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Hot Spot Temperature Prediction Models Including Loss Of Life Of Transformers Using Asaba Transmission Sub-Station As A Case Study

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Abstract
This study is on hot spot temperature (HST) prediction models, including loss of life (LoL) of transformers, and uses the Asaba transmission substation as a case study. One year loading profile data was collected from the substation while Artificial Neural Network (ANN) and Bagging Regression (BR) algorithms were modeled using this data on MATLAB and Python to predict the HST for Day-Ahead (24-Hours), Week-Ahead (120-Hours), and Weekend (48-Hours). The results show the nonlinear relation between Load and HST, as an increase in load values from 305.8A – 328.9A resulted in an increase in HST from 52.23°C – 54.88°C. Model performance was compared using Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE). Using MATLAB indicated ANN had MAPE values of 2.51, 2.74, and 2.48 with RMSE values of 1.83, 1.71, and 1.85, respectively, for Day-Ahead, Week-Ahead, and Weekend prediction. In contrast, BR had MAPE values of 5.93, 5.83, and 5.77 with RMSE values of 4.30,4.86, and 4,43, respectively, for the same prediction period. Using Python indicated ANN had MAPE values of 6.67, 7.29, and 6.96 with RMSE values of 3.34, 4.27, and 1.95, respectively, for Day-Ahead, Week-Ahead, and Weekend prediction, while BR had MAPE values of 6.16, 6.07, and 6.5 with RMSE values of 5.7, 5.85 and 4.5 respectively for same prediction period. MATLAB software gave better results than Python, which had a higher percentage error for the ANN and BR models, likely due to the model's ability to better capture consistent thermal responses during sustained high loads. LoL for a 24-hour load cycle gave a cumulative age hour of 0.029959 hours, revealing how the HST significantly impacts the transformer's insulation and life expectancy. It is recommended that different modeling techniques be explored for prediction analysis for medium-term transformer HST prediction if better results are desired. Also, operators should incorporate monitoring systems like Arduino to shut down the network and protect the transformer anytime the temperature exceeds set limits. This study presents the following contribution to knowledge: Data bank of a 60 MVA transformer can be obtained; Correlation between HST and Load demand has been established.

Keywords: *Transformer Hot Spot Temperature, Loss of Life, Artificial Neural Network, Bagging Regression, Asaba Transmission Substation, Thermal Stress, Insulation Life, Aging Factor.*

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I. Introduction:

Reliability of the power transformer is very critical to maintaining uninterrupted electricity supply in growing cities. Asaba, the Delta State capital of Nigeria, has witnessed significant expansion in commerce, real estate, and industry, driving increased demand for electricy.. The Asaba 330/132kV Transmission Substation, managed by the Transmission Company of Nigeria (TCN), is central to the region's power grid, supplying electricity to residential, commercial, and industrial companies. Ensuring the transformer's operational integrity, including 300MVA and 150MVA units, is essential to avoid disruptions that can affect numerous communities in the Delta North Senatorial District.

One of the most critical parameters influencing transformer performance and longevity is the hot spot temperature (HST). HST if not monitored carefully, directly affects the thermal aging of insulation, leading to accelerated degradation and loss of life. Load-related variables significantly influence HST, including load current, ambient temperature, and load cycles. Predictive models are, therefore, indispensable for forecasting HST and computing insulation loss of life, enabling proactive maintenance and reducing the likelihood of faults or downtime.

The aim of this study is to compare predictive models for medium-term HST forecasting using Artificial Neural Networks (ANN) and Bagging Regression models. Data was collected from the Asaba substation for a period of one year and was used to compute insulation loss of life. The findings provide some insights into transformer performance, which may be useful for operators imaintenance strategies in real-world power system operations.

II. Literature Review:

Predicting the transformer hot spot temperature (HST) and computing the insulation loss of life are critical in ensuring reliable power network operation. A number of studies have proposed models and ways to address this challenge, each with unique strengths and shortcomings.

Elle et al. (2023) proposed a dynamic thermal model for predicting transformer loss of life, noting the effect of parameters such as thermal capacity and oil time constant. The model performed well, however, he recommended improvement for estimating hot spot temperatures during under-load phases to enhance accuracy. Also, Rommel et al. (2021) proposed a method which leverages voltage and current measurements to estimate the winding hot spot temperatures using a virtual-twin based on transformer nameplate data. The approach however, neglected ambient temperature, limiting its applicability in the dynamic operational setting.

Sun et al. (2021) proposed support vector regression for HST prediction in distribution transformers, using inputs such as ambient temperature and cooling fan status. Despite achieving high accuracy, the model's dependency on hot spot temperature data restricted its use to dry-type transformers. In contrast, Bracale et al. (2021) developed a probabilistic framework for load exceedance prediction and alarm-setting but needed more real-time quantitative insights for dynamic grid operation.

Juarez-Balderas et al. (2020) validated an Artificial Neural Network (ANN)-based prediction model using finite element method (FEM) simulations and experimental data. Although the model achieved an average error of 2.71%, its focus on indoor medium voltage/low voltage (MV/LV) transformers and the omission of ambient temperature limited its broader applicability. Afifah (2019) proposed a differential equation-based model for 24-hour HST prediction, though it fell short in accounting for the internal dynamics of transformers.

Qin et al. (2019) utilized a support vector machine model for thermal calculations, verified through comparisons with backpropagation neural networks. While the model was feasible for short-term prediction, it needed to be better suited for medium- or long-term forecasting. Gupta et al. (2019) used numerical solutions to differential equations for transient thermal processes in transformers, showing superior performance with MATLAB-based simulations. However, the study focused solely on ONAF cooling arrangements during peak loads.

Arabul et al. (2018) employed a regression model based on fiber optic temperature measurements, improving lifetime calculations while reducing input data requirements. Lastly, Haritha et al. (2009) demonstrated a finite element thermal model using thermal-electrical analogies, though its application was limited to small, single-phase transformers.

These various studies underscore the importance of noting and using diverse factors such as load dynamics, ambient conditions, and advanced modeling techniques. Gaps, however, still need to be covered in achieving predictive accuracy for medium-term forecasts, particularly in outdoor transformers under varying environmental conditions. This study has built on these findings by comparing ANN and Bagging Regression models using real-world data collected from the Asaba Transmission Substation and emphasizing practical implementation and maintenance strategies for utility operators.

III. Methodology

Study Area and Transformer Specifications

The Asaba 330/132kV Transmission Substation, located in Delta State, Nigeria, was selected as the study area due to its critical role in regional power distribution. The 60 MVA, 132/33kV transformer at the substation operates under ONAN/ONAF cooling and serves residential and industrial areas. Its specifications include a rated current of 262.4A (HV) and 1004.1A (LV), with a maximum ambient temperature of 45°C and winding and oil temperature rises of 55°C and 45°C, respectively (Table 3.1).

Table 3.3: 60 MVA 132/33kV Power Transformer Specification

Description	Rating
Rated Voltage (HV)	132kV
Rated Voltage (LV)	33kV
Rated Current (HV)	262.4A
Rated Current (LV)	1004.1A
Weight of core/ coil	40,300kg
Weight of tank and fittings	58,900kg
Weight of oil	17,600kg
Maximum Ambient Temperature	45°C
Winding Temperature Rise	55°C
Oil Temperature Rise	45°C

Data Collection
Hourly data over a year were collected from the substation, including:
Ambient Temperature: Measured externally to gauge the impact of environmental conditions.
Oil Temperature and Winding Temperature: Indicators of internal transformer heating.
Load (A): Transformer load current influencing thermal dynamics.

A dataset sample is presented in Table 3.2, and full readings are provided in Appendix B.

Date	Hour	Ambient Temperature Reading (°C)	Oil Temperature Reading (°C)	Winding Temperature Reading (°C)	Load (A)	Ambient Temperature Reading (°C)
01/01/2023	1	31	48	46	327	31
01/01/2023	2	31	48	46	324	31
01/01/2023	3	31	48	46	305.8	31
01/01/2023	4	32	48	46	328.9	32
01/01/2023	5	32	48	46	336.6	32
01/01/2023	6	32	48	46	356	32
01/01/2023	7	33	48	46	353.3	33
01/01/2023	8	34	48	46	336.6	34
01/01/2023	9	34	50	48	370.8	34
01/01/2023	10	35	50	48	322	35
01/01/2023	11	35	50	48	329.7	35
01/01/2023	12	35	50	50	356.6	35
01/01/2023	13	35	50	48	348.2	35
01/01/2023	14	35	50	48	361.7	35
01/01/2023	15	35	50	48	353.3	35
01/01/2023	16	35	50	48	328	35
01/01/2023	17	35	50	48	341.5	35
01/01/2023	18	33	50	48	344.9	33
01/01/2023	19	32	50	48	320.1	32
01/01/2023	20	32	50	48	368.2	32
01/01/2023	21	32	50	48	342.3	32
01/01/2023	22	31	50	48	312.7	31
01/01/2023	23	31	50	48	334.6	31
01/01/2023	23	31	50	48	323.7	31

Data Pre-Processing
To ensure data quality and compatibility with predictive modeling:
1. **Normalization**: All data points were normalized between 0 and 1 using the formula:

$$x_{\text{norm}} = \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}}$$

2. **Segregation**: Data were split into weekday (Day-Ahead and Week-Ahead) and weekend (Weekend) subsets for different load patterns.
3. **Corrupt Data Handling**: Outliers and corrupted entries were detected and corrected using MATLAB and Python scripts.

Predictive Modeling
Two algorithms were employed for medium-term prediction of Hot Spot Temperature (HST):
1. **Artificial Neural Network (ANN)**: This algorithm captured nonlinear relationships between HST and load variables. It was implemented using MATLAB (R2024a) Neural Network Toolbox.
2. **Bagging Regression**: A robust ensemble learning method implemented in Python was used for comparative analysis.

Both models predicted HST for three forecast horizons:
Day-Ahead (24 hours)
Week-Ahead (120 hours)
Weekend (48 hours)

Model Training and Testing

Data from 60 days within each quarter (January–March, April–June, July–September, October–December) were used for training the models. Testing was conducted on the week following each training period. The models' performance was assessed based on two metrics:

1. **Mean Absolute Percentage Error (MAPE)**:

$$\text{MAPE} = \frac{100}{N}\sum_{i=1}^{N}\frac{|y_{\text{predicted}} - y_{\text{actual}}|}{y_{\text{actual}}}$$

2. **Root Mean Squared Error (RMSE)**:

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_{\text{predicted}} - y_{\text{actual}})^2}$$

Correlation Analysis

Cross-correlation was conducted between HST and load variables to measure the impact of load changes on HST. Results from MATLAB were compared with Python-generated outputs for validation.

Insulation Loss of Life Calculation

The following steps were carried out to compute the transformer's insulation loss of life:

1. **Aging Acceleration Factor (FAA)**: Calculated from predicted HST.
2. **Cumulative Aging Hours** derive from the FAA over the forecast period.
3. **Percent Loss of Life**: Determined using IEEE standards.
4. **Visualizations**: Plots of Aging Acceleration Factor, Loss of Life, and remaining insulation life were generated for analysis.

IV. Results And Discussion

Comparison of Model Performance

Results record from the model's performance evaluation, as shown in Figures 4.20 to 4.25, highlight clear trends in predictive accuracy between MATLAB and Python implementations of Artificial Neural Networks (ANN) and Bagging Regression models.

Day-Ahead Predictions (Figures 4.20 and 4.21): MATLAB's ANN consistently aligned closely with actual Hot Spot Temperature (HST), outperforming both MATLAB and Python implementations of Bagging Regression. Python's ANN shows the predicted values deviated more from the HST actual values during sharp peaks, which shows that Python's reduced capability to handle sudden variations in load values.

Figure 4.20: MATLAB and Python ANN

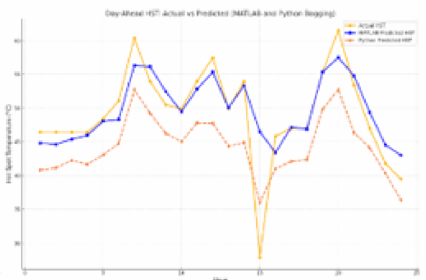

Figure 4.21: MATLAB and Python Baggy

Week-Ahead Predictions (Figures 4.22 and 4.23): MATLAB's ANN exhibited superior performance, effectively capturing higher peaks and maintaining lower deviations across the 120 hour forecast period. The result from MATLAB's Baggy Regression showed more slightly accuracy compared with the Python's Baggy Regression which lagged in predicting periods with variations in loads.

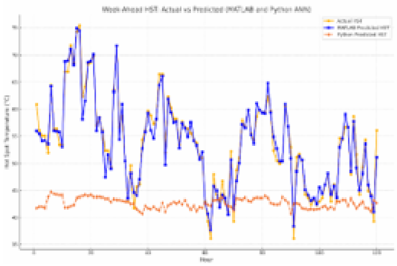

Figure 4.22:- MATLAB vs Python ANN

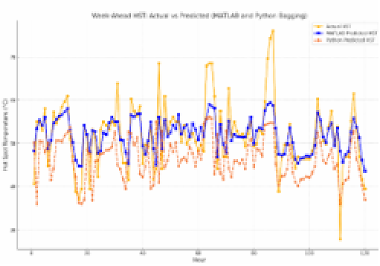

Figure 4.23:- MATLAB vs Python Baggy

Weekend Predictions (Figures 4.24 and 4.25): MATLAB's Baggy Regression also showed accuracy during shorter prediction intervals, particularly in capturing short-term variations. However, MATLAB's ANN remained the most reliable model, maintaining consistency across all prediction types.

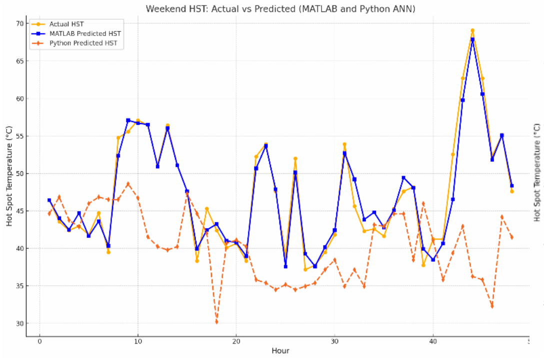

Figure 4.24: MATLAB vs Python ANN

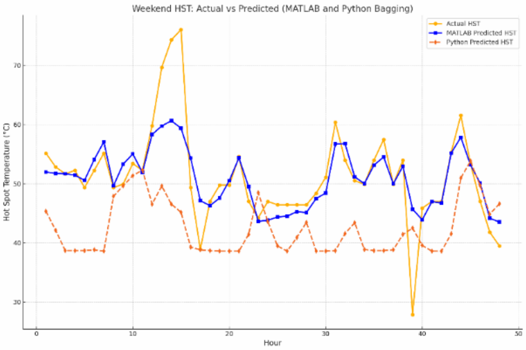

Figure 4.25: MATLAB vs Python Baggy

The findings indicate that MATLAB's ANN was an effective predictive model for medium-term forecasts for Day-Ahead, Week-Ahead, and Weekend prediction periods.

Aging Acceleration Factor

The Aging Acceleration Factor (FAA) results, as shown in Figure 4.26, reveal the strong dependence of the FAA on HST:

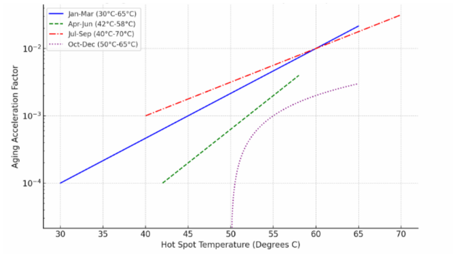

Figure 4.26: Aging Acceleration Factor

January–March shows FAA increases steadily as HST rises from 30°C to 65°C, peaking at 10^{-3}. This steady linear trend reflects moderate thermal stress under seasonal conditions. April–June indicates FAA demonstrates a narrower temperature range (42°C–58°C) with a consistent but lower aging acceleration, suggesting reduced thermal stress during this period. July–September shows the most comprehensive temperature range (40°C–70°C), which results in a steep rise in FAA, indicating significant thermal stress, particularly at higher temperatures. October–December indicates the FAA rises sharply due to high temperatures (50°C–65°C), which represents the highest thermal stress and insulation degradation.

These findings underscore the importance of maintaining HST within safe limits, particularly during periods of higher thermal stress.

Loss of Life

The cumulative Loss of Life (LOL) over a 24-hour period, as shown in Figure 4.27, shows insight on the impact of HST on transformer aging:

Figure 4.27: Loss of Life vs Time

January–March shows that Loss of Life increases steadily, reaching 1.2×10^{-5} by the 24th hour. The trend reflects a controlled aging rate during this period. April–June**:** The cumulative Loss of Life reaches 0.9×10^{-5}, the lowest across all quarters, indicating minimal thermal stress. July–September shows the Loss of Life rate is minimal, peaking at 2.5×10^{-6}, suggesting reduced thermal stress and load impact. October – December has the highest Loss of Life rate, peaking at $3.5 \times 10{-}5$, which correlates with the increase in HST and significant insulation degradation.

The indicated trends show thermal stress increases during high load periods, as seen in the October – December quarter. This highlights the need for targeted maintenance strategies to minimize insulation loss during these periods.

Transformer Insulation Life

Figure 4.28 illustrates the impact of HST on transformer insulation life across all quarters:

January–March**:** A steep decline in insulation life is observed as HST exceeds 50°C, with the sharpest drop occurring above 60°C. April – June**:** A gradual decrease in insulation life corresponds to the moderate thermal stress in this quarter. July – September**:** The most comprehensive temperature range (40 °C – 70 °C) reduces insulation life, particularly at higher HST values. October – December shows insulation life decreases steadily due to high temperatures.

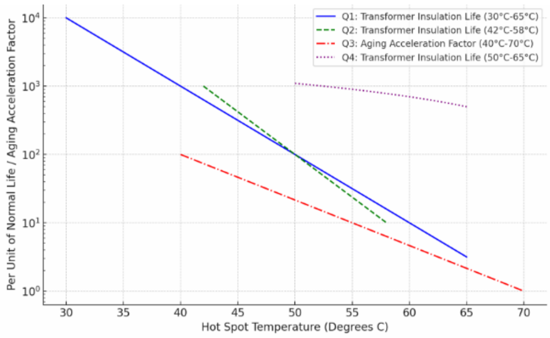

Figure 4.28: Transformer Insulation Life

These results emphasize that maintaining HST below critical thresholds (e.g., 65°C) is crucial for prolonging transformer insulation life.

Key Findings

1. **Model Performance**: MATLAB's ANN consistently outperformed other models for Day-Ahead, Week-Ahead, and weekend predictions.
2. **Thermal Stress**: The FAA increases linearly with HST, peaking during high-load periods, highlighting the correlation between temperature and insulation aging.
3. **Insulation Life**: Sustained high HST values (>65°C) significantly reduce insulation life, emphasizing the need for effective predictive models and maintenance strategies.
4. **Loss of Life**: LOL trends reveal accelerated aging during high-load periods, particularly in the October–December quarter.

V. Conclusion:

The hot spot temperature (HST) of a transformer's winding is an important parameter that influences the transformer's insulation performance, thermal fault prevention, and operational life. In a developing country like Nigeria, where electricity is a fundamental necessity, accurate prediction and monitoring of HST are imperative to meet increasing demands and ensure uninterrupted supply. This study has focused on predicting transformer HST to estimate the loss of life of transformers, using the Asaba transmission substation as a case study.

Artificial Neural Network (ANN) and Baggy Regression models were employed to predict the HST of the 132/33kV 60MVA distribution transformer under diverse operational conditions. The result revealed that MATLAB's ANN model consistently outperformed the Baggy Regression model for medium-term predictions. The study highlighs the impact of thermal stress on transformer insulation life and aging, confirming that insulation performance is directly dependent on hot spot temperature.

By calculating insulation life and aging factors, this study has provided insights into the relationship between HST and the long-term reliability of transformers. The results emphasize the need for accurate predictive models, real-time monitoring, and strategic maintenance planning to optimize transformer performance and extend operational life.

VI. Recommendations

Exploration of Alternative Predictive Models:

Different modeling techniques should be explored to improve medium-term transformer HST prediction results. The choice of the predictive model should align with the specific prediction horizon and the desired trade-off between minimizing prediction error and explaining variance in the data. Datasets spanning five years or more should be utilized for longer time horizons, especially when using complex models like Artificial Neural Networks. This approach ensures better generalization and predictive accuracy.

Incorporation of Monitoring Systems:

A real-time monitoring system, such as an Arduino-based controller, should be integrated into transformer networks to prevent overheating and protect transformers from thermal damage. Such systems can automatically shut down operations when HST exceeds predefined safety thresholds, preventing overloads, overheating, and insulation degradation. This proactive approach enhances operational safety and ensures the longevity of the transformer.

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