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An IoT-Enabled Edge Intelligence Framework for Real-Time Fault Monitoring in Power Distribution Networks

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ABSTRACT

To ensure reliable operation of the distribution system, feeder faults, transformer stress and abnormal operating conditions need to be detected in a timely fashion. This paper proposes an edge-intelligent monitoring and real-time communication system for a three-phase 11 kV/415/230 V power distribution system, which is based on IoT. The proposed system combines the sensing of the voltage, current, active power and the LT-side and transformer-side temperature sensors with local decision logic based on thresholds and remote communication through a dedicated mobile phone and control-room interface. A mathematical model was derived to explain the following: phase voltage, phase current, power utilization, voltage deviation, overcurrent, imbalance and temperature state. The system was tested using scenarios in MATLAB/Simulink representing various operating conditions such as overloading, undervoltage, overvoltage, overheating, line-fault and normal operating conditions. The simulation results showed that the monitoring logic maintained a normal state correctly without triggering false alarms, generated alarm at warning stage when progressive overload occurred, triggered alarm at undervoltage and over-voltage at 8.0 s, and generated the alarm in the line-fault state when the voltage collapsed in combination with current surge, and triggered the alarm at warning state during the overheating simulation. Under the line fault condition, the maximum current was increased to 203.43A as compared with 94.48A under normal condition, and the overheating condition reached 98.34 °C. The results show that the integration of electrical and thermal monitoring with edge-level decision logic leads to a better situation awareness and quicker operator response. The proposed framework provides a scalable smart distribution monitoring platform and a future enhancement path towards implementation with hardware, event logging, fault-location techniques and machine-learning based fault classification.

Introduction

Background and Motivation

The reliable operation of electric power distribution systems is essential for maintaining continuity of service to residential, commercial, and industrial consumers. In practical utility networks, distribution lines and transformers are exposed to a wide range of disturbances and abnormal operating conditions, including single line-to-ground faults, line-to-line faults, three-phase faults, overload, overvoltage, undervoltage, phase imbalance, and thermal stress. When such events are not detected and communicated in a timely manner, they can lead to equipment degradation, feeder outages, increased maintenance costs, and reduced service reliability. Recent review literature has shown that fault diagnosis in modern electrical distribution networks has become an increasingly important research area because smart distribution systems now require faster, more accurate, and more intelligent monitoring capabilities than traditional inspec-tion-based practices can provide [1-2]. At the same time, the rapid development of the Internet of Things (IoT) has created new possibilities for condition monitoring of distribution assets. New IoT monitoring platforms allow for the real-time, on-the-field acquisition of operating information into a local dashboard, the cloud, or into a control room for supervision and response. In the case of transformers, systematic re-view of evidence reveals the most prevalent monitored parameters are voltage, current, temperature and associated health indicators, while the use of IoT frameworks is gaining traction to support predictive maintenance, minimize downtime and enhance grid reliability [2,3]. For instance, some recent studies on transformer monitoring using the Internet of Things (IoT) have shown the efficacy of voltage, current, oil temperature, body temperature, and load-related indicator sensing, which are mostly focused on the condition of the transformer, but not on a larger monitoring system of the feeder-transformer [3]. Simultaneously, the recently conducted distribution-network fault diagnosis research has shown that the research is increasingly into the fusion of signal processing and artificial intelligence, for the detection and classification of various types of faults in a smart distribution network [4,5]. This division of transformer monitoring and feeder fault intelligence puts a practical constraint on utilities. In real-world 11 kV/415/230 V distribution systems, operators often require a unified platform that can simultaneously observe electrical and thermal operating conditions, detect abnormal events, and communicate both routine parameters and emergency alarms to designated personnel.

Literature Review

A monitoring system that only reports transformer temperature, for example, may not provide sufficient situational awareness when a feeder fault, load imbalance, or phase-specific overcurrent occurs elsewhere in the distribution chain. Likewise, a fault-classification algorithm that performs well in simulation may still have limited field usefulness if it is not integrated with communication and supervisory functions. Recent reviews of machine-learning applications in power-system protection and emergency control likewise emphasize that data-driven methods must ultimately be integrated into practical protection and monitoring environments rather than treated as isolated analytical tools [6,7]. For this reason, there is a clear need for an integrated monitoring architecture that combines real-time sensing, local decision logic, and remote com-munication for distribution systems. Such a system should be capable of measuring three-phase current, voltage, power, and transformer or LT-side temperature, while also identifying major fault and abnormality conditions and transmitting alerts to both a dedicated mobile phone and a con-trol-room interface. The literature on IoT-based transformer monitoring confirms the technical feasibility of low-cost real-time supervision, while the literature on AI-enabled fault diagnosis confirms the growing importance of intelligent disturbance recognition in smart grids [8]. However, the combination of these two functions within one coherent and implementation-oriented platform remains comparatively underdeveloped in the published literature. Accordingly, this study proposes an IoT-enabled fault monitoring and real-time parameter communication system for power distribution system lines and distribution transformers. The proposed framework is intended for a three-phase 11 kV/415/230 V distribution environment and is designed to monitor line and transformer parameters continuously, detect important fault con-ditions, and communicate this information in real time to dedicated users through an IoT-enabled communication layer. This study is organized as a smart distribution monitoring framework that combines sensing, event detection and remote supervisory communication in one structure. This positioning is in line with the recent research trends towards more practical, scalable and intelligent architectures for power-system monitoring and protection [9].

Contribution

- This study presents the design and testing of the fault monitoring and real-time parameter communication system using IoT for power distribution lines and distribution transformers in a three-phase 11 kV/415 V/230 V environment. The following are specific contributions:
- To develop an integrated IoT monitoring architecture for a three-phase 11 kV/415/230 V distribution system;
- To monitor real-time current, voltage, active power and transformer/LT-side tem-perature;
- To detect line and transformer abnormalities, including overload, voltage variation, overheating and fault events;
- To communicate operating parameters and fault alarms to a dedicated mobile phone and control-room interface;
- To establish a scalable framework that can be extended with hardware deployment, event logging and intelligent fault classification.

Materials and Methods/Methodology

Proposed IoT-Enabled System Architecture

The proposed system was designed as a layered cyber-physical monitoring framework. It consists of a sensing layer, local processing layer, communication layer and supervisory interface layer. The sensing layer acquires three-phase voltage, current and transformer/LT-side temperature. The local controller processes these measurements, calculates electrical indicators and compares them against operational thresholds. The communication layer transmits normal status updates and abnormal-event alarms through Wi-Fi, GSM/GPRS or another IoT-enabled interface. The super-visory layer displays information on a dedicated mobile phone and control-room screen. Figure 1 presents the integrated architecture of the proposed system.

Data Flow and Operating Principle

The monitoring process follows a continuous loop of sensing, processing, decision-making and communication. Phase voltages, phase currents and temperature are sampled by the meas-urement subsystem and sent to the controller. The controller computes RMS voltage, RMS current, active power, apparent power, utilization index, voltage-deviation state, overcurrent state and thermal state. If all variables remain within permissible limits, the system sends routine status updates. If any variable crosses warning or critical thresholds, the controller generates an event label and triggers the IoT communication layer. Figure 2 summarizes the data-flow logic used in the proposed framework.

The proposed system is designed as an IoT-enabled monitoring and fault communication framework for a three-phase 11 kV/415/230 V power distribution system. The primary purpose of the system is to provide continuous monitoring of electrical and thermal parameters, detect ab-normal operating conditions and line faults, and communicate this information in real time to a dedicated mobile phone and control-room center. The proposed architecture combines sensing devices, a local processing and decision-making unit, a fault notification module, and an IoT communication layer within a single operational framework. This design approach will align with the prevailing transformer health monitoring smart-grid supervision design trends, emphasizing the importance of real-time data collection, remote condition awareness, and communication-enabled response [10]. The design of the proposed system differs from the traditional monitoring system which relies heavily on field inspections or independent protection devices. It monitors line voltage, line current, active power, and transformer or LT-line temperature under normal operating conditions. At the same time, it is structured to recognize abnormal conditions such as overcurrent, overvoltage, undervoltage, overload, transformer overheating, and line fault events. Once an abnormal event is detected, the system sends the relevant information through the IoT communication layer to both a mobile user and a control-room endpoint. In this way, the architecture supports both continuous operational visibility and event-driven alarm reporting, which the literature identifies as an important re-quirement for practical deployment in modern distribution networks [11,12].

System Architecture

The proposed system architecture consists of four major layers: the sensing layer, the local processing layer, the communication layer, and the supervisory interface layer.

Sensing Layer

The sensing layer is responsible for acquiring real-time electrical and thermal measurements from the distribution network. In the proposed system, voltage sensors are connected to the three phases of the low-voltage side of the 11 kV/415/230 V distribution transformer to measure phase voltages continuously. Current sensors are placed on each phase to monitor line current magnitude and detect abnormal loading or fault-related overcurrent conditions. A temperature sensor is in-stalled at the transformer body or appropriate thermal monitoring point to capture temperature variation associated with loading, fault stress, or incipient thermal abnormality. Based on the literature of the transformer and distribution monitoring, the selection of current, voltage and temperature as the main sensed parameters is justified since these are generally considered as the most practical and informative parameters for real-time condition monitoring [13]. The measured signals serve as a building block for both normal monitoring and abnormal event detection. Since the intended work is to be of an implementation-oriented and scalable nature, the sensing arrangement is designed to be based on the physically measurable quantities that can be obtained from field-available sensor devices and not solely on the virtual results of simulations.

Local Processing Layer

The local processing layer is the brain in the proposed monitoring system. This layer is realized by using a microcontroller or edge processing chip, like an ESP32 or a NodeMCU or similar circuit board that is embedded in the device that gets the raw sensor data and processes it on the fly. There are three main functions the local controller will carry out. First, it takes and processes sensor data at fixed time intervals. Secondly, it calculates the necessary electrical parameters, including the phase currents, the phase voltages and the active power. Third, it compares these parameters against pre-defined operational thresholds to determine whether a fault or abnormal event has occurred. The use of local intelligence is important because many practical monitoring systems require imme-diate preliminary decision-making before cloud transmission or control-room interpretation. Re-cent literature on power-system protection and intelligent monitoring has emphasized the need for such local or edge-level processing, particularly where rapid response, communication efficiency, and operational robustness are important [14]. In the proposed system, the local processing layer therefore serves as the first decision point for abnormality recognition.

Communication Layer

The communication layer is designed to transmit both routine operating data and abnor-mal-event alerts to remote users. In the proposed system, this layer may employ Wi-Fi, GSM, GSM/GPRS, or equivalent IoT-enabled communication technology depending on field availa-bility and deployment requirements. Under normal conditions, the system periodically sends line and transformer parameters to the supervisory interface. Under abnormal conditions, the commu-nication layer immediately sends a fault message or alarm signal to the dedicated mobile phone and control center. This communication structure is based on the understanding that a monitoring system is not operationally complete unless measured information is delivered to decision-makers in usable form. The transformer-monitoring and substation-monitoring literature has repeatedly shown that remote alerting significantly improves the usefulness of condition-monitoring systems by reducing response delay and supporting early maintenance action [15,16]. Accordingly, the present study treats communication as an essential system component rather than as an optional add-on.

Supervisory Interface Layer

The user-facing endpoints in receipt of and displaying information of monitored are included in the supervisory interface layer. Within the proposed framework, two main endpoints are considered: a dedicated mobile phone and a control-room monitoring interface. The mobile endpoint allows for remote alerts and monitoring of basic operating conditions by authorized field personnel or for maintenance. The control-room interface will give a more comprehensive supervisory perspective and can show trends of parameters, alarm notifications of abnormal events, and phase-level information for system evaluation. Mobile and control room supervision provide added flexibility in the operation. Mobile endpoints are particularly effective for providing instant notifications to individuals, and control-room interfaces are effective for decision-making and event logging in a centralized manner. One of the advantages of the architecture proposed in this document is its dual-endpoint design, as some previous systems have only simple mobile alerts or simple dashboards, but none both in a coordinated monitoring system.

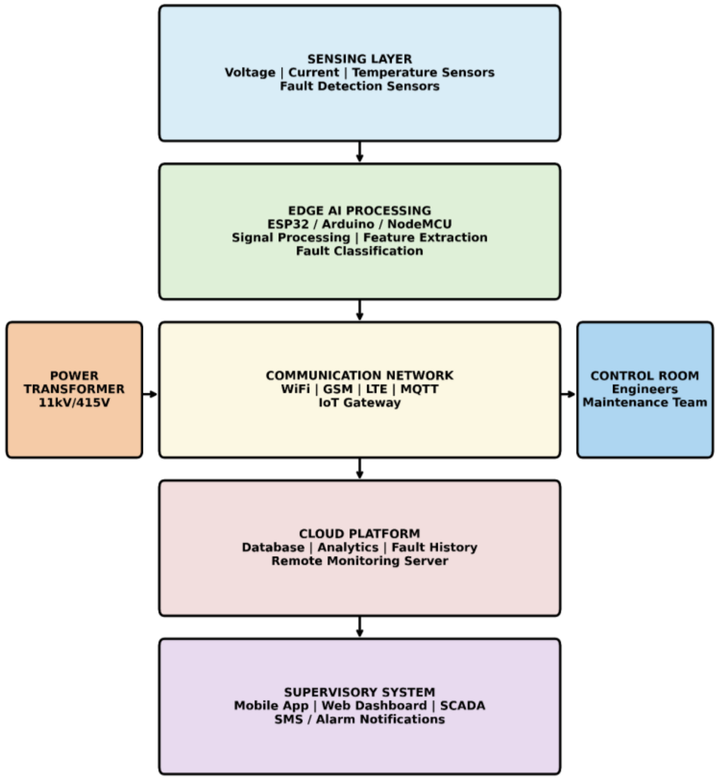

Figure 1. IoT-enabled fault monitoring system architecture for power distribution lines and distribution transformers.

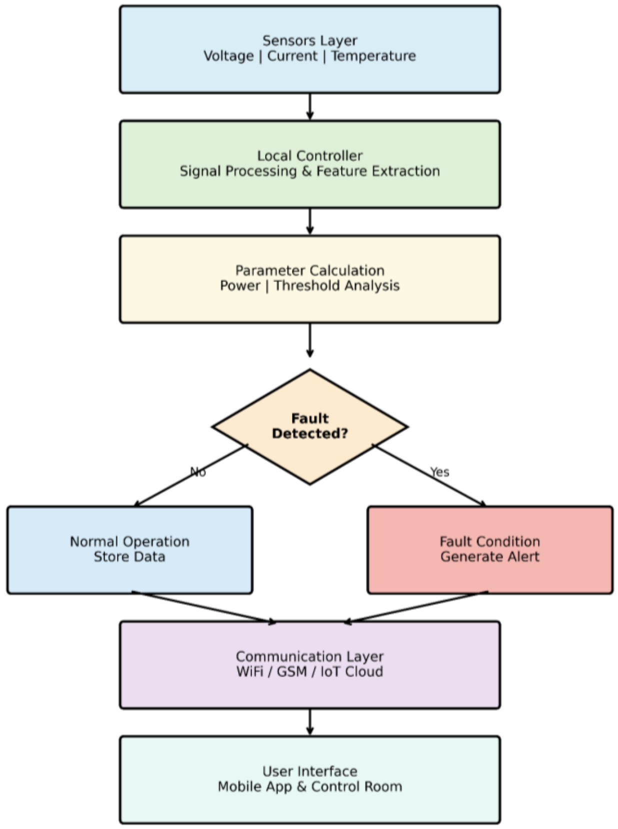

Figure 2. Data-flow architecture of the proposed IoT-enabled fault monitoring system.

Mathematical Monitoring Model

The three phase voltages taken at low voltage side of the transformer are $\boldsymbol{V_a}$, $\boldsymbol{V_b}$, and $\boldsymbol{V_c}$. These are the maximum and/or RMS values of the three phases. RMS values are used for monitoring since they give a stable representation of the effective operating voltage.

The RMS phase voltage of each phase can be written as:.

The RMS phase voltage for each phase can be expressed as:

$$\boldsymbol{V_{a,\mathrm{rms}}} = \sqrt{\frac{1}{T}\int_0^T v_a^2\,(t)\,dt} \quad (1)$$
$$\boldsymbol{V_{b,\mathrm{rms}}} = \sqrt{\frac{1}{T}\int_0^T v_b^2\,(t)\,dt} \quad (2)$$
$$\boldsymbol{V_{c,\mathrm{rms}}} = \sqrt{\frac{1}{T}\int_0^T v_c^2\,(t)\,dt} \quad (3)$$

where $\boldsymbol{T}$is the observation period and $\boldsymbol{v_a(t)}$, $\boldsymbol{v_b(t)}$, and $\boldsymbol{v_c(t)}$are the instantaneous phase voltages.

The embedded implementation samples the three-phase voltages and numerically computes the RMS voltage values within a specified window. These RMS voltages are then compared with the rated operating range. Any phase voltage exceeding the set limits will trigger an over voltage or under voltage event in the controller. In distribution systems, the importance of voltage based monitoring is especially great because long periods of voltage deviation can also impact the performance of equipment on the consumer side and transformer health [17,18]. Let the phase currents measured in the three conductors be represented by $\boldsymbol{I_a}$, $\boldsymbol{I_b}$, and $\boldsymbol{I_c}$. As with voltage, the RMS current values are used for practical monitoring.

The RMS current values are given by:

$$\boldsymbol{I_{a,\mathrm{rms}}} = \sqrt{\frac{1}{T}\int_0^T i_a^2\,(t)\,dt} \quad (4)$$
$$\boldsymbol{I_{b,\mathrm{rms}}} = \sqrt{\frac{1}{T}\int_0^T i_b^2\,(t)\,dt} \quad (5)$$
$$\boldsymbol{I_{c,\mathrm{rms}}} = \sqrt{\frac{1}{T}\int_0^T i_c^2\,(t)\,dt} \quad (6)$$

where $\boldsymbol{i_a(t)}$, $\boldsymbol{i_b(t)}$, and $\boldsymbol{i_c(t)}$ are the instantaneous phase currents. These present values will be used to check the loading conditions, abnormal overcurrent, phase imbalance and possible line fault behavior. A rapid rise in current in practical systems may be a fault or a very large disturbance, but if the rise is maintained then the problem may be that there is overload or abnormally high loading of the system. One of the most informative indicators of feeder stress is current, which is why it is used as a key component in the proposed system's monitoring logic [18,19]. The real or active power of a 3-phase system can be determined from the phase voltage, phase current and power factor. Considering the balanced operating assumptions, the total active power Pcan can be estimated as:

$$\boldsymbol{P = \sqrt{3}\,V_L I_L \cos\phi} \quad (7)$$

where $\boldsymbol{V_L}$is the line voltage, $\boldsymbol{I_L}$is the line current, and $\boldsymbol{\cos\phi}$is the power factor.

For a more phase-wise representation, total active power may also be written as:

$$\boldsymbol{P = P_a + P_b + P_c} \quad (8)$$

with

$$\boldsymbol{P_a = V_a I_a \cos\phi_a, P_b = V_b I_b \cos\phi_b, P_c = V_c I_c \cos\phi_c} \quad (9)$$

where P_a, P_b, and $P_c$are tthe powers in the three phases, respectively. Power monitoring is crucial as it gives a fuller picture of operation than voltage or current alone. For instance, a feeder could be distorted or have an excessive current due to an increase in demand for power service, not because of a fault; however, the power, voltage and current could all be utilized for a more discriminating interpretation. For the proposed monitoring system, therefore, active power is fed into the system as an added indicator of overload and prolonged abnormal operating conditions.

The apparent power Sin the three-phase system is expressed as:

$$S = \sqrt{3}\, V_L I_L \qquad (10)$$

and the reactive power $Q$is:

$$Q = \sqrt{3}\, V_L I_L \sin\phi \qquad (11)$$

The main monitoring function of the proposed system is voltage, current, power and temperature but the apparent power calculation is also helpful when considering the utilisation of the load against the transformer/feeder capacity. The load utilization ratio $L_u$may be defined as:

$$L_u = \frac{S}{S_{\text{rated}}} \qquad (12)$$

where $S_{\text{rated}}$is the rated apparent power capacity of the transformer or monitored feeder section.

If $L_u$exceeds unity for a sustained period, the system may classify the condition as overload. The formulation is similar to the typical conditions of transformer and feeder monitoring, in which the operating values are evaluated in relation to the rated capacity of the equipment. The measured phase voltages are compared with the nominal rated voltage to detect the overvoltage and undervoltage conditions. Let V_{nom}denote the nominal phase voltage. The voltage deviation for each phase can be defined as:

$$\Delta V_a = \frac{V_{a,\text{rms}} - V_{\text{nom}}}{V_{\text{nom}}} \times 100 \qquad (13)$$

$$\Delta V_b = \frac{V_{b,\text{rms}} - V_{\text{nom}}}{V_{\text{nom}}} \times 100 \qquad (14)$$

$$\Delta V_c = \frac{V_{c,\text{rms}} - V_{\text{nom}}}{V_{\text{nom}}} \times 100 \qquad (15)$$

If the voltage deviation is greater than the set upper or lower percentage, controller detects the abnormal voltage condition. Let the upper and lower acceptable voltage limits be $V_{\max}$and $V_{\min}$. Then: if $V_{x,\text{rms}} > V_{\max}$, an overvoltage event is declared, and, if $V_{x,\text{rms}} < V_{\min}$, an undervoltage event is declared, where $x \in \{a, b, c\}$. This voltage-deviation model facilitates abnormality detection in every phase and helps to detect poor power-quality conditions which may not be immediately apparent as classic line faults but could be operationally important. One of the most obvious signs of abnormal system behavior is overcurrent. Let I_{rated}denote the rated current of the monitored feeder or transformer. An overcurrent index for each phase can be expressed as:

$$OC_a = \frac{I_{a,\text{rms}}}{I_{\text{rated}}}, OC_b = \frac{I_{b,\text{rms}}}{I_{\text{rated}}}, OC_c = \frac{I_{c,\text{rms}}}{I_{\text{rated}}} \qquad (16)$$

If any overcurrent index exceeds a preset threshold OC_{th}, the controller flags an overcurrent condition: $OC_x > OC_{\text{th}} \Rightarrow$ Overcurrent event, where $x \in \{a, b, c\}$. To avoid false alarms caused by noise or brief transients, the condition is maintained for a short time interval τ. Thus, an overcurrent event is formally recognized only if: $OC_x > OC_{\text{th}}$for$t \geq \tau$. This persistence criterion helps to maintain stability of the monitoring system and is based on practical protection logic: very short variations are not necessarily considered as fault conditions. A general fault condition could then be considered when the fault current is observed to rise rapidly and the voltage is observed to fall significantly, particularly in one or more phases. Therefore the approximate fault condition is simplified to:

$$\boldsymbol{F_x} = \begin{cases} \mathbf{1}, & \text{if } \boldsymbol{I_x} > \boldsymbol{I}_{\text{fault,th}} \text{ and } \boldsymbol{V_x} < \boldsymbol{V}_{\text{fault,low}} \\ \mathbf{0}, & \text{otherwise} \end{cases} \qquad (\mathbf{17})$$

where $\boldsymbol{F_x} = \mathbf{1}$indicates a probable fault state in phase $\boldsymbol{x}$. It is just a nice logic for systems in which the behavior of feeder protection and monitoring should be defined on simple embedded rules, as is the case in implementation-oriented systems.Three-phase distribution systems may experience certain abnormal operating conditions that can be detrimental to the system, such as phase imbalance, which can result in losses, equipment overheating and power quality degradation. The imbalance factor is a simple current imbalance and can be defined as:

$$\boldsymbol{I}_{\text{avg}} = \frac{\boldsymbol{I_a} + \boldsymbol{I_b} + \boldsymbol{I_c}}{\mathbf{3}} \qquad (\mathbf{18})$$

$$\textbf{Imbalance}_{\boldsymbol{I}} = \frac{\max(|I_a - I_{\text{avg}}|, |I_b - I_{\text{avg}}, I_c - I_{\text{avg}}|)}{I_{\text{avg}}} \times \mathbf{100} \qquad (19)$$

Similarly, a voltage imbalance factor may be defined as:

$$\boldsymbol{V}_{\text{avg}} = \frac{\boldsymbol{V_a} + \boldsymbol{V_b} + \boldsymbol{V_c}}{\mathbf{3}} \qquad (\mathbf{20})$$

$$\textbf{Imbalance}_{\boldsymbol{V}} = \frac{\max(|V_a - V_{\text{avg}}|, |V_b - V_{\text{avg}}|, |V_c - V_{\text{avg}}|)}{V_{\text{avg}}} \times \mathbf{100} \qquad (21)$$

The controller detects a phase-imbalance event when either imbalance factor is greater than a predetermined value. This type of detection is also beneficial because certain distribution anomalies can not be detected as a significant fault but are still a sign of an unhealthy feeder or load. In the case of transformers, thermal monitoring is especially significant as this raises the likelihood of insulation aging and failure due to the extended heating period. Let Trepresent the temperature of a measured transformer or LT-line. The temperature monitoring logic is direct temperature comparison with safe operating temperatures.

If $\boldsymbol{T}_{\text{safe}}$denotes the normal upper temperature limit and $\boldsymbol{T}_{\text{crit}}$denotes the critical temperature threshold, then: if $\boldsymbol{T} \le \boldsymbol{T}_{\text{safe}}$, the transformer is considered to be operating within safe temperature range, if $\boldsymbol{T}_{\text{safe}} < \boldsymbol{T} < \boldsymbol{T}_{\text{crit}}$, the system identifies a thermal warning state, if $\boldsymbol{T} \ge \boldsymbol{T}_{\text{crit}}$, the system identifies an overheating event. This can be written formally as:

$$\text{Thermal State} = \begin{cases} \text{Normal}, & \boldsymbol{T} \le \boldsymbol{T}_{\text{safe}} \\ \text{Warning}, & \boldsymbol{T}_{\text{safe}} < \boldsymbol{T} < \boldsymbol{T}_{\text{crit}} \\ \text{Critical}, & \boldsymbol{T} \ge \boldsymbol{T}_{\text{crit}} \end{cases} \qquad (22)$$

This thermal-state logic can be used in real-time alarm generation and can also help with predictive maintenance decisions because the system can differentiate between an early warning and critical overheating. The overall monitoring system is defined by event decision logic, which is the combination of the aforesaid indicators. Let the system state variable be denoted by $\boldsymbol{S_t}$, where:

$$\boldsymbol{S_t} \in \{\text{Normal, Warning, Fault}\} \qquad (\mathbf{23})$$

The state is calculated based on the current, voltage, power, imbalance and temperature at every sampling moment. When all the measured variables are within their allowable range, the system is said to be in the Normal state. It changes from Normal state to Warning state if any of the following conditions are detected: sustained overload, moderate voltage deviation, or thermal rise. It moves to the Fault state when one of the variables reach critical levels that are associated with the potential for a feeder fault, severe overcurrent, severe voltage collapse or critical transformer overheating. In simplified form:

$$\boldsymbol{S_t} = \begin{cases} \text{Normal}, & \text{if all monitored variables are within limits} \\ \text{Warning}, & \text{if at least one variable exceeds warning threshold} \\ \text{Fault}, & \text{if at least one variable exceeds fault threshold} \end{cases}$$

The state Normal to Warning or Fault triggers a controller communication trigger. This trigger is then passed to the IoT communication module for notification of the mobile endpoint and control center. This mathematical formulation is simple enough to be implemented in an embedded system, but has a clear decision structure to the proposed system. Let $\boldsymbol{C_t}$denote the communication status at time $\boldsymbol{t}$. Then:

$$C_t = \begin{cases} \mathbf{0}, & \text{no abnormal event detected} \\ \mathbf{1}, & \text{warning message transmitted} \\ \mathbf{2}, & \text{fault alarm transmitted} \end{cases}$$

If S_t = Normal, the system may send periodic status updates at predefined intervals. If S_t = Warning, the controller transmits a cautionary message to the designated interfaces. If S_t = Fault, the controller transmits an immediate high-priority alarm. This structure ensures that the communication burden remains efficient while preserving fast notification of critical events.

The mathematical model from this section will be the basis for converting raw data from the sensors into operational intelligence. The condition of the distribution system is characterized by voltage, current, power, apparent power, temperature and imbalance. Then, the rules based on the thresholds distinguish the normal operation from the warning and the fault. The resulting state variable determines the communication behavior of the IoT system and allows for timely communication with mobile and control-room users. The selected modeling approach is suitable for the study proposed due to the combination of the engineering clarity, embedded-system feasibility, and compatibility for future intelligent enhancement. It also reflects the direction of practical research on smart distribution monitoring, which is to use mathematically simple but operationally meaningful indicators as the basis for monitoring frameworks suitable for fields [20-22].

Simulation Model and Case Study Setup

Purpose of the Simulation Study

The aim of the simulation study is to assess the functional performance of the proposed fault monitoring and real-time communication with parameters system using IoT under normal and abnormal operating conditions. The proposed framework incorporates electrical monitoring, event detection, and communication via the Internet of Things, therefore the simulation environment should reflect the electrical characteristics of the distribution system as well as the monitoring logic that is programmed into the local controller. The case study is developed to mimic the 3-phase 11 kV/415/230 V distribution arrangement so that the real-time measurements can be captured, processed and interpreted for communication to the remote user.

This study employs a simulation-based validation approach since the majority of the recent diagnosis studies for power system faults and the intelligent monitoring for power system are based on controlled scenarios to investigate the power system's response under various fault conditions before field deployment (Cao et al., 2024; Porawagamage et al., 2024). In this case the simulation is the first step of the evaluation and becomes a repeatable foundation for testing the resilience of the suggested architecture.

Distribution System Under Study

The test system studied in this paper is a three-phase 11 kV medium-voltage feeder connected to a three-phase 11 kV/415 V distribution transformer that powers a low-voltage (415 V/230 V) distribution network. The transformer provides a balanced and moderately varying load characteristic that represents practical load service in an LT.The transformer is furnished with a balanced and moderately varying load characteristic, typical of practical load service in an LT. The monitoring system is installed on the transformer and LT side, where the phase voltage, phase current, power and temperature can be monitored continuously.

Choosing an 11 kV/415/230 V configuration is suitable since it is a common configuration in practical distribution networks and is matched to the actual operating context of the study proposed. This makes the research more "how to" oriented than studies targeting abstract benchmark feeders in the absence of a distribution-utility context.

The system consists of a 3-phase 11 kV source that represents the upstream distribution feeder, a step-down distribution transformer of 11 kV/415 V, an LT-side 3-phase load network, current and voltage measurement blocks on the low-voltage side, a temperature monitoring block to represent the thermal behavior of the distribution transformer, a controller block that implements the monitoring logic, and an IoT-event emulation block that represents the message transmission to the mobile phone and the control center.

Assumptions of the Simulation Model

To keep the simulation both realistic and computationally manageable, several assumptions are made in the case study.

First, it is assumed that the source at the top of the line, the 11 kV source, is stable under normal operating conditions, except for intentional fault events. Second, the transformer is, respectively, modeled as an ideal or practical three-phase step-down transformer with standard impedance and load transfer behavior. Third, it is assumed that the sensors are accurate enough to be used in the controller's processing for the measurements of phase voltage, phase current and temperature. Fourth, it is assumed that the communication layer can deliver the message once the controller creates an event, although the time to transmit the message can be modeled as a small communication delay. Fifth, the system is tested mainly as an event recogniser and communicator triggering system, not as one concerned with detailed hardware aspects of electromagnetic transients.

Summary of the Case Study Setup

In summary, the case study is built around a realistic three-phase 11 kV/415/230 V distribution configuration that includes a medium-voltage feeder, a step-down transformer, an LT load network, a sensor layer, a local controller, and an IoT communication mechanism. The simulation evaluates the proposed system under normal operation, overload, overcurrent, voltage abnormality, overheating, and line-fault scenarios. The study design allows the integrated behavior of monitoring, decision-making, and communication to be assessed systematically.

This simulation setup provides the operational basis for the results presented in the next section. It also strengthens the implementation relevance of the proposed work by showing how the architecture would behave in a practical distribution-monitoring context rather than in a purely theoretical environment.

Simulink Model Title

The proposed architecture was evaluated through a simulation-based case study representing a three-phase 11 kV source, 11 kV/415 V distribution transformer, LT-side load, fault insertion block, measurement block, monitoring controller, IoT communication block and display/data logging subsystem. MATLAB/Simulink with Simscape Electrical or an equivalent platform can implement this layered simulation. Figure 3 illustrates the top-level simulation structure, while Table 1 summarizes the main model components and their functions. Figure 3. Top-level Simulink structure of the proposed IoT-enabled monitoring and communication model.

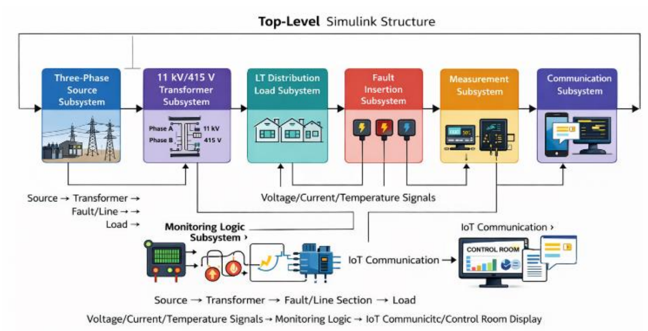

Figure 3. Top-level Simulink structure of the proposed IoT-enabled monitoring and communication model.

Table 1. Simulink model components and functions used in the proposed monitoring framework.

Component	Simulink block	Function
Source	Three-Phase Source	Represents the upstream 11 kV feeder supply
Transformer	Three-Phase Transformer (Two Windings)	Steps voltage from 11 kV to 415 V
Fault unit	Three-Phase Fault	Injects LG, LL, LLG and LLL fault conditions
Load	Three-Phase Parallel RLC Load	Represents LT consumer loading
Voltage sensing	V-I Measurement + RMS	Measures phase voltages
Current sensing	V-I Measurement + RMS	Measures phase currents
Thermal unit	Transfer Function / Signal Builder	Models transformer temperature
Monitoring controller	MATLAB Function block	Executes event-detection logic
IoT unit	Triggered subsystem	Generates alert communication
Display unit	Scope / Dashboard / To Workspace	Visualizes and stores results

The operating scenarios employed were normal operation, overload, undervoltage, overvoltage, overheating and line-fault condition. The false-alert immunity was tested under normal operation. Progressive load stress and thermal warning behavior overload tested. Power quality related fault detection by undervoltage and overvoltage. The system's ability to detect thermal deterioration was tested in the overheating scenario, while the line-fault scenario tested the system's ability to detect severe electrical disturbances. Evaluated indicators were: parameter monitoring, state classification, first alert time, total alert samples, warning/fault samples and communication triggering performance.

Results

The simulation results showed distinct parameter behavior under the six operating scenarios. The normal case remained within safe limits and produced no alarm. Overload increased current, power and temperature and generated a warning response. Undervoltage, overvoltage and line-fault scenarios generated immediate fault detection at 8.0 s. The overheating scenario produced a progressive transition from warning to fault, which reflects the gradual physical nature of transformer thermal stress. Table 2 summarizes the numerical outcomes.

Table 2. Summary of simulation outcomes across operating scenarios.

Scenario	$I_{\max}$ **A**	$V_{\phi,\min}$**V**	$P_{\max}$ **kw**	$T_{\max}$**°C**	t_{alert}**s**	**Detected Event**	**Alert Status**
Normal	94.48	225.55	57.01	49.15	-	None	Normal
Overload	141.08	225.43	82.57	76.17	15.5	Thermal Warning	Warning
Undervoltage	104.56	176.19	56.99	52.44	8.0	Undervoltage	Fault

Overvoltage	94.83	225.28	66.64	51.40	8.0	Overvoltage	Fault
Overheating	105.16	224.89	62.83	98.34	9.1	Thermal Warning	Warning to Fault
Line fault	203.43	79.64	61.52	70.43	8.0	Line Fault	Fault

Note. Results are based on the developed IoT-enabled monitoring simulation for a three-phase 11 kV/415/230 V distribution system. First alert time indicates the first simulation instant at which the controller generated a warning or fault communication trigger. The event-detection behavior confirmed that the proposed system did not produce nuisance alarms during healthy operation. Immediate and sustained fault detection was obtained for undervoltage, overvoltage and line fault, while overload produced a late-stage warning response due to gradual temperature rise. The overheating case produced both warning and fault samples, indicating staged thermal recognition. These results are summarized in Table 3.

Table 3. Event-detection performance of the proposed monitoring system.

Scenario	Total alert samples	Warning samples	Fault samples	Detection behavior
Normal	0	0	0	No abnormal event detected
Overload	6	6	0	Late-stage warning response due to gradual thermal rise
Undervoltage	81	0	81	Immediate fault detection at disturbance onset
Overvoltage	81	0	81	Immediate fault detection at disturbance onset
Overheating	70	43	27	Progressive transition from warning to fault
Line fault	81	0	81	Immediate and sustained fault detection

Note. Alert samples represent the number of simulation samples during which the communication status exceeded the normal condition. The abnormality window was imposed between 8.0 s and 16.0 s. The proposed controller used coordinated interpretation of voltage, current and thermal indicators rather than depending on a single measured quantity. This helped distinguish load stress from voltage abnormality, thermal deterioration and line fault. Table 4 provides a qualitative interpretation of the major parameter patterns.

Table 4. Interpretation of monitored parameter behavior under each scenario.

Scenario	Voltage behavior	Current behavior	Thermal behavior	System interpretation
Normal	Near rated value	Within allowable range	Safe operating range	Healthy operation without alert generation
Overload	Largely stable	Increased substantially	Gradual rise above warning threshold	Load stress identified before critical failure
Undervoltage	Deep phase-voltage depression	Moderate increase	Mild increase	Severe voltage abnormality classified as fault

Overvoltage	Voltage exceeds normal upper limit	Near normal	Mild increase	Sustained overvoltage classified as fault
Overheating	Near normal	Slight-to-moderate increase	Critical rise beyond fault threshold	Thermal deterioration captured progressively
Line fault	Severe voltage collapse	Very large surge	Moderate rise	Combined electrical fault identified correctly

The overheating response in Figures. 3-6 show that thermal stress may develop even when voltage remains close to nominal and current rises only moderately. This supports the need for transformer temperature monitoring in addition to current-based protection. In contrast, the line-fault response in Figures. 7-9 show severe voltage collapse and a large current surge, validating the composite electrical-fault logic used in the controller. The results demonstrate that an integrated IoT monitoring architecture can distinguish healthy operation, warning-level stress and fault-level abnormality in a practical 11 kV/415/230 V distribution context. The absence of false alerts during normal operation is important because frequent nuisance alarms reduce operator confidence. The immediate detection of undervoltage, overvoltage and line fault indicates that the threshold-based edge logic was sufficiently responsive for severe voltage and current dis-turbines. The overload and overheating cases are especially important because they show that not all abnormal conditions should be interpreted as instantaneous faults. Overload produced a delayed warning response due to progressive thermal rise, while overheating produced a warning-to-fault transition as temperature increased toward a critical region. This staged response is operationally meaningful because transformer thermal stress usually develops over time. The study also supports the broader direction reported in recent literature. IoT trans-former monitoring studies emphasize real-time sensing and remote supervision [2,3,5-8], while fault-diagnosis studies emphasize advanced event recognition in smart distribution systems [1,12-14]. Machine-learning approaches can further improve classification of complex faults [15-23], and high-impedance fault studies show that some events may require richer feature extraction than basic thresholds [24-28]. Nevertheless, the present results show that a physically interpretable edge-monitoring layer remains valuable as a first operational step because it is simple, transparent and feasible for embedded implementation. Compared with systems that only display raw sensor values or only classify faults offline, the proposed architecture links sensing, decision logic and communication. This integration is the main contribution of the manuscript. It allows routine parameter supervision and event-driven mo-bile/control-room alerting within one framework. Such communication integration is consistent with IoT monitoring studies showing the value of mobile dashboards, GSM/Wi-Fi notifications and control-room interfaces for reducing response delays [29].

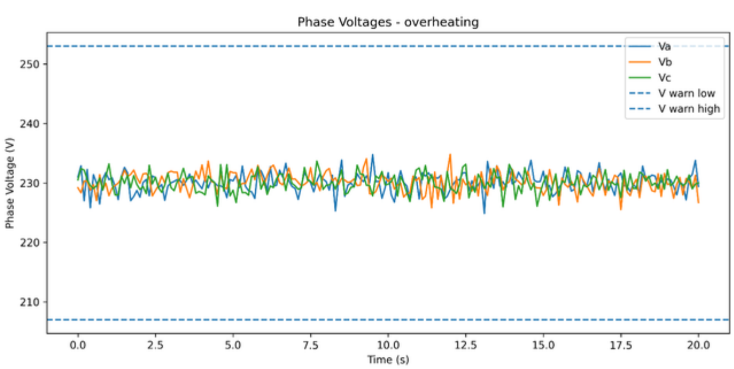

Figure 4. Representative overheating response: phase voltages remain close to nominal.

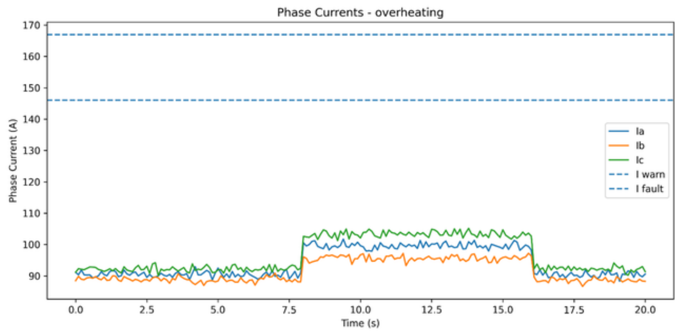

Figure 5. Representative overheating response: phase currents rise moderately.

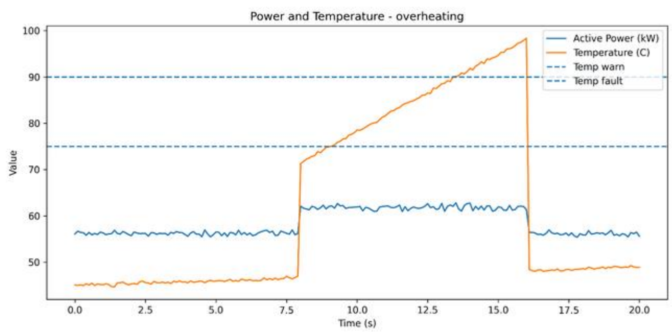

Figure 6. Representative overheating response: estimated transformer temperature rises beyond the critical threshold.

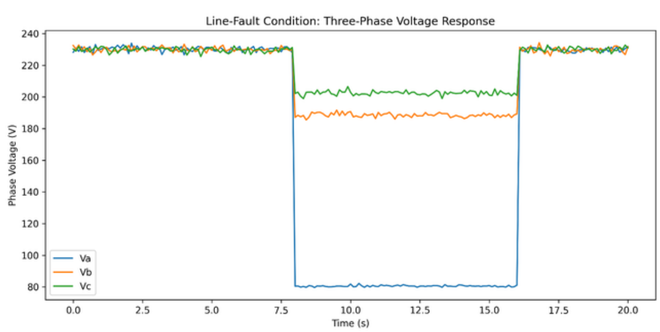

Figure 7. Representative line-fault response: phase voltage collapses during the fault window.

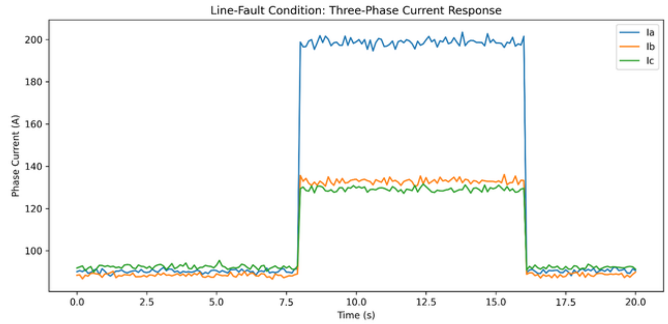

Figure 8. Representative line-fault response: current magnitude increases sharply.

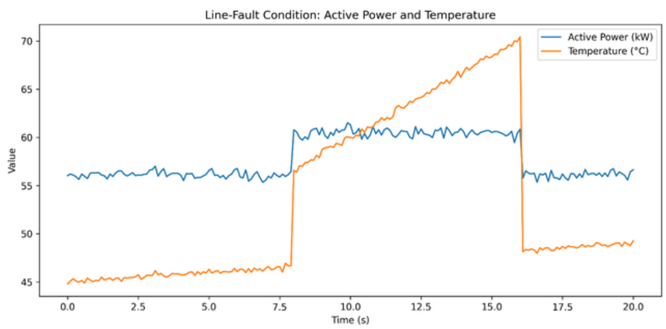

Figure 9. Representative line-fault response: the dominant abnormality remains electrical rather than thermal.

Conclusion and Future Work

This study transformed an idea of monitoring a distribution-line and transformer into an IoT-enabled, edge-intelligent framework of a 3-phase 11 kV/415/230 V system. The design proposed consisted of the incorporation of voltage, current, power and temperature measurement, mathematical monitoring logic, state classification and triggering of communication. Simulation results under six different scenarios showed that the controller remains stable under normal operation, generates warning behavior when the device is overloaded, detects the undervoltage and overvoltage status of the line immediately, and continuous thermal degradation during the overheating period. The framework thus offers a practical and scalable foundation for enhancing situational awareness of smart distribution networks. It has a major advantage in providing the feed-er-fault awareness, transformer condition monitoring and remote communication in one implementation-oriented architecture. Its usefulness in practice will be further enhanced with future hardware validation and intelligent fault-classification enhancement.

The study doesn't address the issue of simulation validation. The IoT layer was implemented in the form of event-based communication logic, not in the form of an actual GSM/Wi-Fi device, and the transformer temperature model was not the actual temperature of the transformer, but an estimate of its thermal condition. Threshold values were chosen for evaluation of the scenarios and should be adjusted to suit specific field equipment ratings prior to use. This model also emphasized wide-spread abnormal state detection and not specific fault-location and fault-type classification. These constraints suggest the need for the implementation and field testing of hardware before being adopted at the utility level.

A future work would be the incorporation of the system using voltage and current sensor, temperature sensor, an edge controller like ESP32/NodeMCU and a practical IoT platform. The communication layer should be tested for real latency, network failure and reliability of messages. The framework can be also extended by adding machine learning or hybrid machine-learning/rule-based classifiers for fault type, fault location and high-impedance fault recognition. Event logging and dashboard analytics in a long term manner would further enhance predictive maintenance and operational decision support.

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