Data Driven Model Agnostic Methodology for Transformers Top Oil Anomaly Detection

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***Abstract*— Predictive maintenance and advanced asset management strategies have emerged to accurately diagnose transformer failures, helping to mitigate safety risks, reduce service interruptions, and enhance operational efficiency. Among various indicators, oil temperature is a key parameter for assessing a transformer's operational health. This work presents a methodology for detecting anomalies in transformer top-oil temperature, aiming to identify potential critical conditions and assist system operators in making informed maintenance decisions. The proposed approach leverages historical data typically collected through the transformer's online monitoring system. A machine learning (ML) model is developed to predict the expected top-oil temperature under normal operating conditions. To detect deviations from this baseline and identify them as anomalies, Statistical Process Control (SPC) techniques are applied. The effectiveness of the methodology is validated using additional transformer measurements, which serve as reliable indicators of anomalous behavior, as well as an existing published algorithm.**

Keywords—advanced asset management, Top Oil Temperature Anomaly detection, Fault prediction, machine learning, statistical process control

I. INTRODUCTION

Transformers play a vital role in the operation of power systems. Beyond their high replacement costs, transformer failures can trigger cascading effects, potentially leading to widespread power outages across larger regions of the grid. According to [1], 41% of failures in transformers are due to tap changers, 19% due to the windings, 13% due to leakage 12% due to the bushing, 3% due to the core and the remaining 12% to various other causes.

Traditional fault detection methods were reactive and labor-intensive, highlighting the need for predictive maintenance approaches that can proactively identify potential issues, reduce downtime, and minimize safety and financial risks. Intelligent algorithms have been developed to enhance transformer condition monitoring and fault diagnosis using machine learning, physical modeling and advanced online monitoring systems. In [2], dedicated example cases report that the use of on-line transformer monitoring systems can result in a 75% reduction in annual maintenance and repair costs assuming early detection repair to major repair ratio of 20%.

Diagnostic techniques are very often based on Dissolved Gas Analysis (DGA) which is the analysis of the measured concentration of the gasses dissolved in the oil of the transformer. While valuable, this approach relies on gas concentration measurements, which are not always available, especially in distribution network transformers. Additionally, DGA gases change at a slow rate, making it difficult to detect anomalies in the short term horizons.

The transformer's top-oil temperature is a key parameter for monitoring, as it reflects the cooling efficiency and is directly associated with the degradation rate of the paper insulation. As seen in [3], the oil temperature measurement has the highest impact on predicting the fault state of a transformer. More recently, in [4] the top oil temperature is predicted by a Back Propagation (BP) neural network assisted by a multi-model fusion prediction method.

Reference [5] uses the existing top oil temperature monitoring to calculate the oil exponent using Particle Swarm Optimization (PSO) to detect potential fan malfunction. This approach relies on an accurate model of the system and involves the knowledge of the ratio of rated load loss to no-load loss. Similarly, in [6] thermal faults are detected using the top oil temperature and radiator temperature that are computed using a thermal model that includes ambient, top-oil, winding, and radiator temperature and are compared to measured temperatures that are provided by a thermal camera.

Reference [7] proposes a thermal model of six thermal points (ambient, top oil, radiator top, radiator middle, radiator bottom, and coil) to estimate the top oil temperature using nonlinear regression estimation. This algorithm is proposed to be used for implementing fault detection. In [8], the use of machine learning is proposed for time-series hot-spot

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temperature forecasting using load, tap position, ambient temperature, solar radiation and wind speed and then compared to field measurements for detection of anomalies.

Reference [9] uses an adaptive neuro-fuzzy inference (ANFIS) technique to estimate the hot spot temperature. As an intermediate step, an ANFIS structure predicts the top oil temperature based on the load and ambient temperature.

The work presented in [10] uses four Boolean indicators (Winding Temperature Indicator, Oil Temperature Indicator Alarm, Oil Temperature Indicator Trip, Magnetic oil gauge indicator) that are trained on a rich dataset including the current and voltage measurements and a suitable ML model out of twelve possible, in order to assess the condition of fault of the transformer. The same dataset and four indicators are used in [3], where the importance of the features is quantified contributing to the transparency of the model. The dataset is also used in [11] where the Magnetic Oil Gauge indicator' fault is predicted. An overcurrent relay based on a numerical algorithm is used for the protection from the fault. Finally in [12] this dataset is used to train a stacking ML model, identifying if the oil temperature indicator is tripped, if the oil temperature indicator is alarmed and the state of the oil level using as inputs the measured voltages and currents.

A TCN-Transformer Model is proposed in [13] that uses load current, ambient temperature, and operating voltage for the classification of the operating condition of the transformer. The input power, output power, the rate of change of oil temperature to ambient temperature and the frequency concentration degree at 100 Hz are used to identify abnormal states of the transformer.

In [14] , an unsupervised model based on autoencoders and gated recurrent units (GRUs) is used to model the normal behavior of a transformer using the top and bottom oil temperature, the load ratio, tap changers' position and ambient temperature. Exponentially Weighted Moving Average (EWMA) control chart is used to identify abnormal behavior and the algorithm is validated using an open dataset.

This paper aims to develop an alternative methodology for estimating top oil temperature using machine learning, designed to enhance thermal condition monitoring. The approach helps identify issues such as restricted oil and air flow or faulty cooling pumps and fans. A key contribution of this work is that it relies on minimal measurements—specifically, current, top-oil temperature, and ambient temperature—collected from available sensors. The methodology combines machine learning and Statistical Process Control (SPC) for model-agnostic top-oil temperature modeling and anomaly detection. The model is tested using data from actual transformers and validated with additional measurements to demonstrate its performance. The results are also validated with the use of the algorithm [14] on our case studies.

The remainder of the paper is structured as follows: Section II outlines the methodology used to develop the Oil Temperature Anomaly Detection system, including details on data cleaning, model training, and real-time post-processing. Section III presents the case studies where the tool is applied. Section IV discusses the results obtained from testing the tool on the case studies. Finally, Section V provides a discussion on the results and evaluates the effectiveness of the tool.

II. METHODOLOGY

This section outlines the methodology used to develop the proposed Top Oil Temperature Anomaly Detection system. A flowchart illustrating the complete methodology is provided in Fig. 1. The approach consists of three key components: data cleaning, top-oil model prediction training, and statistical process control (SPC) for anomaly detection.

The main steps of the methodology include:

- Data Cleaning: To build a ML model agnostic predictor of top oil temperature for normal operating conditions the training data must represent the typical operation of the transformer. Thus, data cleaning, outlier removal, and binning techniques are applied.
- Model Training: Models representing normal transformer operation are developed, trained and evaluated.
- Real time and post-processing: The real measurements of the top-oil temperature and the predicted values of the model are processed using a Statistical Process Control (SPC) method to identify potential dates of fault.

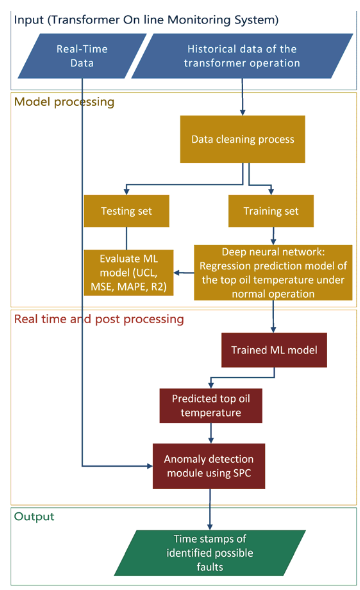


Figure 1 Oil Temperature Anomaly detection tool flowchart

A. Data cleaning process

The collected data include the top oil temperature, the load current and the ambient temperature in accordance to the typical physics based thermal model [15]. Data quality must be carefully assessed to ensure accurate system representation. Anomalous data points must be removed to prevent misinterpretation of system performance and ensure the model reflects the healthy state.

Historical data contain transformer current, ambient temperature and top oil temperature. The data are divided in clusters of two-dimensional bins of 5A range regarding the load current and 10 degrees Celsius regarding the ambient temperature. For each bin, the 5% and 95% quantiles of the top oil temperature are calculated and the outlier measurements are removed. This approach ensures that the data accurately represent the typical behavior of the transformer under each operating condition. In addition, samples where at least one input or output is missing are removed. If failure dates or additional online monitoring data, such as DGA gases or bushing insulation measurements, are available, they can be used to exclude data from the training set corresponding to periods when fault conditions, as defined by standards, are detected.

B. *Deep neural network*

After data cleaning, the training data are formed, which consist of the previous hour's top oil temperature, transformer current, and ambient temperature, with the target being the top oil temperature for the following hour.

The training dataset is used to train a Deep Neural Network (DNN), specifically a feedforward neural network with two hidden layers of 32 neurons. Regression is performed by minimizing the Mean Squared Error (MSE), which penalizes larger errors, while the Adaptive Moment Estimation (Adam) optimizer is employed to efficiently minimize the MSE. The DNN regressor was selected because among the various regression models evaluated, the DNN achieved the best performance on our dataset. DNN hyperparameters—learning rate (0.001), layers, and neurons—were selected via grid search, optimizing for root mean square error on the validation set.

C. *Real time and post processing*

To evaluate the errors in top oil prediction (measured sensor value and predicted values by the model), a statistical process control was used to identify anomalies. The Shewhart control chart [16] is used to evaluate the deviations (errors) as they evolve. The fault threshold is defined by two control limits used to evaluate abnormal behaviors: Upper Control Limit (UCL) Lower Control Limit (LCL). The two control limits describe the sensitivity of the control chart, which is expressed as multiples of the standard deviation of the error distribution. The following equations (1)-(3) describe the control input MR_i definition and the UCL and LCL limits. The $\overline{MR}$ and σ are computed on the MR_i.

$$MR_i=|error_i-error_{i-1}| \quad (1)$$

$$UCL = \overline{MR} + 3\sigma \quad (2)$$

$$LCL = \overline{MR} - 3\sigma \quad (3)$$

The predicted values represent the healthy state of the transformer over time. When the transformer's measured values align with the healthy state, deviations on the chart will follow a normal distribution with a mean of zero and a standard deviation similar to the standard deviation of errors computed in the training set. In contrast, the presence of anomalies is indicated by randomness, with non-conformity defined as data points exceeding the fault threshold or control limits, or shifts in the average. Anomaly is defined by data points beyond the fault threshold/control limits, for at least three consecutive intervals. This parameter could be optimized in relation to the sensitivity that the operators want to achieve. In Fig 2. the anomaly detection prediction graph for two days when a possible fault is identified is presented, along with the thresholds.

III. Case Studies

The case studies involve two 400/150/20 autotransformers in operation at the Greek Transmission System. The available data for the first transformer covers the period from 14/03/2024 to 30/09/2024, with the training set including data up to July 2024. The test set for this transformer spans from August to September 2024. For the second transformer, the available data extends from 30/09/2024 to 13/03/2025, with the training set including data up to 22/01/2025, and the test set covering the period 23/01/2025 to 13/03/2025. The available data of the second transformer had days with missing data so the splitting to train/test was made based on the 2:1 ratio on the available timestamps rather than the months themselves. In addition to the top-oil temperature data, the dataset includes measurements of DGA, bushing capacitance, and tan δ. These additional measurements provided an effective means of cross-referencing and confirming the consistency of the anomaly detection results. The neural network (NN) model was developed using the TensorFlow library in Python, enabling efficient model training and implementation [17].

IV. Results

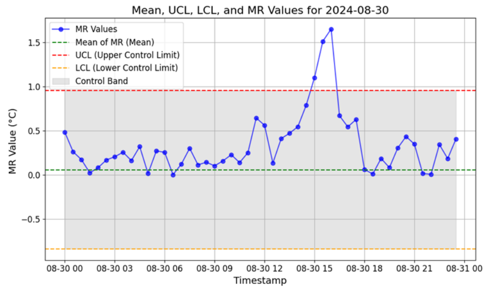
Following the methodology described earlier, the testing datasets were used to evaluate the performance of the trained model against the actual measured values from the same period. The same data cleaning procedures were applied to the test sets to isolate data that reflect normal operating conditions. The model's predictive accuracy was assessed using standard evaluation metrics, including Mean Squared Error (MSE in °C²), Mean Absolute Percentage Error (MAPE in %), the Pearson correlation coefficient (r), and the Coefficient of Determination (R^2). The Upper Control Limit (UCL) is computed based on the mean and standard deviation of the prediction errors in the training set. All evaluation metrics are summarized in Table I for both transformers under test.

TABLE I. Evaluation metrics for the two case studies

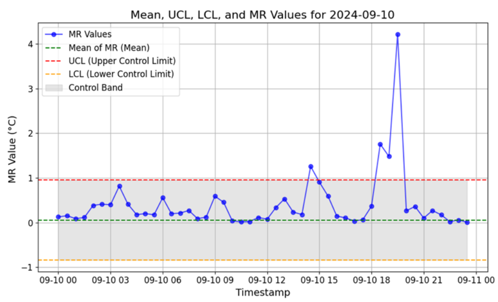
Transformer #	UCL (°C)	MSE (°C²)	MAPE (%)	R^2 (-)	r (-)
Transformer 1	0.84215	0.08201	0.00500	0.99438	0.99729
Transformer 2	0.51065	0.16579	0.01022	0.98752	0.99660

The tool identified two periods within the test set as potential indicators of fault conditions for transformer 1, defined by three successive violations of the Upper Control Limit (UCL), specifically on 30/08/2024 and 10/09/2024 (Fig. 2 (a) and (b)).

As no recorded failures occurred during the test period, measurements from existing on-line monitoring systems — that include DGA, bushing capacitance, and tan δ values— were utilised to identify events warranting further consideration according to standards [18] and classify them as anomalies that ideally should be detected by the proposed methodology.



(a) MR value (°C) on 30/08/2024



(b) MR value (°C) on 10/09/2024

Figure 2 Oil Temperature anomaly graph – suspected faults of transformer 1 on 30/08/2024 (a) and 10/09/2024 (b)

According to [18], in the field tests, a transformer insulation systems capacitance, e.g. bushings, should not change by more than 5%. If the results are above 5% and below 10% change, an investigation needs to be conducted to determine the extent or severity of the issue. In Fig. 3, we see that there is a drop of approximately 13% in a bushing of transformer 1 which would require further examination at the exact same interval that the proposed approach detects the anomaly.

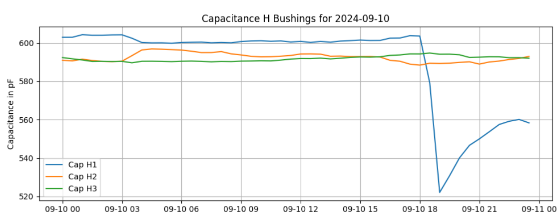


Figure 3 H-Bushing capacitance on the day of suspected fault of transformer 1 on 10/09/2024.

Further, the algorithm in [14] was applied on the test data as the required measurements were available. The output of this algorithm identified the same timestamps as potential indicators of fault conditions for transformer 1 i.e. timestamps on 30/08/2024 and 10/09/2024 (the agreement between the two algorithms also extended in the hour of the day of the detected anomalies). In Fig. 4, the identified anomalies of algorithm [14] are shown for the data of transformer 1.

Thus, it is correct to say that the anomaly detection methodology presented would correctly inform the system operator to act proactively to assess the transformer condition, without any exact knowledge of bushings status. For the other detected anomaly, no significant event or condition indicative of a fault was observed in the available diagnostic measurements.

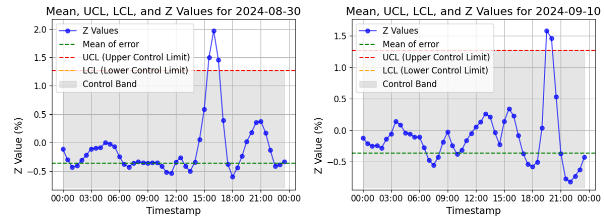


Figure 4 EWMA graph – suspected faults of transformer 1 on 30/08/2024 (a) and 10/09/2024 according to [13]

In Fig. 5, the MR values (in °C) for the training set is presented. The two incidents where MR is above the threshold for three consecutive points on 30/08/2024 and 10/09/2024 are circled in red.

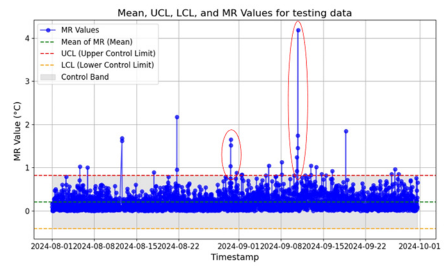


Figure 5 MR value (°C) for training set.

The same procedure of testing and evaluation was followed about transformer 2 for which an anomaly is detected on 03/03/2025. The corresponding graph of MR values is shown in Fig. 6, while the graphs of the capacitance values are shown in Fig. 7.

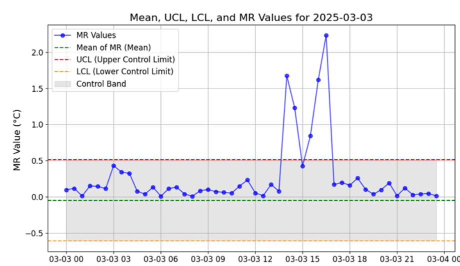


Figure 6 Oil Temperature anomaly graph – suspected fault of transformer 2 on 03/03/2025

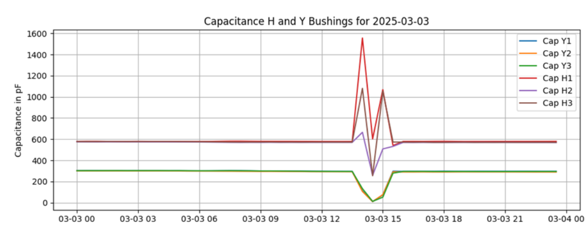


Figure 7 Bushing capacitance on the day of suspected fault of transformer 2 on 03/03/2025

It is evident that on the date and hour identified by our tool as one of the potential points of failure, the capacitance of the bushings underwent a sudden change, with Y bushing capacitances almost reaching zero and H bushing capacitances reaching values in the 50%-250% range of their mean values of the day. According to [18] these changes in capacitance values should result in further investigation by the system operator, thus it is considered that the proposed methodology correctly identified an anomalous condition. Similarly algorithm [14] identified the same timestamp as potential date of fault.

V. Conclusions

This paper presented a data-driven methodology for transformer condition monitoring based on top-oil temperature anomaly detection using machine learning and Statistical Process Control (SPC). The approach relies solely on standard measurements—namely transformer load current, ambient temperature, and top-oil temperature—which are typically available from SCADA systems, making it suitable for practical implementation without requiring additional instrumentation.

The methodology was applied to two real-world autotransformers in operation at the Greek Transmission System. The top-oil prediction results demonstrated high predictive accuracy, with R^2 values exceeding 0.98 in both cases. The effectiveness of the methodology is validated using additional transformer measurements, which serve as reliable indicators of anomalous behavior. In both case studies, the methodology successfully identified as anomalies event that resulted in significant bushing capacitance deviations, which according to diagnostic standards, indicates events requiring further investigation. The results were validated by applying an existing algorithm to our data and identifying the same potential points of failure. Compared to [14], the proposed algorithm requires fewer different channels of measurements making it applicable to a broader range of applications when fewer sensors are available. This confirms the model's capability to provide early warnings of developing issues without relying on specialized diagnostic data.

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