Real-time Transformer Diagnosis using Voltage-Current Signal over Cloud Environment

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Abstract--**Most transformer diagnosis methods can only be performed off-line when the transformer is taken out of service. This study is specifically focused on the V-I locus method for real-time transformer active part evaluation over the cloud environment and assessment of captured data through cloud computing. Experiments are carried out on a test setup to study turn-to-turn short circuit fault created on small transformers. Transformer mechanical fault recognition is discussed and the voltage/current technique is evaluated. Data obtained from practical measurements is analysed over cloud environment and assessment of the transformer condition is performed via application on mobile device. Also, protection relay connected to the transformer can be activated via cloud-based data assessment.**

Keywords—Cloud computing, Internet of Things (IoT) application, Real-time transformer deformation evaluation, Transformer diagnosis.

I. Introduction

The majority of transformer active part evaluation test techniques can only be performed when the transformer is disconnected from the power grid. However, switching the transformer off just for testing purpose is quite costly for utility operators as well as lengthy supply interruption. Therefore, most transformer owners are unwilling to do so. On the other hand, if transformer mechanical defects are not detected at early stages, they may compromise the proper and safe operation of the transformer. Late detection of mechanical defects can result in catastrophic failure and detrimental to utility operations. Therefore, there is a significant demand for real-time transformer winding deformation diagnosis. This study aims to develop a monitoring system which provides access to the real-time transformer winding deformation condition by implementing cloud computing system and utilizing the V-I locus method [1]. Real-time access to transformer active part condition will provide up-to-the-minute intelligence on transformer performance in diverse environmental conditions and decrease the risk of the mechanical defect and its severe consequences. Also, connecting the power grid to the IoT platform through the Internet infrastructure will help to develop an advanced arrangement for real-time transformer winding deformation diagnosis. The practical implementation of this novel approach may become fundamental for smart grid equipment monitoring with cloud computing.

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II. Background

A. Transformer Diagnosis Methods

Transformer mechanical defects can be initiated by short circuit, earthquake or inappropriate transportation [2], [3]. Intern-turn short circuit in the windings damages transformer insulation medium whereas large electrodynamic forces from external short circuit in power networks can cause radial deformation of the windings [4]. The transformer can still operate with slight winding damage; however, its capability to endure forthcoming faults is seriously diminished. The majority of power grids have employed offline mechanical defect recognition methods such as short circuit impedance (SCI), Frequency Response Analysis (FRA) or Low Voltage Impulse (LVI) [5]. However, the main common downside of all the mentioned offline methods is that they require disconnection of transformers from the grid. Off-line transfer function measurement using FRA has been considered as one of the most accurate diagnostic methods for detecting winding displacements in transformers [6]-[8]; however, it still requires equipment to be disconnected from the network [9]. Certainly, there is a need for real-time transformer winding deformation diagnosis method. Hence, various methods based on vibration, electromagnetic waves emission, current deformation coefficient, ultrasonic emission, short circuit impedance, winding stray reactance, transfer function, V-I locus diagram have been introduced in the literatures [1]. In the vibration method [10], recurring movement of transformer inner parts is evaluated with respect to the reference position, and analysis results are employed to determine winding deformation [11], [12]. With the electromagnetic waves method [13], the magnitude and phase of scattering parameters are measured using different antennas. The ultrasonic method detects the defects by analyzing the non-matching acoustic impedance between the winding and oil [14]. The Transfer Function (TF) method can be performed in the time domain or frequency domain [15]. Frequency response analysis (FRA) is one of the effective methods used to detect mechanical deformations in transformer windings. It identifies defects by detecting the changes in the TF. The main limitation is that the TF is sensitive to the time parameters of the signals and variables like oil condition and temperature [16]-[19]. Short circuit impedance diagnosis is performed by regular comparison of short circuit impedance values of a transformer [20], [21]. The short circuit impedance reflects the winding design as well as windings' spaces. Frequency response analysis demonstrates higher accuracy as compared to short-circuit impedance diagnosis [22].

Moreover, real-time transformer winding diagnosis can be

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implemented through analyzing the Lissajous graph [1]. In this method, the operation voltage and current are used to build an ellipse called Lissajous curve [23]. Winding deformation can be recognized by evaluating the recorded graph. The ellipse is susceptible to changes in the load amplitude [24]-[26]. The graph will magnify or diminish with respect to the load value. It is worth noting that integration of real-time monitoring system with the IoT platform will provide a more efficient means for online diagnosis.

B. Cloud system

Cloud system refers to a computational infrastructure which gives immediate remote access to the collected data. Generally, the data can be retrieved through the Internet from any corner of the globe. Such a system plays a prominent role in the interaction between the supplier and consumers. It facilitates easy storage and efficient management of the data by ensuring information transparency and reliability. The servers will communicate with each other using software, and this data exchange is duplicated and stored in the cloud computing system for later access. Interest in cloud systems has significantly increased in the industry due to its cost efficiency, huge storage capacity, backup, recovery feature, automatic software integration and accessibility [27]. Moreover, the cloud system adds value to the implemented system by promoting the Smart Grid concept [28]. The problem of transformers' load regulation has been highlighted as one of the main concerns in the Smart Grid realization [29].

There are different cloud models available on the market. One of them is Google Cloud Platform. It is an internal platform used by the company for end-user products. Google Cloud Platform offers a huge range of cloud computing options including data storage, analyzing and machine learning. However, the users have to register in order to get access to this platform. There is another cloud system called Thinger.io. This platform is oriented on connection between the Internet of Thing systems. Thinger.io is an open source; hence, the codes can be evaluated easily without registering to the system. However, Thinger.io is not as flexible as IBM Watson. This platform is multi-functional and cost-efficient as compared to the other cloud systems [30]. It is more infrastructure-oriented compared to the Google platform, and more reliable compared to the Thinger.io. Moreover, IBM Watson uses NoSQL database [31]. Therefore, it is suitable for big data applications. Finally, there is another cloud computing system called ThingSpeak. It is an open data platform designed for IoT. It collects data in a channel and retrieves data from other systems using their API. Thingspeak offers wireless connection and proper data analysis on the server.

III. Mathematical Model

In order to perform online monitoring, the proposed method utilizes the Lissajous curve for examining the mechanical conditions of the transformer winding. The methodology was originally developed by [1] and another study [23] also discussed over the modeling of this technique. The Lissajous curve is a diagram produced by the intersection of two sinusoidal curves. In the created Lissajous curve, the *x-axis* represents the input current and *y-axis* shows the difference between the input and output voltages [1]:

$$x = I_{inm} \sin(\omega t - \varphi) \tag{1}$$

$$V_{in} = V_{inm} \sin(\omega t + \delta) \tag{2}$$

$$V_{out} = V_{outm} \sin(\omega t) \tag{3}$$

where, V_{in} and V_{out} and I_{in}, are the primary and secondary voltages, and primary current of transformer, respectively. Since the difference of voltages is required, we obtain [1]:

$$\kappa = V_{in} / V_{out} \tag{4}$$

$$y = V_{in} - V_{out} = V_{inm} sin(\omega t + \delta) - V_{outm} sin(\omega t) \tag{5}$$

$$y = 2V_{in}(1-\text{k})\cos(\omega t + \frac{\delta}{2})\cos(\delta)$$

The polar parametric representation of the curve is an ellipse. In addition, the graph of the conic equation of the variables always represents the ellipse. This conic function can be found by eliminating ωt from both x and y [1]:

$$\omega t = \sin^{-1} \frac{x}{I_{inm}} + \varphi = \cos^{-1}(\frac{y}{2V_{outm}}) - \frac{\delta}{2} \tag{6}$$

Having *x-axis* and *y-axis* equations at hand, it is possible to draw the Lissajous curve [1]. Ellipse, parabola, and hyperbola shapes (graphs) are the outcomes for different conditions. For the ellipse, the locus can be drawn using three parameters a, b and θ, where a is one-half of the major diameter, b is one-half of the minor diameter and θ is the ellipse rotation angle. Their formulas in terms of U and I values where $U=V_{in}-V_{out}$ are given by[19]:

$$\tan 2\theta = \frac{2U\ \text{I}\cos\varphi}{U^2 - I^2} \tag{7}$$

$$a = \frac{U^2 I^2}{I^2 + 2UI\cos\varphi\tan\theta + U^2\tan\theta} \tag{8}$$

$$b = \frac{U^2 I^2}{U^2 + 2UI\cos\varphi\tan\theta + I^2\tan\theta} \tag{9}$$

The angle δ can be assumed as zero, due to very slight phase shift between V_{in} and V_{out}, normally. In the same manner, the $\cos\varphi$ between the input current and output current can be neglected. Therefore, the load power factor of the system is considered as phase shift between the input current and the voltage drop.

IV. Case Study and Cloud Computing

A. Hardware Implementation

To develop an experimental setup for real-time evaluation, a small size transformer was selected as the test object. Its specification along with other hardware components are provided in Table I. ThingSpeak cloud system was selected as the IoT platform. Figure 1 shows the flowchart of the proposed monitoring system.

TABLE I. Main physical components

Transformer	0.25kVA 220/24V
Load	Rheostat (max 5 kΩ), RL load
Multimeter	Ammeter and Voltmeter modes
Voltage Source	Power Supply (220V)
Microcontroller	Arduino Mega 2560
Data Transmission Device	Ethernet Shield
Current Sensor	Current Transformer (SCT013)
Voltage Sensor	AC-AC Adapter (AA091ABN)

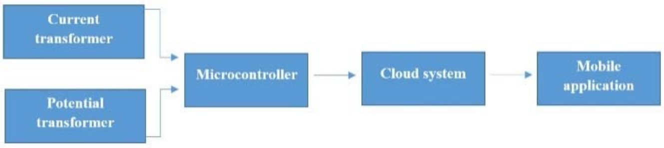

Fig. 1. Flowchart of the system

The schematic of the test setup is shown in Fig. 2. The power supply was connected to the transformer to increase voltage source from 24 V to 220 V. An ammeter was connected in series to the transformer to measure the input current, whereas a voltmeter was connected in parallel to the transformer to record the input/output voltage. A rheostat with an *RL* load was connected in parallel to the secondary side of the transformer. By changing the value of rheostat, transformer load was emulated. Moreover, the short circuit test would be conducted by setting the rheostat value to zero.

Moreover, Arduino IDE, Ethernet, CT and PT have been used to enable real-time monitoring. One end of the current and potential transformers was connected to A1, A2 and A3 ports of the microcontroller respectively and the second end was connected to the ground. These sensors send current and voltage values to the microcontroller, which in turn sends the data to the cloud over the Ethernet shield. Connection with cloud was established by Ethernet cable connection with Ethernet Shield, mounted on an Arduino Mega 2560, see Fig. 2. Fuse F1 and relay RLY1 have been used to protect the circuit against overcurrent conditions.

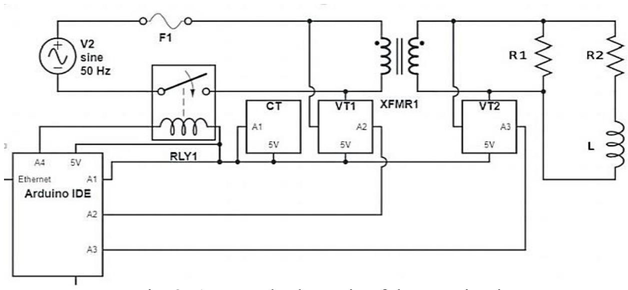

Fig. 2. A general schematic of the test circuit

The circuit design for connection to the current transformer (CT) is shown in Fig. 3. The CT has a turn ratio of 100:5. A burden resistor is required for the CT secondary circuit; the chosen value was 33 Ω which is sufficient to avoid saturation of the CT core. The circuit in Fig. 3 enables the CT to meet Arduino analog input requirements, i.e. a positive voltage between 0 V and 5 V. The voltage divider, using 470 kΩ resistors, is to establish the reference point for the voltage across burden resistor, i.e. mid-value of 2.5 V.

An AC-AC power adapter was used to measure the voltage and power factor across the main test object, see Fig. 4. The adaptor scales down the voltage and a DC offset voltage is added to eliminate a negative component of the voltage waveform. This circuit and its adjustment are required to match the Arduino analog input. The output signal of the adapter has a 9 V RMS value and therefore the peak value can be up to 12.7 V. Thus, the voltage waveform is required to be scaled down to -2.5 to 2.5 V and then the next step is to shift it to the 0-5 V range. The function of the capacitor was to provide a low impedance path to the ground for the AC signal. In addition, a relay was inserted to protect the test circuit. Once there is an overload or unwanted fault condition, the Arduino Mega 2560 microcontroller sends a signal to the relay to disconnect the circuit. Figure 5 shows the setup.

The computational system algorithm flowchart is provided in Fig. 6. It was carried out over the cloud and data obtained via this algorithm can be accessed by a mobile device.

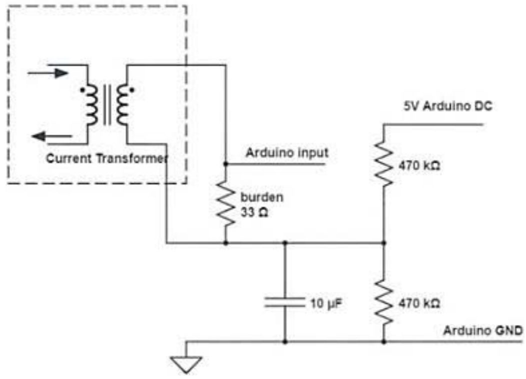

Fig. 3. Current Transformer schematic

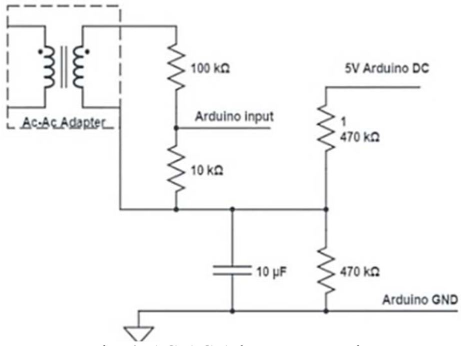

Fig. 4. AC-AC Adapter connection

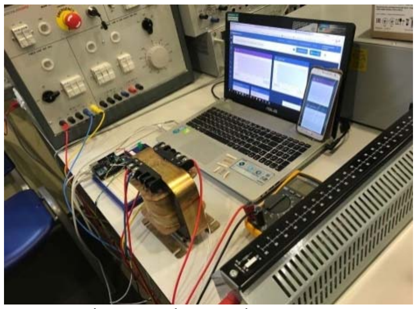
Fig. 5. Implemented test setup.

This system monitors the transformer mechanical condition using *V-I* Lissajous graph and, upon detecting abnormality, activates the protection to prevent transformer damage. First of all, the voltage and current sensors will capture the transformer input current and voltage drop, and the recorded data will be transferred to the cloud. Then, the parameters of the ellipse (a, b and θ) will be calculated and the Lissajous curve will be constructed. Afterwards, the curve is analyzed by comparing its shape with other fingerprint figures in the database using image processing. Finally, based on cloud analysis, the protection relay can be activated to prevent transformer deformation in undesirable conditions.

B. Cloud computing

To implement the IoT system, an Arduino microcontroller was connected to the Thingspeak platform through the local network Ethernet connection. The next step was to provide the gateway between the hardware and cloud system that enables output information to reach cloud services. To achieve this objective, machine-to-machine connectivity protocol was utilized which is AMQP messaging protocol for Advanced Message Queuing. This messaging protocol provides services of messaging, queuing, routing and adequate security. The connection between the device and cloud is illustrated in Figure 7.

ThingSpeak provides facilities to build IoT applications. Moreover, it is an open-source IoT and MATLAB integrated platform. It allows aggregating, visualizing and analyzing the system. It has built-in features like MATLAB analysis and instant visualization. Therefore, it enables collection and visualization of real-time data and facilitates the development of mobile applications. Hence, the Lissajous curve can be easily analyzed over the cloud environment via a portable device connected to the cloud, see Fig. 8.

V. RESULTS ANALYSIS

The locus diagram is constructed using the input current and voltage drop between the primary and secondary side of the transformer. The curve has been plotted every cycle (20 ms based on a 50-Hz network) using rms V and I values. The locus is generated for each measurement and compared with the previous locus. Here, it is quite crucial to differentiate fault from other disturbances such as load change or power factor variation. Therefore, this study needs to identify the influence power factor and load variation over the Lissajous curve.

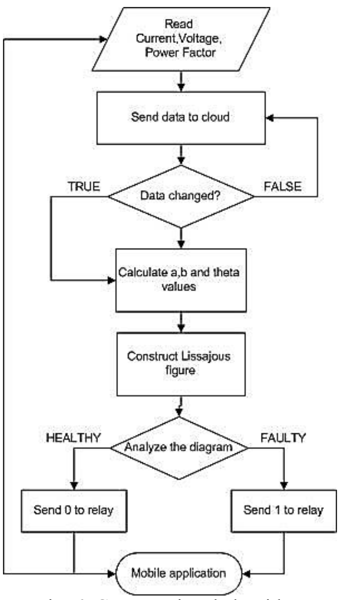

Fig. 6. Computational algorithm

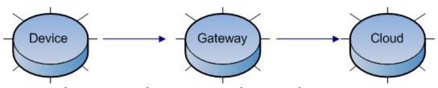

Fig. 7. Device connection to the Internet

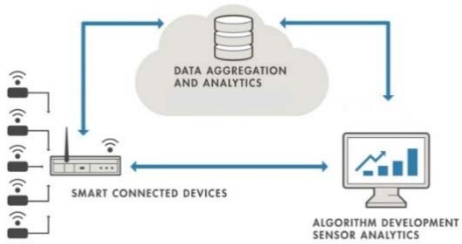

Fig. 8. ThingSpeak Cloud Platform

A. Power Factor Influence

The effect of power factor was examined by carrying out experiments on a 220V/24V, 0.25 kVA step-down transformer. Figure 9 shows the Lissajous curves of the transformer operating at three different power factors: 0.8 leading, 0.8 lagging and 0.9 leading. As it can be observed from Fig. 9, there is only minor change between the curves. Thus, it can be concluded that the power factor has negligible influence on the Lissajous curve.

B. Load Influence

The load influence was examined by conducting experiments on the same transformer. The primary side of the transformer was connected to a constant power supply, whereas the load was adjusted using the rheostat. The measurements were taken for three different loads and results shown in Fig. 10. It can be observed that the load variation only affects the magnitude of the curve. The change in the load factor has a negligible effect on the rotation or graph's angle.

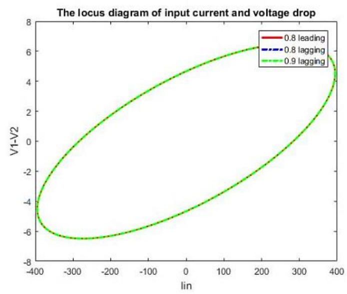

Fig. 9. The impact of power factor on the Lissajous curve

C. Fault

The influence of the fault on the Lissajous graph was examined by carrying out an experiment on different models of transformer. Four transformers were used to conduct four case studies. The experimental results are provided in Table II which shows the measurements for normal and faulty transformers. It can be seen that the input current and input-output voltages have changed after the short circuit test. This, in turn, resulted in variation of the Lissajous curve. Its size and angle have been altered due to the deformations caused by the short circuit test.

I. Case 1

In the first experiment, a 220V/24V, 0.25kVA step-down transformer was tested with an *RL* load, where R and X_L were 3 kΩ and 2.2 kΩ, respectively. From Figure 11, it can be seen that the transformer was not seriously damaged by the short circuit test. Even though a small number of windings were shorted, there is still noticeable change in its rotation angle. Moreover, despite the fact that the load was the same for healthy and faulty conditions, there is an increase in curve size. Hence, change of locus area and its rotation angle can reveal early state of transformer winding deformation.

TABLE II. Measurement results

Case	*State*	*V_{in} (volts)*	*V_{out} (volts)*	*I_{in} (amps)*
1	healthy	24.00	213.00	2.16
	faulty	23.50	210.5	3.30
2	healthy	36.00	151.00	4.30
	faulty	35.4	170.00	4.83
3	healthy	36.01	220.00	1.10
	faulty	32.70	190.90	1.54
4	healthy	218.90	208.50	2.92
	faulty	218.20	190.50	5.30

II. Case 2

In the second experiment, a 36V/220V, 1kVA step-up transformer was tested with a total load of 194 Ω. The results can be observed from Fig. 12. The locus diagram in this test object is slightly different to what demonstrated in the last test object as the size of the objects is different. However, it follows the same pattern. Introduction of fault into the transformer winding resulted in an increase of Lissajous curve area and change in its rotational angle.

III. Case 3

In the third experiment, a 36V/220V, 0.4kVA step-up transformer was tested with an *RL* load, where *R* and X_L were 2 kΩ and 2.2 kΩ, respectively. Figure 13 shows that the transformer was not significantly damaged by very fast short circuit application. However, a slight rotation can be observed from the graph. Moreover, there is a substantial increase in the locus area. Although there is a slight deformation in the transformer winding, it still can operate.

IV. Case 4

The last experiment was conducted on a 220V/220V, 0.63 kVA transformer. Figure 14 illustrates the Lissajous graph for the normal and faulty transformer condition at the constant load of 75 Ω. As it can be observed, there is a huge difference in the locus diagram after the short circuit. The area and rotation angle of the faulty transformer is significantly different as compared to the fingerprint data for healthy transformer condition. This variation in the locus diagram can be used to detect the fault in transformer windings and provide an immediate real-time reaction to prevent further transformer damage.

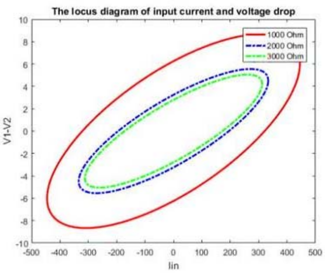

Fig. 10. Load effect on Lissajous curve

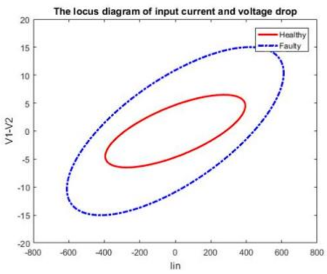

Fig. 11. Lissajous curve for Case 1

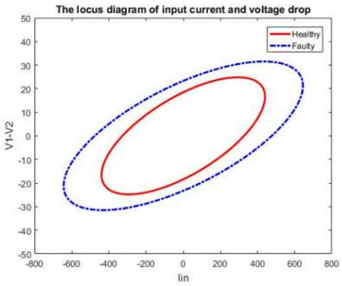

Fig. 12. Lissajous curve for Case 2

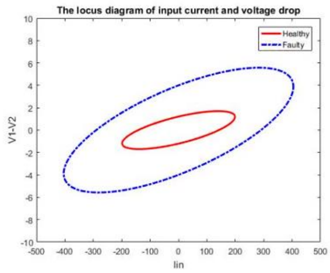

Fig. 13. Lissajous curve for Case 3

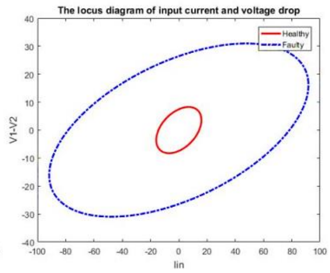

Fig. 14. Lissajous curve for Case 4

VI. Discussion

The input and output voltage and current parameters of the transformer are used to construct the Lissajous curve. This diagram is used to detect transformer winding deformation. Specifically, it identifies an inter-disk fault in the system. As the Lissajous diagram is constructed based on the current and voltage measurements, it is very susceptible to power change. Small fluctuations in the system may affect the figure, hence, the analysis. Therefore, it is essential to identify external factors that influence the figure and determine their effect on the diagram. In this paper, the sensitivity of the figure on two main factors has been considered. Particularly, effects of power factor and load variation. Fig. 9 illustrates power factor influence on the diagram. It presents the Lissajous diagrams for three distinct power factor ratings. Even though the power factor readings are different, the V-I locus diagrams of the transformer are the same. Hence, power factor does not have an effect on the Lissajous curve.

The influence of the load can be observed from Fig. 10. It illustrates Lissajous diagrams for transformer load of 1 kΩ, 2 kΩ, and 3 kΩ. The area of the curve decreases with the increase of the load. The reason is that the current reduces when the resistance of the system increases. Even though major and minor diameters of the V-I locus diagram change, its rotation angle remains almost the same. Hence, it can be concluded that load variation influences only the area of the ellipse and the rotation angle is not susceptible to that change.

The summary of readings for faulty and healthy transformers is given in Table II. From that, it can be seen that the input and output voltage and current parameters change significantly. This, in turn, resulted in variation of the Lissajous diagram. Figures 11-14 illustrate V-I locus curve for healthy and faulty transformers. As it can be observed, there is a change both in the area and rotation angle of the ellipse. After short circuit, the major and minor diameters of the figure considerably increase, and ellipse rotates in an anti-clockwise direction. This shift in angle plays a critical role in identifying the fault. As it was discussed previously, the load variation influences only the area of the ellipse. Hence, area change does not contribute to the fault case unless there is an overcurrent in the system. On the other hand, change in the area and rotation angle indicates presence of a fault. These results totally align with theoretical expectations. Hence, the Lissajous diagram can be used to discriminate fault in the transformer winding.

The system has not been trialled in the field yet. However, the test can be applied to higher voltage transformers as well as small transformers. The result and analysis of the Lissajous test is not susceptible to the type and size of the transformer.

The main disadvantage of the Lissajous curve is its accuracy. This method is not as accurate as the FRA method which requires expensive test equipment. As Lissajous figure is susceptible to the voltage and current values, it may not detect small internal turn-to-turn faults where the voltage drop is not apparent.

The research can be further extended by analyzing other types of fault. This paper mainly focuses on identification of inter-disk faults. Inter-disk fault contributes to 80% of transformer failure. However, there are other faults like axial displacement, buckling stress, leakage fault and disk space variation fault. These faults have not been simulated due to constraints in physical setup and experimental design. However, according to literature review and theory, it is expected that after each fault, the V-I locus diagram experiences some particular change. These faults can be simulated and tested. The algorithm can be updated to identify the type of fault. This extra feature adds value to the system and enhances its functionality. The recordings can be stored in the cloud system. The information regarding type and frequency of the fault can be used for statistics. This data, in turn, will be valuable in developing preventive measures for transformer winding deformation.

VII. Conclusion

This study proposed a system which was able to perform real-time diagnosis of transformer winding deformation. Current real-time evaluation techniques and also offline methods to identify winding distortion was discussed. In the proposed design, cloud computing was incorporated into the system to enable online access to the transformer data. A circuit with transformer and rheostat was designed to test cloud platform. Current and potential transformers were integrated into the system to measure current and voltage difference and to send measurement results to the cloud system through Ethernet shield installed on an Arduino Mega microcontroller. Besides, ammeter and voltmeter were connected to the circuit to obtain current and voltage drop measurements and to compare them with cloud readings. The instrument transformers and measuring instruments revealed the same results. The Lissajous curve was drawn over the cloud using these current and voltage drop measurements. This curve was compared to the fingerprint curve for the healthy transformer to detect the fault. The results of the analysis were stored over cloud platform for later access. An application was developed on Android Platform to instantly display attained results on a mobile device. Current and voltage drop readings and transformer status were available via application over the mobile application. In case of a fault, the system activates the protection relay to trip the circuit and prevent the transformer from further damage.

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