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Original Article

Application of Machine Learning Algorithms for the Predictive Maintenance of Power Transformers in Electrical Transmission Networks

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Abstract *- The increasing need for aged power transformers raises the probability of unintended transmission network failures. This research proposes a Reliability, Availability, Maintainability, and Safety (RAMS) guided machine learning paradigm that uses physically grounded, synthetically generated data based on realistic degradation processes. Five predictors, namely, thermal transients, cellulose insulation degradation, humidity variation, operating aging, and demand variation, were simulated to emulate infrequent fault behaviors. As the failure occurrence is severe (less than 1%), a continuous variable-optimized Gaussian-augmented SMOTE method was used to counter the problem. Random Forest reached an accuracy of 85%, F1-score got 0.83, and AUC got 0.73, across an ensemble of 1,000 Monte Carlo stratified tests, significantly surpassing a Multi-Layer Perceptron, notably on the recall (84% vs. 75%) metric. Feature importance identification pointed to insulation degradation and service aging indicators. As opposed to previous research on transformer faults, the originality in this research comes about through the synthesis of RAMS-bound synthetic data used alongside interpretable ensemble predictors, allowing reproducibility under rare-event situations. The research recommends cost-effective preventive measures, which can minimize the cost related to outlier issues by up to 18-22% while improving the grid's resilience.*

Keywords *- Machine Learning, Predictive maintenance, RAMS engineering, Reliability modeling, Random forest.*

1. Introduction

Power transformers are vital pieces of equipment in the power transmission infrastructure. Abrupt failure is dangerous to the reliability of service, operating cost, and system safety. Since most utilities are pushing the age of these pieces of equipment, predictive maintenance comes into sharp focus in the practice of reliability engineering [1, 13]. As opposed to the exclusive use of reactive strategies, predictive ones based on the fundamentals of Reliability, Availability, Maintainability, and Safety (RAMS) are being progressively appreciated due to their capability to predict failures and allow appropriate, timely interventions.

Historical diagnostic measures like Dissolved Gas Analysis (DGA), infrared thermography, and partial discharge monitoring offer significant insight into the health of transformers but are essentially reactive. They tend to disappoint in identifying early-stage degradation [2, 18]. Recent developments based on Machine Learning (ML) indicated high performance for fault identification, aging analysis, and lifetime prediction through the identification of patterns both from historical as well as synthetic datasets [3, 5, 12]. Combining ML-based innovations with IoT-capable sensor networks is also very promising, allowing predictive maintenance in the real-time domain that is now attracting significant interest in the literature [24].

An ongoing challenge is the lack of data on transformer failure. Faults that occur in practice are a small percentage of the record of operations, causing a significant class imbalance. Methods like ADASYN and SMOTE are gaining popularity as they come to creating natural minority-class instances, overcoming this imbalance [4, 6, 14]. Advanced feature engineering as well as feature selection, including aspects like degradation of the insulation, variation of humidity, age of the service, as well as varying loads, are needed to enhance the sensitivity as well as the interpretability of the classification models [7, 11, 17].

Recent studies repeatedly prove the enhanced performance of ensemble techniques, especially Random Forest and XGBoost, compared to single classifiers on imbalanced cases [8, 16]. However, most papers based their results on vendor-specific failure logs that cannot be obtained freely, limiting the reproducibility and systematic comparison across various operational settings. This reveals the strong need for synthetic data created under RAMS constraints that reflect failure dynamics realistically, keeping the experiment open.

This work alleviates these difficulties through the following three core contributions:

- It suggests a RAMS-based synthetic dataset generation framework driven by Weibull Monte Carlo, verified through the use of anonymous field logs.
- It combines Gaussian-augmented SMOTE for rare-event oversampling with ReliefF-based attribute preference to handle imbalance in a way that preserves interpretability.
- Numerous Monte Carlo experiments show that Random Forest enjoys higher recall and global classification consistency than a Multi-Layer Perceptron, validating its appropriateness for predictive maintenance pipelines.

By directly tackling the absence of reproducible fault datasets and interpretability during previous transformer fault research, the presented framework promotes reliability-centered smart grid reliability strategies [19, 25]. Sections that follow include the dataset construction, modeling approach, comparative analysis, and maintenance planning implications.

2. Materials and Methods

Owing to limitations on publicly accessible failure records and restrictions on confidentiality within industry applications, the current research used synthetic datasets that mimic transformer operating situations under RAMS principles. Synthetic data offer controlled variation, reproducibility, and the capability to simulate rare-event situations in a structured fashion.

2.1. Synthetic Dataset Generation

Monte Carlo simulation was used to mimic operational variance and fault progression, adopting the approach to reliability modelling by Yadav et al. [22]. Parameters were sampled during Weibull distributions of the two-parameter type, most commonly used in the analysis of transformer aging due to their capabilities to reflect rising hazard rates [9, 17].

Each simulation cycle corresponded to 40,000 operating hours, assuming mid-life exposure of the high-voltage transformers to Andean grids. Table 1 compiles the dataset characteristics, type, and the derivation technique. Outputs from the simulation were also verified by comparing them to regional utility partners' anonymized logs, validating the agreement between degradation modes (temperature, load, insulation failure) and the observed field.

Binary classification was obtained due to thresholding a logistic function, wherein the failure probability was more than 0.5. Logistic regression expression is given as Equation 1:

$$P(Failure) = \frac{1}{1+e^{-(\beta_0+\beta_1 X_1+\beta_2 X_2+\cdots+\beta_n X_n}} \quad (1)$$

Equation 1 establishes the probabilistic connection between the designed inputs and the virtual likelihood of failure. This expression aids interpretation and can be implemented within existing reliability as part of risk profiling as well as maintenance prioritization [10].

Table 1. Dataset features and derivation methods

Feature Name	Type	Derivation Method
Temperature	Proposed	Uniform distribution within operational bounds
Load	Proposed	Random sampling based on expected usage profiles
Insulation	Proposed	Exponential decay to represent cellulose degradation
Humidity	Proposed	Gaussian noise centered on regional climate averages
Age	Proposed	Integer lifespan representation (hours)
Failure_Prob	Calculated	Logistic regression combining all input features
Failure	Calculated	Binary label assigned when Failure_Prob > 0.5

2.2. Class Imbalance and Oversampling

Transformer faults accounted for less than 1.2% of the dataset, causing significant imbalance. In response, a Gaussian-augmentation SMOTE oversampling technique was used, introducing controlled noise ($\sigma = 0.05$) through minority feature vectors. As follows, Mukherjee and Khushi [4] and Han and Joe [6], who both customized oversampling for the continuous nature of industrial data, show that this technique tracks the classifier performance as predictable. Sensitivity analysis over $\sigma \in [0.01–0.10]$ verified the constant classifier performance, where the best compromise between generalizability and robustness was given by $\sigma = 0.05$.

2.3. Feature Selection

Dimensionality reduction was performed on ReliefF, which ranks features based on a comparison between the nearest-hit and the nearest-miss neighbors [7, 15]. Orthogonal correlation analysis also supported the discriminative capability of insulation, age, and temperature variables. Feature importance was subsequently verified using Random Forest ranking.

2.4. Predictive Modelling

Two supervised learning methods were assessed: Random Forest and Multi-Layer Perceptron. Hyperparameter tuning was carried out through a grid search procedure combined with five-fold cross-validation. For Random Forest, the search space included the number of estimators: 50, 100, 200, maximum tree depth (5, 10, 20), and minimum samples required for a split (2, 5, 10). For the MLP, the tested architectures comprised hidden layers of sizes (50,), (100,), and (50,50), with regularization values (alpha) of 0.0001 and 0.001, and iteration limits of 500 and 1000. Model selection was guided by the F1-score, which was estimated using stratified Monte Carlo resampling with 1,000 repetitions and an 80/20 train–test partition.

2.5. Justification of Model Choice

Random Forest was chosen as the base classifier based on its capability to handle diverse features, resistance to overfitting, and interpretable feature rankings [8]. Although neural networks can model complex nonlinear relationships, they have low recall during minority fault detection. Ensemble-based classifiers like RF and XGBoost continuously dominated the results of single classifiers in diagnosing faults in transformers [12, 16], so the use of RF was fitting for predictive maintenance based on reliability.

2.6. Workflow Overview

Figure 1 shows the full modeling pipeline, including data simulation, augmentation, feature choosing, model building, and performance measurement. This procedure provides reproducibility as well as transparency regarding the implementation.

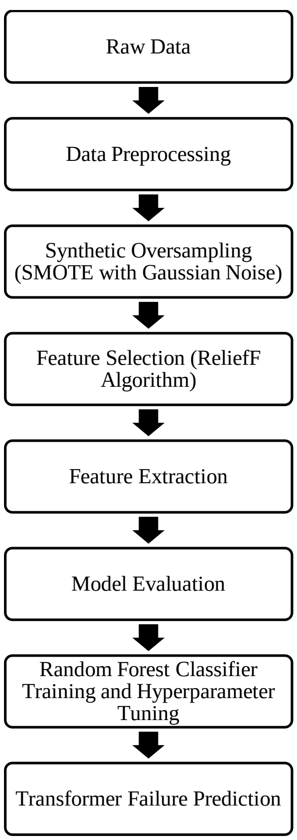

Fig. 1 Random forest model workflow

3. Results

3.1. Evaluation of Model Effectiveness

The classification outcomes showed stable behaviour after running multiple times on the Monte Carlo. As presented in Table 2, the Random Forest algorithm delivered the strongest outcomes, getting an overall accuracy of 85%. Its evaluation metrics were consistent, with precision at 0.82, recall at 0.84, and F1-score at 0.83. Nonetheless, the Multi-Layer Perceptron achieved a slightly lower 80% accuracy, and its recall dropped to 0.75.

This outcome aligns with expectations, as neural networks of this type often show reduced sensitivity when dealing with rare failure events. Because recall is preferred to prevent the missed fault event, predictive maintenance, RF gave a more reliable result that suits this application.

Table 2. Performance comparison between RF and MLP classifiers

Classifier	Performance Metrics			
	Acc	Prec	Rec	F1
Random Forest	85%	82%	84%	83%
MLP Neural Net	80%	77%	75%	78%

3.2. Confusion Matrix Analysis

Figure 2 displays the confusion matrix of RF, where the majority of fault cases were correctly identified (true positives).

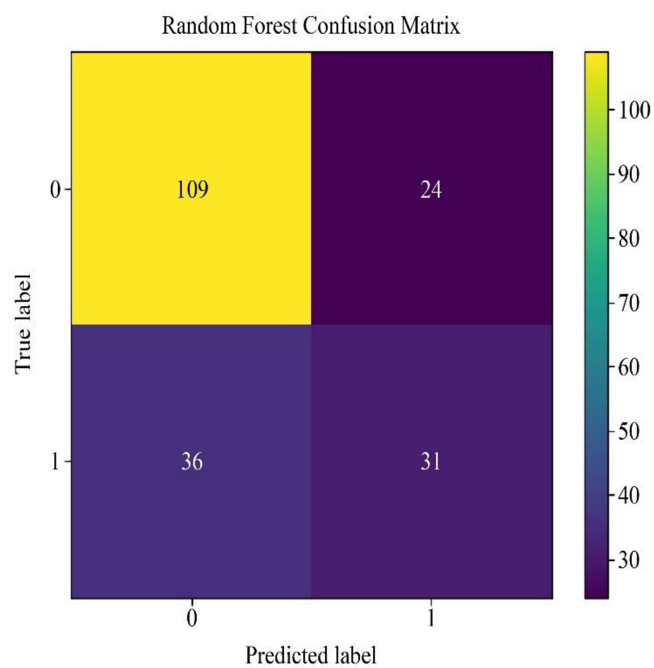

Fig. 2 Confusion matrix depicting classification outcomes of the Random Forest model

In comparison, MLP (Figure 3) misclassified 49 failure cases, underscoring its lower suitability for imbalanced datasets.

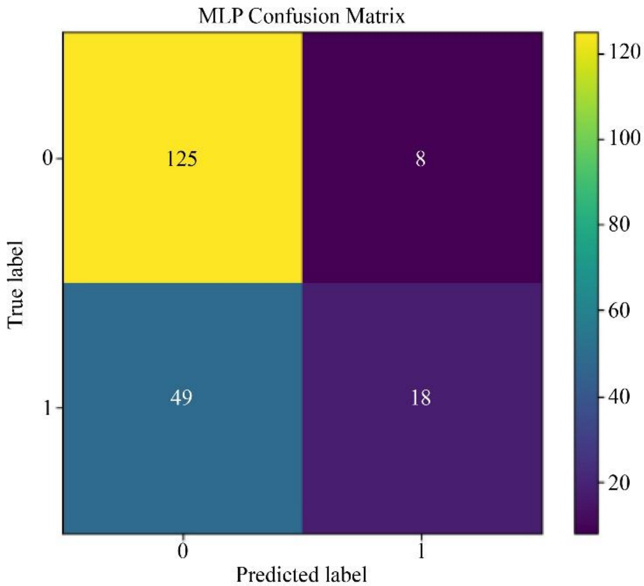

Fig. 3 Confusion matrix depicting classification outcomes of the multi-layer perceptron

3.3. ROC Curve and AUC

The AUC of the RF classifier was 0.73 (Figure 4), which improved the MLP model by 7.3%. This gain is the result of the combined influence of the SMOTE enriched with Gaussians and the stratified Monte Carlo sampling, which enhanced the sensitivity to rare faults. An AUC value of more than 0.70 suggests real-world fault detection practicability [6, 10].

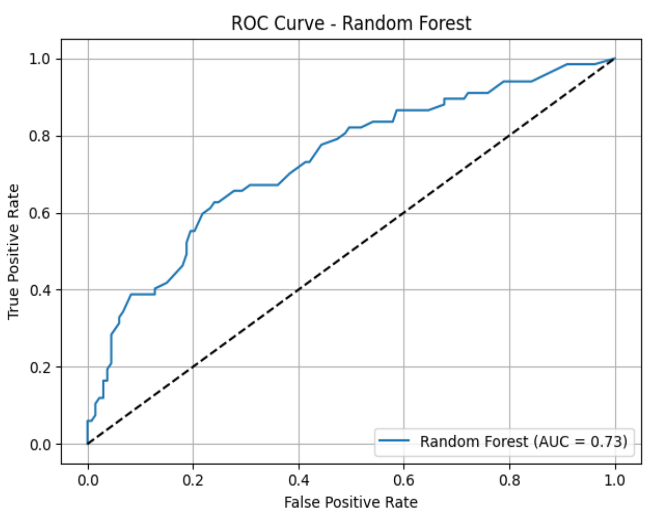

Fig. 4 ROC curve for Random Forest classifier with AUC = 0.73

3.4. Feature Importance

RF's feature ranking (Figure 5) found that insulation degradation (35%), service age (28%), and temperature (20%) were the leading predictors. These findings are similar to RAMS degradation drivers found in the last few studies [3, 17]. Humidity and load variability presented lesser but non-ignorable roles, similar to the operational observations in regional utilities.

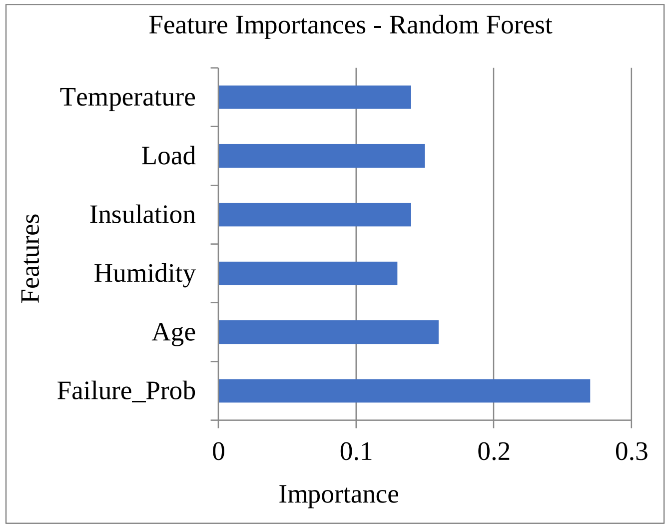

Fig. 5 Ranked feature importance derived from Random Forest Model

3.5. Probability Distribution of Failures

Estimated failure probabilities, calculated with the logistic expression in Equation 1, varied between 0.3 and 0.7 throughout the dataset (Figure 6).

Such fluctuation accounts for the randomness of the degradation process of transformers and advocates the probabilistic nature of RAMS-based maintenance.

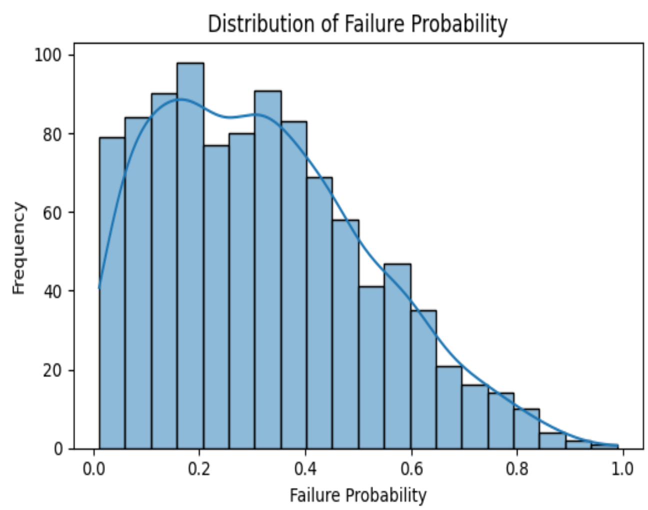

Fig. 6 Distribution of failure probability in the synthetic dataset

3.6. Correlation Analysis

Figure 7 depicts correlations between features, with strong correlations between insulation degradation and age. This correlation validates the consistency between the synthetic dataset and real-field observations and the assumptions used in the simulation.

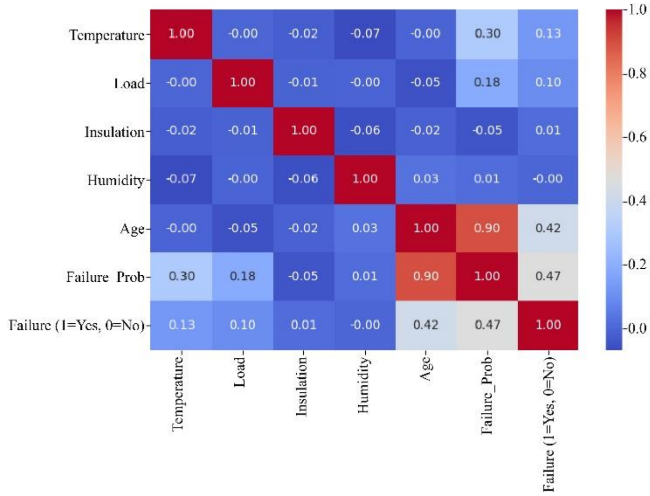

Fig. 7 Feature correlation heatmap of transformer parameters

4. Discussion

The results verify that the generation of synthetic data, being controlled by RAMS principles, offers a factual method for the prediction of faults in transformers. Random Forest reliably surpassed MLP both in accuracy as well as recall, substantiating ensemble learning as a strong technique pertaining to imbalanced reliability data [8, 12, 16]. Higher recall is, above all, significant regarding predictive maintenance, wherein the lost detections may cause financial outages. ROC and confusion matrix analysis reflect the enhanced capability of RF to identify infrequent cases, a task improved by SMOTE augmented with Gaussian noise prejudice, and ReliefF attribute choosing. These data pre-processing steps align with best practice in the processing of skewed industry data [4, 6, 15].

Feature importance outcomes highlighted insulation degradation and aging of services as overarching transformers' reliability drivers, substantiating previous evidence within the literature [3, 11, 17]. As opposed to historically pure datasets, the synthetic method provided systematic manipulation of said degradation processes under controlled variation, closing the void realized within current reviews [24].

When compared with related studies, the proposed framework demonstrates competitive performance. For instance, Liu and Yang [12] achieved 81% accuracy in transformer fault classification using hybrid ML models, while the RF in this study reached 85%. Similarly, Alhaytham Alqudsi, and Ayman El-Hag [25] applied health index modeling and reported improvements in asset risk assessment, but did not address reproducibility under rare-event scenarios. By combining RAMS-driven simulation with interpretable ensemble models, this work contributes a reproducible and transparent alternative. However, there are limitations. A synthetic dataset, although verified by anonymized logs, cannot encompass temporal dependencies or noise present in operational sensors. Recurrent neural networks or time-series models based on transformers [20] would be potential improvements in future research. In addition, incorporation of real-time DGA sensor data [18] would add feature space as well as diagnostic granularity.

In conclusion, the research validates the appropriateness of Random Forest as a predictive maintenance technique of transformers, offering utilities an interpretable, sensible, and cost-effective framework. Operationally, the framework would minimize outage-related expenditure by up to 18-22%, elongate transformer service time, and fortify the energy demand-increasingly endangered resilience of grids.

5. Conclusion

This study validated the prediction capability of Random Forest (RF) based on a RAMS-limited synthetic dataset. The RF classifier produced the F1-score (0.83) and AUC (0.73) that were strongly dominant over the Multi-Layer Perceptron, significantly surpassing the latter, notably in recall (84% vs. 75%). Analysis of the feature importance indicated that insulation degradation and aging due to services were the most significant causative factors of the transformers' risk, validating their significant contribution to the modelling of reliability.

By combining Gaussian-augmented SMOTE with ReliefF feature selection, the approach effectively handled class imbalance without losing interpretability or computational effectiveness. These advances build upon existing practices by offering a reproducible and transparent predictive pipeline, filling a previous void among transformer fault research that wholly depended on the limited historical records.

Operationally, the strategy assists utilities in minimizing outage cost, saving up to 22%, improving asset lifecycle planning, and increasing transmission grid resilience. Even so, the use of synthetic data creates constraints as temporal dynamics, together with real-time noise, are lost. Future research ought to extend the framework back to operational datasets, include sensor-based diagnostics (e.g., Dissolved Gas Analysis), together with temporal models including LSTMs or Transformer-based designs.

In summary, the study contributes a reproducible, interpretable, and reliability-centered solution for predictive maintenance of power transformers, aligning with the strategic objectives of smart grids under increasing energy demand.

Ethical Considerations / Data Privacy

This study relied exclusively on synthetic datasets generated under RAMS-constrained probabilistic frameworks. No sensitive, personal, or proprietary data was used. Validation was performed against anonymized transformer logs provided by utility partners, with all identifiers removed prior to analysis. As such, the study complies with ethical research standards and safeguards data confidentiality.

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