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Real-Time Condition Monitoring of Power Transformers Using IoT and Advanced Analytics

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Abstract: *Power Transformers (PT) are vital components in electrical power systems, playing a key role in voltage regulation and ensuring the reliable transmission of electricity. The performance and condition of transformers significantly influence the stability and efficiency of the entire power grid. Regular monitoring of transformers is essential to detect potential issues before they lead to failures, thereby minimizing downtime and maintenance costs. This paper introduces a real-time condition monitoring system for PT, utilizing Internet of Things (IoT) sensors and advanced analytics. The system collects real-time data on key operational parameters such as temperature, vibration, and load. By predictive analytics, the data is analyzed to identify anomalies and predict potential failures. This research focuses on the integration of IoT technology with advanced data analytics to enhance the detection of faults and improve maintenance practices. The results demonstrate the effectiveness of this approach in enhancing transformer reliability, optimizing maintenance schedules, and reducing the risk of unexpected breakdowns in power systems.*

Keywords: *Power transformers, Internet of Things, Fault, Long Short-Term Memory.*

1. INTRODUCTION

A transformer uses the principle of electromagnetic induction to modify voltage levels. It is a static magnetic device. It makes up as much as 60% of the total budget for a high-voltage substation, making it one of the most important and expensive components of an energy grid. Although improving a transformer's longevity and efficacy requires optimal design [1, 2], continuous supervision is also vital to avoid breakdowns. Given the transformer's critical importance in the grid, ongoing evaluation is imperative for proactive maintenance and asset management. Depending on the insulating and cooling mediums, transformers can be classified as either mineral oil-immersed or dry-type cast resin transformers. This study examines the state and performance of transformers by reviewing various assessments and data, such as operational details, laboratory analyses, and visual checks. A comprehensive and intricate system, the transformer consists of multiple components. The traditional method of simply combining all indices for evaluation does not capture the multi-level differences within a transformer, resulting in poor accuracy in the assessment. Thus, classifying evaluation levels based on the actual structure and operational mechanism of the inspected transformer is essential. The transformer can be broken down into five major components: the cooling mechanism, on-load tap changer, bushing, body, and non-electrical electrical protection device. Important parts of the operation are the body and bushing, which are prone to failure and may withstand a variety of loads over time. Consequently, it is necessary to take into account the failure types of these components. On-load tap changers, cooling systems, and non-electrical power protection devices, on the other hand, lack a distinct problem classification, therefore other indications can accurately reflect their condition throughout operation. Infrared pictures, regular test results, real-time monitoring info, and other metrics make up the transformer's multisource heterogeneous signals. These indicators provide insights into the transformer's operation from multiple angles and levels. Consequently, selecting and processing state quantities in a reasonable and accurate manner is the fundamental challenge in evaluating the transformer's condition. Currently, state evaluation systems are built using guidelines such as the "Guide for Condition Assessment of Oil-Immersed PT (Reactors)" and the "IEEE Guide for Assessment and Maintenance of Liquid-Immersed PT," which address the various sources and types of state variables related to transformers. The core purpose of the IoT is to connect physical entities with the digital realm, facilitating data exchange and communication. IoT technology integrates sensors and actuators into physical objects, encompassing not only man-made items but also natural elements, humans, and animals [3]. These sensors detect changes such as temperature or movement and transmit data over wired or wireless networks to computational systems [4]. The term "IoT," which was first used by Kevin Ashton in 1999, referred to the integration of Radio-Frequency Identification (RFID) chips for supply chain goods tracking. Since then, everything like smart homes and medications have been transformed by the Internet of everything. A variety of gadgets may now connect and share data thanks to the IoT, when before only smartphones, tablets, and computers were Internet-enabled. IoT devices have been increasing at a rapid pace; by the end of 2023, there will be about 16.1 billion linked devices [5]. Several utility operators have successfully extended the service life of transformers through preventive maintenance, which involves assessing the lifespan of components and performing maintenance before any breakdowns occur. Despite the ongoing challenges of high labor costs, scheduled downtimes, and underutilization of components throughout their operational life, this approach effectively averts unexpected and severe failures. The rise of the IoT has led utility managers to adopt predictive maintenance models that enhance maintenance schedules, incorporating both corrective and preventive strategies. A key aspect of predictive maintenance is just-in-time component replacement, which not only reduces unforeseen maintenance and labor costs but also helps prolong the life of components by replacing those nearing failure. Early investigations into the use of IoT technology in transformers began emerging only in 2014 [6,7].

2. LITERATURE REVIEW

Bethalsha et al., have highlighted that in recent years, the domain of maintenance expertise within the power sector has undergone significant transformations. Traditionally, transformers in the production area are immediately taken offline upon detecting a fault to avoid adverse consequences. However, such actions often lead to substantial time consumption and financial setbacks, making it preferable to perform them during strategically chosen periods [8]. Kwarteng et al., have noted that utility operators have therefore introduced an innovative maintenance strategy aimed at mitigating faults and reducing financial burdens. Maintenance strategies can generally be categorized into two types: reactive and proactive. Reactive approaches involve addressing faults post-occurrence, often resulting in economic repercussions. In contrast, proactive strategies prioritize cost-efficiency and the maintenance of peak system performance. Consequently, predictive methods (anticipate and prevent) have replaced diagnostic methods (fail and repair) in modern maintenance strategies [9, 10]. Prasojo et al., have suggested employing the Analytical Hierarchy Process (AHP) to assign weighting coefficients to the Health Index (HI) parameters of transformers through pairwise comparisons among parameters like oil quality, paper condition, and fault factors [11]. Maulidevi et al., have illustrated the calculation of HI in scenarios where data on insulation paper condition is incomplete by utilizing Multiple Linear Regression (MLR) and Adaptive Neuro-Fuzzy Inference System (ANFIS) [12]. Jian et al., have proposed updating the weights of HI parameters using the Statistical Product and Service Solution (SPSS) method, followed by recalculating the HI values with these revised weights [13]. Silva et al., have introduced an innovative diagnostic factor that incorporates the historical average daily load curve of a Power Transformer to estimate and account for insulation degradation. This model was compared against the traditional scoring weighting-based methodology to verify the precision of methods powered by AI [14]. Rediansyah et al., have emphasized the advantage of accommodating HI computations even when some data is missing [15]. Tamma et al., have described a correlation model for transformer aging and HI values derived from factors such as fault, oil quality, and paper conditions [16]. Yamuna et al. have demonstrated that it is possible to integrate the Internet of Things with a distribution transformer control and monitoring system. The study used ThingSpeak to examine graphical variations in variables like voltage, current, oil level, ambient and oil temperature, winding temperature. For processing, visualisation, and data storage, this system used a microcontroller, seven embedded sensors, and ThingSpeak [17]. Likewise, Thangiah et al. investigated a method for producing visual aids to track five power transformer parameters: electrical current, voltage, oil level, ambient and winding temperature [18]. Navamanikumar et al., have enabled early fault detection through parameter readings, and Pushing Box issued alerts to operators when thresholds were exceeded [19]. Elmashtoly et al., have developed an IoT-based system offering enhanced protection for PT, employing an ESP32 microcontroller alongside two embedded sensors—specifically, temperature and flow sensors [20]. Furthermore, Peter et al., have proposed a system that uses a GSM modem to transmit SMS notifications to a central database for additional analysis [21]. Mharakurwa et al., have observed that PT, as essential monitoring devices within substations, produce extensive data. However, accurately determining their operational condition is complicated by various challenges. The current model for assessing transformer status remains imperfect, heavily dependent on state detection analysis and expert evaluation [22]. Similar to this, Abbasi et al. have observed that manual intervention is frequently necessary due to inconsistent power grid information system design and ineffective integration and sharing of operating maintenance and repair data for transformer hardware. Existing methods that show the condition of transformer equipment have multi-source data of inadequate quality. This problem is especially noticeable when it comes to online monitoring data, which frequently causes monitoring staff to misunderstand or make mistakes [23]. Furthermore, it can be challenging to accurately diagnose and predict faults, particularly when there are multiple or complicated issues present. Further restricting the efficient use of tracking data is the absence of strong frameworks for data integration and exchange across various systems. It is important to note that noise and other disruptions frequently decrease the quality of online tracking information for precise fault detection. Ravindran et al. and Zhang et al. have investigated defect alert systems for PT, which resulted in notable progress. For example, linking fault modes with status data via online tracking, calculating the probability of a fault occurring, and conducting a thorough evaluation of operational risk and dependability through state perception have all been used to diagnose transformer faults. This method combines random forest with the synthetic minority class oversampling methodology [24,25]. Furthermore, Zhang et al. have presented a fault diagnosis technique for PT that combines a domain knowledge graph with an enhanced graph convolution network. With this approach, a knowledge network with nodes and edges is created, and the relationship between the knowledge graph and the fault samples is mapped to create a thorough framework for understanding transformer faults [26]. Jia et al. have presented a novel technique that combines artificial neural networks with multi-frequency ultrasonic technologies for non-destructive measurement of the loss of dielectric factor. Transformer oil quality is accurately predicted by this method, which uses an Elman neural network optimised with the Whale Optimisation Algorithm (WOA) and Kernel Principal Component Analysis (KPCA) [27]. Peng et al. used Density Functional Theory (DFT) to study the absorbing and sensing behaviours of Ru3-SnS2 on four common dissolved gases in oil used for insulation (H2, CO, C2H2, and C2H4). Their findings offer theoretical insights for its use in oil-immersed transformers [28]. Li et al. have created a novel technique based on multi-frequency ultrasound and a Particle Swarm Optimization-Elman Neural Network (PSO-ENN) forecasting model for determining the dielectric loss rate of transformer oil, which helps to establisha online tracking system [29].

3. RESEARCH METHODOLOGY

A transition across states is an unpredictable event in state space called a Markov chain, where the probability distribution for the next state depends only on the present state [30]. The probability distribution determines whether the system will change states or stay in its current condition at any given time. The possibility of staying in one state or moving to another is known as the transition probability, whereas this change between states is known as a state transition.

A Markov chain is a sequence of random variables $X_0, X_1, X_2, \ldots$ representing the state of a system at time steps *t* =0,1, 2,….. The process satisfies:

$$P\,(X_{t+1} = s_{t+1} \mid X_t = s_t, X_{t-1} = s_{t-1}, \ldots, X_0 = s_0) = P\,(X_{t+1} = s_{t+1} \mid X_t = s_t)$$

Here, s_t is the state at time *t*, and the probability depends only on the current state X_t.

A Markov chain's basic idea is that the probability distribution of the subsequent state is determined entirely by the current state, independent of previous states. The different transformer states are regarded as states inside the Markov chain in the transformer functioning state shift model. Then, using previous information, transition probabilities are calculated. This makes it possible to create a model based on Markov chains that can explain how the transformer's operational state changes over time. The transformer's operational states are S1–S4, as previously mentioned. Actual operating factors including active power, current, reactive power, and load rate serve as the foundation for defining each state. According to predetermined probability, the state transitions take place. Statistical analysis of previous data, for example, can be used to determine the transition probabilities from an average operational condition (S1) to a moderate fault state (S2). This approach not only enables a description of how the transformer's operating state changes but also facilitates the prediction of fault probabilities, supporting the formulation of more effective maintenance strategies. Figure 1 shows the power transformer monitoring system.

Transformer operation data feature extraction

Transformers can efficiently record shifts in their circumstances, including load, overload, aberrant current, and temperature rise, in its operational data. In order to build a connection with the electrical performance data of transformers and their functional states, this article uses a data-driven method. After being transformed into a supervised learning format, the transformer electrical monitoring time series data is utilised as input for model training. The LSTM recurrent neural networks are the basis of a suggested defect prediction technique. The sigmoid formula is used to determine the expected defect levels for transformers in the structure. The Attention structure, which preserves interim results from the LSTM encoder, is included to improve the accuracy of the model by enabling selective training of the input pattern and its association with the series of outputs. Reduceddimensional evaluations, oil temperature data, weather data, transformer aberrant factors and indications for nearby circuit breaker operations or bus voltage range exceedance warnings are among the input data used by the model. The several fault classifications are depicted in Figure 2.

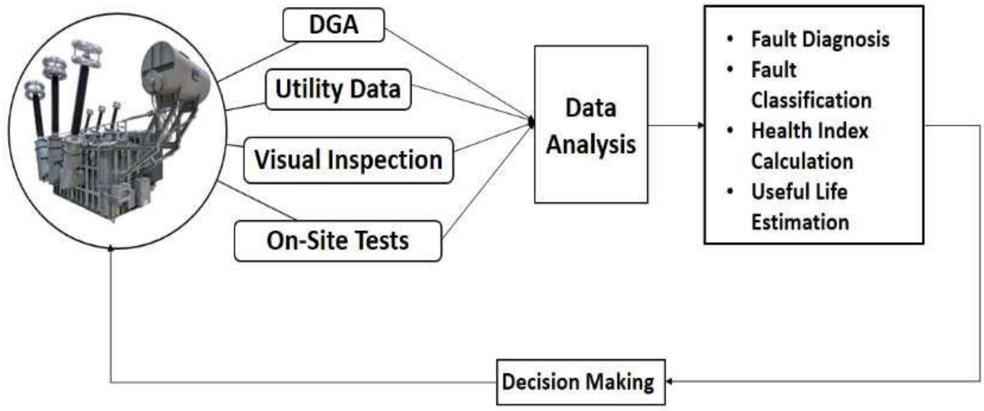

FIGURE 1. Power transformer monitoring system

Causes	Fault Classes			
	Arcing	*Partial Discharge*	*Overheating of Paper*	*Overheating of Oil*
Short circuit turn to turn	✓		✓	
Open circuit	✓		✓	
Overloading			✓	✓
Moisture	✓	✓		
Floating particles	✓	✓		
Cooling system malfunction				✓
LTC operation	✓			
Winding displacement		✓	✓	

FIGURE 2. Various fault classes

Transformer abnormal inducement feature set

Power failure trials, online tracking, live testing, background warnings, light gas alarms, assessments, and other techniques are used to identify anomalies in transformers by the investigation of transformer defect situations. Defects may persist until a problem arises, even in cases when appropriate measures are implemented to minimise issue escalation. After reviewing the reasons behind transformer deviations, Table 1 presents the feature set that was produced. Any abnormal cause identified prior to transformer failure is labeled with the appropriate serial number from Table 1, while a value of 0 is assigned if no cause is found.

Serial number	Abnormal inducement
1	External short circuit
2	Magazines or foreign objects
3	Vibration during long-term operation
4	Aging or wear
5	Damp or water
6	Overvoltage
7	External short circuit, extreme weather or earthquake
8	Extreme weather or earthquakes
9	External short circuit, aging or wear
10	External lead pull
11	DC bias

TABLE 1. Transformer anomalies

LSTM network feature extraction

Six sets of one-minute sample time-series information from the same kind of transformer were utilised for training the model. Statistical analysis revealed that the data exhibited minimal variation within a 30-minute window. Resampling the time series data at intervals of thirty minutes and assigning data labels based on the current functioning levels of the transformer were done to maximise the model's processing rate. As a result, the multifaceted time series was converted into a format for supervised learning. The LSTM model was applied to train the model, resulting in a feature extraction model to predict the transformer's deterioration level.

Through parameter tuning, an optimal Learning Rate (LR) of 0.01 was selected. Furthermore, other normal-state samples' time-series information were used for cross-validation. After optimisation, the LSTM model produced reliable and accurate predictions, as evidenced by an overall correlation coefficient of 0.89 and mean root-mean-square error of 0.0053 on the test data set.

Quantification of overload effects

An examination of load ratio data prior to and following transformer malfunctions indicated that not every failure occurred under high or overloaded situations. Transformers that undergo substantial variations in load ratio within a brief period have an elevated risk of malfunction, even when the load ratio stays between 40% and 60%, especially if the variation surpasses twice the initial load ratio. Additionally, when a transformer hasn't been subjected to excessive load but the load ratio rises by more than 100% over three days, the probability of failure can be utilized as a quantifiable overload effect indicator, according to the statistical trends of failure occurrences, as expressed in Equation 5.

$$K = \frac{L}{l}$$

Here, L represents the overall count of instances where the transformer's load rate rises by more than 100% within a 3-day period, while l denotes the number of those instances that resulted in failure.

Calculating the probability of transformer state shift

The transition likelihood from the starting optimal condition, S1, is determined: This research measures the degradation levels of transformers across three specific criteria in a numerical manner. Evaluations based on expert judgment, are incorporated as prior knowledge for the multi-layer perceptron (MLP) model. Input data is used to train the model, where the operational status is designated as the corresponding label. A solution to the transformer's functioning reliability is established within the Softmax layer of the MLP framework. The result from this model predicts the probability of the transformer shifting to its subsequent condition, representing the transition likelihood from the optimal starting condition, S1.

When the transformer begins in a typical state, S2, the transition likelihood is calculated. Transformers in S2 display irregular behavior or a deterioration level in one evaluation criterion exceeding 0.6, considering factors such as operational lifespan and environmental conditions. These transformers are designated for heightened scrutiny. Consequently, when abnormalities are resolved through servicing, the transformer can revert to an optimal condition, unlike the scenario observed in S2.

Transformer critical state warning

The peak value in the pertinent row vector of the current state transition matrix is selected as the anticipated future condition after evaluating the transformer's state's transition possibility. It is possible to figure out the transformer's future state and the chance of a condition transition five hours in advance by taking into account the duration periods of the three evaluation factors. In this paper, the indication for the alert system is the 0-norm of the main state vectors in the transformer's state transition matrix, as shown in following equation.

$$\|\lambda_{i4}\|_{\infty} \geq \min b_4 = 0.7$$

where λ is the chance of moving from state S1 to state S4 and i = 1, 2, 3, 4.

4. CONCLUSION

Constant surveillance of PT is vital, as it helps utility providers pinpoint and resolve issues while the transformer remains in use. Real-time data about electrical transformer efficiency can be gathered through the application of advanced sensors and the IoT. For IoT systems to function effectively, they must accommodate various communication protocols while maintaining a balance between resource consumption and capabilities. Issues like scalability, uniformity, flexibility, and compatibility may hinder the advancement of IoT. Through the establishment of guidelines for data interchange and communication across linked devices, IoT homogeneity can speed up the integration process and address issues with scalability and connectivity, and ensuring swift, seamless links with stable performance, safety, and dependability. The gathered information can be processed using machine learning algorithms to uncover trends, detect irregularities, and diagnose issues with the transformer. This method helps save expensive repairs and prevent power disruptions. To increase the transformer's duration, utilities can spot patterns and improve performance by continuously observing the manner in which the transformer is operating. Furthermore, real-time monitoring helps improve the overall stability and efficiency of the electrical grid.

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