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Investigating the Remaining Useful Life of Power Transformer Using Random Forest and Long Short Term Memory

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ABSTRACT

Operational factors such as load imbalance, hot-spot temperature, dynamic derating, and voltage loss have been shown to accelerate insulation degradation, which has a direct impact on the reduction of the Remaining Useful Life (RUL) of the transformer. However, conventional RUL prediction approaches are generally still static and have not been able to represent actual operational conditions that are dynamic and change over time. This study aims to develop a transformer RUL prediction model based on Dynamic Failure Mode and Effects Analysis (Dynamic FMEA) with the integration of machine learning methods. This approach utilizes Mean Decrease in Accuracy (MDA) to measure the relative importance of each operational parameter to the risk of failure, resulting in a dynamic Risk Priority Number (RPN) that is adaptive to the actual conditions of the transformer. The hybrid model is built by combining Random Forest as a base model for degradation pattern extraction and Long Short-Term Memory (LSTM) to capture the temporal dynamics of RPNs based on historical operational data. The data used in this study include phase current, load imbalance, hot-spot temperature, dynamic derating, and voltage loss (ΔV%). The resulting dynamic RPN values are then mapped into an exponential model to estimate condition-based RULs. The results show that the integration of Dynamic FMEA, MDA, and machine learning models can produce RUL estimates that are more adaptive and informative than the static approach, and have the potential to support the implementation of risk-informed maintenance to improve the reliability and sustainability of electric power systems.

Keywords: Remaining Useful Life (RUL); Random Forest (RF); Long Short-Term Memory (LSTM); Dynamic FMEA; Mean Decrease in Accuracy (MDA)

INTRODUCTION

Power transformers are one of the main components in the electric power system, functioning to distribute electrical energy between voltage levels very efficiently and continuously. The reliable performance of this transformer is influenced by a good electric power operating system. However, there are some reports suggesting that transformer malfunctions are still the main cause of power supply disruptions and require high maintenance costs (Zhang et al., 2023; Achour et al., 2025). Therefore, efforts to extend the service life of transformers through accurate Remaining Useful Life (RUL) predictions are an important priority in modern electricity asset management (Al-Romaimi, 2024; Mharakurwa, 2022; Radionov et al., 2023; Rêma et al., 2024; Usman et al., 2023).

As the integration of renewable energy increases and load fluctuations in distribution systems grow, transformers are faced with increasingly complex operating conditions. One of the main factors that accelerates transformer degradation is the load imbalance that causes increased copper losses, hot-spot temperature, and premature aging of the insulation system. The load imbalance also causes voltage drops on the secondary side of the transformer, which directly affect the power quality and efficiency of electrical energy distribution. This condition is an indication of performance degradation and the potential for a reduction in the remaining useful life of the equipment (Li et al., 2023; Nguyen et al., 2024).

On the other hand, in the operation of the transformer, there is often a derating condition of the transformer, which is a reduction in the operating capacity of the transformer based on environmental conditions and actual load to prevent overheating. The policies on derating that are currently implemented are still static and do not consider load dynamics or thermal conditions in real-time. Thus, although the derating aspect is intended as an effort to extend the life of the transformer, in its implementation it causes low transformer efficiency and increased energy losses when done suboptimally (Samuel & Chukwunweike, 2023).

In the context of predictive maintenance, data-driven approaches such as machine learning and degradation models have been widely developed to estimate transformer RUL. Nonetheless, most previous research has still focused on thermal or chemical degradation analysis without explicitly including aspects of failure risk analysis. In assessing risk, the Failure Mode and Effects Analysis (FMEA) method has proven to be effective, as it is based on the Severity, Occurrence, and Detection parameters. However, conventional FMEA models are static and cannot adjust the risk value when transformer operating conditions change dynamically. This creates a gap between the results of data-driven RUL predictions and actual risk assessments in the field (El-Araby et al., 2022).

Recent research shows the direction of development of Dynamic FMEA, which is an approach that allows the adaptive update of Risk Priority Number (RPN) values based on changes in actual operational conditions. However, the integration between Dynamic FMEA and the field data-based RUL prediction model is still very limited. Most existing studies have not linked the results of residual life predictions with system performance indicators such as voltage losses (ΔV%), even though the magnitude of voltage losses can represent the impact of degradation on transformer electrical performance (Alghamdi et al., 2022; Li et al., 2024).

Previous studies have developed various models to predict Remaining Useful Life (RUL) in electrical equipment, especially power transformers, using methods such as Random Forest (RF), Long Short-Term Memory (LSTM), and a combination of both. These studies, such as those conducted by Munhamoh & Musiiwa (2025), Mu et al. (2022), Wu et al. (2022), and Marouane et al. (2024), show significant results in improving the accuracy of RUL prediction using hybrid techniques that combine RF and LSTM, as well as the use of multi-sensor data and deep learning. However, these studies have not integrated the dynamic Failure Mode and Effects Analysis (FMEA) approach with RUL prediction based on actual operational data of transformers that consider variables such as load imbalance, dynamic derating, and the impact of voltage losses. Therefore, this study aims to fill this gap by developing a hybrid Dynamic FMEA-based RUL Prediction model to improve the accuracy of transformer RUL prediction in real operational environments.

Power transformers experience performance degradation due to the influence of load imbalance, hot-spot temperature, and dynamic derating that fluctuate continuously. The degradation process will have an impact on reducing the Remaining Useful Life (RUL) and increasing voltage losses in the power system. Meanwhile, the existing RUL prediction model is still static, unable to capture the dynamic behavior of the system and the relationship between operational variables in an adaptive manner. Based on these problems, this study is designed to answer the following questions: 1) How do load imbalances and dynamic derating affect hot-spot temperature changes and accelerated power transformer degradation based on actual operational data? 2) How can the Dynamic FMEA method be used to identify and prioritize the risk of power transformer failure adaptively as operational conditions change? 3) How can the integration of the Dynamic FMEA method with machine learning algorithms (Random Forest and LSTM) improve the accuracy of transformer RUL predictions compared to conventional approaches? 4) What is the relationship between RUL predictions and the impact of voltage losses ($\Delta V\%$) in assessing the performance and reliability of power transformer systems? 5) How can the results of this hybrid model be used to support risk-informed maintenance decision-making and optimization of power transformer operational derating?

The following are the research objectives for the thesis titled "Hybrid Dynamic FMEA Model to Determine the Remaining Useful Life (RUL) of Power Transformers Using Random Forest (RF) and Long Short-Term Memory (LSTM)": 1) Develop the Dynamic Failure Mode and Effects Analysis (Dynamic FMEA) method based on Mean Decrease in Accuracy (MDA) to produce a Risk Priority Number (RPN) that is adaptive to changes in the operational conditions of power transformers. 2) Build a Random Forest (RF) model as a base model to identify and model the influence of key operational variables on transformer degradation rates. 3) Implement the Long Short-Term Memory (LSTM) model to capture the temporal patterns and dynamics of transformer degradation and predict RPNs based on time sequences. 4) Integrate RF and LSTM models in a hybrid scheme to estimate the Remaining Useful Life (RUL) of power transformers based on actual conditions and evaluate model performance using RMSE, MAE, and coefficient of determination (R^2) validation metrics.

METHOD

This study used an experimental quantitative approach based on historical data on the operation of power transformers. The methodology applied combines Dynamic Failure Mode and Effects Analysis (Dynamic FMEA) with machine learning regression, namely Random Forest and Long Short-Term Memory (LSTM), to predict the Remaining Useful Life (RUL) of the transformer based on condition-based prognostics.

The approach used is data-driven, where the actual operational parameters of the transformer are processed to form a dynamic failure risk indicator in the form of a Risk Priority Number (RPN). Furthermore, RPN is used as the basis for degradation modeling and estimation of transformer residual life.

The research was conducted at the Substation #2 150 kV Srondol – Semarang, one of PLN's operational units which represents the condition of the power transformer of the transmission system with variations in daily dynamic loads. These transformers were chosen because they operate continuously and have long operational historical data for medium to long-term degradation analysis.

The research was carried out in the period from January 2025 to December 2025, which included the data collection, modeling, and validation stages of the DFMEA hybrid model.

The data used is historical data on transformer operations obtained from the field monitoring system. The data is stored in comma-separated values (CSV) format and includes the following parameters:

Table 1. DFMEA Data Processing Requirements

Parameter	Symbols	Units	Remarks
Phase current R	Ia	A	Sensor measurement results
Phase current S	Ib	A	Sensor measurement results
Phase current T	Ic	A	Sensor measurement results
Transformer hot spot temperature	Tw	°C	From the results of IEC 60076-7 calculations
System Voltage	V	Volt	From load voltage measurement
Active Power	P	MVA	Based on measurement results
Reactive Power	Q	MVAR	Based on measurement results
Measurement Time	T	-	-

The pre-processing stages include:

1) Data preparation based on time-series ordering.
2) Missing value handling using the median imputation method.
3) Data normalization uses Min-Max Scaling to maintain the stability of the model learning process.

Load imbalance is a condition when the current in each phase of the three-phase system does not have the same value. In power transformers, this condition is generally caused by uneven load distribution, variations in single-phase load characteristics, and temporal changes in energy consumption patterns. Load imbalance can lead to increased copper losses, an increase in *hot-spot temperature*, and an acceleration of insulation degradation, which ultimately reduces the reliability and operational life of the transformer (IEEE, 2011; IEC, 2018).

A 10% increase in load imbalance can raise hot spot temperatures by up to 7°C, accelerate insulation degradation by 12%, and decrease system reliability by 8–10% (Nugroho et al., 2022).

Load imbalance accelerates thermal degradation and insulation mechanics, increasing the Occurrence value (O_j(t)) as the frequency of abnormal conditions occurring. This imbalance data can be included as one of the sensor inputs in the LSTM to model temporal degradation.

Derating is the reduction of the nominal capacity of the transformer that is permissible due to actual operating conditions such as ambient temperature, humidity, or overload. Dynamic derating allows adjustment of transformer working capacity based on real-time data (IEC 60076-7, 2018; IEEE, 2011).

This variable affects the Severity (S_j(t)) component because the higher the derating, the greater the consequences for the life of the transformer.

Voltage losses describe energy losses that occur due to the transformer's internal impedance and load imbalance. Random Forest as a Transformer Degradation Prediction Base Model.

The research stages in sequence include:

1. Data collection and pre-processing
2. Calculation of operational parameters
3. Random Forest and MDA Modeling
4. Dynamic FMEA and RPN calculation
5. RPN prediction using LSTM
6. Formation of hybrid models
7. RUL Estimate
8. Validation and analysis of results

RESULTS AND DISCUSSION

Transformer Operational Data Description

The data used in this study is operational data for the Substation #2 150 kV Srondol – Semarang in 2025 which includes daily electrical and thermal parameters. The parameters analyzed included three-phase current (Ia, Ib, Ic), active power (P), reactive power (Q), voltage (V), and winding temperature (Tw).

Based on preliminary data, the current values in all three phases showed relatively small but not completely balanced variations. This indicates the existence of a light to medium load imbalance, which corresponds to the operating conditions of the dynamic load distribution transformer. The winding temperature is in the range of 50–55°C, reflecting normal operating conditions but being quite sensitive to fluctuations in load and power quality. These data characteristics support the application of the condition-based monitoring approach, as the parameters used are physically directly correlated with the degradation process of transformer insulation as described in the previous chapter.

Load Imbalance Analysis and Its Impact

Load imbalances are analyzed using the Current Unbalance Index (CUI) and Current Imbalance (I_imbalance) calculated from three-phase currents. The results of the calculation show that although the difference in current between phases is relatively small, this variation still contributes to the increase in copper losses and the inuniformity of winding heating.

As per the theory in Chapter II, the current imbalance causes uneven heat distribution in the transformer winding. This condition increases the Occurrence (O) in the Dynamic FMEA scheme as the frequency of abnormal conditions increases, even though it has not yet reached the critical limit. Thus, the load imbalance parameter proved relevant as an input variable in data-driven degradation modeling.

Dynamic Derating and Thermal Conditions of Transformers

Dynamic derating is calculated based on the actual winding temperature (Tw). In periods with an increase in winding temperature, the effective power of the transformer decreases relative to its nominal capacity. Although the derating values that occur are still within safe limits, the trend of increasing temperatures indicates the accumulation of thermal stress.

These results are in line with the dynamic derating theory in the previous chapter, where the rise in temperature above the reference value accelerates the rate of aging of the isolation. Therefore, the winding temperature parameters and the rate of temperature change play a dominant role in the Severity (S) component of Dynamic FMEA.

Voltage Losses and Electrical Stress

Voltage losses are analyzed using the per-unit impedance approach of the transformer. Variations in active and reactive power in the data cause small fluctuations in the voltage drop value (ΔV). Although not significant in terms of power quality, these voltage losses still reflect an increase in electrical stress on the transformer windings. In the context of Dynamic FMEA, voltage losses contribute to:

- **Severity (S)** → impact of voltage quality degradation,
- **Detection (D)** → early indication of degradation through monitoring of electrical parameters.

Thus, voltage losses serve as an additional indicator that enriches condition-based risk modeling.

Random Forest Modeling Results as a Base Model

The Random Forest model is used to map the nonlinear relationship between operational parameters and degradation proxies in the form of winding temperature (Tw). The model is trained using a number of decision trees with limited depth to maintain a balance between accuracy and generalization.

The modeling results show that Random Forest is able to capture the complex relationship between load, temperature, and current imbalance. The model output in the form of RPN_RF serves as an initial estimate of the risk of degradation based on actual data.

In addition, Random Forest generates a Mean Decrease in Accuracy (MDA)-based feature weight, which is used to objectively compile Dynamic FMEA and reduce the subjectivity of expert judgment.

Building Dynamic FMEA and Mean Decrease in Accuracy

Dynamic FMEA is built by dynamically mapping operational parameters into Severity (S), Occurrence (O), and Detection (D) components. MDA-based weighting allows each component to reflect the actual contribution of the parameter to transformer degradation.

The resulting RPN_MDA value indicates fluctuations following actual operating conditions. As winding temperatures and load imbalances increase, RPN values also increase, signaling a higher risk of degradation.

This result proves that Dynamic FMEA is more adaptive than conventional FMEA which is static.

Risk Priority Number Prediction using LSTM

The LSTM model is used to predict RPN_MDA values by taking into account the temporal dynamics of historical data. With a lookback window approach, LSTM is able to capture the cumulative effects of thermal and electrical stress that static models cannot represent.

LSTM predictions generate RPN_MDA_LSTM, which represent projected future degradation risks. This model is particularly relevant for transformers because degradation occurs gradually and depends on the history of operation.

Hybrid Dynamic FMEA Results

The **RPN_Hybrid** score is obtained from the average of RPN_MDA and RPN_MDA_LSTM. This approach combines actual risk conditions and future predictions to produce a more stable and realistic risk estimate.

The results of the Hybrid Dynamic FMEA show that RPN values are not very sensitive to momentary fluctuations, but remain responsive to medium-term degradation trends. This supports the research goal of producing adaptive and predictive risk models.

Estimasi Remaining Useful Life

Remaining Useful Life (RUL) is calculated using an RPN-based exponential function. The actual RUL value is obtained from RPN_MDA, while the prediction RUL is calculated from RPN_MDA_LSTM. With this approach, RUL not only reflects current conditions but also future degradation trends.

Normalization of RUL into the form of a Health Index makes it easier to interpret transformer conditions. Based on the simulation results, the transformer is still in the **normal to warning** category, but there are certain periods that show an increase in *criticality* due to rising temperatures and load imbalances.

General Discussion and Implications

Overall, the results show that:

1. The actual operational parameters are able to effectively represent the degradation of the transformer.
2. The integration of Random Forest, Dynamic FMEA, and LSTM results in an adaptive and condition-based RUL prediction model.
3. Hybrid Dynamic FMEA provides an advantage over conventional approaches because it is able to combine actual conditions and future projections.

This approach is particularly relevant to support risk-informed maintenance and proactive management of power transformer assets.

CONCLUSION

A Dynamic FMEA framework based on Mean Decrease in Accuracy (MDA) was successfully developed to produce an adaptive Risk Priority Number (RPN) that responds dynamically to actual transformer operating conditions, including hot-spot temperature variations, load imbalances, voltage losses, and load fluctuations. A Random Forest (RF) model was employed as the base degradation model to map the nonlinear relationships between operational variables and transformer degradation indicators, with hot-spot temperature (Tw), voltage losses (ΔV), and load imbalance (CUI) identified as the dominant contributors, consistent with thermal aging and load imbalance theory. A Long Short-Term Memory (LSTM) model further captured temporal degradation patterns through a lookback window and multivariate time series approach, generating RPN predictions that closely follow actual historical trends. The integration of RF and LSTM within a Hybrid Dynamic FMEA scheme proved capable of estimating the Remaining Useful Life (RUL) of the transformer under actual and projected conditions, with model validation yielding low RMSE, small MAE, and an R^2 approaching 1, while the dashboard visualisation — incorporating Health Index, Criticality, and operational status indicators — successfully supports risk-based maintenance decision-making. For future research, it is recommended that the hybrid model be extended to incorporate real-time sensor data streams and validated across transformers of varying ratings, ages, and environmental contexts, so as to assess the model's generalisability and robustness in broader operational settings.

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