive approach to transformer maintenance that should exceed the preventive approach. Typical organizational maintenance activities have included periodic inspection, setting control, performance checks, troubleshooting, identification of minor repair work and other recommendations on special directions. Many of these procedures are done with a view of avoiding transformer failure and to have a smooth service interval throughout the transformer equipment service life. From here above outlined methods of routine maintenance, those applied in this context relate to the transformers that have not developed the symptoms of severe state of deterioration, though design for average conditions of operation. In traditional practices, ensuring equipment reliability is critical, however, extensive maintenance methods can be inflexible, and do not provide a prognosis of a possible failure. This research seeks to incorporate big data analytics and ML to the maintenance plans so as to develop a Predictive Maintenance model. This kind of model can predict the state of a transformer and perform preventive maintenance before experiencing a failure; this can help in the reduction of failure rates and the overall maintenance expenses [5]. The procedures suggested in this work are similar to the recommended procedures from transformer manufacturers to accommodate existing maintenance practices. However, this study builds on these objectives by improving these procedures with the help of some predictive analytics. We further assume that all officials involved in the maintenance are well trained and experienced in maintaining the transformers, to enable them to follow all practice as far as both the traditional and the predictive maintenance practices as highlighted by [3].

Power transformers are indispensable components in the flow of electrical power in general and in electric power systems in particular. It is important to keep them in the best working condition, as a breakdown can make a huge dent in operations and lead to major revenue losses and some effects that put the stability of the power system at risk. Like most other transmission sub-stations such as the Akangba transmission sub-station in Nigeria, power transformers for the sub-stations have faced several constraints in terms of maintaining their operational reliability; issues that have exposed the inefficiencies of conventional maintenance models. Transformer maintenance is performed mainly in failure mode, meaning when there is a failure, a transformer is taken for maintenance. Although using such products appears to be a good way of saving money in the short run, it only means a lot of downtime and expensive repairs in the long run. Most importantly, the transformer breaks down unpredictably and this causes outages that are both unanticipated and disruptive of the power supply in the grid and inconvenient to consumers. As mentioned earlier the practice of reactive maintenance also downtimes the whole transmission network and thus has a cascading effect on power delivery. Schedules the maintenance activities to occur at periodic intervals, that is time based or preventive maintenance schedules the maintenance activities no matter the state of the transformer. While this strategy helps eliminate some failures, it results in a range of other unnecessary maintenance actions that make the reliability higher but operation costs more. It is possible to replace or service components that are still active and this is usually a waste of man-power and resources. This paper focuses on the Akangba transmission sub-station, one of the important TSs in the power transmission system where various problems concerning the reliability of transformers and techniques of improving maintenance performance have been recurrent. The sub-station has experienced an emergence of many unforeseen transformer breakdowns which cause outages. These outages interrupt power supply to residential and commercial consumers together with industries and may lead to serious losses. This work aims to develop and implement a model that will predict the required maintenance time for the 60 MVA power transformer at the Akangba 330kV/132kV transmission sub-station.

2. Materials and Methods

In reality, several tests are conducted when power transformers are newly bought to ensure their reliability and efficiency. These include insulation resistance (IR) tests, power factor (PF) tests,short circuit (SC) tests, transformer turns ratio (TTR) tests, and oil analysis, among others. These tests are crucial in identifying potential issues early and ensuring the transformer operates optimally from the start. At the Akangba substation, power transformer (PT) maintenance primarily involves daily routine inspections, preventive maintenance, and periodic breakdown maintenance, including thermographic inspections, dissolved gas analysis, and regular cleaning of bushings and radiators. However, this study proposes a predictive maintenance approach for power transformers at Akangba Substation. This section discusses the materials and method adopted to achieve the aim of the research.

2.1 System Architecture

In this research paper, a binary classification prediction of power transformer maintenance was performed using a random forest classifier model, with the Akangba 330kV/132kV transformer substation as a case study. The dataset includes two different scenarios: one where the transformer was in good condition and one where it was faulty (i.e., in need of repair). Both scenarios include several tests conducted before and after preventive or breakdown maintenance to ascertain the effectiveness and necessity of the maintenance actions. This implies that the transformer maintenance is formulated as a supervised binary classification task. Several calculations were performed to determine the threshold that indicates the good working condition of a transformer, using features in the dataset, as carried out in the Feature Extraction and Selection stage. The convention is that a '1' indicates failure (i.e., maintenance is needed), and a '0' indicates a good working condition of the transformer (i.e., no maintenance is needed). To ensure easy maintenance scheduling, we forecasted the prediction result along with all the days in a whole year using the date as a determining factor. As in Fig. 1, the system architecture involves several stages necessary to develop the predictive maintenance model, which include collection of data, preprocessing of data, dataset feature selection, model training, and maintenance prediction.

2.2 Akangba Transmission Substation Power Transformer

The Akangba Transmission Substation (ATS), located at Ilorin Street, off Adelabu Street, Surulere, Lagos, is essential for distributing power at 132kV and 33kV levels to various regions, including Amuwo, Sanya, Iganmu, Ijora, Itire, and Ikeja West. Its power network comprises three interconnected substations operating at 330kV, 132kV, and 33kV. Although these substations are situated within the same premises, they are managed by separate personnel. ATS has three transformer ratings which includes the 150MVA, 90MVA and 60MVA. However, this study focuses on the 60MVA Double Copper Wound transformer, which step down the 132kV common bus to 33kV, serving as the main source of our dataset. Fig.2 shows an image of the transformer at the Akangba substation, and the transformer ratings are provided in Table 1.

2.2.1 Description of Dataset

Data comprises detailed records from the Akangba 330kV/132kV transformer transmission substation, covering the years 2021 to 2023. It includes 90 samples and 9 features, with some data manually inputted and others in structured CSV format. The dataset's features are derived from several diagnostic tests, including 3-phase ratio tests, short circuit tests, core balance, and insulation tests. This transformer was tested as a stand-alone (i.e. when all other equipment was disconnected) with an initial tap position of ‘5’. However, the first two tests (3-phase ratio tests and short circuit tests) were used for this prediction due to the inconsistency of the other tests’ dataset, which includes the primary and secondary phase voltages, magnetizing current, tap positions, date, and the type of maintenance (Preventive and Breakdown). This comprehensive dataset features in Table 2, enables the RF classifier model to analyze various aspects of transformer performance and predict maintenance needs.

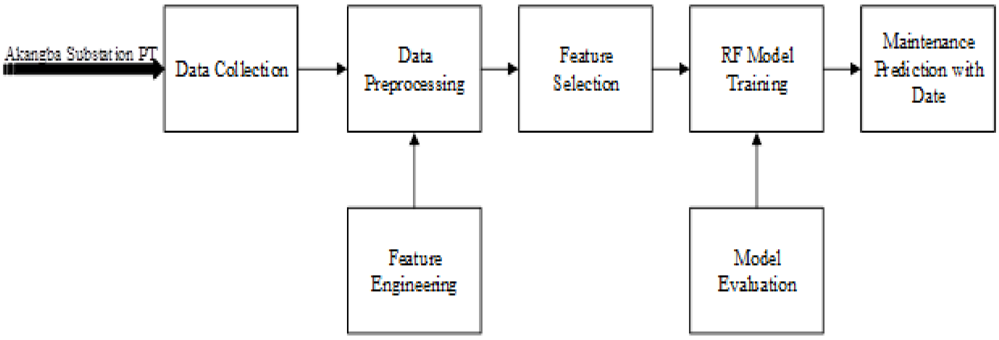

Figure 1: Block of proposed predictive maintenance model

Figure 2: Akangba transmission substation (ats) power transformer

Table 1: ATS 60MVA Power Transformer Ratings

S/N	Components	Specifications
1	Cooling	ONAN/ONAF
2	KVA Rating	45000/60000
3	Rated Voltage (V)	High Voltage (HV): 132000 Low Voltage (LV): 33000
4	Full Load Current (A)	HV: 196.82/262.43 LV: 787.30/1049.73
5	Basic Insulation Level Impedance (kV)	HV: 550/230 HVN: 95/38 LV: 145/70
6	GTD. Temperature Rise @50°C	Oil: 60°C Winding: 65°C
7	Date of Manufacture	05-Dec-2008
8	Ref. Standard	IEC-60075
9	Frequency (Hz)	50
10	Phases	3
11	Vector Group Ref.	YNd 11
12	Core & Coil Mass (kg)	42500
13	Tank & Fitting Mass (kg)	22500
14	Mass of Oil (kg)	20000
15	Oil Quantity (Ltrs)	22470

International
Journal
Of Advanced Research in Engineering & Management (IJAREM)
ISSN: 2456-2033 || PP. 39-53

Table 2: Dataset Features

Feature Name	Description	Data Type
Date	Timestamp of the recorded data	Datetime
Tap Position	Position of the transformer's tap changer	Integer
Ph-IVP	Phase Injected Voltage Primary	Float
Ph-MVS	Phase Measured Voltage Secondary	Float
Ph-MCP	Phase Magnetizing Current Primary	Float
SC-IVP	Short Circuit Injected Voltage Primary	Float
SC-MCS	Short Circuit Measured Current Secondary	Float
SC-MCP	Short Circuit Magnetizing Current Primary	Float
Type of Maintenance	Encoded type of maintenance (e.g., preventive, breakdown)	Object/Strings

2.3 Preprocessing of Data

Preprocessing data crucial to dataset preparation for model development. It was observed that the dataset contains neither missing values nor outliers, hence, feature engineering, Data transformation with Standardization and Data splitting was done to enhance quality and suitability of the dataset for predictive maintenance analysis.

2.3.1 Feature Engineering

Feature engineering involved deriving fresh attributes from the existing set of data to improve predictive performance result of the dataset collected. It is essential to develop new features to extract the target variables. Therefore, the present work adopted the apparent power and the voltage-to-current ratios in establishing when the transformer condition was beyond a known working state. The features derived and calculation used are stated as follows:

1. Phase IVP-MCP: This is the relationship between injected voltage and magnetizing current and used in assessing electrical efficiency and load-carrying capacity. It is calculated as:

$$Phase\ IVP - MCP = \frac{Phase\ Injected\ \ Voltage\ \ Primary}{Magnetizing\ \ Current\ \ Primary} \tag{1}$$

2. Phase MVS-MCP: This is the quotient of the phase measured voltage secondary by the magnetizing current primary, and this determines voltage regulation and energy transfer efficiency. It is calculated as:

$$Phase\ MVS - MCP = \frac{Phase\ Measured\ \ Voltage\ \ Secondary}{Magnetizing\ \ Current\ \ Primary} \tag{2}$$

3. SC IVP-MCP: It is the ratio of short circuit or SC voltage to magnetizing current used for determining maintenance requirements under high level stress. It is calculated as:

$$SC\ MVS - MCP = \frac{SC\ Injected\ \ Voltage\ \ Primary}{Magnetizing\ \ Current\ Primary} \tag{3}$$

4. SC IVS-MCS: This is the ratio between secondary voltage and current during short circuits, indicating the transformer's response and stability. It is calculated as:

$$SC\ IVS - MCS = \frac{SC\ Injected\ \ Voltage\ \ Secondary}{Magnetizing\ \ Current\ \ Secondary} \tag{4}$$

5. Apparent Power in Phase tests (Ph-AppPower): It measures the total power consumption of the primary components during phase tests. It is calculated as:

$$Ph - AppPower = Phase - IVP \times Phase - MCP \tag{5}$$

6. Apparent Power in Short Circuit tests (SC-AppPower): It measures the total power consumption of the primary components during short circuit tests. It is calculated as:

$$SC - AppPower = SC - IVP \times SC - MCP \tag{6}$$

7. Type of Maintenance: This is a categorical feature that comprises the types of maintenance from the dataset. It has four categories, which is the Preventive and breakdown maintenance due to; (a) Ground Transformer (GT), (b) Differential due to cut strands of conductor, and (c) Overcurrent. The label encoding was done to encode this feature as it is typically used for ordinal type of data.
8. Target: This feature was derived from the apparent power of both the phase (Ph-AppPower) and short circuit (SC-AppPower) features. Knowing full well that transformer operate well with a ±0.5% deviation tolerance

limit, the mean and standard deviation of both features (Ph-AppPower and SC-AppPower) were used to determine the binary condition for the 'target' feature, serving as a threshold to indicate when maintenance is necessary.

2.3.2 Data Transformation

Standardization was applied to ensure all features contributed equally to model training and prediction. It rescales the data to meet the condition for Gaussian distribution, which are zero (0) mean and standard deviation value of 1. The formula used for standardization is:

$$z = \frac{x-\mu}{\sigma} \tag{7}$$

Where; x= value of original feature, μ= feature mean, and σ= feature standard deviation.

2.3.3 Dataset Splitting

To establish the model's performance, dataset is split to 70% of training data and 30% of testing data. To retain a structural resemblance to classes Class, stratified sampling techniques are adopted to the 'train_test_split' of 'scikit-learn' that sharpen the accuracy of predictive maintenance forecasts in operation.

2.4 Selection of Feature

Preprocessing of data requires feature selection to identify the best featuresin the dataset in terms of relevance, that promote the predictive ability of the model. Feature selection process does reduce data dimension to minimize computational cost and improve the performance of the model by removing features that are redundant or not relevant. This study uses feature importance scores from the trained RF classifier to select the most significant features. The random forest algorithm generates an intrinsic measure of feature importance, which is calculated on the ground of each feature impurity (Gini impurity or entropy) decreasing ability in the data. The higher the importance score of a feature the more relevant it is for the predictive task. The methodology used are explained as follows:

1. Train Initial Model: The initial RF model was trained using all the features that are available in the dataset as shown in Figure 3.
2. Calculate Feature Importance: The trained model provides the extraction of the feature importance scores that indicate each feature importance in predictions.
3. Select Top Features: The feature importance scores are used to select the top features for the final model. This selection was guided by a threshold, typically the top N features, where N is determined based on the cumulative importance or a pre-defined cutoff value.
4. Retrain Model: The RF classifier was retrained using only the selected top features to ensure optimal performance and interpretability.

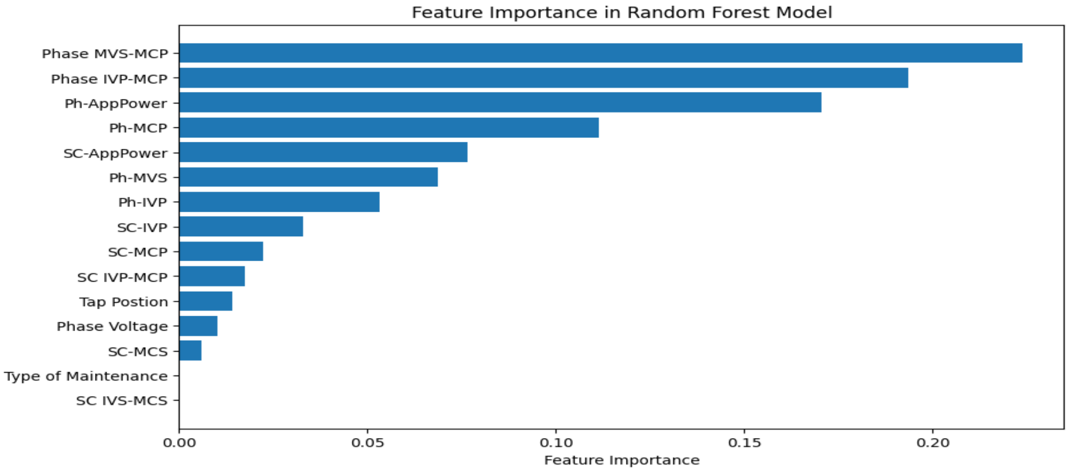

Figure 3: Feature Importance in RF Model

To avoid redundancy, the last four features were dropped, which was then used to retrain the model. The selected features for the final model in order of importance are:

1. Phase MVS-MCP
2. Phase IVP-MCP
3. Phase Apparent Power (Ph-AppPower)
4. Phase Magnetizing Current Primary (Ph-MCP)
5. Short Circuit Apparent Power (SC-AppPower)
6. Phase Measured Voltage Secondary (Ph-MVS)
7. Short Circuit Injected Voltage Primary (SC-IVP)
8. Phase Injected Voltage Primary (Ph-IVP)
9. Short Circuit Magnetizing Current Primary (SC-MCP)
10. SC IVP-MCP
11. Tap Position

2.5 Random Forest (RF) Training and Evaluation

The RF algorithm was selected for its ability to handle complex datasets and provide robust predictions. To prepare the dataset for model training, it was first divided into 7 ratio 3 split comprising 70 percent training and 30 percent testing sets. This split helped in making certain that the model had enough information to learn on while retaining some of the data for testing of the model's efficiency in predictions on unseen data. During the model training process, the Random Forest classifier was set up with default number of trees (n_estimators=100) and a seed was used for reproducible results (random_state=42). Finally, to get improved results hyperparameters were adjusted by Random Search cross-validation. This method looks through exhaustively a broad spectrum of hyperparameters to identify the most optimal set-up that results to a higher level of the model's accuracy and robustness. These were the different conceivable hyperparameters tweaked learned: number of trees, maximum depth of trees, and minimum samples split. The trained model has been tested and the normal classification parameters (accuracy, precision, recall, and F1 score) have been computed. Also, the model's detailed results in respect of true/ false positive and true/ false negative are presented using the confusion matrix, which is useful in making the changes for the improvement of the model.

2.6 Simulation Environment

This learning environment used both Microsoft Excel and Google Colab to offer the simulation element of this research. In this task, Excel was used as the tool to structure the dataset and pre-process data in such a way that would allow for easier cleaning and analysis. Its capability in handling data meant that the dataset was cleaned to a required level in preparation for the next step. The main simulation was then done from Google Colab partly because of its highly computational power as well as integration with the Python libraries. This platform helps in seamless execution ofdata preprocessing, selection of feature, training of dataset, and evaluation of the model. This paper has proved that using Excel for initial cleaning of the dataset and Google Collab for simulation offered an effective working model to execute the predictive maintenance study on the Akangba Transmission Substation dataset.

2.7 Performance Metrics

The separate/original components of the predictive maintenance model were tested. The metrics of accuracy, precision, recall, and F1 score were applied to measure the performance of the simulated model.

2.7.1 Accuracy

Accuracy calculates the ratio of instances with correct predictions to the total instances in the dataset to determine the complete correctness of the model. It is an essential metric to understand the general performance of the model. However, in cases with imbalanced datasets, accuracy alone might not be sufficient to evaluate how effective the model is. It is calculated as:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{8}$$

Where; TP, TN, FP and FN refer to true positive, true negative, false positive and false negative respectively.

2.7.2 Precision

Precision indicates the proportion of TP predictions among all positive predictions made by the model. It is a critical metric in assessing the exactness of the positive class predictions, particularly important in situations where FPs are expensive. It is calculated as:

$$Precision = \frac{TP}{TP+FP} \tag{9}$$

2.7.3 Recall

Recall (or sensitivity)is a measure of the proportion of actual positive instances that the model correctly identified. It is an important parameter that helps to understand the ability of the model to capture all relevant cases in the dataset, especially where missing a positive instance can have severe implications. It is calculated as:

$$Recall = \frac{TP}{TP+FN} \tag{10}$$

2.7.4 F1 Score

F1 score is obtained by finding the harmonic mean of the model's precision and recall. It balances the precision and the sensitivity of the model and is beneficial when the class distribution is not even, as it considers both FPs and FNs.

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{11}$$

2.7.5 Confusion Matrix (CM)

The CM is a table that gives an elaborate analysis of the competence of the model by illustrating TP, TN, FP and FN. It provides ideas on the sort of mistakes the model produces and is vital for extensively reviewing its functionality.

2.8 Transformer Maintenance Prediction Model Algorithm

This section depicts how the PT Maintenance particular event prediction is done as highlighted in Fig. 4.The outlines are given below:

1. **Import Data:**
   - Read the csv file of the transformer data into a pandas Dataframe.
2. **Data Preprocessing:**
   - Compute new features: Some of the signals/variables which should be acquired are \`Phase Voltage\`, \`SC Voltage\`, \`Phase IVP-MCP\`, \`Phase MVS-MCP\`, \`SC IVP-MCP\`, \`SC IVS-MCS\`, \`Ph-AppPower\` and \`SC-AppPower\`.
   - Taking \`Ph-AppPower\` and \`SC-AppPower\` as the threshold, compute the mean and standard deviation which can be used as the point of comparison.
   - Determine the maintenance target: If \`Ph-AppPower\` or \`SC-AppPower\` falls outside their respective thresholds, label as failure (1), otherwise no failure (0).
   - Encode the \`Type of Maintenance\` using \`LabelEncoder\`.
3. **Feature Selection:**
   - Drop less important columns based on domain knowledge and feature importance.
   - Split data: 70% training set, 30% test sets.
4. **Train RF Classifier:**
   - Input training data (\`x train\`, \`y train\`).
   - Initialize and train the RF classifier.
5. **Evaluate Model:**
   - Input test data (\`x test\`, \`y test\`) and trained model.
   - Make predictions on the test data.

- Calculate accuracy and display the classification report.

6. **Hyperparameter Tuning:**
    - Use `RandomizedSearchCV` to find the best hyperparameters.
    - Retrain the model with the best hyperparameters.
7. **Predict Future Maintenance:**
    - Use the predictions (`y_pred`) from the test data to simulate future maintenance needs.
8. **Plot and Save Results:**
    - Plot actual vs predicted maintenance targets.
    - Save prediction results to a CSV file.

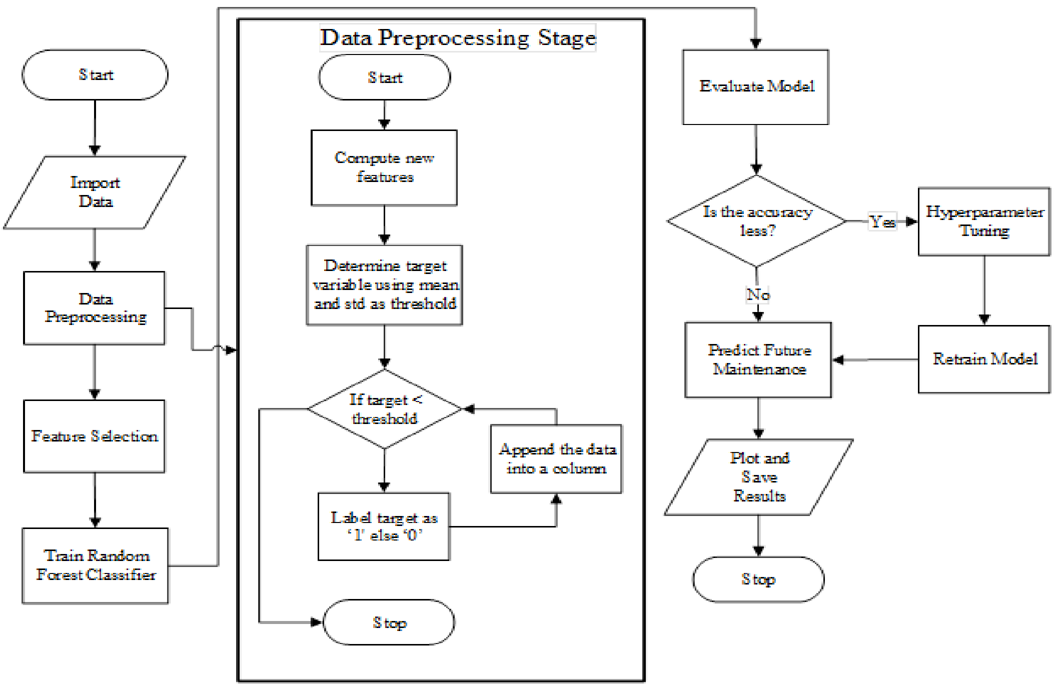

Figure 4: Flowchart of PT maintenance prediction process

3. Results and Analysis

The results of the study are presented in accordance with the stated aims and objectives in this section. Due to the unavailability of structured data from the Akangba Transmission Substation (TS), this study uses only the 3-phase and short circuit tests from both breakdown and preventive maintenance scenarios. However, the data processing conducted in the previous section allowed for a good prediction accuracy of the proposed model, which we further tuned by adjusting its hyperparameters and evaluating it using confusion matrix metrics. We then compared the results with previously developed algorithms. The remaining parts of this section are structured as follows: Statistical and Exploratory Analysis of the datasets, Model Performance Metrics, and Comparison of the Proposed Model with other Models.

3.1 Statistical and Exploratory Analysis of the Dataset

As discussed in the previous chapter, the dataset used in this study was recorded during diagnostic tests conducted in both breakdown and preventive transformer maintenance scenarios at the Akangba TS between 2021 and 2023. The data consists of 9 features and 105 samples, which were divided into two subsets: a 70% training set (73 samples) and a 30% testing set (32 samples). For better understanding, Table 3 provides a detailed statistical description of the dataset excluding the 'Date' and 'Type of Maintenance' features. It includes descriptive measures such as mean, maximum, minimum, and standard deviation. However, as stated above, the target variable was engineered using the mean and standard deviation of the apparent power of both Phase and Short Circuit features. The target variable was observed to consist of 97 data points labeled '0' (i.e., no maintenance needed) and 8 data points labeled '1' (i.e., failure/maintenance required) as shown in Fig.5, which also includes the histogram plot of other features for a quick understanding of the dataset. Additionally, the correlation heatmap as shown in Fig.6 reveals several important relationships among the features in the dataset. Firstly, Tap Position (the position of the transformer's tap changer) is strongly related to 'SC-MCP' (Short Circuit Magnetizing Current Primary) and 'Ph-MVS' (Phase Measured Voltage Secondary), suggesting a positive correlation between the tap position and both features. The 'Ph-IVP' (Phase Injected Voltage Primary) is positively correlated with both 'SC-IVP' (Short Circuit Injected Voltage Primary) and 'Ph-MCP' (Phase Magnetizing Current Primary), reflecting a shared variation among these voltage and current measurements. Similarly, 'Ph-MVS' shows strong positive correlations with 'Ph-MCP' and 'SC-MCP', indicating that these features tend to increase together. Furthermore, SC-IVP shares positive relationships with 'Ph-IVP' and 'Ph-MCP', suggesting a close connection among these features in the primary circuits. SC-MCS (Short Circuit Measured Current Secondary) is also positively correlated with 'SC-MCP', indicating that these features are likely to vary together.

Table 3: Statistical Description of Dataset

Feature	**Min**	**Max**	**Mean**	**Standard Deviation**
Tap Position	2	16	9	3.5
Ph-IVP (V)	250	400	350	20
Ph-MVS (V)	85	115	100	10
Ph-MCP (A)	2	6	3	1
SC-IVP (V)	340	410	370	15
SC-MCS (C)	20	35	27	5
SC-MCP (C)	6	11	8	1.5

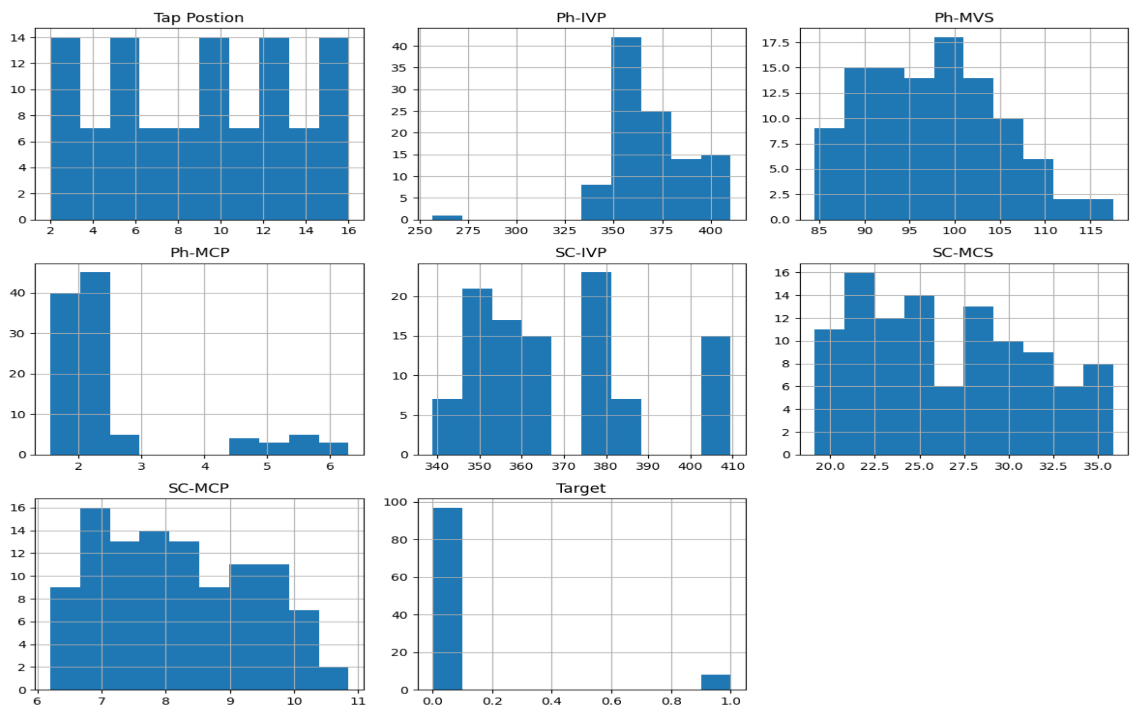

Figure 5: Histogram plot of each feature

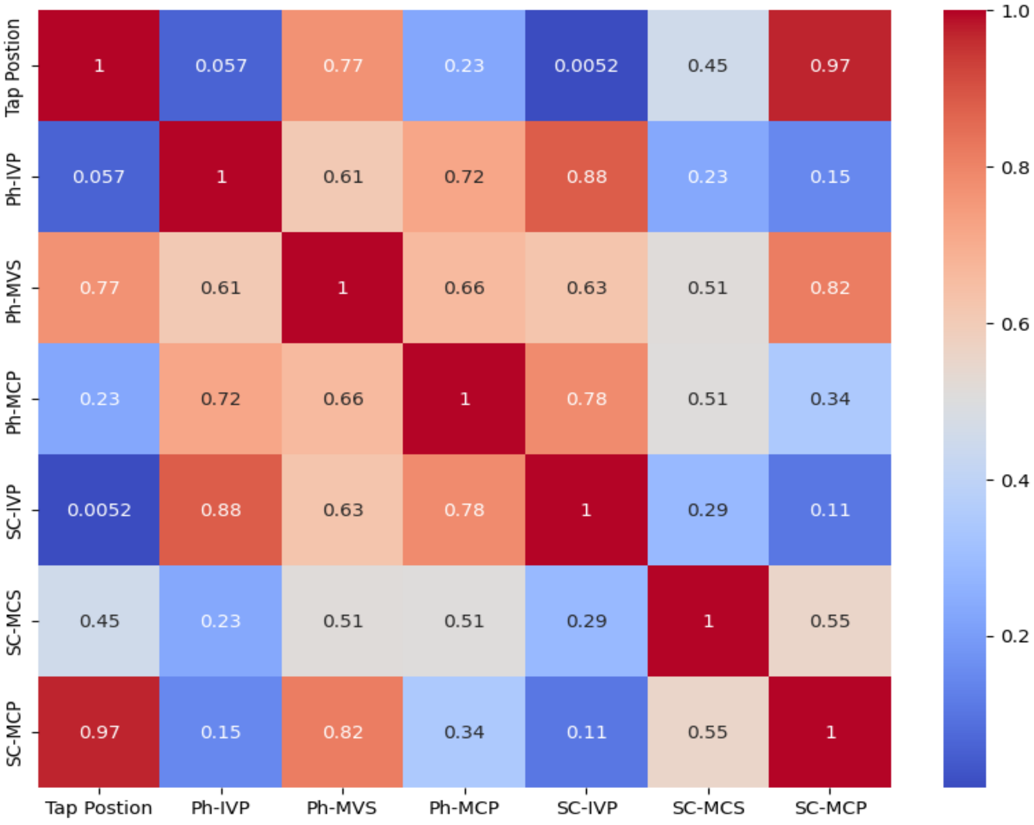

Figure 6: Correlation heatmap of each feature

Table 4: Classification Report for RF Model

Class Type	Precision	Recall	F1-score	Support
0	0.97	1.00	0.98	28
1	1.00	0.67	0.80	3
Accuracy			0.97	32
Macro average	0.98	0.83	0.89	32
Weighted average	0.97	0.97	0.97	32

3.2 Model Performance

The RF Classifier model performance is represented in the classification report in Table 4 and the confusion matrix (CM) in Fig. 7. As shown in Table 4 and Figure 7, the model achieved 97% accuracy which isanalyzed based on both binary class scenarios as follows.

Class 0: This class represents a good operating condition of the transformer; hence no maintenance is needed. The RF model demonstrates excellent performance, which achieved a 0.97precision, 1.00 recall, and 0.98 F1-score. This means that out of all the instances predicted as Class 0, 97% were correct, and the model successfully identified all actual instances of Class 0. The perfect recall indicates that the model did not miss any instances of Class 0, resulting in 29 true positives and no false negatives.

Class 1: This class shows that the Transformer is due for maintenance. Although, the RF model performance is less robust but it still achieved a perfect precision of 1.00, meaning all instances predicted as Class 1 were correct. However, the recall was 0.67, indicating that the model correctly identified only 67% of the actual Class 1 instances. This resulted in a 0.80 F1-score, which reflects a balance between precision and recall but highlighting that the model missed one of the three actual instances of Class 1 (one false negative).

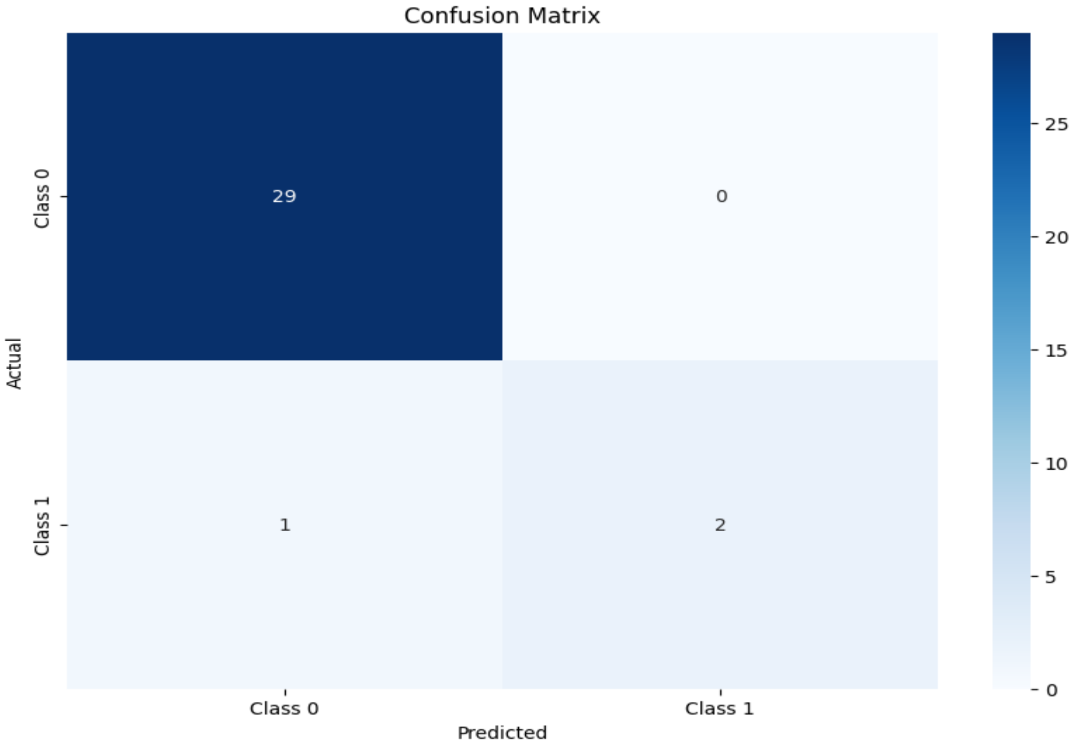

Figure 7: Confusion matrix (CM)chart of the RF model

Table 5: Selected Hyperparameter for the RF Model

Hyperparameter	**Value**
n_estimators	82
min_samples_split	10
min_samples_leaf	1
max_features	Sqrt
max_depth	98
Bootstrap	True

3.2.1 Hyperparameter Analysis of the RF Model

To optimize the RF model performance, this study used the Random Search method to select the best RF hyperparameters, as shown in Table 5. Although other methods like Grid Search and Bayesian Search were tested, the former showed similar accuracy but required more computational time. Therefore, we chose the Random Search method for selecting the best RF hyperparameters, which we observed a 6% increase in the model accuracy.

3.2.2 Predicted Transformer Maintenance with Date

Based on the dataset used for this study, the predicted transformer maintenance was plotted against the current date. It was observed that '1' appeared twice within a month, with a 14-day interval between these maintenance events, as shown in Fig.8. Therefore, it can be suggested that the maintenance interval is approximately every two weeks (14 days). This implies that the regular maintenance check (i.e. condition maintenance) could be done or scheduled once in two weeks (bi-weekly). However, the usual annual preventive maintenance can still be done just to ensure proper working condition of all components of the power transformer.

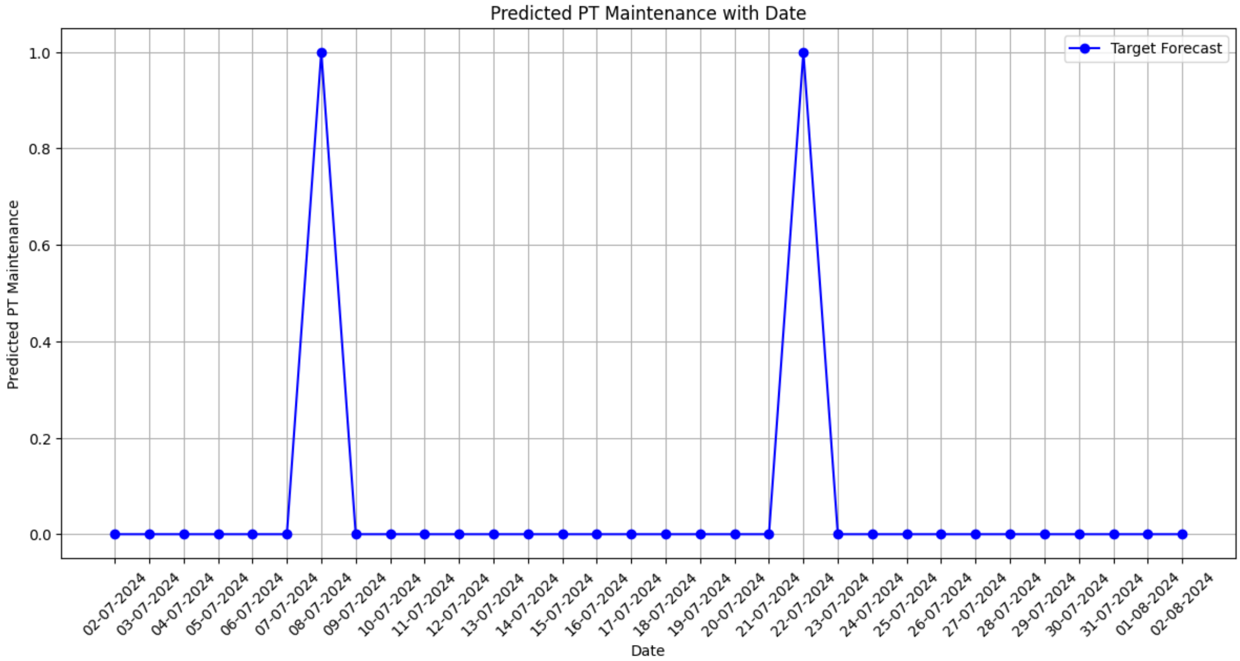

Figure 8: Predicted PT maintenance with date

3.3 Comparative Analysis of the RF and Other Tree-based Models

The RF model's performance was compared with other tree-based models such as Extreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine (LightGBM), and Adaptive Boosting (AdaBoost), as well as the Artificial Neural Network (ANN) model, to demonstrate its effectiveness in predicting PT maintenance. As shown in Table 6, all models, including RF, achieve an accuracy of 97%. However, RF still outperforms the other models based on several factors. Firstly, RF is simpler to implement, requiring minimal hyperparameter tuning, while XGBoost, LightGBM, and ANN involve more extensive tuning. Additionally, RF trains much faster, with a training time of 20-40 seconds, compared to the longer training times for XGBoost, LightGBM, and ANN. Further, as we saw before, RF demands a moderate amount of computational resources compared to othermethods, but it is promising for numerous real-world applications as long as low cost, simplicity, and fast implementation are desirable. Although there is better scalability and rich features in XGBoost, LightGBM, ANN, RF has more computation loads and complexity, which is more useful. Moreover, as compared to other models, RF illustrates high resistance to overfitting with appropriate tuning requiring a small amount of fine-tuning when the studied dataset is applied.

Table 6: Comparison of Random Forest with Other Models

Factor	**Random Forest (RF)**	**XGBoost**	**LightGBM**	**AdaBoost**	**Artificial Neural Networks (ANN)**
Ease of Use	Simple to implement	Moderate complexity	Moderate complexity	Moderate complexity	High complexity
Accuaray (%)	97	97	97	97	97
Training Time (seconds)	20-40	60-120	50-100	40-80	120-240
Computational Resources	Moderate	High	High	Moderate	High

Robustness to Overfitting	High	High (with tuning)	High (with tuning)	Moderate	Moderate
Hyperparameter Tuning	Minimal	Extensive	Extensive	Moderate	Extensive

4. Conclusion

The approach of this study is aimed at analyzing the difficulties involved in the conventional PT maintenance schedules by offering an RF-based model in the PT maintenance prediction. The objective is to minimize the occurrence of unplanned failures and expenses in exceptional situations, such as breakdown and preventive maintenance situations. Based on a dataset from several diagnostic tests done during breakdown and preventive maintenance, including the 3-phase and short circuit tests, the study intended to forecast the maintenance interval rate to schedule correct PT maintenance.

The strategy we employed for approach development defined transformer maintenance as a supervised binary classification problem, in which the two classes included good running state (Class 0) and a state requiring maintenance (Class 1). The developed RF model's accuracy was excellent, standing at 97% and signifying that this model was effective in predicting maintenance requirements for power transformers. The system architecture included data acquisition, data cleaning, data reduction, model development, and maintenance prediction steps. The above analytical results of the RF model were shown to possess high precision, a high recall rate, and an F1-score, especially to ascertain transformers in well-maintained status. It was observed that while plotting the maintenance predictions along the current dates, the regular maintenance check was needed twice in a month with a gap of 14 days.

Besides, when performing feature importance analysis, it was observed that RF model has low complexity, fewer hyperparameters have to be tuned, it takes less time for training and it consumes less computational resources than the other tree-based models such as XGBoost, LightGBM, AdaBoost, ANN, etc. This shows that RF is a viable as well as accurate solution for predictive maintenance in real-world applications. However, even when achieving a higher level of RF model accuracy compared to the study by [6], which is closely connected to our investigation, certain deficiencies are inevitable. These can be improved upon as follows:

i. Scale up the size of the dataset by incorporating more sample data from different types of transformer substations to enhance the generality and reliability of the model under different operating circumstances.
ii. Incorporating several models may show better recognition of the moving pattern and better prediction accuracy.
iii. Though the real-time data acquisition is already in practice, ensure the systems help in collecting, processing and providing the necessary data in real time to aid monitoring and immediate predictions. Such would enable the planning of maintenance actions to be highly responsive, in a way that would eliminate long undesired stoppages and frequent failures.

Conflict of Interest

No conflict of interest

Authors' Contribution

Author 1: Conceptualization and preparation of original manuscript;
Author 2: Interpretation of results;
Author 3: Editorial work and manuscript review;
Author 4: Data analysis and editing of manuscript;
Author 5: Proofreading of manuscript;
Author 6: Data collection;
Author 7: Data collection

Reference

[1]. Erol, N. (2021). Joint Research Project Autoplan. *Surveillance, Search and Rescue Craft Conference 2021*. https://doi.org/10.3940/rina.surv.2021.07

[2]. Laayati, O., Amaziane, O., Bouzi, M., El-Bazi, N., El Hadraoui, H., & Chebak, A. (2023). Smart Energy Management System: Predictive Maintenance for Dry Power Transformers Using Transfer Learning. *International Conference on Electrical, Computer, Communications and Mechatronics Engineering, ICECCME 2023*, *September*. https://doi.org/10.1109/ICECCME57830.2023.10253320

[3]. (2024). Predictive Maintenance of Power Transformers in Distribution Network with Energy Management Using Deep Learning. *Proceedings - 2024 5th International Conference on Intelligent Communication Technologies and Virtual Mobile Networks, ICICV 2024*, *March*, 581–586. https://doi.org/10.1109/ICICV62344.2024.00098

[4]. Santarelli, M., Call, M., & Macagno, S. (2004). Design and analysis of stand-alone hydrogen energy systems with different renewable sources. *International Journal of Hydrogen Energy*, *29*(15), 1571–1586. https://doi.org/10.1016/j.ijhydene.2004.01.014

[5]. Perçuku, A., Minkovska, D., & Stoyanova, L. (2018). *the Predictive Maintenance of Power Transformer Using Big Data Analytics*. 233–238.

[6]. Farzana Kabir, Brandon Foggo, & Nanpeng Yu. (2018, December 30). Data Driven Predictive Maintenance of Distribution Transformers. *2018 China International Conference on Electricity Distribution (CICED)*. https://doi.org/10.1109/CICED.2018.8592417