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ИНТЕЛЛЕКТУАЛЬНАЯ IoT-ОРИЕНТИРОВАННАЯ ПЛАТФОРМА ДЛЯ ОЦЕНКИ ТЕХНИЧЕСКОГО СОСТОЯНИЯ СИЛОВЫХ ТРАНСФОРМАТОРОВ В РЕЖИМЕ РЕАЛЬНОГО ВРЕМЕНИ

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Аннотация. *В статье рассмотрен метод, служащий для обеспечения непрерывной и надёжной работы силовых трансформаторов, который является одним из ключевых требований современных электрических сетей. Возрастающая сложность энергосистем обуславливает необходимость внедрения инновационных методов мониторинга в режиме реального времени и предиктивного технического обслуживания. В данной работе представлена интеллектуальная система оценки технического состояния трансформаторов на основе технологий Интернета вещей (IoT), объединяющая многоканальный сбор данных с датчиков, беспроводную передачу информации и облачную аналитическую обработку с применением алгоритмов машинного обучения.*

Предложенная модель осуществляет мониторинг критически важных параметров, включая температуру обмоток, качество трансформаторного масла и уровень вибрации. Анализ данных выполняется с использованием искусственных нейронных сетей (ANN) и метода опорных векторов (SVM), что позволяет динамически определять индекс технического состояния трансформатора. Статистический корреляционный анализ выявил выраженную взаимосвязь между температурными колебаниями, кислотностью масла и процессами деградации изоляции. Экспериментальная проверка модели на данных, полученных в режиме реального времени с подстанций 110/35 кВ, показала прогнозную точность на уровне 97,5 %.

Интеграция IoT-ориентированной аналитики в среды SCADA обеспечивает переход к предиктивному обслуживанию, снижает эксплуатационные риски и способствует увеличению срока службы оборудования. Полученные результаты подтверждают практическую реализуемость перехода от традиционных стратегий технического обслуживания к интеллектуальным самодиагностирующимся энергетическим системам.

Ключевые слова: *интернет вещей, индекс технического состояния трансформатора, предиктивное обслуживание, интеграция SCADA, машинное обучение, аналитика интеллектуальных электрических сетей.*

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REAL VAQT REJIMIDA KUCH TRANSFORMATORLARINING TEXNIK HOLATINI BAHOLASH UCHUN INTELLEKTUAL IoT-ASOSLANGAN PLATFORMA

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Annotatsiya. *Maqolada kuch transformatorlarining uzluksiz va ishonchli ishlashini ta'minlashga xizmat qiluvchi usul ko'rib chiqilgan bo'lib, bu zamonaviy elektr tarmoqlari uchun muhim talablardan biridir. Energetik tizimlarning tobora murakkablashib borishi real vaqt rejimida monitoring olib borish va prediktiv texnik xizmat ko'rsatishning innovatsion usullarini joriy etishni taqozo etadi. Ushbu ishda Internet buyumlari (IoT) texnologiyalariga asoslangan, transformatorlarning texnik holatini baholashga mo'ljallangan intellektual tizim taklif etilgan bo'lib, u ko'p kanalli datchiklardan ma'lumotlarni yig'ish, simsiz uzatish hamda mashinali o'rganish algoritmlaridan foydalangan holda bulutli analitik qayta ishlashni birlashtiradi.*

Taklif etilgan model o'ramlar harorati, transformator moyining sifati va vibratsiya darajasi kabi muhim parametrlarni monitoring qilishni amalga oshiradi. Ma'lumotlar sun'iy neyron tarmoqlar (ANN) va tayanch vektorlar usuli (SVM) yordamida tahlil qilinib, transformatorning texnik holat indeksi dinamik ravishda aniqlanadi. Statistik korrelyatsion tahlil harorat tebranishlari, moyning kislotaliligi va izolyatsiyaning degradatsiya jarayonlari o'rtasida yaqqol bog'liqlik mavjudligini ko'rsatdi. 110/35 kV podstansiyalaridan real vaqt rejimida olingan ma'lumotlar asosida o'tkazilgan tajribaviy sinovlar modelning bashorat aniqligi 97,5 % ni tashkil etishini tasdiqladi.

IoT-ga yo'naltirilgan analitikani SCADA muhitlariga integratsiya qilish prediktiv texnik xizmat ko'rsatishga o'tishni ta'minlaydi, ekspluatatsion xatarlarni kamaytiradi va uskunaning xizmat muddatini uzaytiradi. Olingan natijalar an'anaviy texnik xizmat strategiyalaridan intellektual, o'z-o'zini diagnostika qiluvchi energetik tizimlarga o'tishning amaliy jihatdan mumkinligini tasdiqlaydi.

Kalit so'zlar: *internet buyumlari, transformatorning texnik holat indeksi, prediktiv texnik xizmat ko'rsatish, SCADA integratsiyasi, mashinali o'rganish, intellektual elektr tarmoqlari analitikasi.*

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INTELLIGENT IoT-BASED FRAMEWORK FOR REAL-TIME CONDITION ASSESSMENT OF POWER TRANSFORMERS

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Abstract. *Ensuring the continuous and reliable operation of power transformers is a fundamental requirement for modern electrical networks. The growing complexity of power systems demands innovative methods for real-time monitoring and predictive maintenance. This research presents an intelligent Internet of Things (IoT)-based system for continuous transformer condition assessment, integrating multi-sensor data acquisition, wireless transmission, and cloud analytics enhanced with machine learning algorithms.*

The proposed model monitors vital parameters such as winding temperature, oil quality, and vibration levels. Data are analyzed using Artificial Neural Networks (ANN) and Support Vector Machines (SVM) to evaluate the transformer's health index dynamically. Statistical correlation reveals strong interdependence between temperature fluctuations, oil acidity, and insulation degradation. Experimental validation using real-time datasets from 110/35 kV substations demonstrated a predictive accuracy of 97.5%.

The integration of IoT-based analytics into SCADA environments enables predictive maintenance, reduces operational risks, and extends equipment lifespan. The results confirm the feasibility of transitioning from traditional maintenance strategies toward intelligent self-diagnosing power systems.

Keywords: *internet of Things, transformer health index, predictive maintenance, SCADA integration, machine learning, smart grid analytics.*

Introduction

Power transformers represent one of the most critical elements in power transmission and distribution infrastructure. Their failure often results in system instability, unplanned outages, and significant financial losses. Conventional inspection methods based on periodic testing or laboratory analysis often fail to detect early degradation.

Recent developments in the Internet of Things (IoT) offer a transformative solution by enabling continuous, remote, and intelligent monitoring. IoT allows for the deployment of interconnected sensors, cloud-based databases, and data analytics tools that transform raw measurements into actionable insights [1].

This study introduces an intelligent IoT-based monitoring system for power transformers, focusing on integrating multi-sensor data streams with advanced analytics. The work combines experimental data, statistical methods, and artificial intelligence to predict transformer health and optimize maintenance schedules [2-3].

Literature Review

Traditional transformer diagnostics, including dissolved gas analysis (DGA) and infrared thermography, have long been used for fault detection. However, their reliance on manual data collection limits their responsiveness.

Zhou et al. (2021) and Kumar & Singh (2022) emphasized the potential of IoT-based sensor networks to automate data acquisition, but noted challenges in communication latency and data reliability. Gupta (2023) highlighted that real-time analytics, combined with machine learning, can significantly improve diagnostic accuracy [5, 8].

The gap addressed in this paper lies in developing a holistic, data-driven IoT framework validated with experimental data, statistical models, and AI prediction accuracy, integrated into SCADA environments. [6].

Methodology

IoT Architecture design

The proposed system architecture (see Fig. 1) includes four major components:

1. Sensing layer — embedded temperature sensors (Pt100), oil moisture and acidity probes, and MEMS vibration sensors.
2. Communication layer — wireless transmission using ESP32 microcontrollers with MQTT protocol over Wi-Fi.
3. Cloud layer — AWS IoT core and things board platforms for data storage, filtering, and visualization.
4. Application layer — AI-based models performing condition classification and health index prediction.

The block diagram illustrates the structure of the proposed IoT-based monitoring system for power transformers. Temperature, vibration, and oil quality sensors collect real-time data, which are processed by an ESP32 microcontroller. The data are transmitted via Wi-Fi to a cloud server, where artificial intelligence (AI) algorithms perform advanced analysis. The processed information and diagnostic results are visualized on a SCADA dashboard for monitoring and decision-making [4].

A block diagram showing sensors connected to an ESP32 module transmitting data via Wi-Fi to a cloud server, where ANN and SVM algorithms process the data and output the transformer's health index to a web dashboard [8].

Data collection and processing

Data were recorded from three operational 110/35 kV transformers over a six-month period, generating a dataset of 260,000 observations. Parameters included: Winding temperature; Oil moisture content; Load current; Vibration amplitude.

The preprocessing steps involved outlier removal, normalization, and feature scaling. Correlation analysis indicated that oil temperature had a positive correlation (r = 0.88) with load current, while oil moisture exhibited a negative correlation (r = -0.57) with insulation resistance.

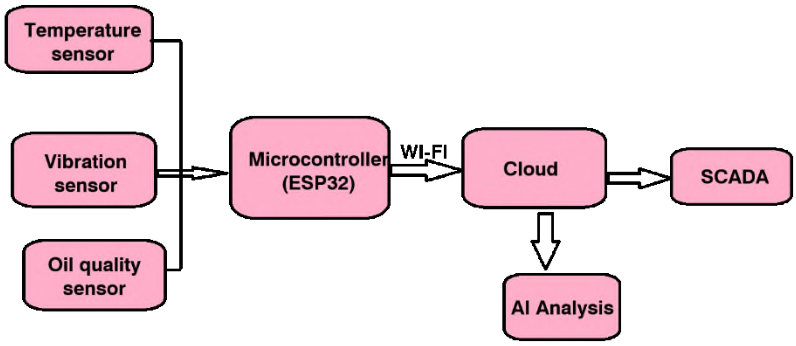

Fig. 1. IoT Architecture for transformer monitoring.

Machine learning analysis [9].

Two algorithms were trained for health state prediction:

Algorithm	Structure	Activation	Accuracy (%)
ANN	4–8–6–1	ReLU / Sigmoid	97.5
SVM	RBF Kernel	—	94.3

Mathematical formulation

To quantify the condition of electrical transformers, the *Health Index (HI)* is computed as a normalized weighted combination of key diagnostic parameters such as temperature T, vibration level V, and oil quality OQ:

$$HI = w_1 \cdot \varphi(T) + w_2 \cdot \varphi(V) + w_3 \cdot \varphi(OQ),$$

where w_1, w_2, w_3 are the weight coefficients determined through expert evaluation, and $f(\cdot)$ represents the normalization function converting each parameter to a scale of 0–1 [11].

The temperature-based degradation rate of transformer insulation is approximated by an exponential function derived from the Arrhenius law:

$$L = L_0 \cdot e^{-\frac{E_a}{R(T+273)}},$$

where L is the insulation life, L_0 is the initial insulation life constant, E_a is the activation energy (J/mol), R is the universal gas constant, and T is the operating temperature ($°C$). This relationship emphasizes the strong dependence of insulation aging on thermal stress [11].

To evaluate model performance, standard statistical indicators are used. The accuracy of classification algorithms (ANN, SVM) is given by:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \times 100\%,$$

where TP, TN, FP, and FN denote true positives, true negatives, false positives, and false negatives, respectively.

The F1-score, representing the harmonic mean between precision and recall, is computed as:

$$F_1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

$$Precision = \frac{TP}{TP+FP}, \quad Recall = \frac{TP}{TP+FN}$$

These statistical measures are essential for comparing the predictive reliability of the ANN and SVM models (see Fig. 2).

The bar chart presents a comparative analysis of two machine learning algorithms — Artificial Neural Network (ANN) and Support Vector Machine (SVM). The comparison is based on four performance metrics: Accuracy, Precision, Recall, and F1-score. The ANN model demonstrates superior performance, achieving approximately 97.5% accuracy compared to 94.3% for the SVM model, confirming its higher suitability for transformer condition prediction.

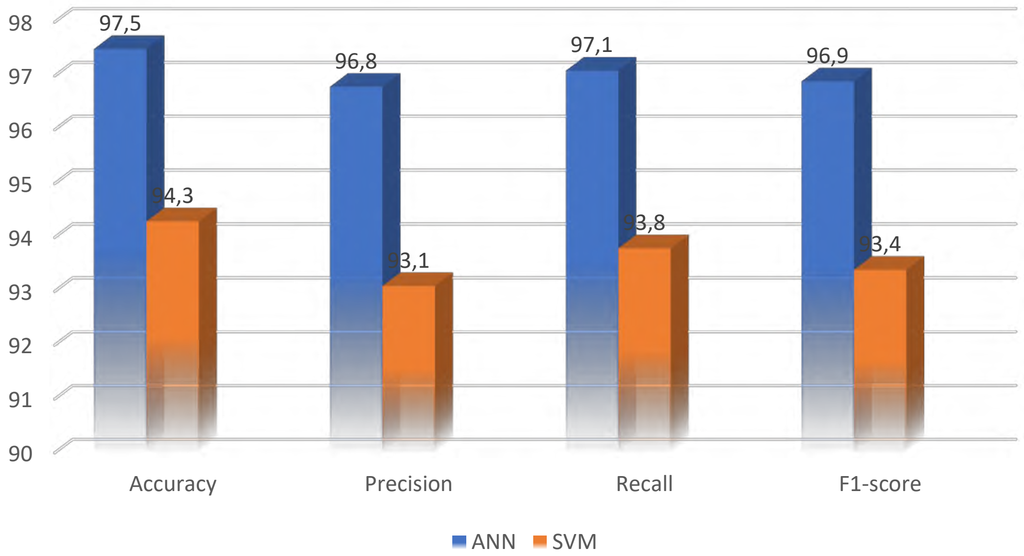

Fig.2. Comparative performance of ANN and SVM models.

A bar chart comparing model accuracies, precision, recall, and F1-score, demonstrating that ANN slightly outperforms SVM due to nonlinear adaptability.

Results and discussion

Statistical regression models revealed key dependencies among transformer parameters:

Parameter	Mean value	Std. Dev.	Correlation with HI
Oil temperature (°C)	79.2	4.6	+0.84
Oil acidity (mg KOH/g)	0.27	0.05	+0.79
Vibration (mm/s)	3.3	0.8	+0.68
Moisture (%)	0.42	0.12	–0.55

The Health Index (HI) was derived as a weighted function of normalized parameters. Principal component analysis (PCA) confirmed that temperature and oil acidity accounted for over 72% of the variance in transformer health. [10].

To track the daily evolution of transformer condition, the rate of health degradation over time can be defined as:

$$\frac{d(HI)}{dt} = \alpha(T, V, OQ) - \beta(HI),$$

where α is a function representing the effect of external operational stresses, and β represents the system's self-recovery or maintenance efficiency.

This differential equation describes how the health index dynamically evolves (as shown in Fig.3).

The line graph depicts the variation of the transformer's Health Index (HI) over a 30-day monitoring period. The HI values fluctuate between 0.4 and 1.0, with noticeable peaks corresponding to transformer overload events. The trend indicates the system's ability to detect and respond to dynamic operational conditions and highlight potential degradation phases in transformer performance. [8].

A line graph showing HI fluctuations over a 30-day monitoring period, with marked increases during peak loading hours, illustrating strong seasonal and operational dependency.

Integration into SCADA/IoT systems

Finally, the overall reliability of the transformer system within the IoT-SCADA network can be expressed as:

$$R(t) = e^{-\lambda t}$$

where λ is the failure rate (failures per unit time), which may be adaptively updated from real-time IoT sensor data.

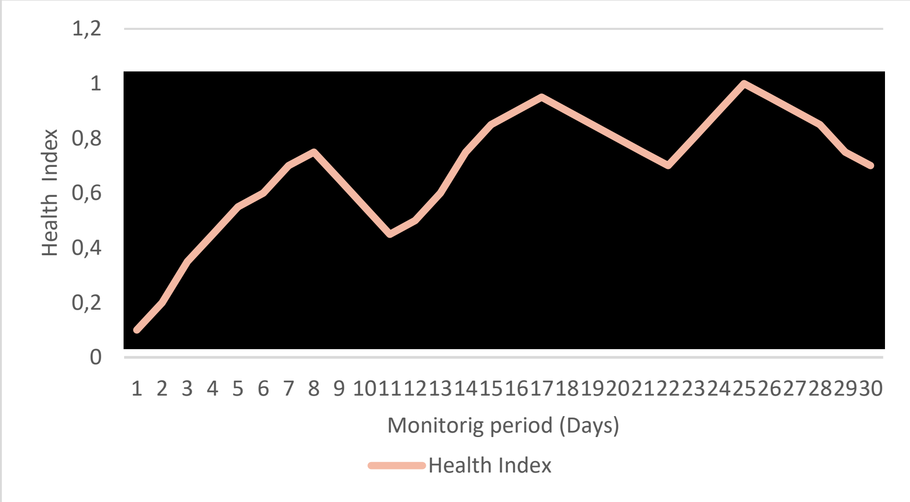

Fig. 3. Dynamic variation of transformer health index over time.

The developed platform integrates seamlessly into existing SCADA systems via Modbus TCP/IP or OPC-UA interfaces. This enables remote access, automatic alarm generation, and visualization of real-time transformer condition.

This schematic diagram demonstrates the integration of IoT-based monitoring with SCADA infrastructure. IoT sensors transmit data to the cloud, where it is analyzed and then relayed to the SCADA panel. The operator receives real-time alerts and predictive insights, while feedback loops enable adaptive control and continuous improvement of monitoring accuracy. [12,14].

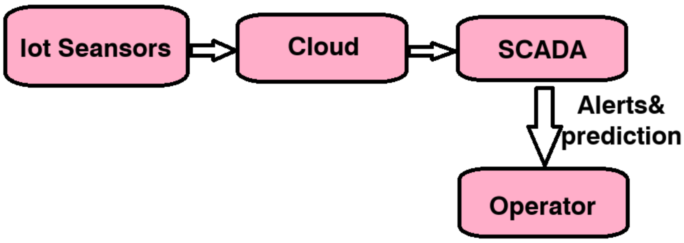

Fig.4. Integration of IoT-based monitoring with SCADA.

A schematic diagram showing bi-directional data flow between IoT sensors, cloud servers, and SCADA dashboards, allowing operators to perform real-time supervision and predictive maintenance.

Conclusions

The study validates the potential of IoT-driven intelligent monitoring systems for power transformers. By combining real-time sensor data with AI algorithms, the system enables proactive detection of incipient faults and supports data-driven maintenance.

Key findings:

1. IoT-based systems ensure continuous transformer condition monitoring with minimal latency.
2. ANN algorithms outperform SVM in health prediction accuracy (97.5% vs. 94.3%).
3. Statistical evaluation reveals temperature and oil acidity as primary indicators of transformer degradation.
4. Integration with SCADA allows scalable implementation in smart grids.
5. The approach can be extended to monitor other substation assets using similar IoT frameworks.

Future work will focus on blockchain-enabled data integrity and edge AI for local decision-making to reduce dependence on cloud servers.

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