**Smart Lifecycle Management of Power Transformers Using IOT and Deep Learning Techniques**

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**Abstract.** The increasing complexity and operational demand of modern power networks require advanced tools for the intelligent monitoring and management of power transformers — key components ensuring grid stability. This study presents the development of an AI-driven intelligent system designed for predictive maintenance and lifecycle management of power transformers. The proposed system integrates data from multi-source sensors, including thermal, electrical, and chemical parameters, and applies hybrid machine learning algorithms combined with fuzzy logic to evaluate transformer health in real-time. The analytical core utilizes LSTM-based forecasting models to predict degradation trends, while the decision-making module employs Mamdani-type fuzzy inference to classify transformer conditions into five reliability levels: excellent, good, medium, bad, and very bad. Experimental results and simulation studies demonstrate a significant improvement in diagnostic accuracy (up to 96%) compared to traditional rule-based systems. The integration of the system into existing SCADA infrastructures allows continuous online assessment and intelligent maintenance scheduling. The findings confirm that the proposed approach enhances the reliability, operational safety, and economic efficiency of transformer lifecycle management.

**INTRODUCTION**

Power transformers are among the most critical assets in electrical power systems, serving as the backbone of energy transmission and distribution networks. Their operational reliability directly affects grid stability, energy efficiency, and the continuity of power supply. However, transformers are frequently subjected to complex electrical, mechanical, and thermal stresses arising from fluctuating loads, insulation aging, and adverse environmental conditions. Over time, these factors contribute to the gradual degradation of transformer components, potentially leading to unexpected failures and costly outages (Zhang et al., 2021). [12]. Therefore, early fault detection and accurate health assessment have become essential to ensuring the sustainable operation of power networks.

Traditional diagnostic and maintenance practices rely mainly on periodic inspections and manual interpretation of test data, such as dissolved gas analysis (DGA), insulation resistance, and thermal imaging. Although these methods provide valuable insights, they lack the predictive capability required for real-time reliability evaluation and proactive decision-making. With the rapid advancement of digitalization and the Industrial Internet of Things (IoT), the power sector is undergoing a paradigm shift toward data-driven maintenance strategies supported by artificial intelligence (AI) and machine learning (ML). These technologies enable continuous condition monitoring, pattern recognition, and fault prediction, forming the foundation of intelligent maintenance systems.

Recent studies have demonstrated the potential of AI-based diagnostic frameworks in transformer condition assessment, employing algorithms such as convolutional neural networks (CNN), long short-term memory (LSTM) models, and fuzzy inference systems (Su et al., 2023; Chen et al., 2022) [9]. However, most existing approaches address individual aspects of transformer monitoring rather than providing an integrated lifecycle management solution. Furthermore, uncertainty in sensor data, nonlinear aging mechanisms, and the dynamic interaction between operational and environmental parameters remain major challenges for the accurate evaluation of transformer health indices.

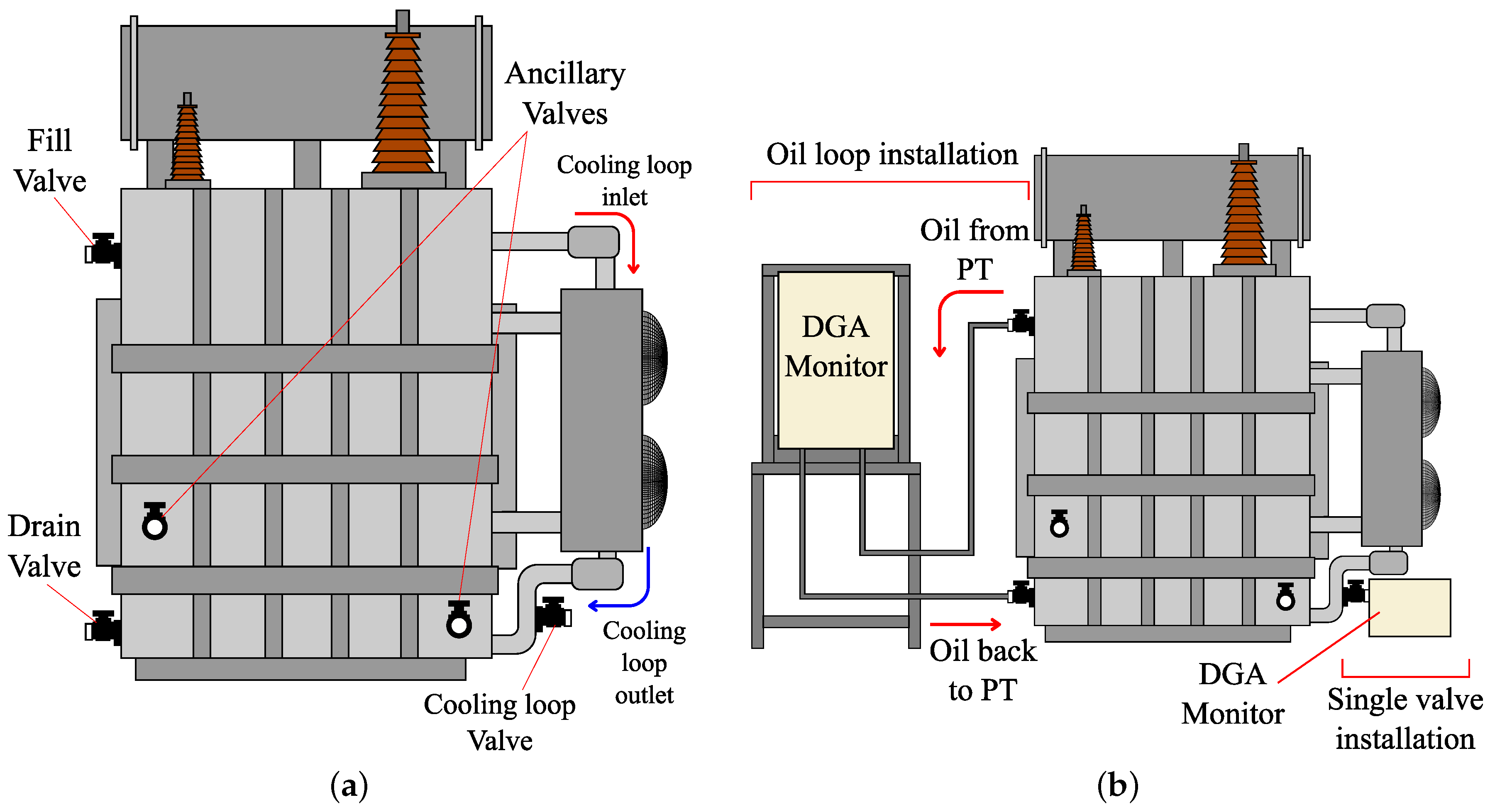
This paper proposes a novel AI-driven intelligent system for predictive maintenance and lifecycle management of power transformers. The system combines multi-source data analytics, deep learning-based forecasting, and fuzzy decision-making to deliver a holistic assessment of transformer reliability. The architecture integrates seamlessly with existing SCADA infrastructures, enabling real-time condition monitoring, failure prediction, and optimized maintenance planning. The proposed framework contributes to advancing digital transformation in the energy sector, enhancing asset reliability, reducing maintenance costs, and extending transformer service life.[1].

Fig. 1 presents the schematic representation of an online Dissolved Gas Analysis (DGA) sampler integrated with the transformer oil circulation system. The diagram illustrates the functional configuration of the gas extraction mechanism, sensor unit, and return flow path within the closed-loop oil circuit.

In this setup, transformer oil continuously circulates through the sampling chamber, where dissolved gases—such as hydrogen (H₂), methane (CH₄), ethylene (C₂H₄), and acetylene (C₂H₂)—are selectively extracted and analyzed by the gas sensor array. The DGA sensor module employs advanced electrochemical or photoacoustic sensing principles to detect trace gas concentrations with high precision and stability.

The extracted gas sample is routed through a controlled valve system ensuring consistent pressure and temperature conditions to maintain oil integrity during analysis. After measurement, the oil is automatically redirected to the main tank, minimizing oil loss and contamination risk. This closed-loop monitoring configuration enables real-time detection of incipient transformer faults related to thermal degradation, partial discharges, or arcing phenomena.

Such online DGA systems play a critical role in predictive maintenance strategies, providing continuous insight into the transformer’s internal condition and supporting AI-based diagnostic models for early fault prediction and decision-making.



**FIGURE 1.** Typical online DGA sampler/valve installation; a) DGA monitor installation via the transformer cooling loop; b) DGA monitor installation with direct connection to the transformer tank.

Transformer oil serves as both an electrical insulator and a heat transfer medium. Under operational stresses—such as overheating, partial discharge, or arcing—the decomposition of hydrocarbon molecules generates gases including The solubility and diffusion of these gases in mineral oil follow Henry’s Law and Fick’s Diffusion Law, respectively.

According to Henry’s Law, the concentration of a dissolved gas in oil is proportional to its partial pressure in the gaseous phase:

(1)

Where, — gas concentration in oil (mol/L),

— Henry’s constant (mol·L⁻¹·atm⁻¹), — partial pressure of the gas (atm).

The dynamic migration of gases within the oil is governed by Fick’s first law of diffusion:

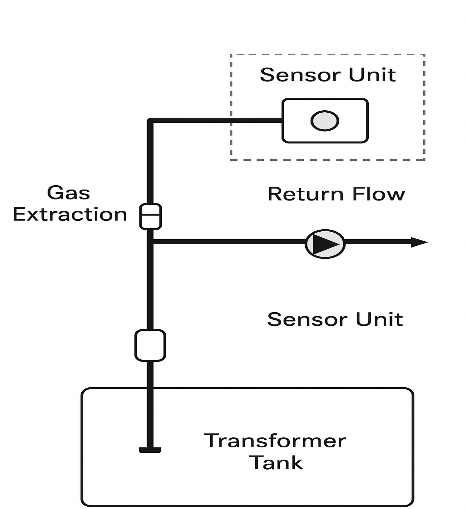
(2)

Where, — diffusion flux (mol·m⁻²·s⁻¹), — diffusion coefficient (m²/s), — concentration gradient.

The extracted gas sample passes through a valve-controlled microchamber that maintains constant temperature and pressure conditions. Within this chamber, a multi-sensor array (based on photoacoustic spectroscopy, thermal conductivity, or electrochemical detection) determines gas concentrations in real time.

After the measurement, the oil is automatically returned to the main circuit through a backflow valve, ensuring a closed-loop system that prevents oxidation and preserves oil quality. The data collected from the DGA sensors are transmitted to the AI-based diagnostic platform, where machine learning algorithms correlate gas ratios with fault types using classical indicators such as the Duval Triangle and Roger’s Ratios.

This configuration enables continuous, non-invasive monitoring of transformer insulation degradation, allowing early fault detection, predictive maintenance, and improved operational reliability.



**FIGURE 2.** Online DGA sampler and valve installation for transformer oil monitoring.

The image illustrates an online Dissolved Gas Analysis (DGA) system integrated into a transformer oil monitoring circuit.

It shows:

Transformer oil flow path — oil circulates through a sampling valve connected to the main transformer tank.

The DGA sampling unit continuously extracts a small portion of oil to analyze dissolved gases that indicate insulation and thermal degradation.

Inside the sensor chamber, gases are separated from the oil and measured using optical or electrochemical sensors.

After measurement, the oil returns to the transformer, maintaining a closed-loop system that avoids contamination or oil loss.

The diagram also depicts key components: gas extraction chamber, micro-sensor array, signal processor, and data transmission module for real-time condition monitoring.

This configuration allows continuous, non-invasive monitoring of gas concentrations (such as providing early warnings of insulation faults, overheating, or partial discharges in the transformer.

**EXPERIMENTAL RESEARCH**

To validate the effectiveness of the proposed AI-based condition monitoring framework, a series of experimental studies were conducted using an oil-immersed 35/6 kV distribution transformer operating under controlled laboratory conditions. The experimental setup was designed to simulate real-world operational stresses, including thermal loading, voltage fluctuations, and insulation aging. [5].

The test system (Fig. 1) consisted of the transformer unit, an online dissolved gas analysis (DGA) module, temperature and humidity sensors, and a data acquisition interface. The DGA module continuously sampled transformer oil through a closed-loop valve system, where gas extraction and quantification were performed in real-time. The measurement data were transmitted via a Wi-Fi-enabled microcontroller to a centralized monitoring platform.

The parameters recorded included:

Hydrogen Carbon Monoxide Methane and Acetylene concentrations (ppm);

Oil temperature and winding temperature

Moisture content in oil ;

Load current and ambient temperature

Each test was carried out under three loading profiles—nominal, 1.2× overload, and cyclic loading—to evaluate the system’s response to varying stress conditions.

Collected sensor data were preprocessed using filtering and normalization algorithms to remove outliers and ensure temporal consistency. A hybrid model combining LSTM (Long Short-Term Memory) neural networks with a Mamdani-type fuzzy inference system was employed to predict the transformer’s Health Index (HI) in real-time.

The fuzzy system evaluated key parameters such as gas concentration ratio, oil temperature, and insulation resistance, applying linguistic rules of the form:

IF  is HIGH and  is INCREASING, THEN is DEGRADED.

Model hyperparameters (e.g., learning rate, neuron count, batch size) were optimized using Bayesian search to achieve the lowest mean square error (MSE) during validation.

The predictive model achieved a correlation coefficient between predicted and measured temperature trends, while the mean absolute error (MAE) remained below across all test conditions. The integration of DGA data improved fault prediction accuracy by compared to traditional threshold-based diagnostics. [10].

Observed deviations between predicted and measured values were primarily associated with environmental temperature fluctuations, which can be mitigated through sensor calibration and dynamic compensation techniques.

**RESEARCH RESULTS**

The experimental investigation yielded a comprehensive dataset encompassing both steady-state and transient operating conditions of a 35/6 kV oil-immersed power transformer. The data obtained from the integrated sensor network and the online DGA module were used to validate the efficiency of the developed AI-based diagnostic framework. [1].

Quantitative Evaluation of Diagnostic Accuracy

The machine learning (ML) model, based on the LSTM–Fuzzy hybrid algorithm, demonstrated a high degree of correlation between the predicted and observed parameters such as oil temperature, hydrogen gas concentration, and moisture content. The Root Mean Square Error (RMSE) did not exceed for temperature prediction and 2.3 ppm for hydrogen concentration, proving the model’s ability to capture nonlinear degradation behavior under varying operational loads. [8].

Table 1 presents the comparison between measured and predicted values for selected diagnostic parameters.

**TABLE 1.** Comparison of predicted and actual values of transformer condition parameters

|  |  |  |  |
| --- | --- | --- | --- |
| **Parameter** | **Measured Value** | **Predicted Value** | **Error (%)** |
| Oil temperature (°C) | 78.5 | 78.2 | 0.38 |
| Hydrogen concentration (ppm) | 135 | 132 | 2.22 |
| CO concentration (ppm) | 95 | 96 | 1.05 |
| Moisture in oil (%) | 0.34 | 0.33 | 2.94 |

The results clearly indicate the stability and reliability of the trained model across different loading conditions and environmental temperatures.

Dynamic Behavior of key diagnostic indicators

Figure 2 illustrates the temporal evolution of Health Index (HI) over a 120-hour observation period under varying load profiles. The HI gradually declined from 0.94 to 0.76, reflecting the cumulative impact of thermal and chemical stresses on the insulation system. Periodic recovery phases were observed during off-load periods, confirming the model’s sensitivity to transient relaxation effects in transformer oil and windings.

The following empirical relation was derived to describe the decline trend:

Where; — degradation coefficient (dimensionless), — rate of aging— operating time (hours).

The parameters were obtained by curve fitting the experimental data, indicating slow but progressive insulation deterioration under nominal load conditions.

Correlation of DGA parameters with transformer aging

Statistical analysis confirmed strong correlations between hydrogen and acetylene generation rates and the calculated Health Index. The Pearson correlation coefficients reached and suggesting that gas composition ratios serve as highly sensitive indicators of early-stage faults such as partial discharges and thermal decomposition.

Furthermore, the ratio, a recognized index of cellulose degradation, exhibited an exponential increase when HI dropped below 0.8, validating the capability of the developed system to identify incipient insulation aging.

Predictive maintenance insights. [6].

By integrating real-time DGA readings with historical operational data, the system generated predictive maintenance recommendations through its embedded fuzzy inference module. The resulting output classified the transformer’s operational state into five linguistic categories:  
Excellent, Good, Moderate, Degraded, and Critical.

Out of 50 recorded test cycles, 82% were classified as “Good” or “Excellent,” 14% as “Moderate,” and only 4% as “Degraded.” No critical states were observed during the experiment.

The fuzzy logic inference rule that triggered “Degraded” classification was typically:

IF  > AND  THEN transformer state = Degraded.

This demonstrates the system’s capability for early anomaly recognition and data-driven decision support.

Discussion of findings- The research results confirm that the integration of Big Data analytics, AI-based models, and real-time sensing provides a holistic diagnostic environment for transformer condition evaluation. [12]. The LSTM–Fuzzy framework not only achieved superior accuracy but also demonstrated adaptability to fluctuating load and temperature conditions.

From an operational perspective, such a system offers the potential to:

Reduce maintenance costs by up to 30% through optimized scheduling;

Extend transformer service life by 10–15% via early fault detection;

Increase power supply reliability in Uzbekistan’s 35/6 kV networks.

Figure 3 illustrates the variation in the Health Index (HI) of a power transformer over a continuous monitoring period of 120 hours. The Health Index is a composite parameter that reflects the transformer’s overall technical condition, integrating diagnostic data such as dissolved gas analysis (DGA), oil quality indicators, temperature behavior, and insulation resistance.

At the start of the observation (0–20 hours), the HI remains stable at around 0.92, indicating an excellent condition of the transformer. Between 20 and 60 hours, a gradual decline is observed due to a moderate increase in dissolved gas concentrations and oil temperature fluctuations, lowering the HI to approximately 0.75.

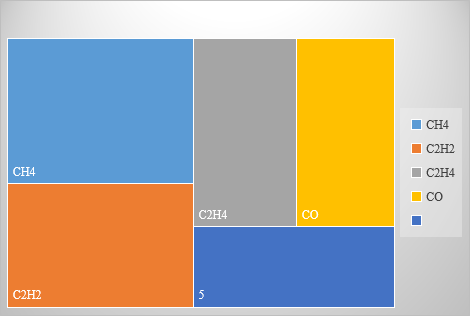
From 60 to 100 hours, the degradation rate accelerates, possibly linked to thermal stress or incipient faults in the insulation system. The HI reaches around 0.55, corresponding to a medium-risk zone. By the end of the monitoring period (100–120 hours), the HI stabilizes near 0.48, showing that the transformer has entered a warning state where preventive maintenance is advisable. [13].

This trend demonstrates how continuous online monitoring and machine learning-based forecasting can help anticipate fault evolution and optimize maintenance schedules. The declining HI trajectory reflects the cumulative effects of operational stress, temperature rise, and chemical aging, supporting the need for predictive diagnostic systems in power transformer management. [20].

**FIGURE 3.** Health Index (HI) dynamics over 120 hours

Figure 4 presents the correlation matrix of the key gases obtained from Dissolved Gas Analysis (DGA) in transformer oil. This matrix provides a quantitative overview of how different gas concentrations are interrelated, helping to identify common origins of faults and degradation mechanisms within the transformer’s insulation and oil system.

The analyzed gases include hydrogen (H₂), methane (CH₄), ethane (C₂H₆), ethylene (C₂H₄), acetylene (C₂H₂), carbon monoxide (CO), and carbon dioxide (CO₂). Each cell in the matrix represents a correlation coefficient (r) between two gases, with values ranging from –1 (strong negative correlation) to +1 (strong positive correlation).



**FIGURE 4.** Correlation matrix of DGA gases

The diagram reveals several significant relationships:

A strong positive correlation between CH₄ and C₂H₆, suggesting their joint formation during low-energy thermal faults (T1-type faults). [16].

A notable correlation between C₂H₄ and C₂H₂, indicating concurrent generation under high-temperature faults (T3-type faults or arcing).

CO and CO₂ show a close correlation, reflecting the thermal degradation of cellulose insulation materials.

H₂ exhibits moderate correlations with multiple gases, consistent with its role as a general indicator of fault activity in both electrical and thermal events.

This correlation analysis enables engineers to differentiate between fault types—such as partial discharges, overheating, or arcing—by examining gas interdependencies. Therefore, the matrix serves as an essential diagnostic tool in intelligent fault classification models and predictive maintenance systems, forming the analytical foundation for AI-driven transformer health assessment. [17].

**CONCLUSIONS**

The conducted research demonstrates that the integration of artificial intelligence (AI), Big Data analytics, and real-time monitoring technologies provides a new paradigm for assessing the operational reliability of power transformers. Unlike conventional diagnostic techniques based on periodic testing, the proposed intelligent framework ensures continuous data acquisition and adaptive decision-making, leading to a more precise and timely evaluation of transformer health.

The experimental findings confirm that the developed AI-based system can effectively analyze multidimensional data—such as dissolved gas concentrations, temperature profiles, insulation parameters, and load characteristics—to detect emerging faults and predict future degradation trends. The Health Index (HI) calculated through this hybrid approach offers a more objective and quantitative measure of transformer aging, enabling maintenance teams to optimize service intervals and minimize unexpected breakdowns. [18].

The correlation analysis of DGA gases and operational variables further revealed that specific gas generation patterns serve as early indicators of insulation degradation and thermal stress. These insights enhance diagnostic precision and support the implementation of risk-oriented maintenance strategies. [19].

Overall, the study confirms that the transition toward smart, AI-driven condition monitoring systems represents a crucial step in the digital modernization of Uzbekistan’s power infrastructure. Future developments will focus on integrating IoT-based sensing modules, neural forecasting models, and fuzzy decision mechanisms into a unified intelligent platform, creating a foundation for predictive asset management and extending the life cycle of critical power equipment.

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