



Intelligent Remaining Useful Life Prediction of Power Transformers Using Machine Learning

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Abstract

Background: Power transformers play an integral role in power generation and transmission. Transformer failures can lead to service interruptions, reduce system reliability, and incur significant failure-related costs. Efficient transformer maintenance requires accurate condition assessment and effective maintenance decision-making.

Objective: The purpose of this paper is to develop a machine-learning-based decision-support framework for power transformer maintenance that integrates health index estimation, Remaining Useful Life (RUL) prediction, and Life Cycle Cost (LCC) evaluation.

Methods: The framework draws on multimodal monitoring data from 166 oil-immersed power transformers collected over a ten-year period. Six machine learning models (XGBoost, Random Forest, Support Vector Regression, Convolutional Neural Networks, Ridge Regression, and K-Nearest Neighbors) were evaluated using various feature sets.

Results: Among the evaluated models, XGBoost achieved the best performance under the basic feature configuration, with an RMSE of 0.285 years, an MAE of 0.199 years, and an R^2 of 0.956. The robustness evaluation showed that the model retained satisfactory predictive performance under moderate feature reduction. Based on the Life Cycle Cost assumptions applied in this study, the predictive maintenance scenario was estimated to reduce the total cost of the transformer fleet by approximately 47%.

Conclusion: The proposed approach combines accurate RUL prediction with technical and economic analyses to provide a practical decision-making tool for transformer asset management.

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INTRODUCTION

The increasing global demand for electricity has intensified pressure on utilities to maintain reliable and efficient power systems. Growth in electricity demand increases the operational burden on transmission and distribution assets, but the immediate maintenance challenge is not demand growth itself; it is the ability to anticipate deterioration of critical equipment before failure. Power transformers are especially important because they regulate voltage across generation, transmission, and distribution stages and are costly, long-lived assets whose unexpected failure can interrupt supply and trigger substantial repair, replacement, and outage costs (Muzayanah et al., 2022; Temiz & Tür, 2024). This link between system reliability and asset condition makes transformer lifespan prediction a direct maintenance requirement: estimating RUL provides a basis for timing inspections, preventive interventions, and replacement

before degradation becomes critical.

The continuity of power supply is heavily influenced by the operational effectiveness of transformers under varying conditions. Transformer failures often have cascading effects, potentially disrupting multiple sections of the network, resulting in prolonged outages, diminished power quality, and increased operational costs for utilities ([Augustine & Thompson Itaketo, 2023](#)). These challenges are particularly acute in regions experiencing rising electricity demand and ongoing network expansion, which place additional strain on existing infrastructure ([Mwinisin et al., 2025](#)).

Due to the substantial investment and extended service life associated with transformers, reliance on basic maintenance routines is frequently inadequate. Many utilities have historically implemented maintenance on a periodic or fixed schedule. Although straightforward, this method does not consistently represent the true condition of equipment. Premature component replacement may occur, or unexpected failures may arise without warning during operation ([Balanta et al., 2023](#)). As a result, there has been a steady shift towards maintenance that is based on conditions and prediction, using information gathered from monitoring and analysis in the process of decision-making.

Traditional approaches to transformer life expectancy estimation are based on statistics and diagnostics. Survival analysis, for instance, utilizes historical failure data to characterize lifetime behavior ([Li et al., 2023](#)). Concurrently, Dissolved Gas Analysis (DGA) is widely employed to detect internal faults in oil-filled transformers ([Nanfak et al., 2024](#); [Walker et al., 2022](#)). Gases produced under electrical and thermal stress serve as early indicators, with interpretation commonly aided by techniques such as the Duval Triangle and Duval Pentagon.

The condition of insulation does not depend on a single parameter but is affected by a combination of oil properties and solid insulation characteristics. Moisture content is particularly important because it accelerates cellulose degradation, reduces dielectric strength, and increases the risk of bubble generation at higher temperatures ([Adekunle et al., 2023](#)). Breakdown Voltage (BDV) is also commonly used to assess oil quality, where lower values frequently indicate contamination or aging. Other indicators, such as specific gravity, interfacial surface tension (IFT), and acidity, provide additional insight into oxidation processes and sludge formation ([Almeida et al., 2020](#); [Nishter & Wang, 2024](#)). In routine practice, even oil color is sometimes used as an initial indication of aging.

Another parameter frequently used to assess insulation aging is 2-furfuraldehyde (2-FAL), which is produced during the thermal degradation of cellulose. Direct measurement of paper insulation is not practical for operating transformers. Because of that, the concentration of 2-FAL in the oil is commonly used as an indirect sign of aging, especially to reflect changes in the degree of polymerization (DP) ([Kanumuri et al., 2019](#); [Nezami et al., 2024](#)). Other parameters are also considered when looking at insulation condition. The dielectric dissipation factor and resistivity provide an indication of insulation quality, although both are quite sensitive to moisture and contamination ([Imarhiagbe et al., 2025](#)). Another factor is temperature, as higher temperatures tend to accelerate several degradation processes simultaneously.

To get a clearer picture, these indicators are usually not assessed on their own. HI is often used to bring them together into a single representation of transformer condition. It is calculated from a combination of diagnostic and operational data, such as DGA results, oil properties, and insulation-related measurements. This combined view makes it easier to understand the transformer's overall condition in a more consistent way. Previous studies have shown that when appropriate weighting and normalization are applied, HI can reasonably well reflect the degradation state ([Guo & Guo, 2022](#)).

In addition to condition assessment, there has been increasing attention on estimating Remaining Useful Life (RUL). This approach determines operation lifetime before reaching a critical condition. For utilities, this information is useful for planning maintenance, scheduling replacements, and lessening the likelihood of sudden outages. Several studies suggest that RUL prediction can provide a stronger basis for decision-making in asset management ([Ramezani et al., 2023](#); [Zahra et al., 2025](#)).

Even with these methods, some limitations remain. Many diagnostic techniques are still focused on determining specific faults rather than describing how degradation evolves over time.

In addition, analyzing parameters separately might fail capturing how different degradation processes interact inside the insulation system.

Recently, machine learning has been increasingly adopted to address these limitations because it can learn complex and non-linear relationships among heterogeneous transformer condition variables that are difficult to represent with fixed diagnostic rules or single-parameter statistical models. By jointly processing dissolved-gas indicators, oil-quality measurements, insulation characteristics, temperature, and maintenance information, machine-learning models can identify interactions and degradation patterns that may not be evident when variables are assessed independently. This capability is particularly relevant to RUL prediction, where degradation is multivariate, time-dependent, and affected by outliers and non-normal distributions. Consequently, data-driven models provide a flexible basis for comparing alternative predictive structures and improving the accuracy of transformer life estimation.

Several studies have reported promising results in this area. Nezami et al. (2025) applied a fuzzy logic approach to insulation health monitoring and reported a MAPE of 0.33%. Aciu et al. (2024) evaluated Support Vector Machine (SVM) models with different kernel functions and found that the cubic kernel achieved 97% accuracy. Endah Septa Sintiya et al. (2025) combined DGA features with Duval-based methods and applied Random Forest (RF), SVM, and Artificial Neural Network (ANN), attaining accuracy levels of around 95%. Rediansyah et al. (2021) and Graili and Farhoudi (2025) also found that Random Forest outperformed several other algorithms, including K-Nearest Neighbor (KNN), SVM, Naïve Bayes, ANN, AdaBoost, and Decision Tree, achieving an accuracy of 97.3% for health index prediction.

Other studies have sought to improve their outcomes through employing pre-processing and hybrid techniques. Prasajo et al. (2023) applied SMOTE and Random Forest to address imbalanced data and achieved an accuracy of 96.2%. Alabdullh et al. (2024) integrated PCA with Back Propagation Neural Network (BPNN) across multiple data types, achieving 98.4% accuracy. Febriani et al. (2025) proposed a hybrid model combining BPNN with a Knowledge Growing System and reported an estimated RUL of 20.55 years. Syahputra et al. (2026) integrated the Random Forest approach with the Analytic Hierarchy Process (AHP) into a hybrid spatial decision-support method and attained an Area Under the Curve (AUC) of 0.96.

Advanced techniques like deep learning, Internet of Things (IoT), and digital twins have been employed in recent research. El-Rashidy et al. (2025) developed a monitoring system based on Fog Computing and LSTM-GRU methods, which exhibited high predictive performance ($R^2 = 0.985$). Furthermore, Wang et al. (2023) proposed an LSTM model to predict dynamic incipient faults in power transformers, achieving greater performance compared to other models, with $MAE < 0.26$, $RMSE < 0.34$, and $MSE < 0.12$. Ngwenyama and Gitau (2024) integrated multiple diagnostic sources with dual neural network models and reported correlation values up to 0.999 for predicting transformer loss of life. Permana et al. (2025) proposed the Transformer-Attentional Copulas for Time Series-2 (TACTiS-2) model, achieving an R^2 of 0.989. These results underscore that more advanced models can reflect complex degradation behavior more effectively.

However, important gaps remain when the present study is positioned against earlier machine-learning research. Prior studies have demonstrated strong performance using Random Forest, SVM, ANN, LSTM, hybrid models, or specialized preprocessing, but many evaluate a single task or prioritize accuracy under a fixed feature set. This limits understanding of whether a high-performing model will remain dependable when diagnostic measurements are missing, whether its advantages persist across heterogeneous transformer-condition variables, and whether the prediction can be converted into a maintenance decision. The literature also shows that more sophisticated architectures can obtain high accuracy, yet greater complexity does not necessarily address model robustness, measurement cost, or the economic consequences of maintenance choices. Accordingly, the unresolved gap is not simply the need for another accurate predictor, but the need to connect multimodal condition assessment, comparative model evaluation, robustness under feature reduction, and economic decision support within one reproducible framework.

Based on these considerations, this study develops an integrated data-driven framework for power transformer health assessment and Remaining Useful Life prediction using multimodal

monitoring data. The novelty of the study lies in combining four elements that are often treated separately: Health Index construction, comparative machine-learning prediction, systematic robustness testing under reduced feature availability, and Life Cycle Cost analysis. Relative to studies that primarily seek incremental improvements in prediction accuracy, this framework evaluates whether the selected model remains operationally useful when monitoring information is incomplete and whether its predictions can be translated into economically informed maintenance decisions.

Specifically, the study aims to: (1) construct a Health Index from the available diagnostic and operational variables; (2) compare six machine-learning algorithms across different feature configurations; (3) identify and evaluate the best-performing model using RMSE, MAE, and R^2 ; (4) test the robustness of RUL prediction when diagnostic features are progressively reduced; and (5) use the resulting predictions, dashboard visualization, and Life Cycle Cost analysis to support maintenance prioritization and transformer asset-management decisions. Through these objectives, the study seeks to bridge the gap between predictive accuracy and practical maintenance implementation.

METHOD

Dataset

The dataset comprises monitoring records from 166 oil-immersed power transformers observed over a ten-year period. The available dataset documentation does not specify the geographic location or utility from which the records were collected. Therefore, no geographic attribution is provided, and this absence is acknowledged as a limitation affecting the external generalizability of the findings. The dataset contains dissolved gas analysis parameters, oil-quality indicators, insulation-condition measurements, and operational information. These variables were analyzed jointly to characterize transformer condition and degradation over time.

Based on data statistics, the variables related to the state of the transformer appear highly variable and nonnormal. Some variables, such as hydrogen (H_2), ethane (C_2H_6), and methane (CH_4), have a high positive skewness because their means are substantially higher than their medians, while their maximum values are very high relative to their upper quartiles. The occurrence of outliers and possible fault conditions that could lead to unusual gas levels can be inferred from the results. Carbon monoxide (CO) and carbon dioxide (CO_2) levels appear to exhibit large variations and standard deviations, indicating ongoing thermal aging processes at varying intensities.

The characteristics of oil quality and insulation can clearly identify degradation trends. The parameters of moisture content, breakdown voltage, interfacial surface tension, and resistivity demonstrate moderate variability, with a tendency towards degradation in dielectric strength and oil condition as contamination increases.

Furanic compounds, despite their low median values, have extremely high maximum values, suggesting severe degradation of paper insulation in only some samples. In addition, the degree of polymerization is highly variable, with an implied decreasing trend, thus underscoring its significance as one of the main indicators of aging. The data set under consideration shows characteristics of skewness and outliers, making machine learning techniques a reasonable choice (Dalila & Turkbek, 2025).

Model

Before the modeling stage, the data were prepared through cleaning, integration, and normalization processes to minimize inconsistencies and reduce potential bias. In this study, a statistical approach was applied in three main stages to support feature selection using correlation analysis. First, a normality test was conducted to determine whether each numerical variable was normally distributed, which subsequently guided the selection of an appropriate correlation method.

Based on the initial results, the Spearman rank correlation was selected because the data were non-normally distributed. A correlation analysis was performed to evaluate the relationships between the dependent and independent variables, yielding correlation coefficients and p-values to support the statistical significance of the results.

Feature engineering was then employed to compute HI using a rule-based approach consistent with commonly adopted standards, as shown in Table 1, where higher values show better transformer condition. Each parameter was evaluated against set thresholds, and all 23 variables were integrated to form the HI, as illustrated in the overall research framework. The overall research steps are illustrated in Figure 1.

Table 1
Multi feature scale

Features	Condition		
	1 (Critical)	2 (Fair)	3 (Good)
C2H2	>2	1-2	<1
H2	>200	75-200	<75
C2H4	>95	50-95	<50
CH4	>150	90-150	<90
C2H6	>175	90-175	<90
CO	>1100	900-1100	<900
CO2	>14000	10000-14000	<10000
Moisture	>30	20-30	<20
BDV	<40	40-50	>50
Specific Gravity	>0.92	0.9-0.91	0.85-0.89
IFT	<22	22-28	>28
Acidity	>0.2	0.1-0.2	<0.1
Color	>6	2-6	<2
Resistivity	<1	1-3	>3
DDF	>0.5%	0.1-0.5%	<0.1%
5-HMF	>0.05	0.01-0.05	<0.01
2-FAL	>0.05	0.01-0.05	<0.01
2-ACF	>0.05	0.01-0.05	<0.01
5-MEF	>0.05	0.01-0.05	<0.01
2-FOL	>0.05	0.01-0.05	<0.01
DP	<340	340-500	>500
CO2/CO	<3	3-10	>10
Age	>15	5-15	<5

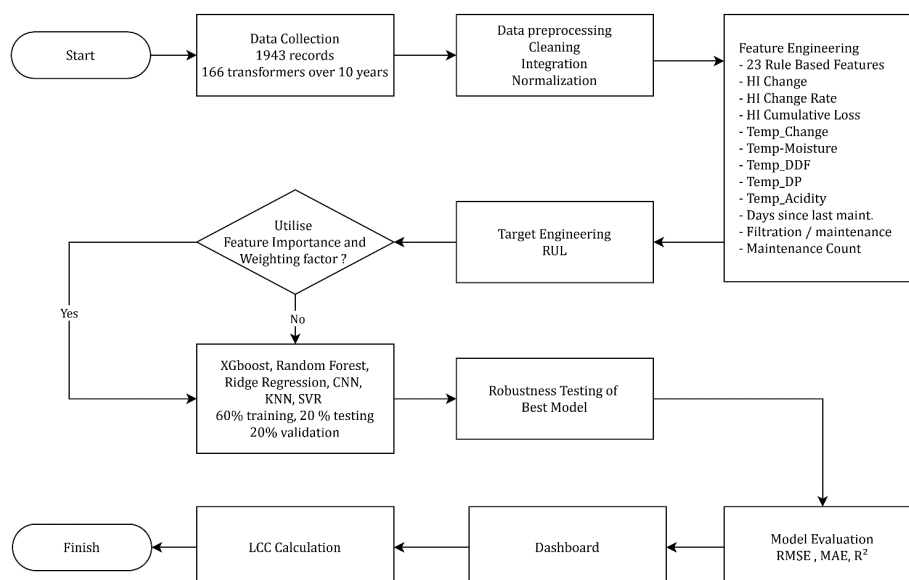


Figure 1. Proposed Method

$$\Delta HI = HI_t - HI_{t-1} \quad (1)$$

$$\frac{dHI}{dt} = \frac{\Delta HI}{\Delta t} \quad (2)$$

$$L_{cum} = \sum_{i=1}^t (HI_{t-1} - HI_t)^+ \\ \text{where } x^+ = \max(0, x) \quad (3)$$

Following the establishment of basic oil quality parameters, a set of engineered features was developed to capture degradation dynamics, thermal stress interactions, and maintenance history. First, Health Index derivatives were computed to track insulation deterioration over time. The HI change was calculated as the year-over-year difference, and the HI change rate normalized the change by time interval as explained in (1) and (2). The Health Index cumulative loss (Lcum) represented the total degradation from the initial healthy state as formulated in (3).

Second, temperature change and interaction between temperature and features were introduced to capture the accelerating effect of thermal stress on key degradation parameters. The interaction between temperature and Degree of Polymerization (DP) was calculated to quantify the extent to which heat accelerates the depolymerization of paper insulation. Similarly, the interaction between temperature and moisture was computed to capture the gradual increase of moisture under higher operating temperatures. Additional temperature interactions included CH₄ and C₂H₆, which represent the combined effects of temperature on DGA gas movements during overheating. These temperature change and temperature interaction features are expressed in (4)-(8).

$$\Delta T_t = T_t - T_{t-1} \quad (4)$$

$$T_{DP,t} = T_t \times DP_t \quad (5)$$

$$T_{Moisture,t} = T_t \times Moisture_t \quad (6)$$

$$T_{CH_4,t} = T_t \times CH_4_t \quad (7)$$

$$T_{C_2H_6,t} = T_t \times C_2H_6_t \quad (8)$$

Third, maintenance-related features were derived from the FILTRATION event indicator as provided in (9). DAYSSINCE_LAST_MAINT measures the time elapsed since the most recent filtration event. This was computed by first determining the time difference from the first recorded observation, then identifying when filtration occurred, and finally forward filling those dates to subsequent years so that any observation after a filtration event shows the days elapsed since that event.

$$Maint = \sum Filtration \quad (9)$$

All additional features were appended to the basic feature set to enhance the predictive accuracy of the remaining useful life (RUL) model. The target variable was defined as a continuous RUL value. The HI is calculated using (10), where S_i denotes the score assigned to each diagnostic feature that contributes to the overall transformer condition, and $m=23$ denotes the total number of diagnostic features considered. The Health Index was normalized to a percentage scale ranging from 0 to 100. Following the assumptions adopted in the dataset and the referenced transformer-lifetime model, the average degradation rate was set at 0.0133 percentage points per day, corresponding to an approximate design lifetime of 20.55 years. RUL was initially calculated in days by dividing the predicted remaining HI percentage by the daily degradation rate. The

resulting value was subsequently divided by 365 to express RUL in years. These values represent model-based estimates rather than directly observed failure times (11).

$$RUL_{(days)} = (HI_{(predicted)}) / (R_d) \quad (10)$$

$$RUL_{(years)} = (RUL_{(days)}) / 365 \quad (11)$$

Description:

RUL_(days) = Remaining Useful Life expressed in days

RUL_(years) = Remaining Useful Life expressed in years

HI_(predicted) = Predicted Health Index value (%)

R_d = Average degradation rate (% per day)

365 = Number of days in one year

To prevent data leakage and ensure realistic model evaluation, a temporal splitting strategy was employed instead of random sampling. This approach is particularly important for time-series prediction because chronological dependencies between observations must be preserved during model development. Previous studies have similarly emphasized the importance of temporal dependencies in sequential prediction tasks. Given the time-series nature of transformer degradation data, future information must not be used to predict past events. For each transformer, observations were sorted chronologically by sampling date. The earliest observations were allocated to the training set, while the more recent observations were assigned to the validation and test sets, following a 3:1:1 ratio (Wang et al., 2024). All numeric attributes were standardized, thereby resulting in each attribute having zero mean and unit variance. This step was necessary for any distance-based technique or neural network, as it prevents attributes with higher magnitudes from overpowering the learning process. The scaling parameters were fitted exclusively to the training data and then applied to the training, test, and validation sets.

The designed framework was implemented in Python 3.13, with Streamlit 1.50 used for visualization. Six machine-learning models were selected to provide a deliberately diverse comparison across major regression paradigms: Ridge Regression as a regularized linear baseline, K-Nearest Neighbors as an instance-based method, Support Vector Regression as a kernel-based nonlinear method, Random Forest as a bagging ensemble, XGBoost as a gradient-boosting ensemble, and a Convolutional Neural Network as a deep-learning alternative. This selection allows the study to test whether transformer RUL is better represented by linear, distance-based, kernel, ensemble, or neural-network learning mechanisms under the same feature configurations and evaluation metrics.

Ridge Regression was employed as a baseline model because of its simplicity, ease in capturing linear relationships, and capability to mitigate overfitting through regularization (Shi et al., 2025), although its performance may be limited with more complicated data patterns. The parameters used in the study include setting a value of 10.0 for the regularization parameter (α), inclusion of an intercept, and the Cholesky solver as a method for solving the linear least squares problem to find the regression coefficients while decreasing multicollinearity.

A CNN is a deep learning architecture that automatically extracts multi-level features from input data through convolutional operations and nonlinear activation functions. Backpropagation was then used to train the network where the weight values of the network, were changed after each epoch using an optimizer with initial learning rate (Moradi et al., 2025; Taha et al., 2021). In this model, 64 and 32 filters and a kernel size of 3 with an activation function of ReLU are selected. The dropout rate is 0.3, and the number of epochs is 150.

SVR is one of the machine learning techniques for predicting continuous values through learning of the regression function from the error boundary (Du et al., 2021; Zhao & Pattanadech, 2025). The use of the RBF kernel may help in building a model capable of learning nonlinear associations in the input data. In the present research study, the SVR model is tuned to have a regularization parameter (C) of 10, epsilon-insensitive loss of 0.1, and scale gamma.

KNN is a nonparametric technique in which the prediction of a target variable is made using the k nearest data points in the feature space (Dalila & Turkben, 2025). In this study, the model was configured with five nearest neighbors, distance-based weighting, giving greater influence to closer observations, and automatic algorithm choice for efficient neighbor searching.

The Random Forest algorithm uses an ensemble approach in which several decision trees generate predictions, rather than relying on a single tree (Abdulkareem et al., 2024). In each decision tree, bootstrapped samples with random feature selection are used during training to build more resilient models that overfit less. The hyperparameters were set to 200 estimators, unlimited maximum depth, a minimum of 1 sample per leaf, sqrt feature selection, and 2 samples required for node splitting.

XGBoost is built step by step, with each new tree added to improve what the model has not captured well in the previous stage (Ghoneim et al., 2025). Instead of treating all trees equally, more attention is given to the sections that are difficult to predict. The parameters that include learning rate of 0.2, maximum tree depth of 3, 500 estimators, and L1 and L2 regularization factors (reg_alpha=0.5, reg_lambda=2) have been chosen to keep the model complexity low and avoid overfitting. These parameter settings provide a stable baseline for evaluating the effects of different feature engineering strategies on model accuracy.

To systematically assess the impact of feature engineering, four separate operational modes were implemented:

Basic mode: utilized only the 23 standard oil quality and paper parameters as defined in Table 1, serving as the baseline reference for model comparison.

Additional Mode: augmented the 23 standard features with all engineered features, including HI derivatives, temperature interaction terms, and maintenance history variables, affording a comprehensive feature set for degradation modeling.

Advanced Mode: employed feature selection and weighting based on Random Forest feature importance scores. The n -most informative features are selected and assigned relative weights according to their contribution to prediction accuracy.

Robustness Testing Mode: To assess model stability and resilience under real-world industrial conditions where certain diagnostic measurements may be unavailable, a robustness testing mode was implemented. This mode systematically evaluates model effectiveness across ten distinct feature availability scenarios, simulating common field constraints such as incomplete laboratory analyses or cost-driven measurement reductions.

Ensemble methods such as Random Forest and XGBoost have shown strong performance in handling structured diagnostic data, making them suitable for transformer condition assessment (Hechifa et al., 2024).

Model evaluation is another important part of the process. Several metrics are typically used to assess model performance. Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2) are typically used in regression (Cui et al., 2025).

Life Cycle Cost Integration

LCC analysis was incorporated in this study to evaluate the economic impact of transformer degradation and support maintenance decision-making. The LCC model considers five main cost components: initial cost (C_1), operating cost (C_2), maintenance cost (C_3), failure cost (C_4), and end-of-life cost (C_5).

The LCC is calculated using the following formulation in (12).

$$LCC = C_1 + C_2 + C_3 + C_4 + C_5 \quad (12)$$

In this study, the predicted Health Index and RUL from machine learning models were used as key inputs to estimate maintenance and failure costs. Transformers with lower HI and shorter RUL were associated with higher failure probability, leading to increased failure and maintenance costs.

By integrating LCC with predictive models, this approach enabled a more comprehensive assessment that combined technical condition and economic impact, thereby supporting optimal asset management strategies.

RESULTS AND DISCUSSION

Result

The dataset analysis identifies the most influential factors affecting transformer degradation through normality testing and Spearman correlation analysis, while examining the role of temperature as an accelerator of insulation aging. The RUL distribution and the correlation between temperature and RUL are also provided based on the data. Then, six machine learning algorithms (XGBoost, Random Forest, Support Vector Regression, Convolutional Neural Network, Ridge Regression, and K-Nearest Neighbors) are evaluated across three feature configurations to determine the optimal prediction model.

Finally, robustness testing assesses the impact of systematic feature reduction on prediction reliability and identifies the minimum diagnostic information required for reliable RUL estimation. LCC analysis quantifies the economic consequences of transformer degradation and the potential cost savings achievable through machine learning-based predictive maintenance. The main findings are presented in the following subsections.

Dataset and Feature Correlation

Normality test results indicate that none of the variables tested are normally distributed at the 5% significance level. This conclusion is based on comparing the calculated test statistics with the critical value of 0.785, with all variables yielding values well above the threshold. Parameters such as H₂, CH₄, C₂H₆, DP, acidity, resistivity, and several furan compounds exhibited particularly large deviations from normality. Furthermore, all variables have been classified as “Not Normal,” indicating that the assumption of normality is violated across the entire dataset.

This kind of non-normality can be related to the degradation pattern of power transformers because condition-based parameters are characterized by skewed distributions, nonlinear behavior, outliers, and time-varying behavior. This property is commonly observed in practice because transformer aging, as reflected in DGA and moisture levels, follows a nonlinear path. Consequently, techniques such as XGBoost, Random Forest, Support Vector Regression, Neural Networks, Ridge Regression, and K-Nearest Neighbors, which do not require normality assumptions, are better suited for transformer RUL estimation than traditional parametric statistical models.

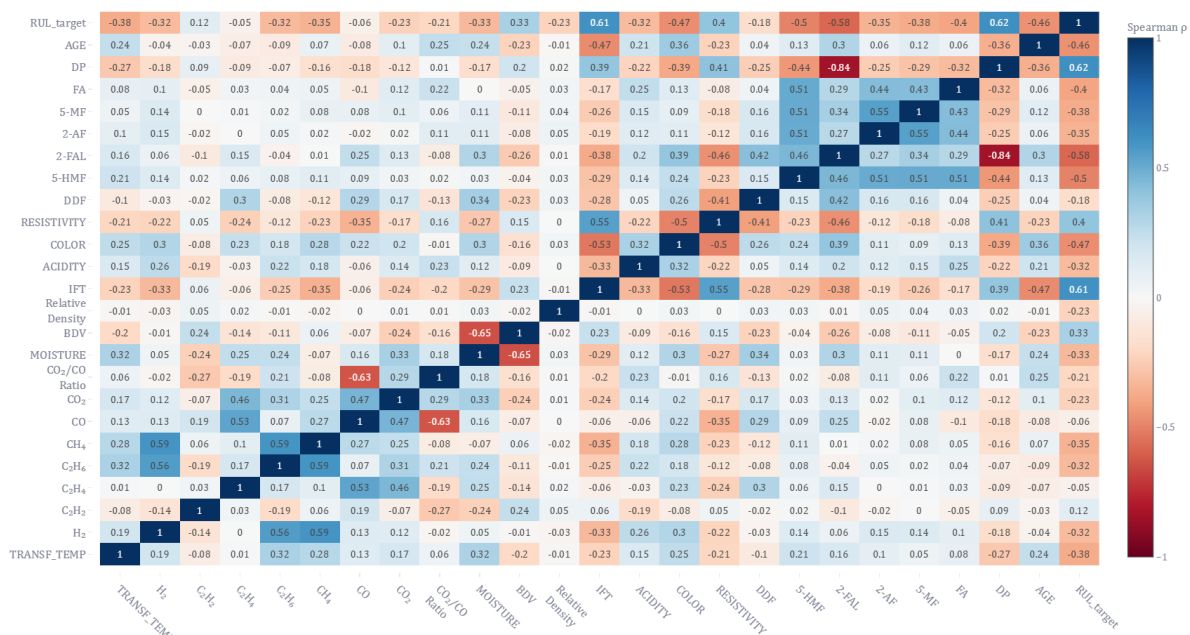


Figure 2. Correlation coefficient on features and target

From the Spearman correlation matrix in Figure 2, DP shows the strongest association with the RUL target, with a correlation coefficient of 0.62. This is followed by acidity, 2-FAL, HMF, and color. Other factors with significant association are DDF and moisture content. Moisture and breakdown voltage (BDV) exhibit a strong negative correlation ($r = -0.65$). Since moisture has a

stronger direct relationship with RUL, it may be retained as the preferred predictor, whereas BDV could be excluded unless dielectric strength assessment is specifically required. Similarly, acidity and color exhibit overlapping information, although acidity shows a stronger correlation with RUL and is therefore the more informative variable.

Furthermore, DP exhibits very strong correlations with both 2-FAL and HMF, while these two furan compounds are also highly correlated with each other. Among these indicators, DP emerges as the most informative predictor because it has the strongest direct relationship with RUL and is widely regarded as the industry gold standard for assessing the condition of paper insulation.

The analysis also highlights the significant influence of operating temperature on transformer degradation. Temperature indicates positive correlations with moisture content, DDF, and acidity, while exhibiting a negative correlation with BDV. More importantly, temperature shows a strong negative correlation with DP, confirming that elevated operating temperatures accelerate paper insulation depolymerization, the primary irreversible aging mechanism in transformer windings. Overall, the results indicate that DP and acidity are the most influential parameters affecting transformer remaining useful life, while temperature acts as a key degradation accelerator by promoting DP loss and acidity formation.

The distribution of RUL across the transformer fleet depicted in Figure 3a indicates that most units operate under normal conditions and have moderate to high remaining useful life, whereas some have lower RUL and thus require immediate attention. The differences in RUL values arise because transformers age differently depending on the operating conditions prevailing on-site. The subsequent economic analysis further indicates that higher-risk transformers account for a disproportionate share of maintenance and failure-related costs, making them primary candidates for predictive maintenance and condition-based asset management.

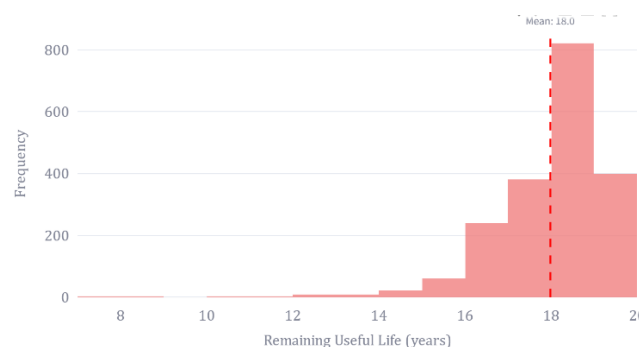


Figure 3a. RUL distribution on dataset

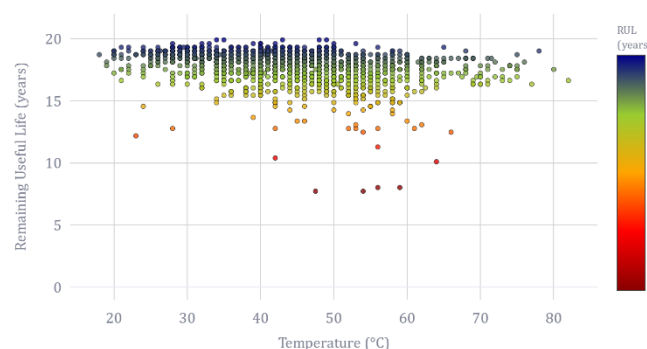


Figure 3b. Temperature-RUL correlation (bottom)

The scatter plot in Figure 3b presents the relationship between transformer operating temperature and RUL. The data points are widely distributed across the temperature range (approximately 18–82°C), yet most transformers consistently maintain good RUL. A few transformers with lower RUL values are observed across different temperature levels. Based on these observations, it is concluded that temperature alone does not exhibit a strong visual relationship with RUL, and that remaining useful life is likely influenced by additional factors.

Machine Learning Model Performance

The findings reported in Table 2 present a comparative evaluation of six machine-learning algorithms across three feature configurations. With the 23 diagnostic features in the basic mode, XGBoost achieved the lowest RMSE (0.285 years) and MAE (0.199 years), together with the highest R^2 (0.956), followed by Random Forest. The advantage of XGBoost is consistent with the dataset structure: the predictors are predominantly tabular, heterogeneous, skewed, partly correlated, and affected by nonlinear degradation relationships and outliers. Gradient-boosted trees can repeatedly partition this type of feature space and correct residual errors while capturing interactions without requiring normality or a global functional form. CNN, in contrast, is typically most effective when abundant observations contain strong local spatial or sequential patterns; those conditions are less pronounced in the present structured dataset. SVR and KNN are also more sensitive to feature scaling, redundancy, and neighborhood geometry. Therefore, XGBoost outperforms the alternatives not merely because it is more complex, but because its inductive structure is better aligned with the statistical characteristics of these transformer measurements.

Table 2

RUL Prediction evaluation

ML	Basic Mode with 23 features		
	RMSE (years)	MAE (years)	R2
XGBoost	0.285	0.199	0.956
RF	0.471	0.331	0.880
SVR	0.937	0.477	0.523
CNN	0.637	0.438	0.780
Ridge Regression	0.668	0.399	0.758
KNN	0.709	0.499	0.727
ML	Additional Mode with basic and 11 additional features		
	RMSE (years)	MAE (years)	R2
XGBoost	0.331	0.212	0.941
RF	0.434	0.271	0.898
SVR	0.911	0.419	0.549
CNN	0.471	0.347	0.879
Ridge Regression	0.521	0.322	0.852
KNN	0.767	0.566	0.681
ML	Advanced Mode with feature importance and weighting		
	RMSE (years)	MAE (years)	R2
XGBoost	0.298	0.209	0.952
RF	0.512	0.333	0.857
SVR	0.969	0.514	0.490
CNN	0.582	0.396	0.816
Ridge Regression	0.740	0.418	0.702
KNN	0.726	0.467	0.714

The inclusion of 11 additional diagnostic features produced different effects across the evaluated algorithms. CNN and Ridge Regression benefited the most from the expanded feature set. These improvements suggest that the additional diagnostic variables provided complementary information that enhanced feature representation, particularly for models that rely on learning global data patterns. In contrast, the ensemble methods exhibited only minor changes. Meanwhile, SVR and KNN continued to demonstrate comparatively weak performance.

The advanced feature-importance and weighting strategy produced mixed outcomes across the evaluated algorithms. XGBoost maintained the best performance in the advanced configuration, with an RMSE of 0.298 years, an MAE of 0.209 years, and an R^2 of 0.952. However, this result remained slightly below the overall best performance in the basic configuration. In contrast, SVR and Ridge Regression experienced performance declines after feature weighting, indicating that manually imposed weights may interfere with the models' ability to identify

nonlinear interactions automatically. Therefore, XGBoost with the 23 basic features remained the best overall model.

Overall, the results suggest that while moderate feature expansion can improve predictive performance, excessive weighting of feature importance may reduce model flexibility. Among all evaluated configurations, the XGBoost model provides the best balance between prediction accuracy and practical applicability for transformer RUL estimation. The RUL estimation based on the best model is shown in Figure 4.

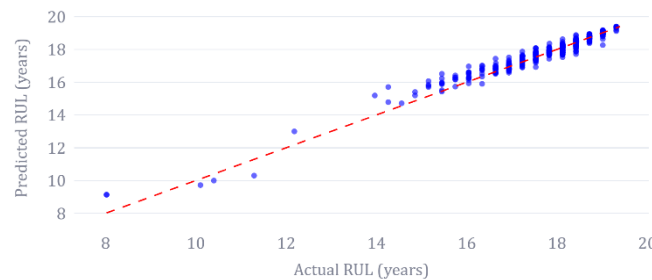


Figure 4. Scatter plot of RUL prediction on XGboost

Robustness Testing Evaluation

Table 3

RUL Prediction evaluation

Scenario	RMSE (years)	MAE (years)	R2	Features
1	0.285	0.199	0.956	23
2	0.328	0.264	0.897	22
3	0.251	0.182	0.940	21
4	0.331	0.250	0.895	19
5	0.346	0.276	0.885	18
6	0.406	0.308	0.842	15
7	0.483	0.364	0.775	12
8	0.811	0.585	0.366	9
9	0.815	0.603	0.360	7
10	0.739	0.554	0.474	2

Table 3 describes the robustness test conducted on the best model. The gradual rather than abrupt performance decline indicates that several diagnostic variables carry overlapping information about the same degradation mechanisms. DP, acidity, furan-related compounds, moisture, DDF, and related dielectric indicators capture complementary but partly correlated aspects of paper and oil aging. Consequently, the model can tolerate the removal of some variables as long as the reduced set retains the dominant degradation signals and enough complementary information to represent thermal, chemical, and dielectric condition. This explains why performance remains satisfactory through Scenario 6 with 15 features, whereas the marked decline in Scenarios 8–10 indicates that too much information has been removed. For industrial implementation, the result supports prioritizing high-information measurements when laboratory access, testing time, or monitoring budgets prevent collection of the complete 23-feature set.

Good predictive accuracy was still observed up to Scenario 6, with only 15 features used in the prediction model. Although prediction errors increased as diagnostic information became more limited, the model retained substantial explanatory power, demonstrating that a reduced subset of key transformer condition indicators can still reliably predict RUL.

Scenarios 8 to 10 showed marked increases in RMSE and decreases in R^2 , indicating that excessive feature reduction removes essential degradation information required for accurate prediction. These findings have important practical implications, suggesting that transformer RUL prediction systems can tolerate moderate reductions in monitoring parameters, thereby reducing data acquisition costs while maintaining acceptable predictive performance.

Dashboard Implementation

To enhance the practical applicability of the proposed framework, a dashboard-based decision-support interface was developed for maintenance engineers, asset managers, and operational personnel responsible for transformer condition assessment. Its key functions are to display Health Index values, predicted RUL, condition trends, and Life Cycle Cost outputs; identify transformers requiring closer attention; and compare technical risk with expected maintenance or failure cost. The dashboard therefore supports maintenance decisions by converting model outputs into asset priorities: users can determine which units should be inspected first, where preventive intervention is justified, and when overhaul or replacement should be considered. Consolidating technical and economic indicators in one interface reduces the need to interpret separate analytical outputs and makes the framework more directly usable in routine asset-management planning.

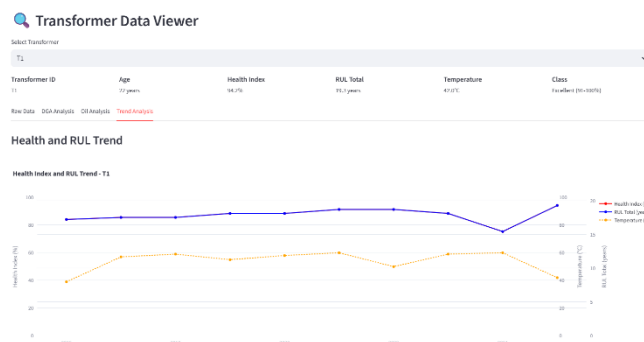


Figure 5. Dashboard of Transformer RUL Analysis

The dashboard as presented in Figure 5 also provides a practical means of translating machine learning predictions into actionable maintenance strategies. Transformers can be categorized by predicted RUL and associated maintenance costs, enabling maintenance personnel to schedule inspections and interventions before severe degradation or unexpected failures occur. Integrating predictive analytics with economic evaluation improves resource allocation and supports more cost-effective asset management. Furthermore, the modular design of the dashboard allows future integration with online monitoring systems, Internet of Things (IoT) sensors, and digital twin technologies for real-time transformer health assessment (Aslan et al., 2025).

Life Cycle Cost Incorporation

The proposed framework extends beyond prediction accuracy by quantifying the economic impact of machine learning (ML)-based RUL estimation on transformer asset management. While prediction metrics demonstrate the capability of the developed models, their practical value ultimately depends on whether more accurate RUL estimation can reduce maintenance expenditure and avoid costly transformer failures. Therefore, the predicted RUL was integrated into an LCC model to evaluate the financial implications of predictive maintenance. The complete LCC parameters used in this study are summarized in Table 4.

Table 4

Individual Transformer Life Cycle Cost (in 1000 USD)

Cost	Group 1 (T1-T29)	Group 2 (T88-T101)	Group 3 (Others)
Initial Cost C1	100	75	50
Routine C2	7.65	6.65	5.65
Offline Maintenance C3.1	36.99	32.10	25
Overhaul C3.2	253.75	200	75
Failure - Replacement C4.1	1,300	450	104
Failure - Commissioning C4.2	300	200	150
Failure - Production Loss C4.3	300	200	150
End of life C5	50	40	30

To reflect differences in asset criticality, the transformer fleet was categorized into three groups according to voltage level and replacement cost. Group 1 (T1–T29) consists of high-voltage generation and transmission transformers that represent the most critical assets within the network. Because of their high capital value, catastrophic failures in this group incur approximately USD 1.95 million per event, including replacement, commissioning, production loss, and end-of-life costs. Group 2 (T88–T101) represents medium voltage transformers with moderate replacement and maintenance costs, whereas Group 3 comprises low voltage distribution transformers with comparatively lower individual asset values.

The economic evaluation demonstrates that the primary financial benefit of ML-based RUL prediction does not arise from reducing routine maintenance costs, which remain relatively small across all groups, but rather from preventing expensive corrective maintenance and catastrophic failures. Accurate prediction enables maintenance activities to be scheduled before severe degradation occurs, thereby avoiding emergency replacement, unplanned outages, and associated production losses. Consequently, the economic advantage increases with transformer criticality, since the cost of failure grows much faster than the cost of preventive maintenance.

Table 5

Aggregate of Economic Impact of ML-Based RUL Prediction on Transformer Maintenance Cost (in 1000 USD)

Economic Evaluation	Group 1 (T1-T29)	Group 2 (T88-T101)	Group 3 (Others)
No Prediction	82,820	22,730	103,86
With ML Prediction	29,590	11,600	59,41
Savings	53,230	6,650	44,45
	64,30%	49.00%	42,80%

This trend is clearly reflected in Table 5. Group 1 achieved the largest economic benefit, where total life cycle cost decreased from USD 82.82 million to USD 29.59 million, corresponding to a 64.3% reduction. The substantially higher savings compared with the other groups are primarily attributed to the extremely high replacement and outage costs associated with high-voltage transformers. In contrast, Groups 2 and 3 achieved cost reductions of 49% and 42.8%, respectively. Although the percentage savings are smaller, they remain economically significant because of the large number of transformers in these categories. When all three groups are combined, the proposed predictive maintenance strategy reduces the total fleet life cycle cost by approximately 47%, indicating that accurate RUL prediction can substantially improve maintenance planning while simultaneously minimizing unexpected failures and long-term asset management costs.

To further assess the practical feasibility of the proposed framework, a cost-benefit analysis was conducted for diagnostic data acquisition. The analysis assumes that annual measurement of the complete set of 23 diagnostic features costs approximately USD 500 per transformer, resulting in an annual monitoring expenditure of about USD 83,000 for the 166-transformer fleet. Feature selection can reduce the number of required measurements without substantially degrading predictive capability, lowering monitoring costs by approximately 34.7% annually. This finding highlights an important trade-off between prediction accuracy and data acquisition cost. Although incorporating additional diagnostic variables may improve certain algorithms, the resulting increase in inspection and laboratory costs may outweigh the relatively small gain in model performance. Therefore, selecting an appropriate feature subset is essential for achieving an economically sustainable predictive maintenance strategy.

Discussion

The comparative evaluation demonstrates that model performance is strongly influenced by the characteristics of structured transformer-condition data rather than by model complexity alone. The superior XGBoost result is consistent with evidence that tree-ensemble approaches can effectively learn nonlinear interactions in transformer diagnostic variables ([Ghoneim et al., 2025](#); [Hechifa et al., 2024](#)). At the same time, the present findings extend earlier work because the

comparison is coupled with feature-reduction robustness testing and economic assessment rather than stopping at predictive accuracy. The weaker CNN performance differs from studies in which deep or recurrent architectures perform strongly on richer sequential monitoring streams (El-Rashidy et al., 2025; Wang et al., 2023), suggesting that architecture suitability depends on data structure and sample characteristics. Likewise, the importance of DP and related insulation indicators is consistent with prior health-index research Rediansyah et al. (2021) and Graili and Farhoudi (2025), but the current study further demonstrates how retaining a compact subset of informative variables can preserve useful RUL accuracy while reducing monitoring burden. These comparisons show that the study contributes not only a high-performing model, but evidence about when and why that model remains useful for maintenance decisions.

The impact of feature engineering varied considerably among the evaluated algorithms, indicating that additional information does not necessarily improve estimation accuracy. Tree-based ensemble models benefited marginally because informative variables were already identified during recursive tree construction. In contrast, Ridge Regression and CNN showed greater improvement, suggesting that the expanded feature set provided complementary information for representing transformer degradation. Nevertheless, CNN remained less accurate than the ensemble models, likely because deep learning architectures generally require larger datasets and are better suited to image or sequential data than structured engineering datasets. Kernel and distance-based methods such as SVR and KNN also remained comparatively less accurate, reflecting their greater sensitivity to redundant and correlated features.

Prediction accuracy did not consistently improve with the implementation of feature importance and weighting strategies. Although the goal is to identify influential variables, most algorithms performed worse than with the additional-feature configuration. This highlights that modern ensemble algorithms already perform effective feature selection during model optimization, while manually assigning feature importance may suppress useful interactions among diagnostic variables. Overall, the results indicate that data-driven feature learning is generally more effective than manually imposing expert-defined weights.

Power utilities rarely possess complete diagnostic records throughout a transformer's service life. Therefore, evaluating model sensitivity to incomplete diagnostic information is essential from an industrial engineering perspective. The proposed framework maintained satisfactory prediction performance using approximately fifteen diagnostic features, indicating that reliable RUL estimation remains feasible under practical operating conditions while reducing monitoring costs. Moreover, the LCC analysis showed that accurate RUL prediction enables condition-based maintenance, replacing expensive corrective actions with planned preventive interventions. Consequently, the highest economic gains were achieved for high-voltage transformers, where failure-related costs are substantially higher than routine maintenance expenses.

In summary, effective transformer asset management requires balancing prediction accuracy with feature selection, model robustness, and economic considerations. The proposed framework demonstrates that integrating machine learning with practical maintenance and cost analysis provides a more comprehensive decision-support tool for utility asset management.

CONCLUSION

This study developed an integrated transformer asset-management framework combining Health Index estimation, machine-learning-based RUL prediction, robustness testing, dashboard visualization, and Life Cycle Cost analysis. XGBoost with the 23 basic features produced the best overall predictive performance, while the robustness evaluation demonstrated that satisfactory prediction could be maintained under moderate feature reduction. The principal scientific contribution lies in connecting predictive performance with model robustness and economic decision support rather than focusing exclusively on improvements in prediction accuracy. In practice, the framework can assist maintenance engineers and asset managers in prioritizing inspections, allocating diagnostic resources, and planning preventive interventions based on transformer condition, predicted RUL, and estimated cost exposure.

The findings should nevertheless be interpreted in light of the use of a single dataset, the absence of documented geographic information, the lack of external validation, and the

dependence of the economic results on the cost assumptions adopted in the analysis. Future research should validate the framework using larger and more diverse transformer populations, actual utility cost data, and real-time monitoring records. Incorporating explainable machine learning, Internet of Things sensing, and digital-twin technologies may further strengthen the framework's transparency, generalizability, and operational applicability.

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AUTHOR CONTRIBUTION STATEMENT

Fanni Mudarris Kurniawan contributed to the conceptualization, methodology, data processing, software implementation, formal analysis, visualization, and preparation of the original manuscript. Dyah Lestari Widaningrum contributed to supervision, methodological validation, interpretation of the results, and critical revision and editing of the manuscript. Both authors approved the final version of the manuscript. Moreover, data is available upon request due to ethical restrictions in <https://doi.org/10.5281/zenodo.20970478>. Contact the corresponding author to request the data.

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