



## EVALUATION ON THE IOT BASED ONLINE METHODS FOR MONITORING TRANSFORMER TURN-TO-TURN FAULTS

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**Cite This Article:** A. Thamijunisha, M. Guhan, D. Lakshmanan, P. Manivasan & S. Nishanth, "Evaluation on the IoT Based Online Methods for Monitoring Transformer Turn-to-Turn Faults", International Journal of Scientific Research and Modern Education, Volume 11, Issue 1, January - June, Page Number 58-65, 2026.

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**Type of Review:** Peer Reviewed as per [C|O|P|E] Guidance.

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**DOI:** <https://doi.org/10.5281/zenodo.19741015>

### Abstract:

The Transformers are indispensable assets in electrical power distribution systems, ensuring reliable energy transmission and grid stability. However, traditional inspection and diagnostic approaches often rely on manual monitoring and periodic testing, which fail to detect early-stage transformer faults such as turn-to-turn short circuits, overheating, insulation breakdown, oil level reduction, and abnormal mechanical vibrations. These undetected issues can escalate into catastrophic failures, causing unplanned outages, costly repairs, and operational inefficiencies. To address these limitations, this paper presents an Internet of Things (IoT)-based real-time transformer monitoring and fault detection system designed to enhance the reliability, safety, and performance of power networks. The proposed framework integrates multiple sensors temperature, voltage, oil level, and vibration sensors to continuously monitor transformer health parameters. The ATmega328P microcontroller acts as the central processing unit, acquiring sensor data, executing threshold based analysis, and identifying potential faults. The system features an LCD display for local condition visualization and utilizes IoT connectivity for remote data transmission to a cloud platform, enabling real-time access and historical data analytics. When abnormal conditions such as excessive temperature rise, voltage imbalance, low oil level, or increased vibration are detected, the system promptly activates a buzzer alarm and sends alert notifications through IoT channels to maintenance.

### Introduction:

The transformer condition assessment has relied heavily on periodic manual inspection and offline diagnostic testing methods such as Dissolved Gas Analysis (DGA), thermal imaging, and insulation resistance testing. While these techniques are effective for periodic evaluations, they are limited in their ability to detect real-time changes or early-stage faults that may occur suddenly between inspection intervals. These limitations often result in delayed fault detection and reactive maintenance, which can lead to severe equipment damage or system-wide failures. Moreover, manual inspection requires substantial labor, incurs high operational costs, and cannot provide continuous condition monitoring. Hence, the need for an intelligent, real-time, and automated monitoring system has become more critical than ever before. Recent advancements in the Internet of Things (IoT) and embedded systems have revolutionized the field of industrial automation and monitoring. IoT technology allows the interconnection of sensors, devices, and cloud-based systems to collect, analyze, and transmit data in real time. In the context of transformer monitoring, IoT enables the continuous observation of critical parameters such as temperature, oil level, vibration, and voltage parameters that directly reflect the operational condition and health of the transformer.

This real-time data acquisition and analysis can significantly reduce the risk of unexpected failures by providing early warnings and actionable insights to maintenance teams. The proposed IoT based real-time transformer monitoring and fault detection system aims to bridge the gap between conventional maintenance methods and modern predictive maintenance approaches. The system integrates multiple sensors, including temperature, voltage, oil level, and vibration sensors, to gather comprehensive information about transformer performance. Among these, the vibration sensor plays a particularly important role in identifying mechanical abnormalities such as core loosening, winding displacement, or structural imbalances that often precede serious internal faults. The collected sensor data is processed by an ATmega328P microcontroller, which functions as the system's central processing unit. It performs data acquisition, filtering, and threshold-based fault detection. Whenever the measured values exceed predefined safe limits, the system identifies the potential fault condition. In addition to the local monitoring capability provided through an LCD interface, the proposed system employs IoT communication for remote monitoring and cloud integration. Sensor data is transmitted to an online cloud platform where it can be visualized, stored, and analyzed over time. This cloud-based infrastructure enables operators and engineers to access transformer health information from any location, facilitating timely interventions and long-term performance analysis. Furthermore, the system automatically sends alert notifications via IoT based communication channels when abnormal conditions are detected, enabling maintenance personnel to respond immediately. This predictive and preventive approach not only minimizes downtime but also extends the service life of the transformer by preventing fault escalation.

### Related Works:

Temperature monitoring is one of the most vital aspects of transformer health assessment. Excessive temperature rise can indicate overloading, poor ventilation, or insulation degradation. Prolonged overheating can deteriorate insulation materials, cause

oil oxidation, and ultimately lead to catastrophic transformer failure. The temperature sensor continuously measures the winding and oil temperature to ensure that the transformer operates within safe limits. Voltage sensors are equally important since overvoltage or under voltage conditions can stress the transformer windings and insulation. Fluctuations in supply voltage can also signal load imbalances or issues in the distribution network. By continuously monitoring voltage levels, the system ensures that the transformer remains within its designed operating parameters. The oil level sensor plays a critical role in maintaining the thermal and electrical insulation properties of the transformer. Transformer oil not only provides insulation but also acts as a coolant that dissipates heat generated during operation. A decline in oil level can lead to poor cooling efficiency, overheating, and potential insulation failure. Thus, the oil level sensor helps in detecting leakage or evaporation early, preventing costly repairs and operational hazards. Similarly, vibration monitoring is essential because excessive mechanical vibrations often precede major transformer failures. Vibration sensors detect any irregular motion or resonance that could indicate issues such as core displacement, winding looseness, or bearing wear in transformer cooling fans. The ATmega328P microcontroller, being energy-efficient and cost-effective, serves as the core processing unit that interfaces with all sensors. It performs real-time data acquisition, processes the sensor signals, and implements decision-making algorithms to detect faults. The microcontroller's programmability allows it to execute specific logic for different fault conditions, such as triggering an alarm or sending an alert message when abnormal readings are detected.

The LCD display unit provides an immediate local readout of the transformer's status, allowing field operators to quickly verify operational conditions on-site. The integration of IoT technology adds a powerful dimension to this monitoring system. Through IoT modules, sensor data is transmitted to cloud servers, where it can be stored, analyzed, and visualized in real time. Cloud-based dashboards provide operators with detailed insights into transformer health trends, making it possible to identify patterns and correlations that may not be immediately apparent from raw data. Additionally, cloud connectivity enables the implementation of predictive maintenance strategies, where machine learning algorithms can analyze historical data to forecast potential failures before they occur. This transition from reactive to predictive maintenance greatly enhances system reliability and reduces maintenance costs. Another significant advantage of the proposed IoT based system is its scalability. The same framework can be expanded to monitor multiple transformers across different substations or distribution networks. The use of cloud-based analytics allows for centralized supervision of geographically distributed assets, thereby improving grid management efficiency. This kind of remote monitoring system is particularly beneficial for large-scale utilities that operate multiple transformers in remote or difficult-to-access areas. By reducing the need for manual inspection visits, the system saves time, reduces human error, and ensures continuous observation even in challenging environments.

Moreover, the proposed system aligns well with the ongoing evolution of smart grid technology, where real-time data exchange, automation, and intelligence are the cornerstones of future power systems. The fusion of IoT, sensors, and cloud computing not only enhances fault detection accuracy but also contributes to energy efficiency and sustainability goals. It provides actionable intelligence that can be integrated with other smart grid components, such as load management and demand forecasting systems. In summary, the introduction of an IoT based real-time monitoring and fault detection system for power transformers represents a transformative step toward modernizing conventional maintenance practices. By combining multi-sensor data acquisition, embedded control, and cloud analytics, the system ensures continuous supervision, early fault detection, and intelligent decision-making. This approach enhances the operational reliability of power transformers, minimizes unplanned outages, and supports predictive maintenance frameworks. As the energy infrastructure becomes more complex and interconnected, such IoT-enabled monitoring systems will play a vital role in achieving a resilient, efficient, and smart electrical grid for the future.

#### **Proposed System:**

The proposed system introduces an IoT based real-time monitoring and fault detection framework for power transformers, designed to enhance reliability, safety, and operational efficiency in electrical distribution networks. This system continuously monitors vital transformer parameters such as temperature, voltage, oil level, and vibration using dedicated sensors. The collected data is processed and analyzed by an ATmega328P microcontroller, which identifies any abnormal patterns or threshold violations indicative of potential faults. By integrating sensing, data processing, and IoT based communication, the system enables predictive maintenance and minimizes downtime in transformer operations. At the core of the system is the ATmega328P microcontroller, which serves as the central processing unit. It receives analog inputs from various sensors, converts them into digital signals, and executes fault detection algorithms. The microcontroller compares each sensor reading against predefined safety thresholds stored in its memory. If any parameter exceeds its permissible limit, the system immediately detects a fault condition. It then activates an audible alarm through a buzzer and displays the corresponding alert message on an LCD interface, allowing on-site operators to take immediate corrective action.

The temperature sensor continuously measures the thermal condition of the transformer windings and oil. Since overheating is one of the most common causes of transformer degradation, this sensor ensures that the internal temperature remains within the safe operating range. Similarly, the voltage sensor monitors both input and output voltage levels to detect fluctuations, over voltages, or under voltages that could stress the transformer insulation. The oil level sensor plays a crucial role in ensuring the proper insulation and cooling function of the transformer oil. A decrease in oil level can indicate leakage or evaporation, which could lead to overheating or dielectric breakdown. Meanwhile, the vibration sensor detects unusual mechanical oscillations or imbalances within the transformer structure early signs of core loosening or winding displacement. All sensor data is processed in real time, and the IoT module transmits the information to a cloud-based monitoring platform. This integration enables remote supervision and continuous data availability for operators. Through the cloud interface, engineers can visualize transformer health parameters, analyze performance trends, and access historical data for fault diagnosis. If the system identifies an anomaly such as a sudden rise in temperature, oil depletion, voltage imbalance, or abnormal vibration it instantly sends a notification to the designated mobile application or web dashboard via IoT connectivity.



At This image represents a comprehensive block diagram for a fault monitoring and alert system managed by an ATMEGA328P microcontroller. The system is designed to monitor various operational and fault parameters in an electrical environment and to provide real-time alerts and status updates both locally and remotely. The incoming electrical supply passes through a set down transformer and is stabilized by a power supply unit before reaching the ATMEGA328P microcontroller. The system is equipped with a range of sensors for broad fault and condition detection: a temperature sensor for heat monitoring, an ultrasonic sensor (often used for distance or level measurements), and specific fault detection modules including line-to-line fault, line-to-ground fault, double line fault, short circuit switch, and a vibration sensor.

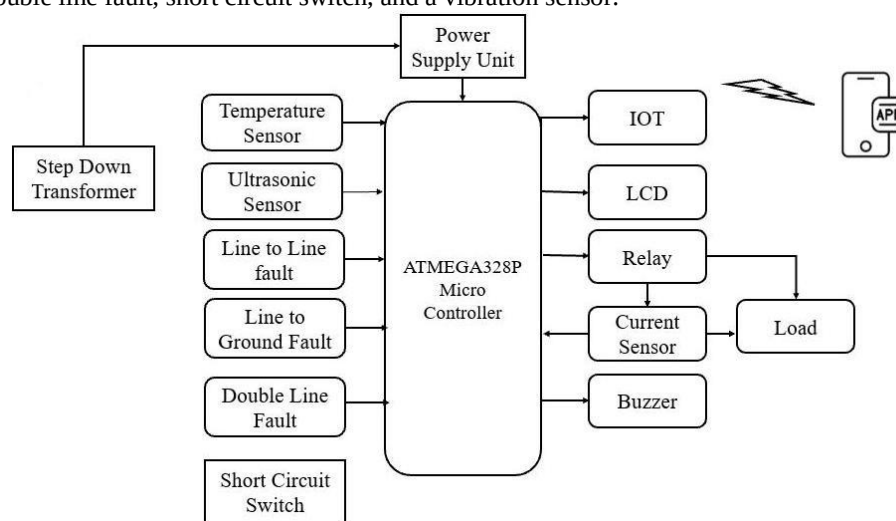


Figure 2: Proposed Work Hardware Block Diagram

The proposed system is designed as a smart and intelligent monitoring and protection unit that integrates modern sensing technology, microcontroller-based control, IoT communication, and electromechanical protection techniques into one complete system. The primary objective of this system is to continuously monitor different environmental and electrical parameters such as temperature, vibration, three-phase line status, short-circuit conditions, and the presence of nearby objects. Based on the real-time data collected from sensors and feedback devices, the system takes corrective actions such as sounding alarms, displaying messages, disconnecting the electrical load, and sending notifications to remote users via IoT. The core of the proposed system is the Arduino microcontroller, which is responsible for data processing and decision-making. Various sensors such as the DHT11 temperature sensor, ultrasonic sensor, vibration sensor, and short-circuit sensing unit provide continuous data to the controller. These signals are analyzed using pre-programmed logic. The system also includes a regulated power supply unit, a 16×2 LCD display, LEDs for status indication, a buzzer for audible alerts, and communication interfaces. The circuit diagram clearly presents the interconnection of all these components, forming a robust smart monitoring and safety solution suitable for industrial, commercial, and academic environments. The vibration sensor adds mechanical monitoring, useful for detecting abnormal vibrations in devices like motors and transformers. On the output side, the microcontroller is connected to an IoT module, allowing for wireless communication and notifications via a mobile app. It also interfaces with an LCD for on-site visual feedback, a relay to control the connection and disconnection of the electrical load, a current sensor to monitor load current, and a buzzer to sound audible alerts in case of any abnormal events or detected faults. This system is ideal for enhancing safety, enabling automated electrical health monitoring, and providing immediate alerts to operators and remote users via IoT connectivity.

#### Methodology:

The transformer as core equipment for power transmission and voltage conversion plays a key role in the fields of power transmission and electronic circuit, so it is crucial to ensure its safe and stable operation, especially for power transformers with huge cost. During its operation, a transformer inevitably suffers from the impact of high transient over-voltage, external short circuit current; these factors tend to deteriorate the According to historical statistical data, winding faults are the main deterioration form. Among different winding faults, turn-to-turn short-circuit (TT-SC) fault with a high incident rate often starts with a minor percentage of the winding turns, and then gradually triggers winding overall failure [6]. Therefore, detecting winding TT-SC fault and implementing preventive measures in advance are imperative to stop transformer failure development. Existing techniques for inspecting winding fault, mainly including short-circuit impedance method (SCI), frequency response analysis method (FRA), are all applied in periodic offline maintenance tests. Nonetheless, as winding TT-SC faults can take place randomly and then quickly trigger transformer overall failures, the periodic offline winding inspections may often fail to prevent transformer failures from happening. Additionally, the interruption of power transmission can result in extra economic cost. Therefore, a growing number of

researchers have been motivated to explore online winding monitoring methods, highlighting its necessity for continuously detecting winding states. Related proposals for monitoring transformer winding TT-SC fault online can be roughly categorized into i) port voltage- current analysis (PVCA) , ii) online FRA, iii) inference by vibration (IV), iv) embedded sensor (ES).

Given each online method has respective limitations remaining to be overcome, there is no suitable method having been applied in practical projects. Besides continually improving single method, the fusion application of multiple methods to integrate their advantages becomes a more promising solution. Essentially, performance evaluations for accurately understanding the method characteristics to guide the targeted improvements and the complementary fusion application become indispensable. Several efforts have been made to conduct evaluations for online winding monitoring methods, yet they mainly rely on qualitative comparisons rather than experiment-based quantitative analysis. On the contrary, Rahimpour et al. state that the load change cannot result in considerable variations of online FRA measurement results. Furthermore, multi-performance indicators mainly including sensitivity, repeatability, and anti- interference capability are essential to evaluate an online monitoring method. The method with the poor indicators, once subject to noise distortions and external interferences, can fail to identify the minor and potential TT-SC faults. Nevertheless, existing evaluations supported by experiment analysis mostly focus on the feasibility of the methods, with very few experiment evaluations aiming for other. In fact, it is the experiment-based quantitative evaluations on the multi-performance that are often needed to help us deeply understand the methods for the targeted improvement and the strategies formulation of the fusion application. Finally, it is worth noting that existing evaluations seem to have largely neglected the ES method, possibly due to its application only in special-customized transformers. In this paper, we intend to conduct a quantitative evaluation focusing on the multi-performance indicators of three TT-SC monitoring methods: the  $\Delta V$ -I locus method (a novel PVCA method), the online FRA method, and the IV method. Nevertheless, conducting such a comprehensive evaluation faces several challenges. First, general transformer platform enabling the multi-performance testing and guaranteeing the results keeping consistent with the ones in actual power transformer does not exist. Second, there is no commodity equipment concerning the three online monitoring methods, especially for the online FRA method still with the low Signal-to-Noise ratio (SNR) problem. Third, since the monitoring data of the three methods involve different types (e.g., time domain for  $\Delta V$ -I locus and frequency domain for Online FRA and IV), the disparity in the features extracted from these data makes a fair quantitative comparison among the corresponding methods very difficult. Finally, there is still a lack of theory interpretations on the multi-performance evaluation results not reported for the three online monitoring methods. To tackle these challenges, we specifically take the following steps.

First of all, we build an experiment platform containing a customized power transformer and its testing system to simulate multiple TT-SC faults and interferences. Second, an integrated online evaluation platform of the three methods is constructed to collect the test data. In particular, to support the quantitative comparison among the three methods, we propose a novel feature extraction algorithm based on image mining to design the multi-performance indicators of the three methods, after mapping the test data into a high-dimensional image. Essentially, our feature extraction algorithm involves noise removal, as well as global and local feature mining: it exploits image-connected domain detection algorithm along with image gussies filter to obtain several sub-domains without noise in the raw image. It then utilizes the image feature mining algorithm to extract simultaneously the global features (domain area, edge length) and local feature (corner point). Last but not least, to explain the quantitative evaluation results, we introduce three theoretical models for the three online monitoring methods. In summary, we are making the following major contributions in this paper: We conduct a comprehensive evaluation of the three TT- SC fault online monitoring approaches by leveraging both experiment and theoretical analysis to fill the existing gap.

Further, its results can support the targeted improvements and the strategy formulation of the three methods fusion application to integrate their respective advantages. We construct an integrated online evaluation platform, especially containing an improved online FRA module to solve the problem of its low SNR, for the fair comparison of the three monitoring methods; it also provides the reliable hardware preparation for the real-world fusion application next step. We propose a novel monitoring data feature extraction algorithm based on image mining to quantify multi- performance of the three methods; it can remove the obstacles caused by the conventional feature disparity to performance comparison. We investigate several influential but non-widely concerned aspects of the three online monitoring methods to derive the results: i) the  $\Delta V$ -I method possesses the best anti interference capacity, ii) the online FRA method with the highest sensitivity can be easily interfered, and iii) the IV method, albeit with poor repeatability, is superior to the  $\Delta V$ -I method in the sensitivity. The remainder of the paper is organized as follows: Sec. II introduces experiment and evaluation platform, followed by the experiment results in Sec. III. Sec. IV conducts the multi-performance quantitative evaluation. And Sec. V reports the theoretical analysis of the results. In last Sec. VI, the conclusions and avenues for future work are introduced.

### **Experiment and Evaluation Platform:**

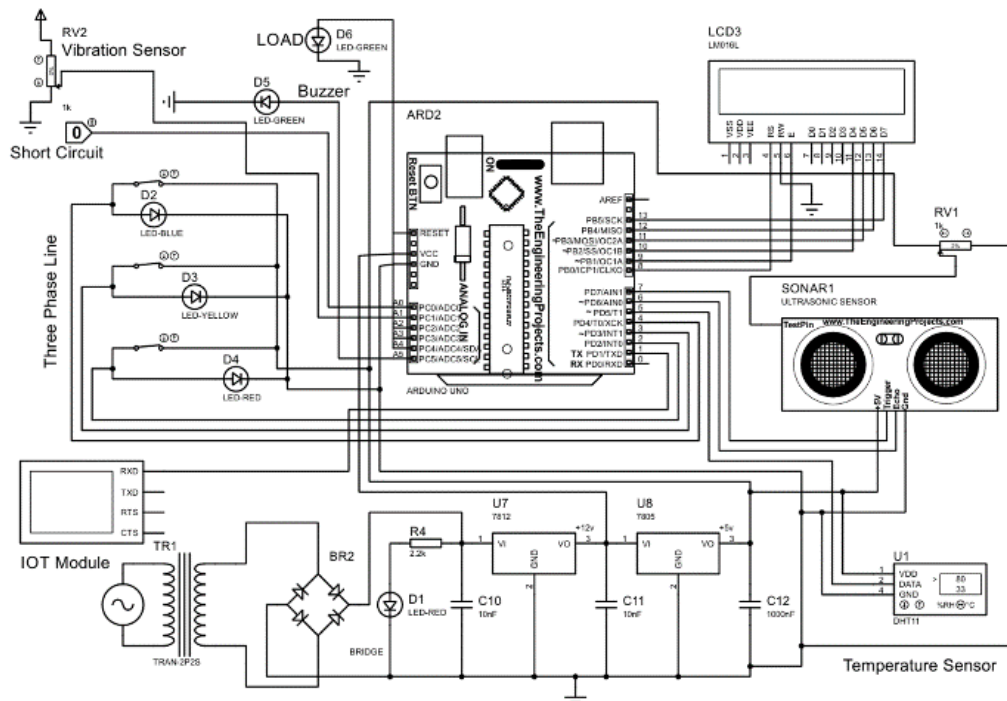
In this section, we first describe the construction of the experiment platform, followed by the design of the integrated online evaluation platform.

#### **A. Construction of the Experiment Platform:**

The test transformer is a 10 kV/0.4 kV 3-phases power transformer with 400 kVA rated capacity. The transformer winding consists of 300 turns of high-voltage (HV) winding and 12 turns of low-voltage (LV) winding; the former has five groups of replaceable winding unit in the middle. And to simulate the different TT-SC faults, the top winding unit, as described in Figure1, is constructed into the structure with multiple short-circuit connectors. Meanwhile, differential relay, as an existing main protection of power transformer, can be known to detect the TT-SC faults involving 10 % or more of winding turns [6]. The additional TT-SC fault online monitoring methods should highly focus on identifying the incipient minor TT-SC fault (below 5 % of whole winding. Therefore, three minor TT-SC faults including 1 turn SC (0.33 %), 4 turns SC (1.33 %), and 8 turns SC (2.67 %) are set as the fault simulation objects in our experiment. The main electrical circuit, with its connection diagram marked by the black line in Figure2, is connected to support the online operation of the test transformer. Specifically, power source (PS showed in Figure2) representing 380 V three phases AC power lines connected to power grid supplies the electrical power to the total experiment platform, and its

access is controlled by a circuit breaker (CB). Since the high rated capacity (400 kVA) of the test transformer cannot be fed by the power source, we short-circuit the LV side of the transformer for reducing the load. Meanwhile, to allow the transformer to work continuously on rated current (23 A/575 A phase current), the phase voltage magnitude of the HV side of the test transformer is adjusted to 285 V by utilizing the voltage-regulating transformer (VR-1 showed in Figure 2). To decrease the reactive power supply from the power source, total inductive load of the test transformer is compensated by the parallel capacitor (C) with a capacitance of 250  $\mu$ F. It is worth noting that the winding vibration, the voltage differences between the HV and LV side and winding current (as two critical parameters of  $\Delta V$ -I locus method) mainly depend on the transformer input current.

Accordingly, that the test transformer works on the rated current can further guarantee that the measurement results of the winding vibration and  $\Delta V$ -I locus are closer to the ones under the rated operating condition. Additionally, the frequency response measurement is mainly affected by the core magnetization. The online FRA measurement under the 285 V (non-nominal voltage) and the nominal voltage is dwindled by the coupling device used in the online FRA monitoring. Power grid structure variation: Other voltage regulating transformer (VR-2 showed in Figure2), as a bypass transformer of the VR-1, is connected into the main electrical circuit for simulating the scenario that the reserve trans- former in power station is connected into power grid. 2) Load variation: The resistor (R) with a resistance of 0.01  $\Omega$  replaces the short-circuit line as the load for further changing the transformer input current. 3) EMI: The HV spark gap switch, as the EMI source, can generate the breakdown corona discharge when its voltage is over 10 kV. The electromagnetic radiation or pulse generated by the discharge EMI (DEMI) source will be coupled into the main electrical circuit. 4) Mechanical structure defect: The tightness of the connecting unit of the upper and lower iron yoke in the test transformer is slightly changed to simulate the transformer mechanical looseness.



## B. Design of Integrated Online Evaluation Platform:

The integrated online evaluation platform of three TT-SC fault monitoring methods, shown in Figure2, is designed to support the joint acquisition of three types of monitoring data. Specifically, these raw monitoring data are first collected by three monitoring modules, and then gathered into a computer for signal processing. Specifically, the short-time Fourier transform algorithm is utilized to filter raw signal noises, with its inverse transform to reconstruct the target signal. Each module is respectively introduced as follows: a)  $\Delta V$ -I locus method: As marked by the blue in Figure2, the instantaneous phase voltages ( $v_1$ ,  $v_2$ ) and phase currents ( $i_1$ ,  $i_2$ ) both at the HV and LV side are respectively measured by the voltage sensors (VS-1, VS-2), current sensors (CS-1, CS-2) with high precision. Then, these signals are synchronously collected by the oscilloscope (OSC-1), and further transmitted into the computer for generating the  $\Delta V$ -I locus. b) Online FRA method: The sweep frequency output signal of existing FRA device (e.g., Omicron Bode100 Network Analyzer with max output amplitude equal to 5 V) is often reduced to below 50 mV through online coupling device into the HV winding. Such small-signal excitation enables the measurement easily disturbed by the noise. In the paper, a new online FRA module with high voltage input and output amplification (marked by the yellow in Fig 2) is designed to solve the challenge for supporting its fair comparison with the other two methods. First, the signal generator (SG) produces the continuous sweep frequency alternating signal at 0.001-1 MHz. Then, the signal amplitude is amplified to 150 V by the voltage amplifier (VA) with an upper limit output value equal to 180 V (1 MHz). Third, the amplified signal is coupled safely into the winding by the protection device and the bushing-end capacitive sensor (BCS) [15], composing a multi-stage capacitor coupling circuit for the high-frequency signal transmission. After flowing through the winding, the signal is decoupled from the neutral line by the high frequency current sensor (HFCS), and then amplified by the signal amplifier (SA) for further increasing the SNR. The BCS input voltage VHFVS, acquired by the high frequency voltage sensor (HFVS), and the neutral point output current IHFCS, acquired by the HFCS, are selected respectively as the reference and response signal of the online FRA. Finally, the FRA curve is obtained from the reference and response signals based on our self-designed algorithm on the computer. c) IV method: Two

vibration sensors (VS) with the sensitivity of 500mV/g are exploited to respectively collect the vibration signals at two measurement points: the top pressing plate of the winding and outside of tank near HV insulator.

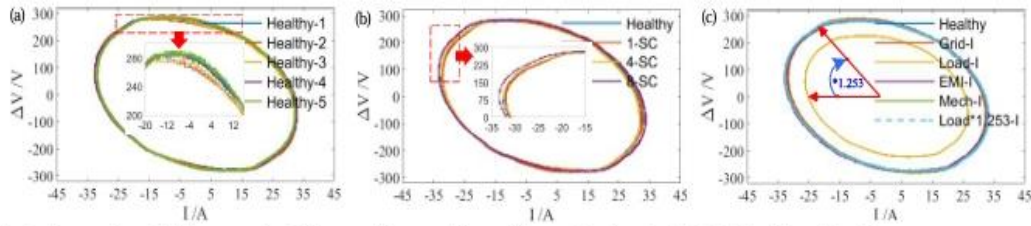


Fig. 3. Test results of  $\Delta V$ -I locus method. (a) repeatability test. (b) sensitivity test for the minor TT-SC faults. (c) anti-interference test.

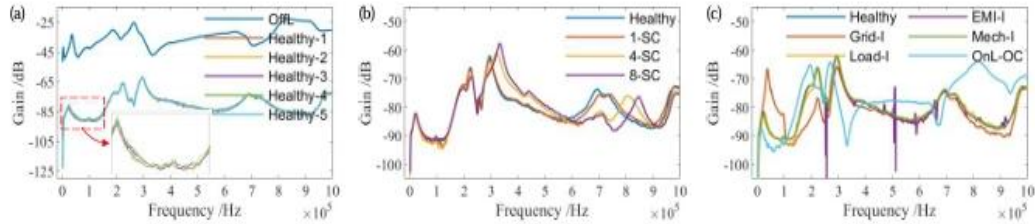
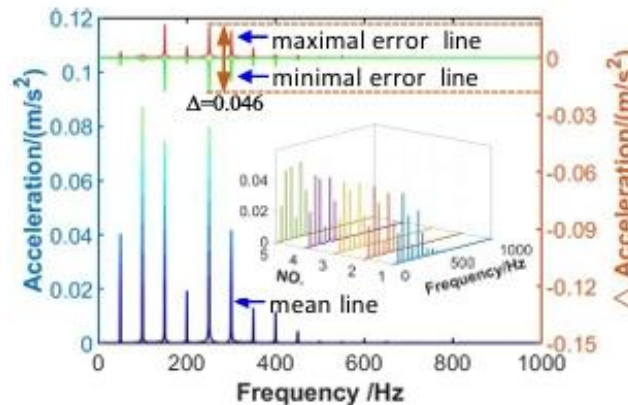


Fig. 4. Test results of Online FRA method. (a) repeatability test. (b) sensitivity test for the minor TT-SC faults. (c) anti-interference test.

### Experiment Results:

In this section, the repeatability, sensitivity and anti-interference test data are processed to generate the test curve graph of the three monitoring methods including Figure3, 4, 5 and 6. In the figures, the Healthy-1, 2, 3, 4, 5 curves represent the measurement results of the 5 repeatability experiment while the Healthy curve denotes their average. The 1-SC, 4-SC, 8-SC curves indicate the results when the short-circuit fault occurs in the 1 turn, 4 turns and 8 turns of coils. Additionally, the results under the interferences, respectively induced by the power grid structure variation, the load variation, the EMI and the mechanical structure defect, are presented by the Grid-I, Load-I, EMI-I and Mech-I curve. A.  $\Delta V$ -I Locus Method The fundamental principle of the  $\Delta V$ -I locus method, as described in [13] [23], is to construct the Lissajou curve of phase voltage difference between the HV and LV side, and input phase current. Referring to the method proposed by Zhao et al. [23], the  $\Delta V$ -I locus function in this paper can be formulated:  $\Delta v^* \Delta V^* - 2 \cos(\varphi_2 - \varphi_1) \Delta v^* i^* \Delta V^* I^* m^2 m^2 - \sin(\varphi_2 - \varphi_1) = 0$ . (1) Where  $\Delta v^* = v^* - v^* = \Delta V^* \cos(\omega t + \varphi_1)$ ,  $i^* = i^* = 1$  can be used to explore the vibration characteristic of the source. The latter point is frequently selected in practical applications due to its vibration-sensitive nature. These vibration signals are transmitted to the computer for further analysis.  $m^2 m^2 I^* \cos(\omega t + \varphi_2)$ . The variables marked with the superscript \* are per unit values while the variables tagged by the subscript m refer to the magnitude. The  $\varphi_1$  and  $\varphi_2$  are the phase angles of  $v^* - v^*$  and  $i^*$  respectively, and the  $\omega$  is the angular 1 Relying on the above platform, the repeatability, sensitivity and anti-interference tests are executed accordingly. Meanwhile, the repeatability test is to conduct the test without the 2 frequency in rad/s. Based on (1), the  $\Delta V$ -I locus in the different tests can be obtained in turn, as shown in Figure4. According to Figure3b, the deformation of the  $\Delta V$ -I locus is Figure5. Vibrations test results at the top measurement point of the winding in the repeatability test. Gradually aggravated with the increase of the winding TT-SC turns number. In Figure3c, the load variation is proven as the prominent interference. However, the new curve (Load\*1.253- I in Figure3c) acquired by amplifying the original Load-I locus by 1.253 times is similar to the Healthy curve. It can be inferred that the load current interference mainly changes the size of the locus rather than the shape. Therefore, all locus data should be processed in advance based on the load compensation approach to eliminate the load interference.



### Target Feature Generation:

The coordinates of single corner point cannot be directly chosen as the feature. Instead, the distance of two relative corner points respectively on the measurement curve and the reference curve is selected as the corner point feature to present the differential information. And the two relative corner points, as a corner point pair, respectively represent the original corner point and its offset point, and are acquired by the sequentially-matching method after removing the cross point of the two curves. The matching results of the corner point pair are marked by the blue circle in Figure8. Ultimately, the area sum A, edge length sum L and the distance sum D of the corner point pair in the image T are determined as the target features, described as follows:

**Multi-performance Evaluation** The multi-performance indicator values for the three methods, as illustrated in Table I, are acquired from the experiment results in Sec. III by the multi-performance quantification approach. Specifically, the S1, S4, S8 in Table I denote the sensitivity value  $S_j$  respectively when the short-circuit fault occurs in the 1 turn, 4 turns and 8 turns of coils. Additionally, the degrees  $I_k$  of interference, respectively induced by the power grid structure variation, the load variation, the EMI and the mechanical structure defect, with the monitoring methods are represented by the I1, I2, I3 and I4. Meanwhile, we measure the TT-SC fault identification accuracy of the monitoring methods, defined as follows: Compared with the two other methods, although the  $\Delta V$ -I locus method possesses the minimum sensitivity; it with the best anti-interference performance can resist the four typical interferences. Specifically, in Table I, all  $I_i$  less than 1 can represent that the feature variations induced by the four interferences are more limited than the one caused by the random noise. Additionally, it is proven that the interference induced by the load variation can be eliminated by the load compensation approach. Similarly, the Accuracy1 of the  $\Delta V$ -I method is equal to its Accuracy0, certifying that the interferences do not affect its TT-SC fault identification. b) Online FRA method: The online FRA method, possessing the minimal (ARmax, LRmax, DRmax), presents an excellent performance in the repeatability, helping to infer that the disturbances induced by random factors (e.g. several component variations in the electrical circuit) are limited. All  $S_i$  of the method far greater than 1 in Table I demonstrate that the big feature variations caused by the minor TT-SC faults can support the fault identification free from the random noise interference. Furthermore, we can use the method to effectively identify all winding TT-SC faults. However, the I1 over the S8 of the online FRA method denotes that the method will be unable accurately identify the minor TT-SC faults once there are interferences induced by the change of the external power grid structure. After observing the I2 over and close to 1, we can infer that the load variation set in our test can slightly interfere with the online FRA measurement result. Meanwhile, it is noted that the fault accuracy of the online

$$Accuracy = \frac{TP + TN}{TP + FP + TF + FN}$$

Where TP, FP, TN and FN stand for the numbers of true positive samples, true negative samples, false positive samples and false negative samples, respectively. Note that positive class means the TT-SC fault state and negative class means the state without faults. The accuracies under the rated operation condition and the interference condition are respectively represented by the Accuracy0 and Accuracy1. According to the indicator values in Table I and the corresponding evaluation criterion at the end of Sec. IV-B, we evaluate the multi- performances of the three monitoring methods in turn.

### Conclusion:

The proposed IoT based real-time transformer monitoring and fault detection system provides a modern, intelligent, and efficient approach to ensuring the reliable operation of power transformers in electrical distribution networks. Traditional inspection and maintenance methods often fail to detect early stage abnormalities such as overheating, oil depletion, insulation degradation, or mechanical vibrations. In contrast, the proposed system utilizes a combination of temperature, voltage, oil level, and vibration sensors integrated with an ATmega328P microcontroller to continuously monitor the transformer's health and operational parameters. This integration enables early fault detection and real-time analysis, minimizing the chances of unexpected breakdowns and costly downtime. By leveraging IoT technology, the system transmits real-time sensor data to a cloud platform for remote monitoring, data logging, and historical analysis. This allows operators to visualize transformer conditions through a mobile application or web dashboard and receive immediate notifications in case of abnormalities. The predictive nature of this system supports proactive maintenance strategies, reducing the need for manual inspections and enhancing overall grid reliability. Additionally, the cloud-based analytics enable long-term performance evaluation and pattern recognition, which are essential for improving maintenance planning and optimizing operational efficiency. The inclusion of local alerts through an LCD display and buzzer ensures quick response during on-site operations, while remote notifications ensure timely intervention even when the transformer is located in distant or unmanned areas. Overall, the system offers a scalable and cost-effective solution adaptable to transformers of varying capacities and configurations. In conclusion, the proposed IoT-enabled transformer monitoring framework not only enhances operational safety and reduces maintenance costs but also aligns with the vision of smart grid modernization. It represents a significant step toward achieving intelligent, data-driven, and sustainable power system management in the evolving era of digital transformation.

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